THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Mixed Substrate Computation

Sensor Based Artificial Cognition for Architectural Design and Modification

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CHALMERS UNIVERSITY OF TECHNOLOGY
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ABSTRACT

A mutual relationship exists between activities and their physical environment. Change of circumstances in the built environment cause change of activities, and vice versa; change of activities cause changes of physical environment. How does information originating from activities influence the environment? And how does the environment provide relevant information for activities to take place?

Digital and material computation has — within architectural design — been used extensively to strengthen the capacity to build novel and more geometrically enhanced structures. However on large and small physical as well as long and short temporal scale there is only poor understanding of the activities and phenomena taking place in the built environment. In particular, a lack in understanding of the relationships between changes in physical conditions and changes of activities. The rationale behind implementations and modifications of the built environment is constituted by many actants simultaneously at play, mainly based on human heuristics, sensemaking and semantics.

Here we demonstrate how digital computation can be combined with material, morphological and other types of computation to create models of the past, current and future scenarios. The concept is coined *Mixed Substrate Computation* and relies heavily on successful *embodiment* and *embodied computation*.

A technology is needed for tracing, extracting and computing both embodied memory and data from activities residing in the environment on different spatial and temporal scales.

This thesis presents a set of methods that combine sensors and algorithms to a novel technique of perceiving activities and phenomena over time.. Consequently, a kind of artificial cognition is demonstrated able to detect recurrent phenomena and in turn perform predictions in seemingly chaotic situations.

This discovery can bring about a paradigm shift in design, taking us from our current situation where architects, designers and planners predict and design for future needs using their present day point-of-view, to a situation where design tools are able to learn from complex situations and predict future needs autonomously.

This capacity for perception and prediction contributes to the current discourse on mixed material and digital practices within architectural design — filling an increasingly widening gap between material and formal computation: the concept of embodiment. The idea of integrating body and soul—or the physical and the abstract—is a concept which is key for understanding the relationships between phenomena and matter.

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PUBLICATIONS INCLUDED

1: Nielsen, Stig Anton. »Physical Form Finding by Embedded Sensors: Using 'sensor chaining' in various temporal and spatial scales«. eCAADe 2013: Computation and Performance–Proceedings of the 31st International Conference on Education and research in Computer Aided Architectural Design in Europe, Delft, The Netherlands, September 18-20, 2013 18, Sep. 2013. p. 413-423

2: Nielsen, Stig Anton, and Alexandru Dancu. »Layered subsumption in intelligent material building systems«. TEI'14, Munich, Germany, Feb. 2014.

3: Nielsen, Stig Anton. »A process where performance drives the physical design«. Rethinking Prototyping, 2013. p. 615-626.

4: Nielsen, Stig Anton, and Alexandru Dancu. »Embodied computation in soft gripper«. Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction 3, Mar. 2014. p. 256-257.

5: Nielsen, Stig Anton, and Alexandru Dancu. »Propositional Architecture using Induced Representation«. What's the Matter? Materiality and Materialism at the Age of Computation, 2014. p. 297-312.

6: Nielsen, Stig Anton. »Propositional architecture and the paradox of prediction«. Archi-doct: The e-Journal for dissemination of doctoral research in architecture 4-Matter, Issue 2-2. ISSN 2309-0103. www.enhsa.net/archidoct, Feb 2015. p.72-84.

7: Dancu, Alexandru et al. »Emergent Interfaces: Constructive Assembly of Identical Units«. Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems 18, Apr. 2015 p. 451-460.

8: Savov, A., Tessmann, O. and Nielsen, S.A., »Sensitive Assembly: Gamifying the design and assembly of façade wall prototypes«. International Journal of Architectural Computing, 14(1), 2016. p. 30-48.

9: Nielsen, Stig Anton. »Event Series Prediction as Decision Support System at Fast Paced Processes« Proceedings of IMCIC—ICSIT 2016, p. 278-283.

ADDITIONAL PUBLICATIONS

9: Burry, Jane; Salim, Flora; Williams, Mani; Anton Nielsen, Stig; Pena de Leon, Alex; Sharaidin, Kamil; Burry, Mark. 2013. »Understanding Heat Transfer Performance for Designing Better Façades« ACADIA 13: Adaptive Architecture [Proceedings of the 33rd Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA) ISBN 978-1-926724-22-5] Cambridge 24-26 October, 2013), p. 71-78

10: Peters, Brady; Tamke, Martin; Nielsen, Stig Anton; Andersen, Søren Vestbjerg; Haase, Mathias. 2011. »Responsive Acoustic Surfaces: Computing Sonic Effects.« RESPECTING FRAGILE PLACES [29th eCAADe Conference Proceedings / ISBN 978-9-4912070-1-3], University of Ljubljana, Faculty of Architecture (Slovenia) 21-24 September 2011, p.819-828

11: Lilley, Brian; Hudson, Roland; Plucknett, Kevin; Macdonald, Rory; Cheng, Nancy Yen-Wen; Nielsen, Stig Anton; Nouska, Olympia; Grinbergs, Monika; Andematten, Stephen; Baumgardner, Kyle; Blackman, Clayton; Kennedy, Matthew; Chatinthu, Monthira; Tianchen, Dai; Sheng-Fu, Chen. 2012. »Ceramic Perspiration: Multi-Scalar Development of Ceramic Material«. ACADIA 12: Synthetic Digital Ecologies [Proceedings of the 32nd Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA) ISBN 978-1-62407-267-3] San Francisco 18-21 October, 2012), p. 97-108.

12: Burry, J., Burry, M., Tamke, M., Thomsen, M.R., Ayres, P., Leon, A.P., Davis, D., Deleuran, A., Nielsen, S. and Riiber, J., 2012. »Process through practice: synthesizing a novel design and production ecology«. In ACADIA (Vol. 12, pp. 127-138).

13: Mani Williams, Jane Burry, Flora Salim, Stig Anton Nielsen, Alexander Peña. »A multimodal toolkit for thermal performance feedback in conceptual design modelling«. 2014. DADA2013: Digital Infiltration and Parametricism. p. 348-358. Tsinghua University Press.

14: Tamke, Martin, Brady Peters, Stig Anton Nielsen, Niels Jakubiak Andersen, Reese Campbell, and David Stasiuk. 2013. »Designing Pliable Structural Skins.« Edited by R. Tarczewski J. B. Obrębski. Beyond the Limits of Man.

15: Nielsen, S.A. and Dancu, A., 2015. »Fusing design and construction as speculative articulations for the built environment«. of Architectural Research, p. 65.

PUBLICATIONS ACKNOWLEDGMENT

Paper 1: Nielsen, Stig Anton. »*Physical Form Finding by Embedded Sensors: Using 'sensor chaining' in various temporal and spatial scales.*« Thanks to Senior Lector Inger-Lise Syversen from Chalmers University of Technology, Dept. of Architecture for making the trip possible for me. All electronic devices and sensors were constructed by me at Chalmers in advance. The image representation program for overlaying and interpolating data was also written me alone.

Paper 2: Nielsen, Stig Anton, and Alexandru Dancu. »*Layered subsumption in intelligent material building systems.*« Written in collaboration with Alexandru Dancu around the experiment done by the author. This collaboration was fruitful as Dancu was able to contribute with many references and theory, and the discussions on the topic accelerated the general discourse of the study.

Paper 3: Nielsen, Stig Anton. »*A process where performance drives the physical design.*« The experiment in the paper builds on ideas from a workshop done in collaboration with Petra Jenning and David Andreen, when I was part of CITA in 2010. In the workshop we focused on an agent based design solution. I, as part of CITA, supported the workshop with sensory devices that could augment the perception of the actants, that in this case were students from KADK taking the workshop. The name of the workshop was Growth Ambitions and was set up at GGGAllery in Sølvgade Copenhagen. During the actual experiment and exhibition presented in the paper, similar ideas were taken further to see how a projected representation and only few instructions could engage the audience at an exhibition to continuously modify a structure of synthetic growth. I designed the system, the electronics, the geometries, and programming of sensors and projector etc. I thank Tabita Nilsson from Chalmers for the help at setup and fabrication of cardboard elements.

Paper 4: Nielsen, Stig Anton, and Alexandru Dancu. »*Embodied computation in soft gripper.*« The gripper design is inspired by other similar mechanical grippers and in particular a design by Dr. Rudolf Bannasch. However the one designed by the author has a higher degree of modularity and thus aggregate programmability. Initiative for the paper was on behalf of co. author and fellow student Alexandru Dancu.

Paper 5: Nielsen, Stig Anton, and Alexandru Dancu. »*Propositional Architecture using Induced Representation.*« Thanks to the discussions and shared knowledge from brilliant colleagues during the exchange stay at CAAD in ETH, the idea for the dimensionality reduction came to use. All augmentation and 3D edge detection experiments and their programming was done by the author alone. Alexandru Dancu provided assistance in writing the paper with appropriate references and deep thoroughness.

Paper 6: Nielsen, Stig Anton. »*Propositional architecture and the paradox of prediction.*« Again the colleagues from CAAD are owed a big thanks for inspiring conversations and support. The ESP algorithm is despite its composite nature, entirely composed and written by the author alone.

Paper 7: Dancu, Alexandru et al. »*Emergent Interfaces: Constructive Assembly of Identical Units.*« This student based project fundamentally uses the embodied design setup from paper 2. The code however is modified to detect different colors by the students Max Witt, Catherine Hedler, Hanna Frank, Axel Pelling, Christian Carlsson. These students designed the game and under supervision from the author and fellow ph.D. student Alexandru Dancu the game was successfully showcased at TEI'14. The contribution of the remaining authors is unknown.

Paper 8: Savov, Anton and Tessmann, Oliver and Nielsen, Stig Anton. »*Sensitive Assembly: Gamifying the design and assembly of façade wall prototypes.*« The collaboration was initiated by Oliver Tessmann and Anton Savov on the basis of my previous publications and overlapping research interest. The experiment was designed at the DDU [Digital Design Unit, TU Darmstadt] and the final incorporation of ESP happened in Frankfurt at the NODE festival after preparation and testing at Chalmers. The paper was written mainly at DDU, and the contribution of ESP aspects was collaboratively included.

Paper 9: Nielsen, Stig Anton »*Event Series Prediction as Decision Support System at Fast Paced Processes.*« Thanks to Ingeborg Zakariassen for participating in the experiment on dance improvisation in interaction with the Event Series Prediction algorithm. Thanks to Sunniva Buynnel for participating in the experiment on musical improvisation in interaction with the Event Series Prediction algorithm. The technical equipment and installation of the experiments were done by the author.

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CONTENT

FOREWORD

The thesis proposal was initially called »*Embedded Sensors*«. A draft of thoughts and formulated at Center for IT-Architecture at Royal Academy of Fine Arts, Copenhagen 2010-2011.

The real body of research started September 2012 at Chalmers University of Technology, Sweden, as part of the larger framework project »*Architecture In The Making*«. In the entire year 2014 the author was guest researcher at the Chair of Computer Aided Architectural Design led by Ludger Hovestadt, at the Swiss Federal Institute of Technology Zurich (ETH). The research dissertation is written at Chalmers University of Technology between 2012 and 2016.

Bewildered, the form-maker stands alone. He has to make clearly conceived forms without the possibility of trial and error over time. He has to be encouraged now to think his task through from the beginning, and to 'create' form he is concerned with, for what once took many generations of gradual development is now attempted by a single individual ... The intuitive resolution of contemporary design problems lies beyond a single individual's integrative grasp.

Christopher Alexander 1964[1]

1 Alexander, Christopher. Notes on the Synthesis of Form. Cambridge Mass: Harvard University Press, 1964. p. 4–5.

1.0 INTRODUCTION

A mutual relationship exists between activities and the built environment. A reciprocity between changes to the built environment and changes in activity. Every modification to the built environment provides opportunities for the emergence of new activities. And vice versa, changes in activities set out the demand for changes over both short and long timescales.

Aldo Rossi explains in *L'*architettura *della città* (›*The Architecture of the City*‹),[2] how political, economic, and social transformation drives the development of cities. He claims that the architecture of the city is a result of political, economic and social transformations through time.[3],[4]

In this interdependence, the built environment—through its structural and material characteristics—enables phenomena and events to take place, while in turn the very same structural and material attributes are affected, rearranged, and shaped by the events and phenomena taking place around and inside it. This relationship can be observed taking place in the built environment over a wide spectrum of physical and temporal scales, constituted by many actants simultaneously at play.

Design and modification of the built environment is driven by the current and future demands of human inhabitants, in congruence other aspects like politics, economy, sociopolitical demands, material availability, material properties, building traditions, manufacturing and assembly technologies are also in the loop.[5] The task of facilitating the interplay between these multiple system intrinsic actants is given to architects designers and planners. A complex and incomprehensible scenario, which must be supported by the most comprehensible information available. Only provided with representations and models of the past, current and future will architects be able achieve the vision of Ed Van Hinte, namely to »*... see themselves as programmers of a process of spatial change ... The inhabitable space would then become an indeterminate design environment subject to continuous processes of change, occurring in different realms and at*

2 Rossi, Aldo, and Peter Eisenman. Architettura della città. MIT Press, 1982.

3 Lobsinger, Mary Louise. »That Obscure Object of Desire: Autobiography and Repetition in the Work of Aldo Rossi.« Grey Room 08 (2002): 38-61.

4 Critchley, M., »Continuity or Crisis?« p.68 (unpublished thesis)

5 Kolarevic, Branko. »Exploring Architecture of Change.« In reForm( )—Building a Better Tomorrow: Proceedings of the 29th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA), p.59. ACADIA. Chicago, Illinois: The School of the Art Institute of Chicago, 2009.

various time scales«[6] »*If we were to accept change as a fundamental contextual condition—and time as an essential design dimension—architecture could then begin to truly mediate between the built environment and the people who occupy it*«.[7] Architects, designers and planners must be given the ability to continuously trace and create temporal models of the past, current and future scenario, based on information through material, temporal and spatial scales.

This information already exists, embodied not only in the long term development of the built environment, but also in the more immediate flows and transformations through society and in day-to-day activities. However technology is needed for tracing, extracting, and handling physical and temporal data from the built environment.

1.1 Aim and Working Hypothesis

The aim is to explore the potential of sensors combined current design technologies and mixed with material, morphological, and other types of physical computation. In a second stage the aim is to make combined physical and immaterial systems able to autonomously trace and make sense of transformations, events, and phenomena. The explorations should create knowledge that strengthen the contemporary discourse on design and modification processes.

The combination of physical computation and virtual computation is here referred to as *Mixed Substrate Computation*. A concept achieved through embodiment and embodied computation and through the facilitation of information flow between different computational substrates.

The included papers discuss of how these experiments handle the embodiment of computation within morphology, material behavior, and formal computation exchanged within the scene by embodied representations. A paradigm conjointly coined mixed substrate computation. The approaches to experimentation will collectively compose a method for investigation named *Embodied Design Setup*.

The use of sensors for architectural design is the outset for the investigation, which in turn lead to a new kind of artificial perception of phenomena over time. Consequently, I propose a kind of artificial cognition that uses the environment, sensors and algorithms to perform predictions in seemingly chaotic situations. Such new

6 Van Hinte, E., 2003. Smart Architecture. 010 Publishers.

7 Kolarevic, Branko. »Exploring Architecture of Change.« In reForm( )—Building a Better Tomorrow: Proceedings of the 29th Annual Conference of the Association for Computer Aided Design in Architecture (ACADIA), p.61. ACADIA. Chicago, Illinois: The School of the Art Institute of Chicago, 2009.

models of future temporal activities are in the documented experiments tested as a basis for continuous modification of the physical, structural, and material composition of the built environment.

The discovery of such a tool could bring about a paradigm shift in design, from a situation where architects, designers, and planners predict and design for future needs informed only by their present day point of view to a situation where design tools are able to learn from complex situations and can predict future needs autonomously. This capacity for perception and prediction makes a significant contribution to the current discourse on mixed material and digital practices in architectural design.

The use of sensors fills an increasingly widening gap between material and formal computation. The idea of integrating the physical and the abstract— body and soul—is a concept which is the key for understanding the distinction between phenomena and matter. These concepts are explored and developed in a series of experiments which describe constructions where computation resides on different material, morphological, or virtual levels.

The experiments[8] combine knowledge from sensor technology, architecture, design, and construction. The systems described are designed to control their own formal development through embedded design, assembly logic, and sensor feedback. The experiments trace physical environments by recording temporal phenomena. Rather than tracing static morphology sensor systems and information processing include a temporal dimension. The reciprocal relation between the physical environment and activities within it is explored through these fully embodied experiments.

Artificial cognition of temporally conditioned phenomena is performed through combining sensor technology with machine learning principles. The composition of known algorithms itself becomes an algorithm on its own, called *Event Series Prediction* (ESP). The phenomena-based design capacities given by ESP are experimentally integrated with remaining aspects of design, modification, and construction.

Ongoing research combines material, morphological and other system intrinsic actants. Achim Menges extends »*the concept of a material system by embedding its material characteristics, geometric behaviour, manufacturing constraints and assembly logics (allows) for deriving and elaborating a design through the system's intrinsic performative capacities. This promotes an understanding of form, materials and structure not as separate elements, but rather as complex interre-*

8 Appendices - Summary of papers, provide an overview of the papers and the experiments.

lations in polymorphic systems resulting from the response to varied input and environmental influences and derived through the logics and constraints of advanced manufacturing processes.«[9]. These polymorphic systems adopt many criteria of a design, assembly, and construction process, but so far the eventscape of current past and future activities has not been modelled or incorporated into this otherwise all encompassing design vision.

Today, sensor technology combined with machine learning allows for unprecedented insights into our physical world. Multidimensional sensor data and their multidimensional patterns through time was previously humanly incomprehensible. However, with the advent of faster computation and machine learning, machines can now autonomously construct non-anthropic semantics. Autonomous formation of understanding solely created through machine learning which is domain specific and non-accessible by humans. Human semantics can thus be hugely different from what machines can be said to »*understand*« from patterns and trends in data. The autonomously formed semantics of machines can be translated and applied to human semantics through physical grounding and strong embodiment within the environment.

Insights into how such systems have been used in other disciplines are presented, are presented and discussed in regards to how they can in the future be used in the entire built environment as continuously informed modification.

The chapters of this dissertation aim at contributing knowledge and understanding of various types of computation and how these have successfully been mixed in other disciplines. The algorithm *Event Series Prediction* (ESP), developed in the course of this study, can be seen as a form of artificial cognition that can be applied to local scenarios in order to predict occurrences based on its experience of previous occurrences. ESP is applied experimentally to test continuous and meaningful modification of the built environment, but also to test fundamental implications of feedforward interaction upon real-time situations.

The main hypothesis of this study is that the materiality of the built environment—is at least partly cognitive, in the form of the inherent computational capacity of matter itself. Various materials in our environment are affected in unique dimensions by the individual activity taking place. This can be seen as a perceptive capacity which can be exploited. This partial perceptive capacity can be complemented by memory and recognition, created through formal computation. To complete the cognitive process of the environment, the massive computational capacity of computers can be used to find patterns in

9 Menges, A 2011, Polymorphism, Time+Architecture, no, 06/2011, p, 118–123.

this manifold of materially affected dimensions. However, computers have limitations when it comes to associating semantic meaning between various types of data patterns and the real world. Due to this difference between human and artificial semantics, it is crucial to ground[10] artificial cognition to the environment. Grounding is used for connecting non-anthropic memory and semantics[11] within the environment, allowing it to be shared with other actants in the environment. This grounding and the use of artificial cognition necessitates a discussion about the relations between the physical and the virtual, matter and activity, physical scales and temporal scales.

As a result of this combined cognitive capacity, patterns from memories collected over time can be correlated with present data to produce predictions of future phenomena.

10 The term 'Grounding' relates to 'The Physical grounding problem' discussed later.

11 On non-anthropic semantics and non-anthropic memory see below.

The reciprocal relationship between activities in the environment and the physical formation of the environment is an assumption that leads to a series of four subsequent questions.

First, this reciprocal relationship needs to be investigated through asking: How can information originating from activities influence the environment? And what is the impact of forced information flowing from the environment towards computational design models?

Second, not only does the environment provide information useful for virtual computational models, it also contains and computes information through material, material aggregates and morphology. Certain computational processes takes place in the environment itself, i.e. before information is recorded, so we can ask: How can natural capacities for computation be intentionally combined with formal computational models?

Third, this combination of different physical and virtual computations described as *Mixed Substrate Computation* leads to systems that demonstrate predictive capacity. Sensors embedded in the environment enable virtual memory and pattern recognition to learn from the environment and predict events within it. Despite the system not being provided any human semantics, it still seems to operate with an understanding of the scenario which it predicts upon. Therefore the third question is: What is the character of semantics established in artificial cognition and other recognition systems?—and how may representational linkage be established to human semantics?

Fourth, this leads to the general question: How is representation used in mixed substrate computation and what is the relation between content and expression in fully embodied processes?

1.3 Modifying the Built Environment

The motivation for this research to focus on the built environment lies both in the nature of the architectural discipline itself as well as a shift in the current challenges architects are facing. Increasing complexity and more vast amounts of urban landscape need to be grasped through other approaches entirely.

First, architecture is an inherently historic discipline. At its core it aims at designing and adapting the built environment in order to facilitate human existence. Changing situations by adapting physical conditions is at the core of design, including architecture.[12] While these situations, namely the existing environment is ingrained with tradition, knowledge, and memory. An architecture capable of adapting to changes in these aspects is arguably more robust, durable, and sustainable through time.[13] Today, the design and construction processes utilized to meet these goals rely increasingly on computer aided design tools that facilitate a persistent adaptive relation to the design task at hand.[14]

Second, refurbishment and modification provide an opportunity to save material and energy. The current building stock is responsible for 40 percent of total energy consumption. It is estimated that through energy refurbishment of existing buildings in the developed and developing countries, energy consumption can be reduced by 30 to 80 percent.[15]

Third, When cities expand and increase density, it is often at the cost of the existing building stock. For simplification of planning and reduction of cost, large scale demolition of existing building stock and construction of new buildings is a common approach 2008.[16] However, the existing building stock presents both cultural memory and heritage and material value. This cultural heritage of

12 Herbert Simon claims that »Everyone designs, who devises courses of action aimed at changing existing situations into preferred ones«. Simon, H.A., 1996. The sciences of the artificial. MIT press. p.111.

13 Christopher Alexander's book »Synthesis of Form« explains the complex interrelations between culture, tradition, memory and knowledge.

14 Ayres, P. ed., 2012. Persistent Modelling: Extending the role of architectural representation. Abingdon, Routledge ISBN 978-0-415.59406-6. p.2

15 United Nations Environment Programme. »Building and Climate Change, Summary for Decision-Makers« http://www.unep.org/sbci/pdfs/SBCI-BCCSummary.pdf

16 Power, Anne. »Does demolition or refurbishment of old and inefficient homes help to increase our environmental, social and economic viability?.« Energy Policy 36.12 (2008): 4487-4501.

existing urban environments provide social cohesion that is nearly impossible to design for in large scale planning, but which may be sustained through gradual modification of the existing.

Although older, run down buildings are energy inefficient, it is in most cases more efficient to renovate than to demolish and build anew.[17] Anne Powers argues that there is an overlooked potential in ongoing refurbishment, infill buildings, and the subdivision of existing building stock. Powers also points to multiple sustainable advantages of increased density. The costly and complex process of determining what buildings to keep may often be the reason for large scale demolition strategies. Hubert Klumpner remarks in 2015: »*We believe that we have enough buildings, enough construction, enough infrastructure. And it is now time to consolidate it and find the qualities within the built. This is not against future production, it is more about a consideration of what we really want in cities.*« [18] Given this abundance of structured built matter of varying degrees and qualities and usability, it seems imperative to find a strategy for what buildings to maintain, how to refurbish them, where to build anew, what to demolish, and how to make ongoing modifications to the vast existing built environment. We must establish knowledge of current and future emerging activities and their needs in order to initiate the most acute and significant modifications to the existing built environment.

1.4 Physical Modification

Modifications to the existing built environment inadvertantly take place within the history of the location and in turn shape it. But how can new purport influence locations if not history or near previous development have informed them.

Mattoni provides a vision that resembles the vision of many cybernetics researchers from the 1960s. » ...*An integrated smart method of planning, assisted by the digital infrastructure for communication and management, would allow to coordinate the city as sentient, homeostatic, and self-repairing organism to behave as a resilient ecosystem. The regulation of the whole system through a dynamic balance is stimulated by the knowledge of the interrelations among subsystems and the real time management of transformations.*« [19] There is however an immense difficulty in obtaining and updating »*the knowledge*

17 Kohler, Niklaus, Philip Steadman, and Uta Hassler. »Research on the building stock and its applications.« Building Research & Information 37.5-6 (2009): 449-454.

18 »Interview with Hubert Klumpner«, ArchDaily, »http://www.archdaily.com/779593/ad-interviews-hubert-klumpner-2015-bi-city-biennale-of-urbanism-architecture

19 B.Mattoni et al. /Sustainable Cities and Society 15 (2015) 105-119

of interrelations among subsystems.« What kind of superior computational unit is supposed to contain this knowledge, and who will update it with the implications caused by this real time management?

Such an approach of reduction and subdivision falls short when dealing with complex systems. More dynamic and robust approaches of embodiment and autonomous learning are needed. The systems testing the algorithm Event Series Prediction (ESP) seek to demonstrate such a system behavior. The included paper 6 introduce such a paradigm of propositional architecture and the experiments in paper 8 and 9[20] document the interactions between changing environments and a local sentient learning system for modification.

These experiments testing ESP suggests omitting semantic assumptions and divisions in between subsystems. Instead, semantics are based on a close spatial and temporal correlation with context. Embodiment, balance, self repair, and construction coordination is instead achieved through the *embodiment* of unsupervised learning systems. This hypothesis will be discussed further in the chapter 5.

1.5 Temporal and Physical Landscapes

To envision the concept of constant modification, we can refer to a local part of the built environment as *the scene*. The modification of this scene over time can be compared to the movement of a *mobile robot*, which moves through an uncharted landscape from location A to location B. These physical locations A and B are thus compared to the temporal development of the scene from its original state A to the modified state B.

As the robot moves, it must—in order to plan its path—observe the environment with all the obstacles and opportunities. In the same manner, the scene transforms through a time based environment where events and phenomena pose opportunities and obstacles. Like the robot, the scene similarly must be aware of its own *temporal landscape with events and phenomena* in order to plan its transformation from state A to state B.

20 Paper 6, Nielsen, Stig Anton. »Propositional architecture and the paradox of prediction«. Archi-doct: The e-Journal for dissemination of doctoral research in architecture 4-Matter, Issue 2-2. ISSN 2309-0103. www.enhsa.net/archidoct, Feb 2015. P.72-84.

Paper 8, Savov, A., Tessmann, O. and Nielsen, S.A., »Sensitive Assembly: Gamifying the design and assembly of façade wall prototypes«. International Journal of Architectural Computing, 14(1), 2016. p. 30-48.

Paper 9, Nielsen, Stig Anton. »Event Series Prediction as Decision Support System at Fast Paced Processes« Proceedings of IMCIC—ICSIT 2016, p. 278-283.

Like the mobile robot which has an awareness of its location and movement through the environment, the scene must be aware and sensitive to its own *temporal landscape*. This awareness, for both the scene and the robot, is like cognition—of location in space for the mobile robot, and for the scene, it is cognition throughout time.

The robot uses sensors to locate itself in its environment while the scene uses sensors for positioning inside this temporal landscape. That means these sensors must perceive temporal *events* and *phenomena*.

The *temporal landscape* can be seen as a dimensional shift from the environment, to the temporal surroundings of the environment. What actuation or movement is to the robot, modification is to the scene. Similar to how the robot must sense *obstacles* in the environment, the scene must sense *events* and *phenomena* in its temporal landscape.

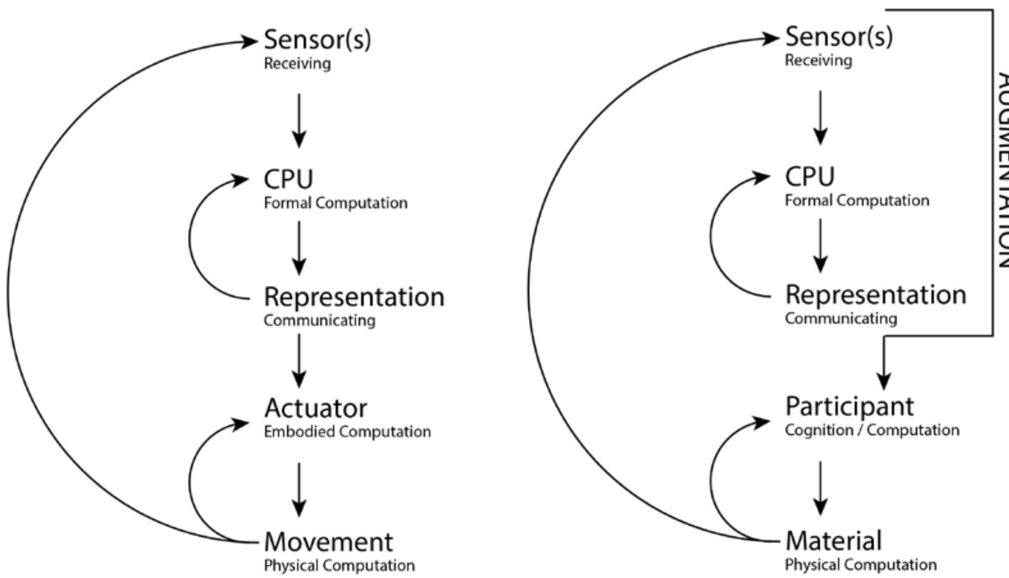


Figure 2. The diagram on the left shows how the robot iteratively coordinates movement, on the right how the scene iteratively coordinates modifications implemented by participants.

1.6 Events and Phenomena

Phenomena, events and the physical environment are mutually influential. However in regards to the temporal and physical scale of the built environment of humans, the physical and material state affects phenomena and behavior more predominantly than vise versa. A balance can be observed in this reciprocal relationship between the two. A balance which has been shifted differently in other traditional building cultures towards more immediate reaction between changing behaviors affecting the physical and material state of the built environment.[21]

Eugene Wigner aptly describes how this relationship exists for quantum mechanics, by means of our perception of the world and the built environment, as to how » *... our knowledge of the external world is the content of our consciousness ... we do not know of any phenomenon in which one object is influenced by another without exerting an influence thereupon...*«[22]

Today the built environment is neither easier nor quicker to modify than in the past — on the contrary buildings and the entire environment have become more complex, but the need for new buildings and the refurbishment of existing buildings has never been greater.[23]

Current strategies for identifying potential refurbishments and new structures are based on human cognition assisted by rather conventional tools for handling this hightened degree of complexity and resolution. These approaches does not respond to the increasing need for large scale observation, learning and reaction toward changing activities and changing physical conditions.

Instead the knowledge creation, tracing and perception of the built environment must be improved through an artificial cognition. A technology able to process and analyse past and current activities can augment human cognition and allow for descriptions of relationships between emerging activities and their physical-material requirements in the built environment.

In order for such artificial cognition to discover and re-establish relationships between activities and environment, the concept of activities has to be elaborated on. Activities being various scales of events and phenomena taking place in our built environment.[24] Once activ-

21 Alexander, Christopher. »Notes on the Synthesis of Form«, Harvard University Press, 1964.

22 Wigner, E. 1962. »Remarks on the Mind-Body Problem«, in Good, I.J. The Scientist Speculates. London: Heinemann. p 290-5.

23 United Nations Environment Programme. »Building and Climate Change, Summary for Decision-Makers« http://www.unep.org/sbci/pdfs/SBCI-BCCSummary.pdf

24 Further discussed throughout section 5 and in particular 5.5.

ities can be traced and investigated they can be related to the past in order to analyze how the present is affected. This would in turn enable qualified models and assumptions about future activities.

The aim argued for in this thesis is to use machines for artificial cognition of the built environment. This is based on the notion that past, present and future consist of parallel, overlapping, and consecutive phenomena. The goal is to use this in order to faster and more reliably predict changes in activities, and in turn infer theappropriate physical changes that can accommodate those predicted activities.

The approach I take to develop an artificial understanding of phenomena is to study the temporal contiguity[25] of the environment, as follows: A timeline can be constructed from a sequence of temporal states, consisting of sensor data gathered from multiple dimensions, such as sound changes, temperature, vibrations, light, etc. Once the artificial cognition analyses sequences of states repeating with a high temporal accuracy, we can conclude that a recurrence of phenomena exists.

As there is no definitive catalog of potential phenomena, the machine must autonomously trace and determine which series of events can be understood as relevant phenomena and which cannot. This again begs the question: what makes a phenomena different from a random series of events recurring?

Different machine learning techniques can be applied to the process of ordering and understanding these temporal sequences, but that in itself does not mean humans will be able to comprehend the same kind of understanding as the one devised by machines. Instead, in order to perceive complex series of events as phenomena, representations must be used that can make virtual, machine perception understandable for humans. With such an achievement, it may even be possible for us to perceive yet undetected temporal phenomena.

»*The intuitive resolution of contemporary design problems simply lies beyond a single individual's integrative grasp ... if we look at the lack of organization and lack of clarity of the forms around us, it is plain that their design has often taxed their designer's cognitive capacity well beyond the limit.*«[26]

Computational intelligence and machine learning is becoming superior to human cognition in regards to an increasing number of specific challenges. Some image recognition experiments have shown higher

25 Contiguity in cognitive science is a serially conditioned stimulus or events or a combination of these.

26 Alexander, Christopher. Notes on the Synthesis of Form. Cambridge Mass: Harvard University Press, 1964.

performances for machines, and in march 2016 the deep neural network based program AlphaGo outperformed master players at the notoriously complex game Go.

Contemporary supervised machine learning techniques make use of experience based data which is manually linked to semantics, for example from images but also games where current-state semantics is linked as a description to the data. Reinforcement learning on the other hand is not relying on manually linked human semantics. Instead the system autonomously learn through performing and experiencing the reactions in the given challenge. A challenge defined through reward and penalty, which is evaluated in parallel with decision making and interaction with the environment thereby it is possible to continuously evaluate previous decisions to improve the basis for new decisions. Unsupervised machinelearning differs from both supervised machine learning and reinforcement learning in that there are no semantical assumptions. It is often used for exploring correlations in unstructured multi-dimensional data.

The success of the machine in these specific challenges is owed to its raw computational capacity—allowing it to train and evaluate multiple decisions whilst simultaneously improving them. The fundamental approach to training and decision making is however to a large degree the same throughout challenges. Machine learning systems must be adapted to solve each specific challenge. Input, output, reward etc. must be defined in order to make use of the already versatile procedural mechanisms i.e. algorithms.[27],[28]

This adaptation to specific challenges becomes key for successful implementation of machine upon a challenge, a difficulty not shared by the versatile human mind and human body. In contrast, humans has the advantage of being hyper adaptable. The human body and mind is easily situated and embodied within what we consider relevant challenges.

When it comes to physical challenges, implementation of machine is even more cumbersome—as the machine's body often requires to be redesigned. Just as machines are constrained by an inflexible and rigid body—if any— suffering poor physical embodiment. On the contrary, human cognition is arguably limited by our own bodies. We have to carry our »*sensors*« with us at all times, preventing the

27 This study documents the recent advances in Computational Intelligence playing the asian game Go. Lee, Chang-Shing, et al. »Human vs. Computer Go: Review and Prospect.« arXiv preprint arXiv:1606.02032 (2016).

28 This study on DNN facial recognition achieved a score close to human level recognition of faces in various angles and environments. Taigman, Yaniv, et al. »Deepface: Closing the gap to human-level performance in face verification. »Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2014.

perception of non localized events, phenomena over extended time frames, and dimensions beyond the abilities of our senses. The character of *embodiment* is thus central to any given challenge.

1.7 Embodiment

Plato makes the distinction between body and soul in order discuss how the two are interdependent.[29] Locke, Hume, and Kant also discuss how the mind is separate but informed by the body through interaction with the world, an interaction that through use of senses is the basis for forming knowledge.[30] This formation of knowledge from experience to mind, in the form of representation or conceptualization, has been contemplated by many, such as Merleau Ponty, Saussure, Hjelmslev, Gibson, Brooks and Gärdenfors, all of whom will be mentioned later.

In the last 20 years, this dichotomy and approach to unification has been at the core of the concept we call *Embodiment*. It has been used similarly in different disciplines such as robotics, where Embodied Computation refers to the computational capacity of the robot body itself. On one hand the robot can make logical computations in its microprocessor, but some aspects of this processing can successfully be distributed to the body of the robot. A principle which is investigated further in paper 4[31]

Gibson's ecological approach emphasizes how the relationship between an object or environment and an organism affords opportunities for that organism to perform an action, an insight which inspired many disciplines.[32] In Artificial Intelligence, the concept of embodiment deals with the inseparable relationship between thought and body, and how both the environment, programming, and body of an actant are mutually essential to its behavior.[33] Rodney Brooks, in 1991, made a similar argument in his paper »*Artificial intelligence without Representation*«,[34] proposing a more robust behavior for robots by means of a higher reliance on interaction and embodiment within the environment. In the 1970s Christopher Alexander described vernac-

29 Ferrari, Giovanni RF, and Tom Griffith. Plato: 'The Republic'. Cambridge University Press, 2000.

30 Kant, Immanuel. »Critique of Pure Reason (translated and edited by Paul Guyer & Allen W. Wood).« (1998).

31 Nielsen, Stig Anton, and Alexandru Dancu. »Embodied computation in soft gripper«. Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction 3, Mar. 2014. p. 256-257.

32 Gibson, James J. »The perception of the visual world.« (1950).

33 Pfeifer, Rolf, and Josh Bongard. »How the body shapes the way we think: a new view of intelligence«. MIT press, 2006.

34 Brooks, Rodney A. »Intelligence without representation.« Artificial intelligence 47.1 (1991): 139-159.

ular building tradition as dependent on the changing requirements afforded by the environment, culture, and locally available materials. Local affordance offers the chance for modification, which in turn may be enforced or constrained by other actants such as culture or tradition. [35]

In 2008, the European Commission initiated a line of projects addressing with this concept, describing »*design paradigms and techniques for purposive agents where behaviour is not strictly programmed but robustly emerges from the interaction of the various components (each with local intelligence), the environment, and its ubiquitous information resources.* «[36]

Embodied Interaction draws on social computing, phenomenology, and tangible computing which augments everyday objects and spaces with computational capabilities so they are able to respond to the environment, people, and other objects around them.[37]

As architecture, planning, and design become more technologically advanced and arguably more detached from their physical context, it is crucial to redefine the character with which technology for design is embodied.

Architecture has a fundamental reciprocity between activities and physical constructions, which relies upon and interact with each other, similar to how the mind builds knowledge from experiences of our senses, activated by interaction with objects.[38] Our activities are based off and develop through interactions with the built environment. The built environment and activities can in turn be made cognizant, informed by events and phenomena taking place, and in turn enhance its capability to change and adapt. Nevertheless, implementations of modifications to the environment are destined to be delayed unless we make continuous predictions from the present, based on information from the past.

35 Alexander, Christopher. »Notes on the Synthesis of Form«, Harvard University Press, 1964.

36 EU Commission. »Embodied Intelligence«, http://cordis.europa.eu/fp7/ict/fet-proactive/embodyi_en.html

37 For more reading on embodiment, the introduction in the article by: Stepney, S., 2007. Embodiment. In Silico Immunology, pp.265-288. Or the article by: MacLennan, B.J., 2008. Aspects of embodied computing. Tech. rep., Technical Report UTCS-08-610, University of Tennessee.

38 Kant, Immanuel. »Critique of Pure Reason (translated and edited by Paul Guyer & Allen W. Wood).« (1998).

1.8 Material Semiotics

Another way of looking at the relationships between phenomena, physical constructions, and a set of concepts or relations governing the constitution of the built environment is by using *Material* Semiotics. Heidegger lays the ground for Material Semiotics in his description of the relation between the craftsman and his tool as something other than instrumental. The creation of an art piece *emerges* through the *assemblage* between the material, the tool, and the craftsman. Each of these parts or objects attain agency and only through their confluence can a work of art *emerge*.[39]

Haraway introduces the concept of a 'knowledge object' and describes this *material-semiotic actant* as that what contributes actively—be it any human or non-human, machine or non-machine.[40]

Similarly, Bruno Latour criticised Realist Social Theory[41] for being too focused on the human's position, and over reliance on the distinction between object/concept or human/nature. Instead, Latour opens the definition of these networked relationships to encompass any concept —objects, subjects, humans, ideas, organizations, scales or sizes— as actants. A definition more radical than both Heidegger's ideas and Material Semiotics.[42] As such the *Actor Network Theory* (ANT, acteur reseau)[43] is an approach to describe significance and relationships in networks between actants. Law has described this as performativity; »*For the semiotic approach tells us that entities achieve their form as a consequence of the relations in which they are located. But this means that it also tells us that they are performed in, by, and through those relations.*«[44] Where embodiment establishes ties between different virtual and material aspects of a local system, we could regard ANT as an expansion of this concept that allows for a more holistic analysis of non-localized situations or scenes. It is

39 Heidegger, M., 1977. The question concerning technology, and other essays.

40 Latour, Bruno. »Reassembling the social-an introduction to actor-network-theory«. Oxford University Press, Sep 2005. ISBN-10: 0199256047 (2005). p.316

41 Contributed by the work of M. Archer (1995), Realist Social Theory and the Morphogenetic Approach is a branch of material semiotics that describe the mutually influential relationships between societal governance and human behavior. She considers humans as a different type of actant entirely from other entities.

42 Latour's ANT ontology is criticized by Dave Elder-Vass for not being nuanced in its attempt at breaking down the dualisms of for example culture/nature or meaning/object. Instead he suggests a more conventional style of critical realism seemingly arguing for a more epistemological approach.

43 Reseau (network), Deleuze and Guattari discuss the Rhizome as its own concept in A Thousand Plateaus. Deleuze, Gilles, and Félix Guattari. »A thousand plateaus.« (1987).

44 Law, J., 1999. After ANT: complexity, naming and topology. The Sociological Review, 47(S1), pp.1-14, quote page 4).

thus capable of establishing networks between ubiquitous concepts, for example across temporal and physical scales, other concepts and entities.

Through the use of ANT the morphogenesis in natural systems can be described. Systems obtain shape and organisation through negotiation and interactions between materiality, geometry, and forces from the surrounding environment. Based on this, Menges criticises the current predominant architectural practice as a top-down-approach that is in contrast to a morphogenetic approach, but rather where form-intention[45] forces other actants to follow creating a unilateral influence between actants. The research on morphogenesis is applicable when shaping the built environment, however where Law argues for an ANT that regards humans as equal actants amongst material, concepts, rule sets, and phenomena, Menges' polymorphism disregards the human daily phenomena, and deals exclusively with materiality, geometry, and assembly logics as intrinsic performative capacities. Menges' material performative capacities are highly relevant and must nevertheless be included in the continuous modification of the environment, along with the fundamental premise of architecture, namely the fulfilling of emerging needs as demanded by activities.

These analytic approaches can be applied when analyzing the continuous modification of the built environment. However, to incorporate the activity and phenomena of inhabitancy as intrinsic actors, it is necessary to trace, describe and generate knowledge of both individual phenomena as well as temporal landscapes, and how they relate to actants of other kinds. This immense task of observation, tracing, and deduction of sequential relations over multiple dimensions and throughout vast spaces may be a more relevant a task for machines than for humans.

45 Understood as architectural design from a top-down approach where formal intention is dominant and little based on local surrounding factors.

2.0 RESEARCH APPROACH

The research approach is based on experiments of varying physical and temporal scales. They investigate the relationships between activities and matter through modification of either physical form or of activities. The experiments have been designed as embodied systems encompassing the complexity of their given environment. At the same time, the individual experiments have targeted the particular individual temporal and physical scales which seemed most plausible. The physical character of these experiments was a crucial component required to address embodiment at this level of complexity, therefore the results could not be achieved through simulation.

Before this thesis project, I was involved with research on fabrication processes and production techniques aimed for highly predetermined construction processes within architecture. Material exploration posed a challenge towards conventional material practice, and was presented, for demonstration purposes, with medium scale built structures. While realizing these structures, iterations and changes in production plans were inevitable, despite the deterministic outset.[46] This lead to explorating the reversed information flow, from material realm towards digital model.

In the course of working on this thesis, a reverse flow was established first from physical constructions to digital models for fabrication. Along with the experience of a reciprocal relation between fabrication and matter, the models in turn became more embodied within the process of fabrication, as real-time feedback processes. And thus the models turned into systems and began to resemble embodied intelligent construction guidance rather than simply fabrication models for construction.

This shift of thought also brought about a shift from a focus on aesthetics in form towards a focus on primary, secondary, and tertiary necessities and performance, leading to other forms and aesthetics.

The first sentient and computationally augmented structure, MCard (cf. Experiments listed below), needed structural balance during construction whist it was simultaneously required to achieve a set of performative criteria. The form remained indeterminate whilst being guided by balance, light, and airflow sensors embedded within the

46 The previous research took place at CITA(Center for IT and architecture) at The Royal Academy of Arts, School of Architecture, Copenhagen between 2009 and 2012.

structure. Cf. figure 35. The experiment is described in further detail in Paper 2, »*Layered subsumption in intelligent material building systems*« *and Paper 3* »*A process where performance drives the physical design.*« Paper 3 describes an additional physical, small scale experiment, CSticks, that prioritize the capacity to sense and make decisions from simple rules designed to contest morphology and materiality of the building blocks. Cf. figure 36.

These first experiments were set over short temporal and small spatial scales. They brought understanding of embodiment and the reliance on the computational capacity of materiality and the environment.

An ensuing experiment took place within large scale structures, over long temporal scales, in Ethiopia and Tanzania (AhouseL). Those experiments brought about the idea of fusion sensor systems as a cognitive capacity. Paper 1 »*Physical Form Finding by Embedded Sensors*« describes these experiments in detail.

Students from the Dept. of Applied IT, Chalmers University of Technology[47] took up the first construction system from paper 2 and 3 and changed it both in morphology and to include two human participants in a competitive game of construction, here called FoamGame. This gamification of the experiment remarkably increased the speed of construction, and more structures could be investigated over shorter timespans, whilst the competitive interaction itself could be investigated procedurally from a computational point of view. The findings are documented in paper 7: »*Emergent Interfaces*«. Cf. figure 42.

This first series of experiments generated experiences such as; generalization of rulesets, reliance on environment, multiple dimension robustness, gamification, and temporal downscaling.

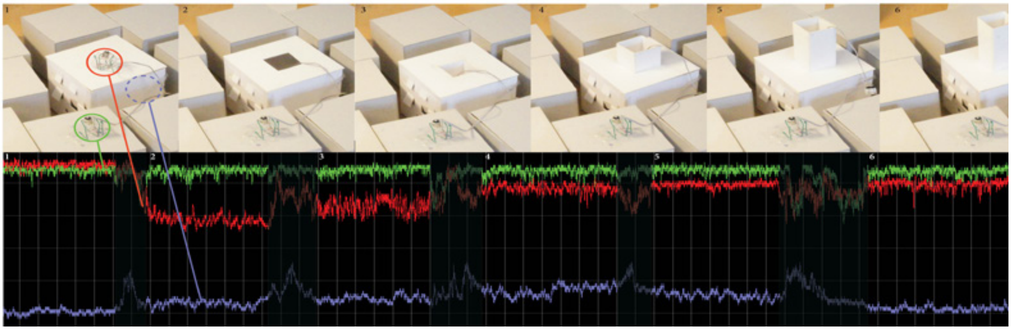
These terms conditioned much of the further experimentation using sensor devices for real-time learning and prediction setups. Using the criteria of small size and short durations made it faster to debug and verify than if experimentation had taken place at large sizes and long temporal scales. Section 6 and papers 5,6,8 and 9 meticulously document a number of these temporally downscaled experiments.

This approach to experimentation with embodied systems is described as research method in chapter 4. Conclusions from the ensuing experiments deal with the role of representations in mixed substrate computation, and the role of representation and semantics between substrates. These aspects are discussed in greater detail in chapter 5, Discussion.

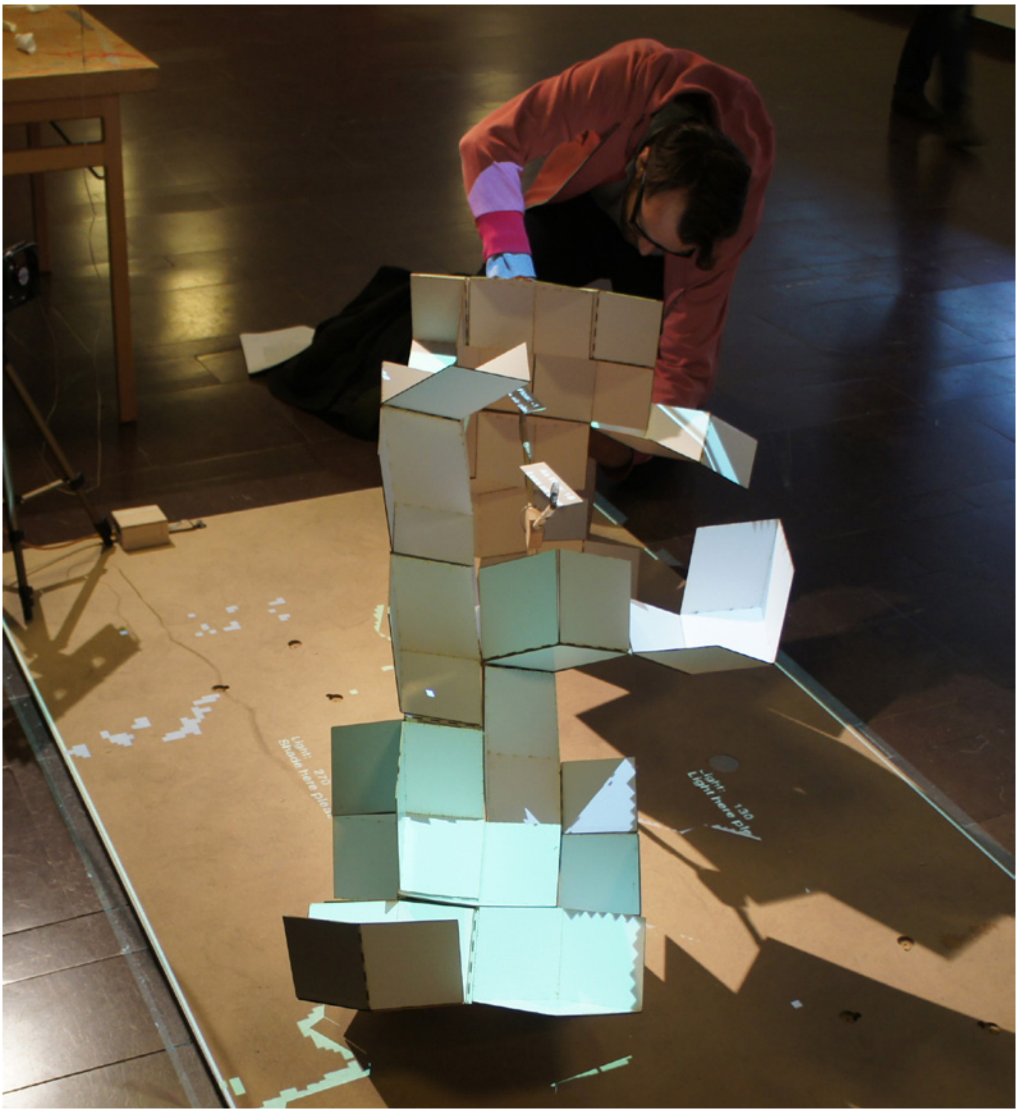
47 The students Max Witt, Catherine Hedler, Hanna Frank, Axel Pelling, Christian Carlsson

The illustrations in the next pages provide an overview of the experiments discussed in the included publications.

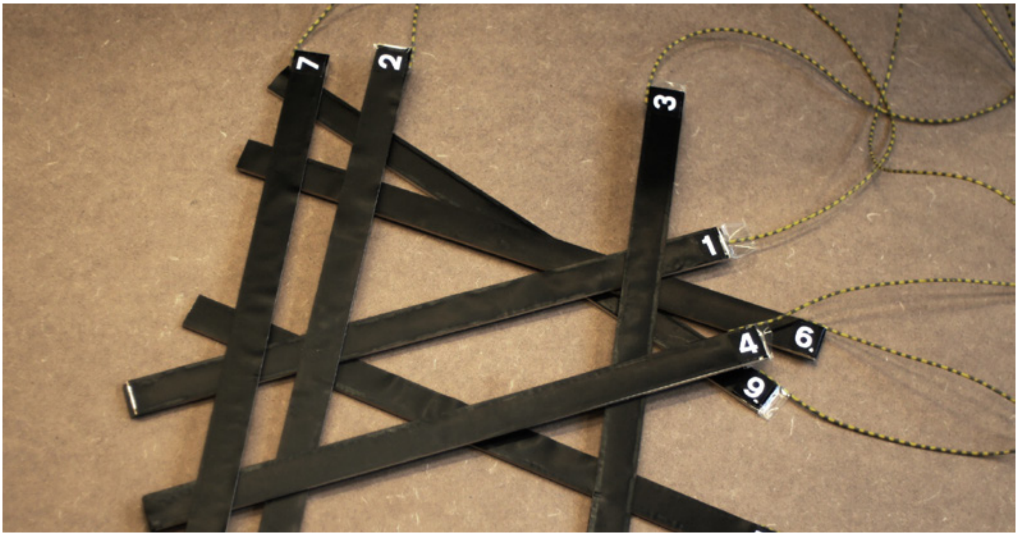
AhouseL - Arab House Typologies Large Scale—paper 1.



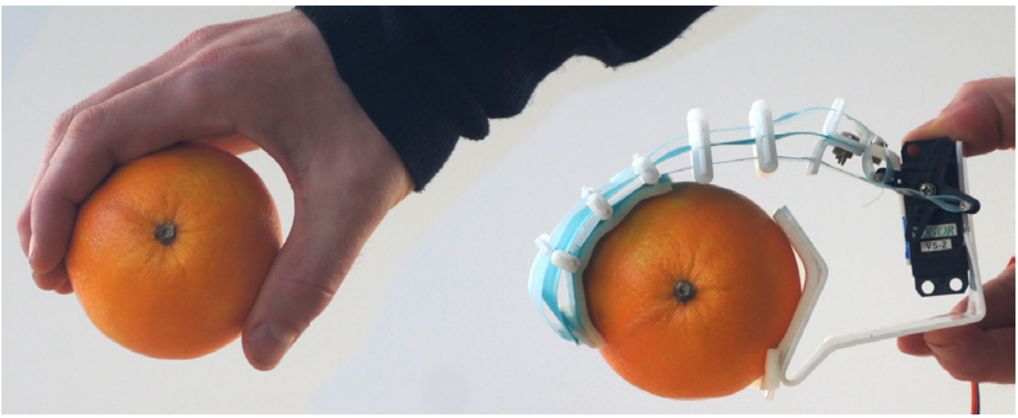
AhouseS - Arab House Typologies Small Scale—paper 1.



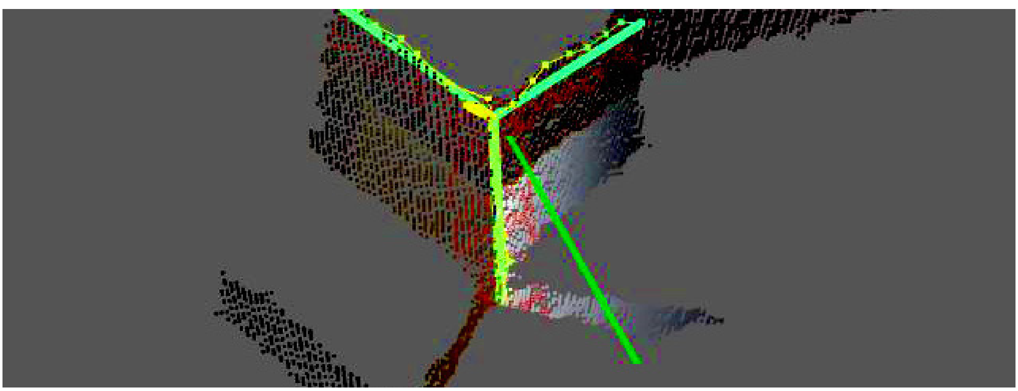
MCard - Cardboard Multi Criteria Structures—paper 2 and paper 3.



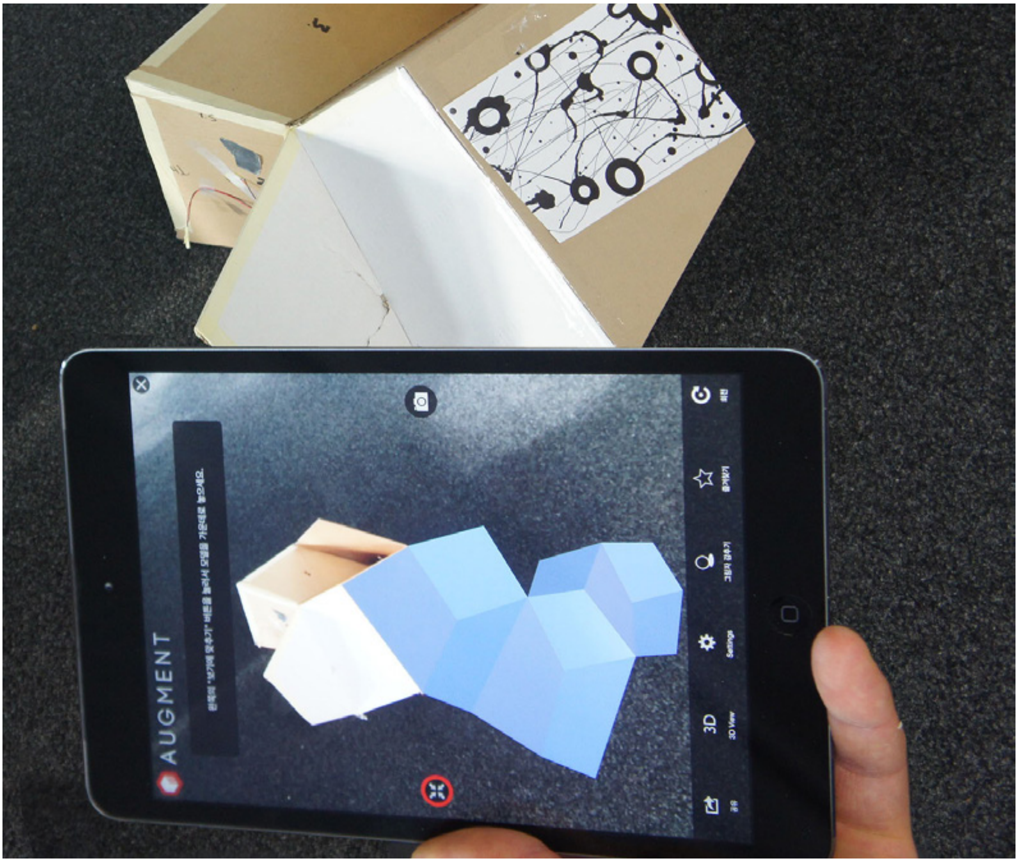
CSticks - Conductive Pressure Sensitive Sticks—paper 3.



UGrip - Underactuated Gripper—paper 4.



3D-Edge - Spatial Edge Detection—paper 5 and paper 6.

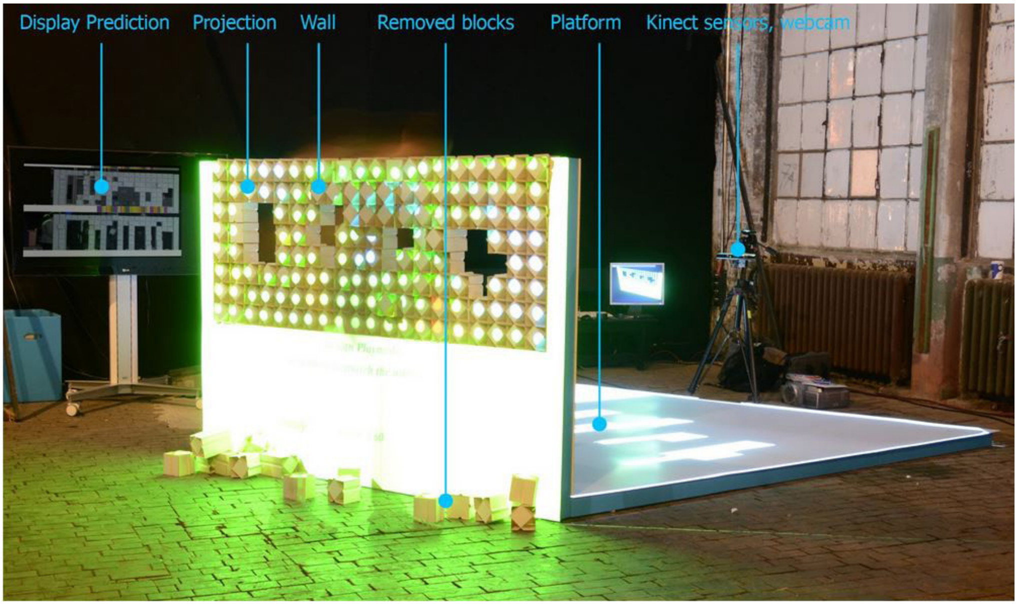


ARC - Augmenting Reality Construction—paper 5 and paper 6.

Musician - Musician and ESP—paper 8.

Dancer - Dancer and ESP—paper 8.

FoamGame - Gamified Foam Blocks—paper 7.



SenseWall - Sensitive Assembly Wall -paper 8 and paper 9.

3.0 LIMITATIONS

The experiments were conducted within a short timespan of opportunity and within a small spatial extent. This reduction in scale has not reduced the complexity but rather has simplified logistic complications. The laboratory-form of setup has been sufficient to arrive at the conclusions I set out to analyze. Larger and prolonged experimentation is not likely to have resulted in different conclusions, however it may have provided extended knowledge, and made the studies more easily transferrable to industrial applications.

The intentional split between physical and virtual has been challenging to document, and the inherent overlap between physical and virtual has challenged the approach of documentation.

The ESP algorithm could have been technically improved in several ways: It could be set to run as parallel processes, and thus be faster, and it could also have had more advanced clustering capability.

ESP could also have been analyzed for algorithmic scalability to demonstrate its versatility as algorithm. However, my work has not been a study in computer science but rather on a transdisciplinary space, focusing on embodiment and a variety of computational substrates to use in the area between architecture, design, and technology.

4.0 RESEARCH METHOD

Research and experimentation with mixed substrate computation suggests to use an empirical methodology, one generated by the findings and speculations brought about by the experiments themselves. The method is generalized to enable it to encompass a wide range of aspects within the proposed practice of mixed substrate computation.[48]

Experiments employing this method generate knowledge about temporally conditioned design and modifications to different temporal and spatial scales within the built environment. Through describing a set of methods, the approaches taken by the experiments can be employed in real-life design and modification tasks. A set of methods based off the archetypical experiments are described below. Conclusions from these different methods allow for existing theoretical frameworks to be used in this dissertation.[49]

The papers demonstrate how computational substrates act design-computationally, embodied within an actual design environment. Therefore I propose a method called *Embodied Design Setups*. This method develops an embodied design process via installations placed in the built environment. It uses setups, understood as installations, that mix different computational entities into one networked real-time design event.

Most physical design tasks are dependent on the context and environment for which the design is implemented. The interplay between design and environment is often hard to forecast. Therefore the solutions arrived at from such embodied design tasks can be said to be ruled by *computational irreducibility*.[50] The method of Embodied Design Setup can thus in such cases provide the means to shed light on relationships that currently seem incomprehensible—relationships that, due to computational irreducibility, only become apparent when physically engaged.

48 Schön, D., 1983 »Den reflekterende praktiker« Klim ISBN8777249364

49 Edmonds, Ernest, and Linda Candy. »Relating theory, practice and evaluation in practitioner research.« Leonardo 43.5 (2010): 470-476.

50 A concept for computational emergence within myriads of smaller programs with unique rulesets. Programs that can only be investigated through running them. Wolfram, Stephen. A new kind of science. Vol. 5. Champaign: Wolfram media, 2002.

Principles from morphogenetic engineering[51] are useful for such material explorations of interplay. The use of physical, material, and morphological computation provides insights into the computational agency of material in congruence with immaterial computational actants. The theory of Material Semiotics can describe the entanglement between entities in open design systems, shedding light on the rhizome-like character of their internal and external relationships.[52] In Embodied Design Setups like ANT and in material semiotics, actants can be immaterial, objects, concepts, descriptive dimensions, etc. By using these methods, hidden potentials can be discovered, potentials that in turn inform the ensuing experiments, creating an iterative progression.[53]

Researchers in design and architecture have previously proposed similar experiments. John Frazer,[54] and lately Petra Jenning, David Andreen, and Rupert Soar have conducted the following two agent based design experiments making use of embodied computation and multi-agency design.

At the first of two workshops given by Petra Jenning and David Andreen, participants are actively given agency. In 2010 at the 'Smart Geometry' event in Copenhagen, the team consisting of Rupert Soar, Petra Jennings, and David Andreen engaged workshop participants with different roles as actants with the goal of building a structure in the manner of termites.[55] Some were given the goal of improving light conditions, others the role of increasing airflow, and some were given the goal of building the structure higher. The resulting structure was monitored by a 3d sensor system, which allowed the growth of the structure to be traced and later analyzed. Cf. the method of Immersed Observation below.

The second workshop was led by Petra Jennings, David Andreen, Martin Tamke, and myself. At this workshop master students in groups, acted as actants with different goals. At this workshop, the cognitive ability of the actants was augmented with sensor-measurement devices of different kind. One group used web cameras to measure light distribution, another used 3d sensors to measure

51 Doursat, René, Hiroki Sayama, and Olivier Michel, eds. Morphogenetic engineering: toward programmable complex systems. Springer, 2012.

52 Latour, Bruno. »Reassembling the social-an introduction to actor-network-theory«. Oxford University Press, Sep 2005. ISBN-10: 0199256047 (2005). p.316

53 Allen, S., 2000 »Practice architecture, technique and representation« Overseas Publishers Association, ISBN9057010720

54 In his book »An evolutionary architecture.« John Frazer describe combined agency of physical and formally computed entities. This paradigm is discussed in relation to other research in chapter 5.3

55 The works at Smartgeometry will become available at the homepage http://smartgeometry.org/

cavities in the structure, and yet another used strategically placed pressure sensor embedded elements to monitor the inert structural forces traveling through the conglomerate structure. This cognitive augmentation ties the morphological and material properties of the elements to the performance goal of each actant. The cognitive augmentation apparatus also attains computational agency. Thereby several inert and active computational substrates are combined using various representational relations to achieve one compound capacity to compute the structure.

4.1 Embodied Design Setup

An *Embodied Design Setup* is defined by the interdependency between a set of physical and virtual actants, in their particular relationships and computational roles. The interactions, interplay, and embodiment between these actants are of utmost importance and influence their capacity to exchange information. This exchange of information signifies their representational relationships and internal semantics.

An Embodied Design Setup can be compared to an experiment displaying a simple chemical reaction. Both are investigatory processes that take place when different actants are combined and catalytically activated. Measurements in a chemical experiment can be recorded for later use, whereas in a design setup measurements are used for creating representations between substrates that can act as regulation for the various catalysts, i.e. other actants. Rather than chemical substances, the actants are various computational substrates and entities connected through representational relationships. An actant could be the morphology of a building block, its materiality, external forces of light, and material flows such as air or heat, rulesets governing actants, robotic actuations, human participants, material properties, etc.

In the design setup, actants are activated and engaged by each other, connected through various representational relationships. These become the key of an embodied design setup as they define how the actants communicate, interact, and actuate, meaning how they individually perform their computational role in the larger compound computation.

The chemical experiment operates in a closed system, in contrast to the embodied design setup which is open and operates in a *scene* fully embodied with the existing built environment. The scene refers to a temporally and spatially limited—but not confined—part of the environment. As the scene is set in the existing built environment, it includes the existing actants of that particular space and time as well as a number of designed and embedded actants. *participants* can be human bypassers, helpers and spectators, or volunteers. We choose to refer to humans in the environment as participants with reference to participatory design, however they are considered in coherence with Latour, in that they are not central or distinct from other non-human entities.

The following archetypes of actants can be differentiated.

*A material actant is characterized by its ability to interact with other actants through morphology and materiality.

*A sensing actant is embedded in the scene or ingrained in the materiality of the scene. It extracts data for storage, which is translated by the data processing unit.

*Central or distributed processing actants can have both managing and storing capacity for sensor information. The processing actants can vary in capacity, and sometimes continuously perform demanding algorithmic operations.

*A representational actant is simultaneously actuating and processing. Although they may perform some processing and actuation, their main role is to relay information between other actants. However this can be ambiguous; although all actants can relay certain information to certain other actants. Sometimes an entity must be designated as a catalyst, having no other role but to relate information between actants.

*A Participatory actant is governed by rulesets of varying degrees, whether they are explicitly given rulesets, common social conduct in the environment, or rules implied by the capacity of their bodies. Their cognitive capacity and motoric skills are actively exploited (incorporated) as part of the compound computation and actuation of the matter in the scene and environment.

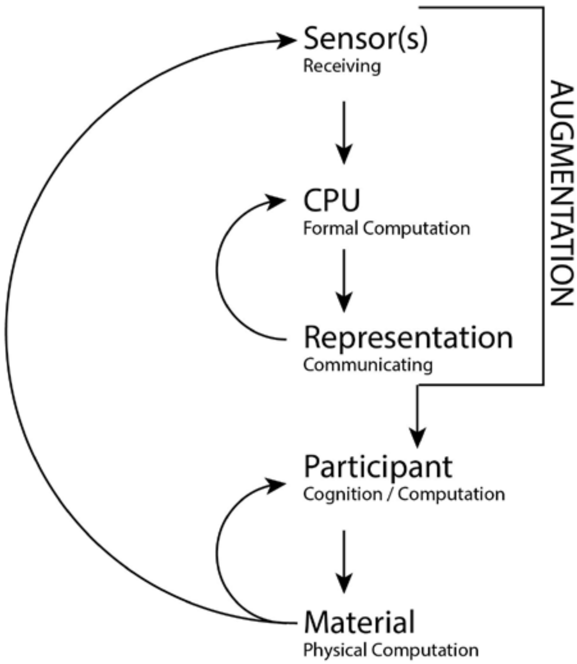


Figure 16. Flow chart of data and information.

4.2 Methodological Approaches

In order to deal with the knowledge created through this method more accurately, it is divided into different approaches. This division is made on basis of the different levels of embodiment, temporal and spatial scales as well as computational approaches. The approaches are explained through their most representative experiment as follows.

Immersed Observation (IO)

The methodological approach of Immersed Observation is demonstrated through the experiment AhouseL (cf. Section 2.0 Documented in paper 1[56]). In this experiment the scene is set inside of two different houses on Zanzibar. One is refurbished, the other is renovated without significant changes.[57]

The different actants involved are:

* A material actant is the house with its particular morphology and materiality.
* Another material actant is the air, flowing through the house.
* A sensor actant is a set of airflow sensors embedded within the scene. It is connected with a processing unit and a locally embedded camera communicating with the sensor units through the processor.
* A representational actant is in this case externalized both spatially and temporally in the form of diagrams representing the captured data as color overlaid on images.
* A Participatory actant is in the scene as the inhabitant that interacts with material actants through actuating the morphology of the house i.e. opening windows and doors.

The purpose is to observe and decode existing phenomena and interactions between actants in order employ specific material alterations at a later stage. Sensors are embedded in the scene for recording various data. This active process of placing data capturing points acts as catalysts for phenomena to take place, which are in turn captured by the sensors, as well as the cognitive capacity (senses and memories) of the participants.

56 Nielsen, Stig Anton. »Physical Form Finding by Embedded Sensors: Using ‘sensor chaining’ in various temporal and spatial scales.« eCAADe 2013: Computation and Performance–Proceedings of the 31st International Conference on Education and research in Computer Aided Architectural Design in Europe, Delft, The Netherlands, September 18-20, 2013 18 Sep. 2013.

57 For overview of the experiment refer to paper summaries, paper 1. »Physical Form Finding by Embedded Sensors«

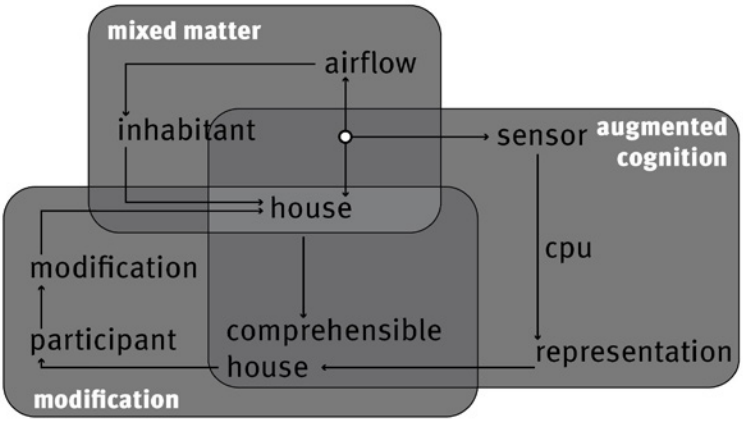


Figure 4. Flow of information show three separate loops that interact through the house.

Environment Modification (EM)

The approach of Environment Modification is illustrated through the experimental cardboard structure installation (MCard) documented in paper 2[58] and 3[59]. An installation where bypassers are engaged to build elementary cardboard blocks onto an existing structure guided by light projections which are informed by data from sensors within and around the structure.

* First material actant is the cardboard units, which with their particular morphology and materiality allow for the formation of strings, planes, and solids.
* Second material actant is the air flowing through the structures.
* Third material actant is the light, reflected and filtered through the structures.
* First sensor actant is a set of pressure sensors ingrained under the two starting ground points of the structure.
* Second sensor actant is the airflow sensors embedded within the scene.
* Third sensor actant is a set of light sensors around the base of the structure.
* One processing and data storage actant is a central CPU external to the scene. This deals with the sensor data and relates through formal computation to the representational actant.
* One representational actant is an electronic light projector and a 3d camera which projects information on the material actant as areas of different relevance in accordance to the formal processing of sensor data, captured from the sensors in response to the interaction between material actant 1,2 and 3.
* Several participatory actants actuate the material actant, on the basis of the representational actant.

Sensors and additional material are installed in an easily understandable scene, and connected to a central computational unit. The CPU generates a representation which augments the material and the cognition of the participants (by being able to provide them more information about the scene). The representation is laid over the

58 Nielsen, Stig Anton, and Alexandru Dancu. »Layered subsumption in intelligent material building systems.« TEI'14, Feb 16 {Feb 19, 2014, Munich, Germany. 2014.

59 Nielsen, Stig Anton. »A process where performance drives the physical design.« Rethinking Prototyping 2013.

scene in the most intuitive way, and is constantly updated based on the changing state of the matter in the scene. The participants from the scene who choose to react with the matter and representation will modify matter in the scene physically. Participants make use of their cognitive abilities, reasoning, and bodies when they modify the scene. This means they are not dictated by the representation, merely informed by it as addition to the material and morphology.

Modification of the environment is made easy by modular elements that can be quickly re-arranged by hand. Elements with a shape contain a ruleset simply because of their morphology and materiality, which in turn imposes on both the overlaid representation and the decision making of the participatory actants.

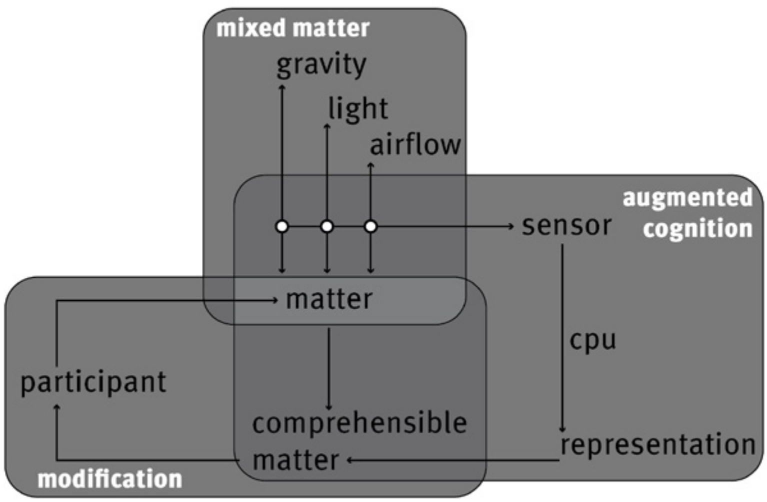


Figure 5. Two loops can be identified, but the sensors are now more heavily represented where the third loop was found in figure 4.

Game-based Modification (GM)

The approach to a Game-based Modification Setup is illustrated through the foam building game, where two players competitively build their own foam structure from identical foam units. (FGame) is documented in paper 7[60]. The goal for each player is made up of multiple criteria: who can capture the most light from above but also gain extra points for building high and picking bonus points. As the competing structures start to interact they can also steal light from their opponent by covering their structure with their own.

* The only material actants are the foam units with their particular morphology and materiality which allows for quick assembly of branching or rhizome structures. The basic unit has five different morphologies, allowing for a study of morphological computation.
* A sensor actant is a set of pressure sensors under the starting points for the structures.
* Another sensor actant is a 3D camera[61] externally mounted over the structures.
* A Processing and data storage actant exists external to the scene.
* A representational actant is present here as an electronic light projector connected to the 3d camera sensor, acting as catalyst by displaying the game score and augmenting the players' cognition.
* The participatory actants are two players who actuate the material actant in response to the representation and the actuation of the competing material structure.

Game-based Modification is similar to Environment Modification (EM), where sensors are connected to a CPU which generates an overlaid representation, and modification is made easy thanks to the modular elements that impose constraints and rules by means of their morphology and material alone. In contrast to EM, participants compete against each other through the conglomerate structures and their morphologies. The participants are also subject to an additional ruleset, beyond their limited cognitive capacity and the rules induced by the morphology of the building units. The sensor-CPU and overlaid representation can play numerous roles in this method: It can augment the cognitive capacities of the actants to assist players, it can keep track of events throughout the game, and keep scores for each participant.

60 Dancu, Alexandru et al. »Emergent Interfaces: Constructive Assembly of Identical Units.« Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems 18 Apr. 2015: 451-460.

61 Microsoft 3D Kinect 360

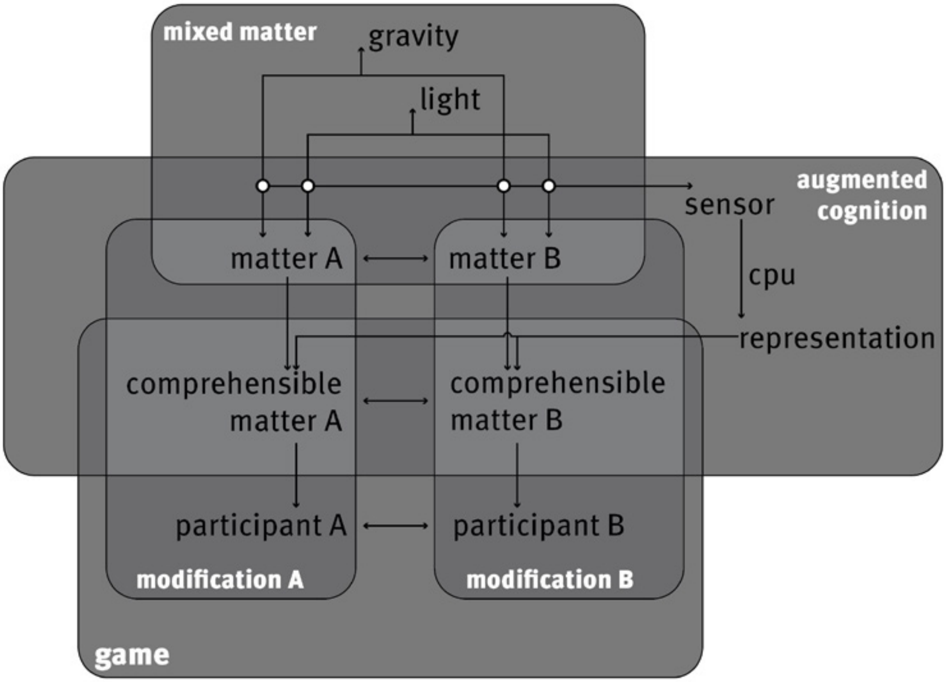


Figure 6. Two main loops as well as interaction between the two competing entities of matter, participants, and comprehensible matter.[62]

62 The concept of Augmented matter is found in: Johns, Ryan Luke, Axel Kilian, and Nicholas Foley. »Design Approaches Through Augmented Materiality and Embodied Computation.« Robotic Fabrication in Architecture, Art and Design 2014 (2014): 319-332.

Feed-forward Modification (FM)

The approach of Feed-forward Modification is illustrated through the embodied design setup called 'Sensitive Assembly'. It is a de-construction game for two players augmented by the Event Series Prediction (ESP) SenseWall described in Paper 8.[63],[64]

* The single material actant is a number of identical cube shaped units initially stacked to form a straight wall.
* The sensor actant is again a 3D camera sensor which monitors the wall from the backside.
* A processing and data storage actant exists external to the scene.
* A representational actant also exists externally, as a large monitor next to the cube wall, displaying results from ESP.
* Two participatory actants compete in turn to actuate the material actant, while observing the ESP results.

This wall made up of identical cubic units is taken apart in a competitive way; The winner is the player who removes the last cube successfully without collapsing the wall. The sensor actant collects data about the wall, and the Processor extracts structurally relevant features used for the ESP algorithm. The representation is also the result of ESP and consists of a short series of 5 images captured from previous games, which expresses the best match between experience and current situation. These 5 images are the model of prediction for the current game.

63 Savov, A., Tessmann, O. and Nielsen, S.A., »*Sensitive Assembly: Gamifying the design and assembly of façade wall prototypes*«. International Journal of Architectural Computing, 14(1), 2016. p. 30-48.

64 The game is also augmented by structural analysis software projected on the building blocks, but this part of the experiment is not discussed as part of this dissertation.

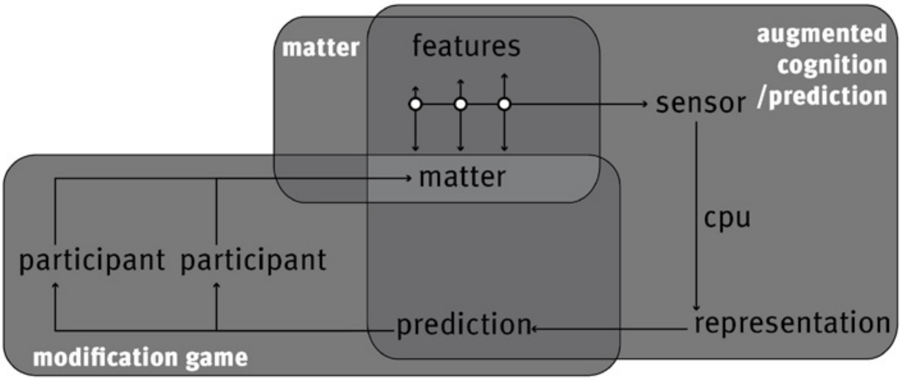


Figure 7. The diagram is very similar to EM, the difference being that comprehensible matter is replaced by prediction.

5.0 DISCUSSION

The reciprocal relationship between events and their physical condition can be discussed from the viewpoint of both technological and philosophical discourses. The conditions for mixed substrate computation are the core interest throughout the discussion, while related research provides arguments and explanatory background for the hypothesis and experiments.

Materially based electronic *sensors* can, through sensor fusion, expand information by incorporating additional dimensions by means of formal *computation*. An argument discussed further in Section 5.1. In section 5.2 we discuss how formal and material computation takes place on distinct *substrates*. Discrete *computational substrates* can be managed and guided through their *representational relationship*. In section 5.3 we identify this as a naturally occurring embodied process in traditional architectural development and discuss it in detail. We discuss general *embodied computation* in relation to human *cognition*, phenomena, and activities in the built environment in section 5.4. Section 5.5 discusses the differences of how science and philosophy have described phenomena and activities. *Semantic* handling of concepts is discussed in section 5.6, and an approach to the *grounding* of semantics is presented in 5.7. *Machine learning* already deals with semantics and concepts through *representations*, an aspect further discussed in 5.8. And finally, in section 5.9, representation and the represented, or *expression* and *content*, is discussed in relation to embodied computational systems.

The implementation and use of mixed substrate computation, as discussed in this chapter, enhances the built environment's capacity to receive, store, process, and emit information in a purposeful way, in turn allowing the environment to recall previous phenomena that took place, and from that successfully predicting what will happen in the near future. We will also present aspects relevant to understanding the ESP algorithm and our experiments.

According to Michel Serres, humans are not the only literate life form. On the contrary, Serres claims all things in the world exchange and are shaped by streams of information running through them. He claims everything adheres to four universal operations; *receiving*, *emitting*, *storing* and *processing* information, and writes that information shapes everything across vast scales of time and space, as well as across matter and non-matter. On thinking, Serres writes: »*... thinking means inventing: getting hold of rarity; discovering the secret of that which has the huge and contingent chance to exist or* *to be born tomorrow.*« [65] Serres says a computer does just that, but he does not claim that everything computes—a standpoint on which both Susan Stepney and Clare Horsman agree. They attempt to define exactly when a physical system can be said to perform computation.[66] However, Serres says thinking is more than just computation, namely inventing and discovering the stuff of tomorrow.

This ESP method of prediction acts similarly to—but is constructed similarly to—a well described concept called Nonlinear difference-differential equations, which learns from data sequences in order to successfully anticipate future sequences.[67] But first we must discuss reception, storage, processing, and emission of information in order to discuss the design of a physical prediction systems.

5.1 External, Ingrained and Embedded Sensors

A mix of computational substrates[68] require that the substrates intended to interact in the assemblage are connected through expression and content planes i.e. a representational relation. All physical substrates are to varying degrees connected through the environment. However strengthening the physical connection can for example be achieved through assigning the computational material with a computational morphology. In that case the two computational substrates share space and matter, but it does not necessarily mean they interact directly through a representational relationship within the computational assemblage. These relationships can alternatively be established using sensors.

Physical and virtual computational substrates can be connected through the use of *sensors*.[69] Sensors are physical components that react to shifts in one or more distinct dimensions of their environment, transducing or changing that dimension from one form of energy to another form—and scale—of energy. Most sensors are purely material based, for example the bi-metal of a thermostat, which reacts to a thermal change in the environment by changing its shape—a shape change of such size and speed that it is useful for adjusting a valve controlling the flow of heat. Such thermostats can be material,

65 Serres, Michel. »Information and Thinking«, Society for European Philosophy and Forum for European Philosophy Annual Conference Philosophy After Nature Utrecht September 3, 2014

66 Horsman, Clare et al. »When does a physical system compute?«, Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences 8 Sep. 2014: 20140182.

67 Grossberg, S., 1967. »Nonlinear difference-differential equations in prediction and learning theory«, Proceedings of the National Academy of Sciences,58(4), pp.1329-1334.

68 Computational Substrates are more in depth discussed in chapter 4.4.

69 Other, more direct ways are described later on.

analog sensors. For more advanced formal computation, electronic sensors are used. These are based on the electromechanical behavior of materials that react on changes in particular dimensions of the environment. The electromechanical behavior of the material in the sensor causes a change in the flow of electrons moving through the sensor. In turn, the electrical flow is translated to numerical signals in order to be used for computation in another substrate, such as a microcontroller. This first simple step can connect computation from material, morphological, chemical or other substrates directly to the computational substrate of a digital computer i.e. formal computation.

Sensors are usually material based, but do not always send electromechanical signals. Figure 8 shows a type of sensor which signals morphologically—its specific change of shape is a result of temperature changes in its environment. This morphologic signal is however not communicable with other computational substrates without undergoing some form of translation.

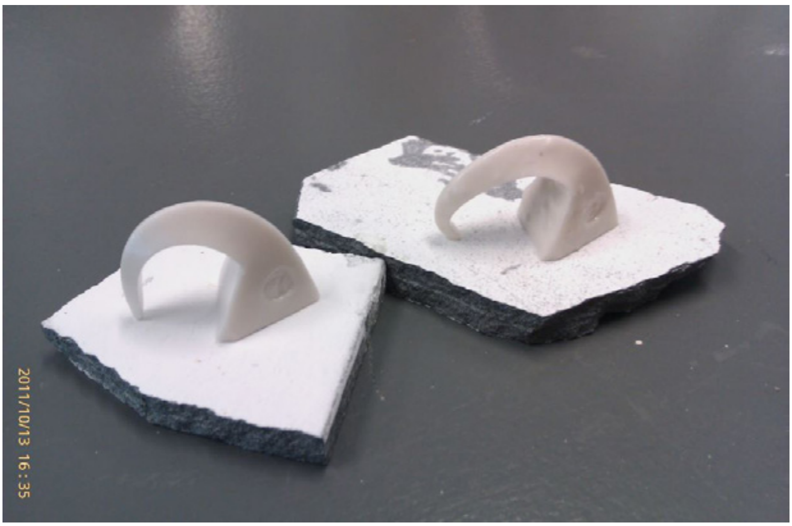


Figure 8. Cones are used mainly in manual kilns as sensors showing when the material deforms it signals when to turn the kiln off. These material sensors are identical in morphology but can be made from different material. The same kind of cones can be used for calibrating electric kilns more accurately to attain even heat distribution. The sample on the left shows correct deformation, which means the temperature for the material was correct, while the right sample had either the wrong material, or was overheated.

The information from a sensor must be communicable i.e. transferrable to another medium or substrate. Steven Glaser writes that »*In order to develop useful transducers (sensors), it is critical to first understand the physics parameters to be measured, only then can appropriate transducers with the necessary operability be developed.*« [70],[71] Contrary to what Glaser says, the experiments here demonstrate how semantics are no longer required. The use of multiple identical or different sensors in conjunction with advanced computation can achieve autonomous formation of non-anthropic semantics.

Three conceptually different ways of implementing sensors leads to different levels of robustness and calibration. *External*, *Ingrained*, and *Embedded* approaches are conceptually described (see fig 9). External sensors are not in direct contact with the matter they sense, whereas *ingrained* and *embedded* sensors have different degrees of contact with the substrate, either on the level of components (embedded) or on the level of the composite (ingrained).[72],[73] The approaches of embedded and ingrained sensors need less contextualization due to the grounding within matter and environment. We could conceive of a fourth approach, where the materials and components themselves are active sensors, similar to what the 'pressure sensitive stick experiment' demonstrates (Figure 12). Figure 10 shows a force sensitive beam, which is an example on the use of ingrained sensors.

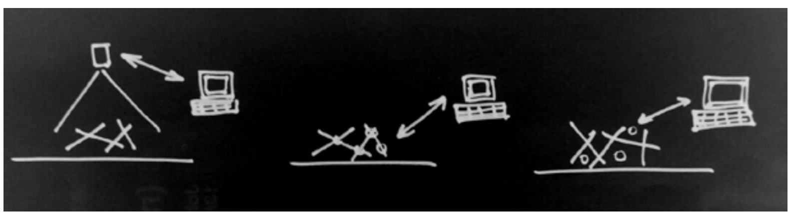


Figure 9. Three different approaches to install sensors to matter or structure in their environment; External (left), Ingrained (middle), Embedded (right).

70 Glaser, Steven D., and Anne Tolman. »Sense of sensing: from data to informed decisions for the built environment.« Journal of infrastructure systems 14.1 (2008): 4-14.

71 Described in paper 3: Nielsen, Stig Anton. »A process where performance drives the physical design«. Rethinking Prototyping, 2013. p. 615-626.

72 The three terms are ambiguous, as the system being sensed can be observed from different levels, which in turn may determine which of the terms to define the sensor by.

73 Nielsen, Stig Anton. »*A process where performance drives the physical design*«. Rethinking Prototyping, 2013. p. 615-626

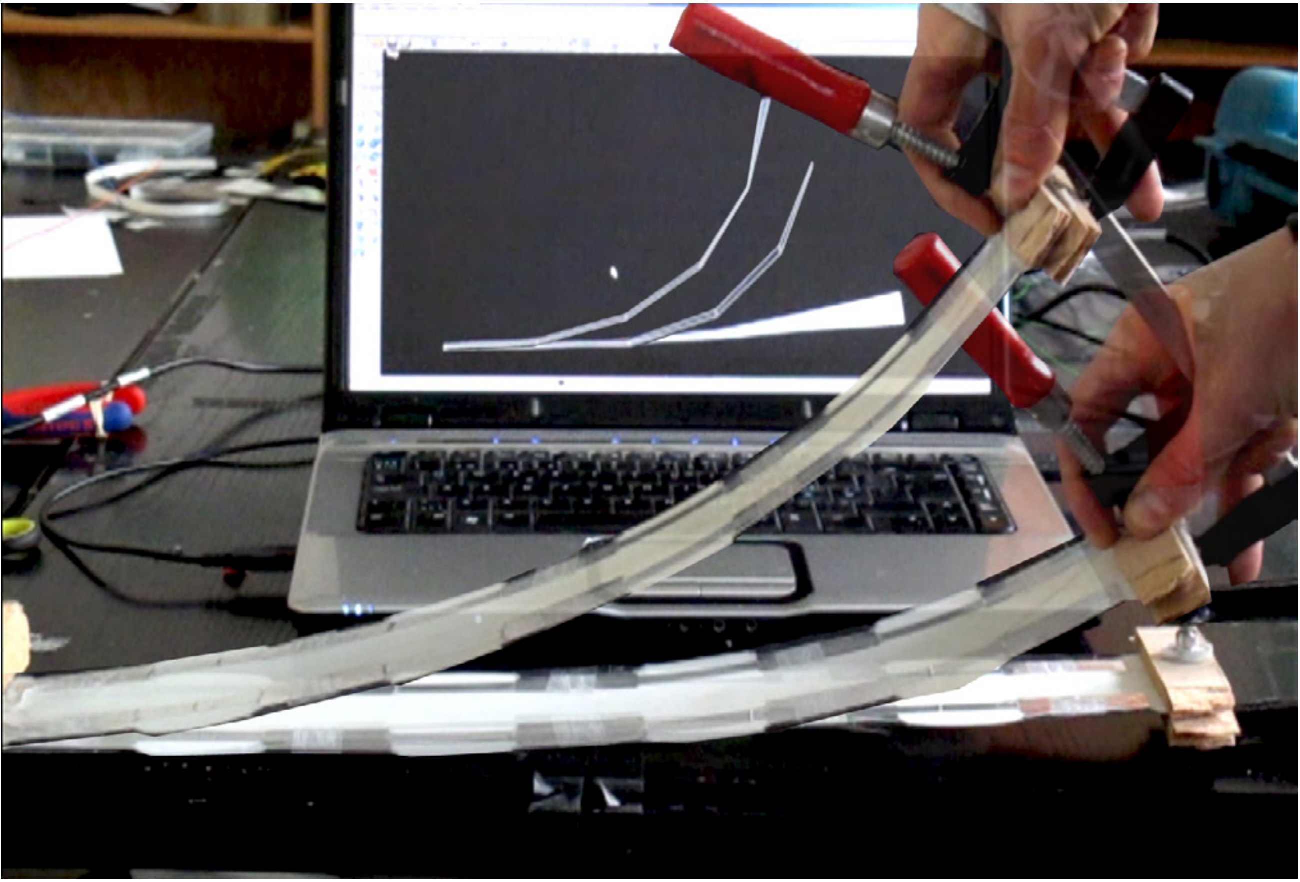


Figure 10. This 'sensor beam' was constructed from a glassfiber polymer reinforced composite where pressure sensitive and conductive material is ingrained in the core of the structure, thus making it able to sense its own internal forces when the beam is mechanically manipulated. The electronic cpu transduces the signal from the pressure sensors and, with the help of a reverse kinematic virtual model, the signals are calibrated so the virtual representation mimics with the deformation of the physical structure. In this illustration, a few frames from a video of the sensor[74] are overlaid to show how different degrees of bending affect the virtual model seen in the background.

Figure 11. 'Sensor active clay tile' is a ceramic tile that can be used as a sensor by measuring the internal resistance of the material. Electrodes are drilled into the material, and in turn, current is sent from each electrode to every other, while resistance is measured. A projection on the material itself shows the resistance value between each electrode. As the humidity in the material changes, the internal resistance changes respectively.

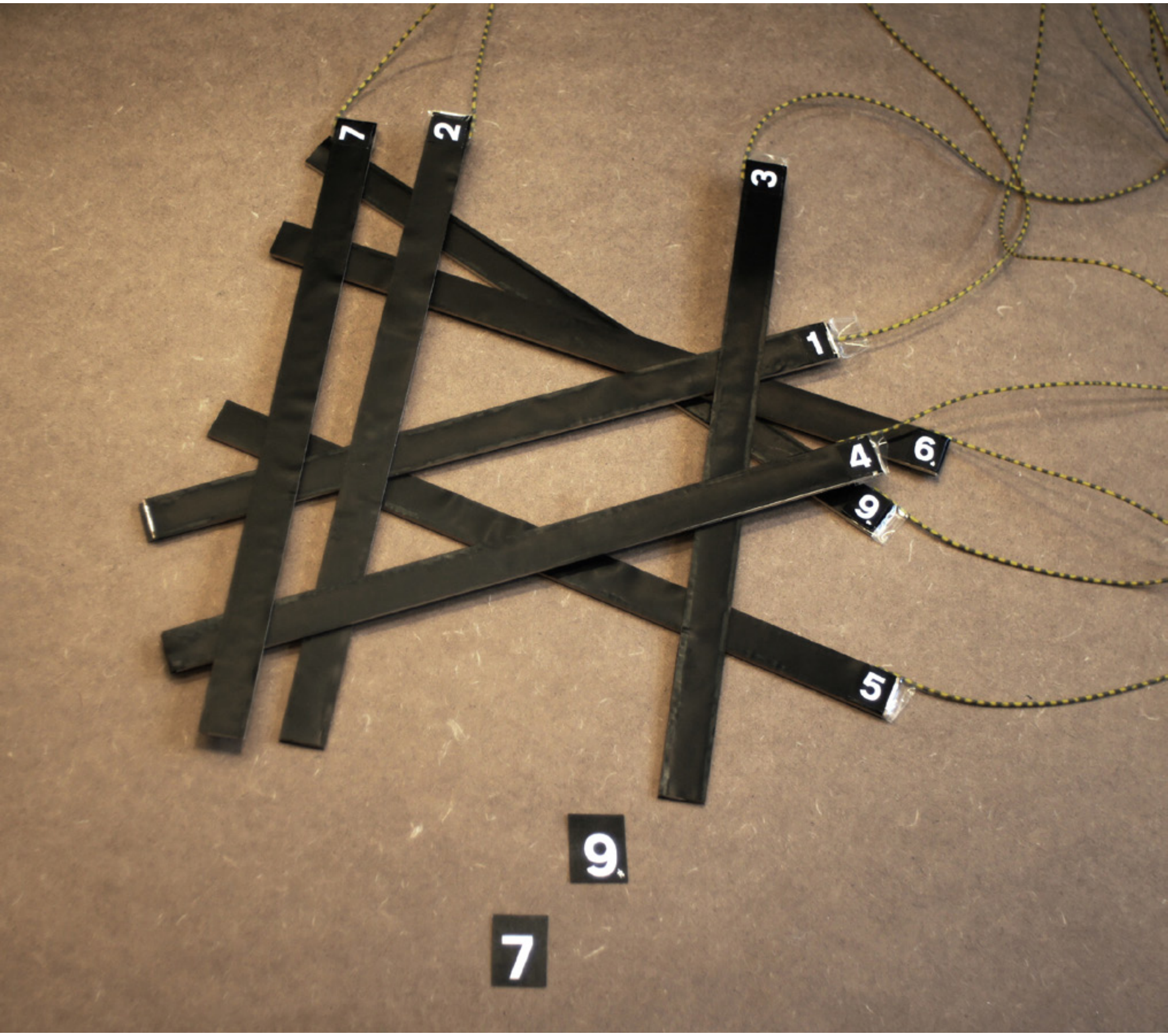


Figure 12. Pressure sensitive sticks experiment (CSticks). Each of these wooden sticks are coated firstly with a fully conductive layer and secondly with a semiconductive layer. As they come in contact, signals between each stick can be read on the CPU and combined, showing which two sticks are least centrally connected—in this case, 4 and 6 which are on the bottom and top of the conglomerate. The experiment investigates the relation between a simple ruleset, sensors, and elementary morphology. The conclusions at the end of the paper describe how the intrinsic aspects of the system perform controvert (paper 3).

Using multiple sensors reduces the need for calibration and limits the amount of coding otherwise required for contextualization.[75] The experiments seen in figure 10,11, and 12 all rely on a multiplicity of similar sensors and the internal differences within the material. The practice of using similar sensors is called *Sensor Fusion*. Sensing capability can in this approach be expanded through a combination of *information* from multiple sensors. An example is the use of two or more cameras, which can—when the data is correctly correlated—provide the dimension of depth to image data. Fusing homogenous sensors is called *direct sensor fusion*, whereas heterogeneous sensor fusion is called *indirect sensor fusion*.

»*.. if you combine the data from a variety of different sensors, you will be able to measure parameters for which no single sensor exists.*«[76]

Global positioning system (GPS) uses homogenous sensors for positioning, whereas indirect sensor fusion can be used for example to detect traffic congestion where multiple criteria can be considered i.e. sound, image, vibration, etc.

Calibration loses significance when using homogenous sensors. The location of an individual sensor correlated with readings from other locations provides more significance than the actual numeric value of the individual sensor.

Instead, sensors are normalized relatively to each other. Not the value of the individual sensor, but rather the difference in value between them, and that difference in location is the relevant *information*.

The idea of fusing and computing sensor data from multiple dimensions simultaneously is essential in order to separate individual states of phenomena taking place in the built environment.

According to Gregory Bateson, information being received by human sensorial input is conditioned by differences over time.[77] Time is thus one factor that conditions acquisition of information, and the second is relative local differences. Relative to these two main dimensions, a multitude of other dimensions can be related.

75 A conclusion shared with Rodney Brooks in the article »Elephants Don't Play Chess« from 1990 p.8. where the robots Tom and Jerry using subsumption architecture can fit their logic program on a single 256 gate programmable array logic chip, as a consequence of the direct physical grounding of the sensors. Brooks, R.A., 1990. Elephants don't play chess.Robotics and autonomous systems, 6(1), pp. 8.

76 Laughlin, C., »Sensor Fusion + New Materials«, editorial, Sensor Review vol 22#4 Emerals Group Publ. Ltd, 2002,

77 Ascott, Roy, ed. Reframing consciousness. Intellect Books, 1999.

To collect increased amounts of information; (1) Use various types of sensors, (2) Use multiple sensors of the same type, (3) Sensors should be distributed in space, and lastly (4) temporal conditions should be recorded. In short, as numerous dimensions are set in relation to the sensor data, the quantity of information can be increased.

To maintain a close relationship between sensor information and the conditions under which it is collected, some form of processing is necessary. The appropriate processing of information should maintain a reversible representation relation.[78] In some computational substrates the representational relation is direct, i.e. Computation results in its own substrate. In others the results must be extracted.

5.2 Towards Material Computation

Computation, namely the processing of information through a well understood method, is inherently tied to a *substrate*.[79] Computation must take place in some form of matter—for example, minimal surface computation takes place in liquid soap film when stretched in a frame. However a similar computation of minimal surface can also take place in the hardware components of a computer insofar as a formal definition for surface tension can be worked out. In that case, certain aspects of the soap film can be said to be *simulated* computationally, the formal computation having a representational relation to the substrate it simulates. When an ant community finds the shortest path to travel, the computation of the pathfinding takes place on a substrate of both ants and the decay of their pheromones left on the trail, computing the shortest path using the dimension of time. This principle can also be formalized and computed using a computer, where a representational relation to time exists. Until the 1930s computational processes were manually computed,[80] or instruments for augmenting that manual process were used. Take for example the abacus as an instrument of manual computation. Other more advanced instruments can make geometrical translations, such as the sextant for navigation or the swiss ballistic computation instrument (cf. figure 8). This boundary between the abacus and the soap film is the border between calling something natural computation or an instrument, and is an interesting place to find new types of computation such as morphological, biological, chemical, or agent based computation, and we should not forget these even when faced with the convenience of simulation tools. Crucial aspects of natural computation can be lost in the construction of simulated systems, as one only reconstructs the aspects one seems to understand.

78 Chapter 4.5 presents the representation relation in more detail.

79 Horsman, Clare et al. »When does a physical system compute?«, Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences 8 Sep. 2014: 20140182.

80 Computer comes from the profession called computer, which was mainly occupied by woman until the advent of analog and later digital mechanical computers.

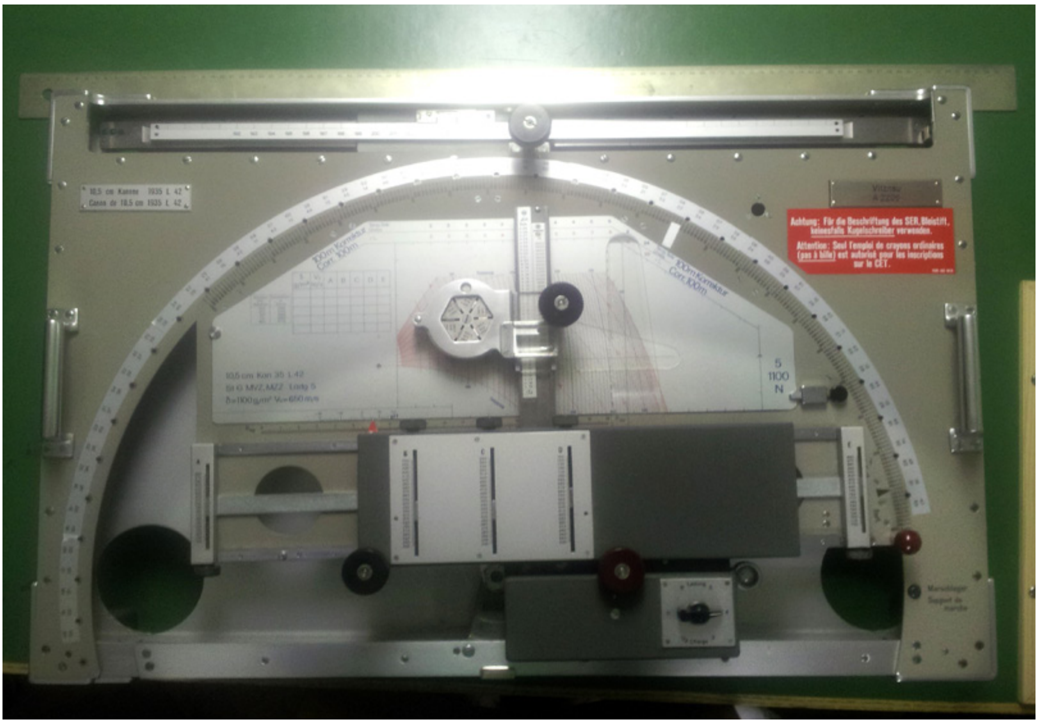


Figure 13. The Swiss ballistic analog computation instrument. Map with height data, weather conditions, and powder charge is given as input. Vertical and horizontal pitch of the cannon is given as output.

Today, most material processes can be modelled principally and computed using abstract computation—but still full scale physical empirical evidence is used to ensure the accuracy of immaterial formalized models. Susan Stepney argues for the importance of understanding organic and inorganic computational principles, because many natural substrates and organisms seemingly effortlessly solve computational problems that still take computers much time and energy. Some of these effective fast and cost free computational capacities can be observed as mentioned in soap films, in large communities of insects, or in the human brain. The advantage of these types of computation is their massive parallel capacity and their robustness to error. However most organic computation is composite computation, making it difficult to understand and model accurately—thus we should, by definition, not call it computation. In cases of such composite computational capacities, as for example with the brain, we instead call it *cognition*: the act of making sense of what is sensed and learned (noscere, latin for learning).

There may be great potentials in natural forms of computation. These natural ongoing, parallel, robust, cost free processes can be adopted for design processes and augmented by formal computation. Researchers from other fields also explore the concept of *Mixed substrate computation* but for other purposes than design and modification.

5.3 Mixed Substrate Computation

The particular distribution and allocation of information conditions the kind of purposeful permeation that would allow for composite and mixed substrate computation to take place. Therefore Mixed Substrate Computation must be designed with distribution and allocation of information in mind. Representations and representational relationships can be used for mediating information between the computational substrates in the assemblage. A strategy found in very different research that applies mixed substrate computation;

John Frazer[81] aims to mix formal computation with the physical design process, thereby augmenting his models to autonomously evolving while they build. He says that architecture could become »*responsive to evolving in not just a virtual but a real environment*«.[82] Frazer's research introduce a form of mixed substrate computation as distinct parts of computation take place in distinct substrates in the

81 Research pioneer in embedded computation and evolutionary architecture from the 1970-ies.

82 Frazer, John. »An evolutionary architecture.« (1995).

experimental physical environments, while other computation takes place in the virtual realm. The substrates are connected through explicit representational relations.

In the article »*Computational Composites*« Johan Redström describes how formal computation can be considered a design material equally viable for material composites.[83] Redström suggests formal computation can be abstracted from its substrate to create artificial constraints that bond it to a material counterpart, creating a composite. Consequently the formal computation is operationalized physically, which means computers can behave materially as part of composites.[84] Today the term 'Robotic Composites' describes combinations of formal computation and material, but in a literal sense, where the actual computational substrate is present in the material, such as with embedded computation.[85] However, the understanding of formal computation as a material is an important notion for operationalizing it as a computational substrate equally available to other physical materials. Again the representational relationships are established explicitly.

Josh Bongaard simulates a material substrate and its actuation using formal computation. In Bongaard's experiment, physical constraints are imitated in a virtual environment in which certain dynamic morphologies evolve through a generative algorithm. Bongaard can thereby quickly and easily vary the constraints and complexity of the virtual environment and study how the complexity of the dynamic morphologies are related to the complexity of the environment it which they evolve.[86] Through simulated virtual substrates, Bongaard in effect studies the computational behavior of evolution.[87] And equally important, the reciprocal relation between environment and embodied entities.

Natural computation comes for free, but it is complex. Stepney explains how the understanding of non-biological computation processes can help us understand far more complex interrelated biological systems.[88] In a sense, Bongaard does what Stepney argues

83 Vallgårda, Anna, and Johan Redström. »Computational composites.« Proceedings of the SIGCHI conference on Human factors in computing systems 29 Apr. 2007: 513-522.

84 »composite algorithms« is on the contrary the act of composing algorithms, purely formal computation, to change or strengthen their performance.

85 Toffoli, Tommaso, and Norman Margolus. »Programmable matter: concepts and realization.« Physica D: Nonlinear Phenomena 47.1 (1991): 263-272.

86 Bongard, Josh C, and Chandana Paul. »Investigating morphological symmetry and locomotive efficiency using virtual embodied evolution.« From Animals to Animats: The Sixth International Conference on the Simulation of Adaptive Behaviour 2000.

87 John von Neumann originally developed the approach to generative learning:

88 Stepney, Susan. »The neglected pillar of material computation.« Physica D: Nonlinear Phenomena 237.9 (2008): 1157-1164.

for; he uses non-biological simulated computational substrates (physical material properties) as substitutes, using them to gain further insight on the biological computational phenomena of evolution. But Stepney is in fact interested in real physical computation and together with Horsman asks: »*When does a physical system compute?*« To define physical computation we can say: A physical system that predictably affects a formally defined relationship (physical material). To link this formal definition to a physical system, the representational relationship is needed between the formal and physical: This could be called the abstraction, the representation, or the 'model for.' Such representational relations are general purpose representations, as is for example the sign '<3' which turned around 90 degrees resembles a heart, referring to the concept of love or affection. The heart icon is bound semantically through an upper ontology creating the link from the human heart to the concept of love. A representation relation can be much simpler, for example 1->warm, 0->cold.

However, as semantic content increase in more specific representations, complexity increases gradually as the possible reversed representation relation becomes infeasible.[89] With such specificity even the forward representation relation can become inaccessible to other entities or substrates. This also means representational relationships can be substrate specific and nonsense to other substrates. In case the representations are such nonsensical to humans we could call them non-anthropic representations. Representations of non-anthropic character are increasingly found in machine-learning and presents both an ethical and systemic issue, in that computers are able to construct features i.e. semantics, for which the representations are inaccessible to humans.[90]

As response to this, complex computation can be kept accessible through grounding. In the article 'Intelligence without representation' Rodney Brooks develops robust robotic creatures which have a well defined relation between internal computational processes and their surrounding environment. Brooks contradicts the prevailing approach of creating cumbersome internal representations for robots, and lets the separate parts of formal computation relate through sensors out directly into the environment.[91] The operation of turning the complexity of the environment on itself is a powerful maneuver when designing mixed substrate computation. Grounding is a funda-

89 Understanding the sign <3 without knowing the concept of love is impossible.

90 Non-anthropic representation is discussed further later.

91 Brooks, Rodney A. »Intelligence without representation.« Artificial intelligence 47.1 (1991): 139-159.

mental approach to contemporary embodied intelligence in robotics, and grounding of representations has arguably been used extensively in the history of architecture as well.

Christopher Alexander reveals how the vernacular building traditions use only embodied representation. One house in traditional building cultures would act the physical -and grounded- representation for the next house. He investigates the evolution of vernacular building traditions and formalizes some of the computational principles he encounters. He emphasizes amongst other, the relation between the change and emergence of cultural and environmental needs as a drivers for change in the morphology of the vernacular built environment. He mentions that tradition can be considered a sensible inhibitor of radical change.[92]

When seeing the vernacular building evolution as mixed substrate computation taking place in the built environment, the morphogenesis takes place between culture, traditions, climate and materials, all as partial computational substrates or actants in the mix. This naturally occurring mixed substrate computation can be characterized as a form of artificial and embodied cognition of the built environment.

5.4 Embodied Cognition or Perception

The environment is partly cognitive of phenomena and activities through the way matter is responsive to stimuli caused by activities. This embodied cognition of the environment can be exemplified both through the the difference between natural science and philosophy, and through several references on embodied and material computation and through examples of naturally occurring computational substrates.

Consciousness is a recurrent topic when discussing *Cognition*. Many philosophers through history have discussed consciousness, many since 1920s using the theories of *phenomenology*:

Bruce Maclennan defines »*Cognition (as) is the emergent pattern of purposeful interactions between the organism and its environment (including other organisms).*«[93]

In contrast to the natural science approach, *Phenomenology* does not make use of reductions and categorizations. Where the natural sciences establish relations between objects in closed systems, phenomenology on the contrary address and understand consciousness and the perception of being *dasein* (being). In this school of

92 Alexander, Christopher. Notes on the Synthesis of Form. Harvard University Press, 1964.

93 MacLennan, Bruce J. »Natural computation and non-Turing models of computation.« Theoretical computer science 317.1 (2004): 115-145.

thought everything is defined through its embodiment—through relationships, presence, and their perception in the environment. In contrast to natural science, Phenomenology focus on structures of experience, consciousness, and cognition.

In natural science, the fundamental 'da sein' and our ability to perceive is taken for granted. Despite the fact that the natural sciences are so very much based on perception and observation, and grounded in the augmentation of perception, the exploration of human perception is not in itself of interest to natural science[94]—.

Husserl and others discuss the subject—object relation as consciousness and *dasein*, describing how events and phenomena are perceived purely through the senses and less so by logical reasoning and object based understanding. Merleau Ponty argued that previous experience—memory—is not perception. Instead experience and memory constructs a landscape around each moment of perception: »*Before any contribution by memory, what is seen must at the present moment so organize itself as to present a picture to me in which I can recognize my former experiences. Thus the appeal to memory presupposes what it is supposed to explain: the patterning of data, the imposition of meaning on a chaos of sense data.*« Merleau Ponty[95]

Figure 14. These three images could exemplify that relation between perception and memory, as image 1 is a stylized version of image 3 (a polar bear on a globe). Image 1 could as well be perceived as a globe with a foot sticking out, as in image 2, however given the memory of image 3, the former meaning is imposed on image 1. Had we never seen image 3, the perception and thereby meaning could be imposed by other random memories, rendering the meaning of image 1 differently.

94 Natural science is occupied with the perception of phenomena, but not in particular the perception itself.

95 Merleau-Ponty, Maurice, and Colin Smith. Phenomenology of perception. Motilal Banarsidass Published, 1996 P.19.

According to Merleau Ponty perceptions, being a stream of chaotic sense impressions, are in a moment correlated with experience in order to be recognized and subsequently contribute to memory. This means experience conditions memory through perception. It also means sense-data requires a *temporal landscape*[96] of experience to become perception. Furthermore it means perception of phenomena are differently conditioned in every individual due to their different experiences.

The algorithm Event Series Prediction (ESP)[97] has the same relation between sense data and experience as what Ponty described: Sense data continuously changes the entire memory, while incoming sense data is compared to the memory. Only through this process might something be perceived.

What seems like artificial cognition and intelligence can emerge from the interplay between environment and body. The idea of *embodied cognition*, *embodied artificial intelligence and embodied computation*[98] is the notion that there is no separation between body—processing and environment, because all are intrinsic components that perform interdependently. Relevant intelligence is dependent on real-world information and real-world influence, therefore the hardware (body) becomes interface to the environment, and when doing so, the body starts to attain processing capabilities—inevitably. The shape and materiality of the body influences the capacity to both attain information, and affect its surrounding environment. This capacity is alternating as the morphology changes, just like

96 See the notion of Temporal Landscapes in introduction.

97 Presented in chapter 6

98 The philosophical study of consciousness arguably led to the field of psychology, but Cognitive science in itself is said to spring from early the cyberneticist movement in the 1930ies. Cognitive science has from its beginning dealt with models of human cognition, and the research laid much ground for the later research into Artificial Intelligence. in 1956 John McCarthy introduced Artificial Intelligence, in collaboration with the scientists Herbert Simon, Marvin Minsky and Allen Newell amongst others. They define this initial type of AI as a general symbol-processing paradigm. An approach where the internal processes of cognition are defined such that they can be performed by any general symbol processor. From 1956 and up to the 1980ies, AI was not concerned with the physical hardware or interface to the world and the environment. Around the 1980ies the interplay between both formal computation, material body with natural computation capacity, and the environment was defined as embodied cognition, embodied artificial intelligence and embodied computation.

changing the manipulation of symbols in an abstract machine, the morphology, mechanical and material composition of the body changes its capacity to perform real world processing.[99],[100]

Embodiment has been described recently in architectural research identified at indeterminate fabrication approaches, where sensors capture information from the material modification process to use it for steering the further manipulation of material.[101],[102]

The implementation of embodied artificial intelligence also requires a representational relationship established as linkage between formal computation and material. Physical computation can exploit material behavior for certain tasks, and through design and aggregation of carefully chosen materials the computation can be refined. This principle of physical aggregate computation is demonstrated in the experiment using an underactuated robotic gripping device capable of adapting its grip to differently shaped items entirely without formal computation (Nielsen 2014[103])[104] The mixed computational substrate of this gripping process lies in the material aggregation and exactly tuned morphology of polyethylene, acrylic clamps, and glass fiber composite When meeting external constraints and an object morphology to grip, it reacts predictably.

As such aggregates are turned into direct design applications, the aggregate capacity to perceive the designtask at hand increase. This can be observed with programmable material systems; Galilei Galileo studied the hanging chain models around 1600, and Gaudi has since then developed the technique in more aggregate and complex models in other materials. Frei Otto expands the method of using material aggregate and material properties for computation in his reknown form-finding experiments. He exploits the material constraints and material properties in quasi-self-optimizing models. Most renowned are the soap-film-in-frame models which make use of surface tension,

99 MacLennan, Bruce J. »Aspects of embodied computation: Toward a reunification of the physical and the formal.« 6 Aug. 2008.

100 For more in depth description, I recommend the introductory chapters in the book: »How the body shapes the mind« by Rolf Pfeifer and Josh Bongard which discuss intelligence and embodiment in respect to robots.

101 Johns, Ryan Luke, Axel Kilian, and Nicholas Foley. »Design Approaches Through Augmented Materiality and Embodied Computation.« Robotic Fabrication in Architecture, Art and Design 2014 (2014): 319-332.

102 Dörfler, K, F Rist, and R Rust. »Interlacing: An experimental approach to integrating digital and physical design methods.« Proceedings of the robots in architecture conference 2012: 82-91.

103 Nielsen, Stig Anton, and Alexandru Dancu. »Embodied computation in soft gripper.« Proceedings of the 2014 ACM/IEEE international conference on Human-robot interaction 3 Mar. 2014: 256-257.

104 Demo video found at https://vimeo.com/stigantonnielsen/gripper

viscosity and low friction, to compute minimum surfaces.[105],[106],[107] This mixed substrate computation is an assemblage[108] of the materially computational model and the researchers' intellect. These in congruence allow for an increased cognitive state to emerge, and increase the computational capacity of the design operation.

Today computational tools that simulate physical forces are easily available.[109],[110] These tools replace the physical self-optimizing models, and allow for increased control of geometry and material property parameters. The new simulation models also make documentation of calculated forms easier than what it was using the foregone physical computational models. In congruence with human intellect of the design they also allow for an increased cognition of virtual non-embodied systems.

These new tools have fundamentally increased our capacity to calculate physical and material properties, however we should not allow the models to detach from the real physical substrate. Physical grounding through the use of sensors(cf. section 5.5) is a viable way to close the gap between material and formal computation.

The digital tools for simulation are far from sufficient for the purpose of simulating the full complexity of architectural phenomena. Other forms of simulated substrates can target other physical processes than material structural performance. Simulated substrates can be inspired by naturally computational substrates such as birds flocking, the ant hive, the brain etc.[111] The concept of validation is of particular relevance in disciplines like architecture and construction, where natural physical systems are more economical to design virtually simulated using a computer rather than through physical modelling. However there are numerous other phenomena within architecture that are not being simulated before construction. Processes that are interdependent, hard to understand and impossible to simulate. These non-material based processes can be entangled with both physical and immaterial temporal processes. Many aspects of architecture

105 Elser, Oliver, and Peter Cachola Schmal, eds. Das Architektur Modell: Werkzeug, Fetisch, kleine Utopie. DAM, Deutsches Architekturmuseum, (2012): 45-49.

106 Nerdinger, Winfried ed. »Frei Otto: complete works.«Basel et al., Birkhäuser Lightweight Construction, Natural Design (2005).

107 Kurrer, Karl-Eugen. »The Beginnings of a Theory of Structures.« The History of the Theory of Structures: From Arch Analysis to Computational Mechanics: 250-305.

108 Heidegger's definition cf. section 1.8

109 Piker, Daniel. »Kangaroo: form finding with computational physics.«Architectural Design 83.2 (2013): 136-137.

110 Kangaroo is a free physics simulator plugin for Grasshopper, a plugin for the cad-program Rhinoceros 3d, is developed by Daniel Piker.

111 Stepney, Susan. »The neglected pillar of material computation.« Physica D: Nonlinear Phenomena 237.9 (2008): 1157-1164.

is as such -*computationally irreducible*. Stephen Wolfram exemplified a computational irreducibility and thus computational emergence through a myriad of unique programs with interdependent rulesets, that in effect could only be investigated through running them.[112] Architecture has that same character, the phenomena are emergent, and only through implementation can the real effects and the phenomena they produce be observed and provide real insights. Insights given by both observation but also from collected data. It is important to consider how to store and man age this for future insights. Data and memory from past situations that can augment our perception of current situations.

5.5 Causality or Phenomena

To achieve a fully cognitive environment it must be enhanced by memory and additional computational capacity, an approach for which the tradition of observing phenomena in combination with recent research on recognition can be useful.

Since enlightenment humanity has augmented perception through tools and instruments. A shift in this augmentation can be observed. From one that deals with adapting physical and temporal scale to human perception, towards one that deals with visualizing patterns and relations of multiple dimensions.

The Enlightenment brought methodical observation of phenomena through scaling temporal and spatial dimensions to fit human perception. Many discoveries, inventions, and machines have augmented the human capacity to perceive and experience phenomena. For example, the invention of the lens offered great advances on spatial scaling,[113] and the advent of the camera brought about the capacity for temporal scaling, cf. figure 16,17.[114]

Machine cognition research today also focuses on perceiving the environment and real life situations. Much attention has been given to image recognition, but in this endeavor reduction of single physical scales does not suffice. The tools developed for recogni-

112 Wolfram, Stephen. A new kind of science. Vol. 5. Champaign: Wolfram media, 2002.

113 The invention of the lens in the eleventh century by Abu Ali al-Hasan ibn al-Haytham was made using understanding of the eye, and is the technology used to augment the eye. Technology starting with the reading stone developed into spectacles to binoculars, telescopes, and microscopes, which in the following centuries brought a range of scientific discoveries. The lens augmented the capacity of the human eye, enabling the observation both large scale, distant phenomena, as well as microscopic phenomena. With the invention of the camera, temporarily inaccessible events could be understood. Howard, Ian P. »Alhazen's neglected discoveries of visual phenomena.« PERCEPTION-LONDON- 25 (1996): 1203-1218.

114 Noah's timelapse through 12.5 years https://www.youtube.com/watch?v=iPPzXlMdi7o

tion instead operate on multiple features or multiple dimensions.[115] Whether image recognition is sufficient for future application can be discussed, but the tools developed for recognition are very versatile and applicable in many other more embodied and temporally conditioned tasks engaging other computational substrates, given adequate adaptation.[116]

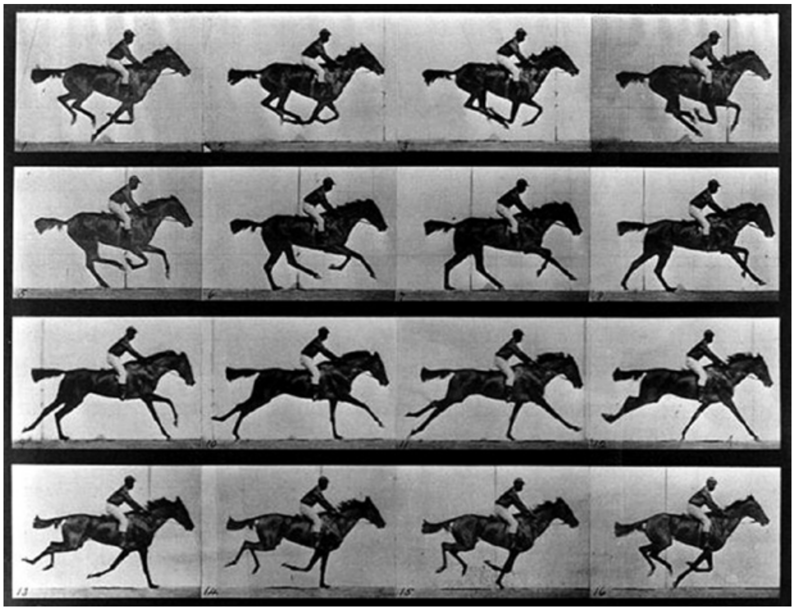


Figure 16. Documents through the use of a camera the leg movement of a galloping horse. This was difficult to document without the use of camera because the movements were too fast to capture by human perception.[117]

115 Bengio, Yoshua, Aaron Courville, and Pascal Vincent. »Representation learning: A review and new perspectives.« IEEE transactions on pattern analysis and machine intelligence 35.8 (2013): 1798-1828.

116 Lowe, D.G., 1999. Object recognition from local scale-invariant features. In Computer vision, 1999. The proceedings of the seventh IEEE international conference on (Vol. 2, pp. 1150-1157). Ieee.

117 In 1877, Leland Stanford settled an argument about whether racehorses were ever fully airborne: he paid photographer Eadweard Muybridge to prove it photographically. The resulting photo, the first documented example of high-speed photography, clearly showed the horse airborne.(Wikipedia:'en.wikipedia.org/wiki/Horse_gait')

Figure 17. Noah Kalina published in 2000 an ongoing time-lapse video showing himself aging through the past 12.5 years.

Current image recognition systems are trained from images appended with human semantics. But in order to recognize phenomena—known and unknown—this approach is insufficient for a number of reasons. Firstly, we no longer have names for the entities we detect. Description or names would require cumbersome explanation in human language. Secondly, there is an infinite number of phenomena to detect.

A strategy of managing and understanding smart cities is formulated but not demonstrated by Benedetta Mattoni; Through the current increased availability of information he attempts to define the entire built environment using anthropic semantics. Categorization of events is his least unsuitable approach to describe phenomena. It departs from the concept of causality and he categorizes events as: 1. Direct being the first event's effect on a second event. 2. *Indirect* being the first event's effect on the second, only via its impact on a third variable. 3. *Mutual* being how two events affect each other. 4. *Spurious* being how two events taking place based on a third event affect them both. 5. *Moderated* which is the third event moderating the ongoing direct dependency between the two events.[118] The attempt seemed futile. The 5th definition overlaps the 1st and 2nd, and there is no clear definition of the term 'event.' More importantly, the categorization is dependant on point of view and subdivision of the observation.

Mixes of computational substrates, although entangled and embodied with their surroundings, will have an order of causal logic. The question remains whether it matters to any given challenge.

Causal relations can be divided in two categories, simple and ambiguous.

If the causal relation is as simple as a mechanical control feedback loop, it will be easily understood and without relevance to its surroundings, as it has no entanglement, it is completely detached or self contained. Figure 18, left.

All other relations are ambiguous and can be referred to as *circular causality*. They can be described as a chain of events for which one or more chain links affects earlier chain links. Circular causality consists of several overlapping feedback loops with relations to the surrounding environment. The intricate interaction between several loops makes circular causality ambiguous. Due to the entanglement and entropy and the resolution of the challenge, it does not seem relevant to seek a level of resolution where individual sub-loops are understood, it is more important to continuously trace and instantly build a sense of phenomena in order to have readily available heuristics.

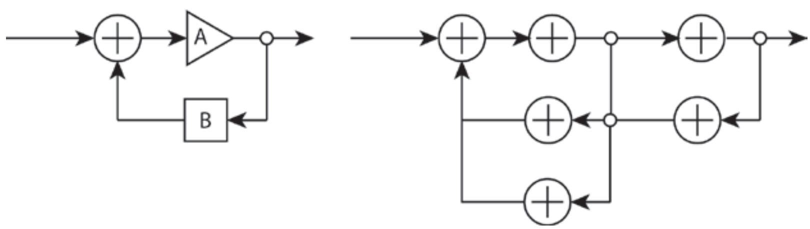


Figure 18. On the left a well understood feedback loop (self contained), on the right a model for circular causal relation.

Events, Episodes, and Phenomena are terms used as abstractions and generalization for different scales of partial processes that we can identify taking place in the environment. The Kantian definition

118 Mattoni, B., Gugliermetti, F. and Bisegna, F., 2015. A multilevel method to assess and design the renovation and integration of Smart Cities.Sustainable Cities and Society, 15, pp.105-119.

of a phenomenon is a thing or event as it appears or is apprehended by an observer though senses, in contrast to a noumenon or a thing-in-itself which is something that exists, but is not perceptible through senses[119].

In probability theory the event is a series of possible but distinct outcomes. For example, when tossing a die, the event of the dots on the die faces being higher than 3 is within the event of them being 4, 5, or 6. The events are used for describing partial outcomes of phenomena with uncertainty. Alternatively: »*An episode is a collection of events that occur relatively close to each other in a given partial order.*« [120]

In other popular definitions found online there is an emphasis on the unusual or extraordinary, however I will use the word phenomenon as alternative to episode or sequence, both because it covers widely without being constrained to localities in time or space, and because it is has the Kantian distinction from noumenon. The noumenon is in contrary to phenomenon: non-observable by our senses, only by other means. This distinction can be useful for comparing human cognition to machine cognition or other non-anthropic cognition.[121],[122]

5.6 The Topology of Concepts

In order to identify and model phenomena, it is relevant to discuss what phenomena consist of, and how they are distinguished one from another. N-dimensional descriptive topology can define and differentiate both in machine recognition tasks but also more complex concepts in language.

Peter Gärdenfors has been dealing with the semantics of words and concepts, where concepts are the general meaning of a word rather than the Deleuzian meaning of concept.[123] One of his main challenges in his work on language is the specificity of the user. The individual's own spectrum of experience and knowledge affects their perception

119 https://global.britannica.com/topic/noumenon http://seop.illc.uva.nl/entries/kant-metaphysics/

120 Mannila, Heikki, Hannu Toivonen, and A. Inkeri Verkamo. "Discovering frequent episodes in sequences Extended abstract." 1st Conference on Knowledge Discovery and Data Mining. 1995.

121 Klein accounts for the idea of machine cognition as sense and decision making using machine learning.

122 Klein, Gary, Brian Moon, and Robert R Hoffman. »Making sense of sensemaking 1: Alternative perspectives.« IEEE intelligent systems 4 (2006): 70-73.

123 Schmidgen, H. 2015, »Cerebral Drawings between Art and Science: On Gilles Deleuze's Philosophy of Concepts«,THEORY CULTURE & SOCIETY, vol. 32, no. 7-8, pp. 123-149.

and understanding of concepts. For example ›apple‹ is perceived differently by a child than by a pomologist due to their difference in memory, experience, and knowledge.

Through a topological approach which Gärdenfors calls 'Conceptual Spaces' he assigns dimensions to words and concepts. Nouns or real world objects can be given dimensions as characterization and description. These could be dimensions such as weight, size, shape, color etc.[124]

The concepts can be placed in a conceptual space. An n-dimensional space, where n is the number of descriptive dimensions. The concepts are placed in this space, in accordance with their dimensions. An apple and a pear would be located in relatively close proximity in the conceptual space, because several of their dimensions have similar values. However, the approach depends what is compared to; When comparing many apples to a pear, the pear seems different, whilst should the comparison be all fruits, then pears and apples seems quite similar.

Objects have similarities and dissimilarities depending on which dimensions are regarded (weighted high). For example, an apple may have the same size as a cup, but the apple is hugely different from the cup in regards to other dimensions. Some of these dimensions are integral which means they rely on each other, for example if the size of an apple increases, the weight increases too. Other dimensions are separable, meaning they are independent of each other.

Gärdenfors' use of *regions* furthers the understanding of the relation between dimensions and provides a way of mapping certain dimensions of one concept onto the same dimensions of other concepts. For example the dimension size is a different metric region when describing apples than the size region of building. This idea of regions may allow certain dimensions of concepts to be normalized.[125]

Gärdenfors' n-dimensional and topological understanding of words and concepts is in this work used for making the machine perceive events and phenomena. ESP uses its specific landscape of experiences to determine the weight of individual phenomena. Gärdenfors' idea of regionalization would be interesting to apply when translating events and phenomena from one environment to another, where certain dimensions need scalar translation. For example the dimension of crowdedness could be scalar translated to compare the Tasmanian Ocean and the Shibuya Neighbourhood through other dimensions.

124 For more high level concepts the dimensions can be less quantifiable.

125 This notion seems very useful in a future development of this research, but at this point is merely introduced.

Data in n-dimensional euclidean space can adopt topologies that signify relationships in data through various topologies. These can be recognized and taken to account through computational ingenuity, relevant in regards to intricate concepts as such found in language and the natural world.[126] At this point I will not venture further into details on this.

The two approaches mentioned above, (1) causality (feedback loop) versus (2) semantics of words and concepts, are different in their understanding of phenomena. (1) Mattoni uses anthropic rationale and deduction to subdivide and reduce the complexity of subject matter. (2) Gärdenfors uses descriptors and comparative aspects, as well as topology and geometry, to relativize the subject matter through general descriptors. The latter is also an approach used in machine learning called categorization. Categorization is used in both the algorithms K-means and Self Organizing Maps (SOM).[127]

For the task of tracing time based events and phenomena, neither language nor anthropic rationale are reliable or fast enough, however the idea of using multiple descriptors in the form of sensor data has proven effective. The fact that sensor data may not be directly causally related to the traced phenomena is a natural consequence of failing to define what should be searched for.

Consider an unknown phenomena of a given scene (like a word or concept of Gärdenfors' conceptual space). The phenomena is time-based but with an unknown duration. States can be traced through multiple dimensions; temperature, sound, light, vibration, force etc. Instead of dimensions referring to specific objects in the scene, dimensions describe a current state of the environment for a given time span.[128] These states in time are considered objects and can now be categorized, creating a timeline of states. Some states persist through longer spans of time, while others are shorter. These accumulated states can be called state-frames or events. The shift between state-frames are caused by changing sensor data which in turn are caused by changes in the environment. These states-frames thus create a timeline of different states with different duration.

126 For references see: Cabanes, Guénaël, and Younès Bennani, 2010. »Learning the number of clusters in Self Organizing Map.« INTECH Open Access Publisher. And for more on the curse of dimensionality see: Domingos, Pedro. 2012. »A few useful things to know about machine learning.« Communications of the ACM 55.10, p.78-87.

127 Kohonen, T. and Somervuo, P., 1998. »Self-organizing maps of symbol strings«, Neurocomputing, 21(1), p.19-30.

128 The timespan is relative to the time-scale being observed. To observe fast paced phenomena the timespan is in scale of milliseconds.

With this approach states are not given names, but rather are merely defined by their relativity to other states in time. In this way states of certain durations are replacing each other in a consecutive line of states or events. One event will end, and another takes over, followed by a third. These three (or any number of) events together can describe a phenomena, but only a relevant phenomena in case the same sequence of events takes place again in a later stage with a similar temporal distribution. A phenomena, not being a thing in itself, but a temporally based series of events.

The problem however is that there is no knowledge of what is traced, only recurrent patterns in the series of events traced. In a normal case of sensor tracing there is a clearly defined object traced for which an internal symbol can be associated. Here there is no preconceived distinction between the events traced, when they start, end, or whether one takes place during another. This distinction happens based on new series of events. Meaning emerges in the temporal sequentiality of sense data. To make this formal computation of sense data relevant to other actants or substrates, it can be grounded through the use of representation or actuation.

5.7 Grounding Semantics

Fundamental to any understanding is the grounding of meaning. In this context grounding is achieved through bringing the representation as close as possible to the physical in order to minimize the need for symbol linkage between form and referent—prediction and environment. A crucial finding through experimentation is observing how representation directly becomes actuation or content rather than expression.

The problem of verifying associations between the symbolic—signifier and signified—expression plane and content plane[129] is described as the symbol grounding problem (SGP).[130] SGP deals with the linkage between symbol and referent. Vogt proposes an approach of embodied cognition, and presents an example where symbols for real objects are constantly negotiated both internally and collectively between physical mobile actants given basic perception and commu-

129 Belpaeme, T., Cowley, S.J. and MacDorman, K.F. eds., 2009. Symbol grounding (Vol. 21) p.115. John Benjamins Publishing.

130 Harnad, Stevan. »The symbol grounding problem.« Physica D: Nonlinear Phenomena 42.1 (1990): 335-346.

nication capability. Vogt considers how the symbol as a structural coupling between the sensorimotor activations of the actant and the actants' environment[131],[132]

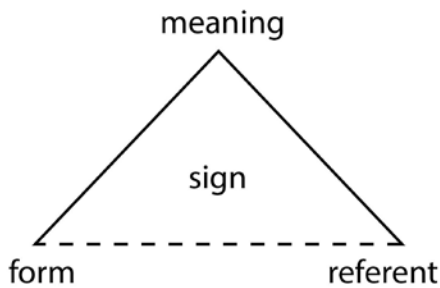


Figure 19. The semiotic triangle reproduced from Figure 1 p.433 of Vogt, 2002.

Brooks' robots are designed with the same approach; The environment becomes part of the representation and carries its own meaning. Vogt discusses semiotics as functional relations between form and referent; as a relation based on the history of interaction, i.e. the actant's experience with a referent. The internal representation of these memorized interactions form a representation of the meaning. It is therefore crucial to be able to both initially build the representation of meaning as well as read it—in order to both use it cognitively and improve and/or forget it.

In ESP the representation of meaning, i.e. phenomena and activities, is built through categorization and sequential mapping of sense data. The spatial representation of sense data is changed continuously and remapped as a temporal sequence.[133] The sequences are linked to an additional representation grounded through time. These temporally grounded representations have so far been image and sound, but also direct actuation will be tested in future research. In case representation is grounded directly as actuation or activity, the system may achieve reinforcement learning through activities directly responsive with the environment, similarly to Vogt's experiment. Such reinforcement learning is arguably already established in the two experiments Dancer and Musician, as the representation in form of sound can be

131 Vogts article is a great source to get a thorough hold on the issues of symbol grounding, and meaning.

132 Vogt, P., 2002. The physical symbol grounding problem. Cognitive Systems Research, 3(3), pp.429-457.

133 Rendered as the colour sequence in figure 24.

seen as the machine actuating sound, and the environment being the musician responding to this actuation. To keep an overview of such actuation, multiple representations can be used. In both the Dancer and the Musician the graphical representation of the temporal sequence was helpful. The experiments are described in more detail in paper 9: »*Event Series Prediction as Decision Support System at Fast Paced Processes.*«[134]

The aforementioned temporal sequences tie representations to referent and cannot be built without events and phenomena taking place in the environment. Likewise the linkage can not occur as artificial cognition until it is being recognized as past similar phenomena.

5.8 Non Anthropic Automated Semantics

When building the internal (non-anthropic) and external (anthropic) representations stepwise procedures are performed for processing the sensor data. The formalized versions of these procedures are common and well know *algorithms*, slightly modified for the particular composition of ESP.

These algorithms are normally used for extracting concealed meaning from data. In their original form they can take input data from any domain, and due to their immaterial character they are able to operate on an abstract level with input data. In order to produce highly relevant information structures from unstructured data, algorithms move about data through apparently arbitrary procedures.

The ESP composite algorithm is made up of two algorithmic principles: 1) the K-means algorithm, which is used for clustering temporal states based on multiple dimensions of sensor readings; 2) Sequential Pattern Mining, which in ESP is constructed using recursion

134 Nielsen, Stig Anton. »*Event Series Prediction as Decision Support System at Fast Paced Processes*« Proceedings of IMCIC–ICSIT 2016, p. 278-283.

and customized fitness criteria to select the most similar previous experience. The two algorithms are commonly used in machine learning.[135],[136]

Machine learning techniques can rearrange data to extract unapparent meaning, which without *representation* would remain difficult to decipher.

An example of an algorithm which is dependent on representation is the algorithm called Self Organizing Maps (SOM)[137], which belongs in the group of dimensionality reduction algorithms and is unsupervised. It reduces n-dimensional data to a lower number of dimensions by creating a visual and measurable n-dimensional topological space where each data-object is placed in proximity relative to its similarity to other data-objects. A common example is the comparison of countries, where input data can be multiple dimensions like BNP, gender equality index, area, population etc.. The countries can in turn be re-organized (self-organized) on a two dimensional matrix such that euclidean distances between data points, which represent similarities to countries, is a measure of relative similarity in relation to chosen feature dimensions, cf. figure 20. This representation can be interpreted by humans but just as well by another algorithm. In that case, the representation does not need to be readable by human at all, especially if it is just a stepping stone between algorithms. The semantics of it can be pertained, refined, or shifted but if it is only sensible to the next step algorithm it becomes a non-anthropic representation.

135 Machine Learning is a computational approach make machines self-encode or self-program. Machines can be programmed to learn from data how to classify objects or find sequences and patterns in series of data. Machine learning consists of three main areas: supervised learning is where training data is associated with semantics. Once the training is complete, the program can be applied. Unsupervised machine learning is where training data is not pre associated with semantics, but where the machine finds patterns in data autonomously. Often the unsupervised will be able to train continuously. The strength of unsupervised learning versus supervised is that unknown relationships in semantics can be identified. Lastly, reinforced learning is a system trained through interaction with natural systems where reward principles guide semantics.

136 On algorithms and their basic applications see: Cormen, Thomas H et al. »Introduction to algorithms second edition.« The Knuth-Morris-Pratt Algorithm«, year (2001).

137 Kohonen, Teuvo. »Self-organized formation of topologically correct feature maps.« Biological cybernetics 43.1 (1982): p. 59-69.

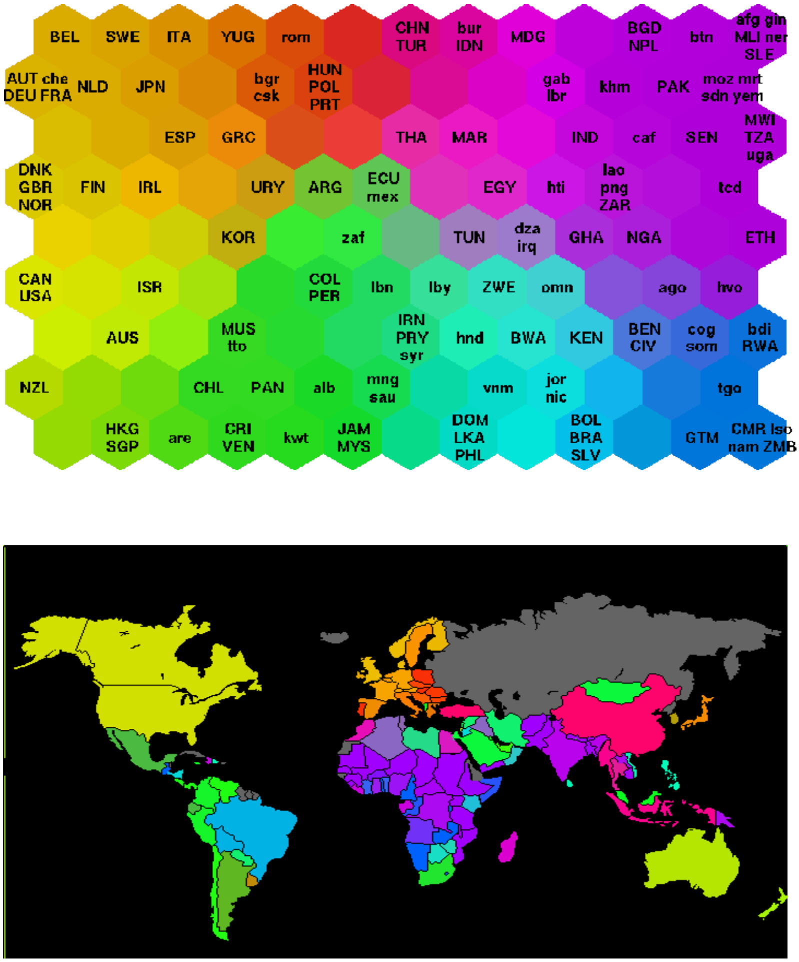


Figure 20. Different living standard features from each county are used for creating the three dimensional similarity representation on the top. Distances indicate similarity, meaning country names located close are similar in the n-dimensional features. Bottom figure shows the colors mapped from the SOM onto the world map.

5.9 Representations and Ontologies

The experiments below exemplify two different types of embodied representation. One, embodied between layers of formal computation. Another, embodied in physical computational substrates and actants. A key argument is that these two are in fact similarly non-anthropic.

Design representations conventionally make use of formalization, simplification, and generalization. Representations extract information and allow for comparison through specific dimensions or through meaning from different objects. An example of design representation can convey selected aspects of the design. A volumetric diagram can describe various volumes of a house, whereas its building schedule describes and compare different stages of construction. As representations become more discourse specific, they require more specific knowledge of the given discipline or *ontology* .[138],[139]

Computational substrates contain their own representational relation to other substrates. For examples through morphology or other significant properties like colour location or temporality. Separating content (represented) from representation can be difficult, as a successfully embodied representation is both expression and content. This means each substrate can offer different representations to different respective actants and substrates.[140] As representations appropriate content relevant to certain domains, they become inaccessible for other domains. This same can be observed for embodied representations where representations are exerted only between certain substrates. Both physical substrates as well as formalized computation demonstrate this behavior. Formalized computation can use content specific representations to convey information between computational layers, while physically computing a substrate does the same, directly through its shape, colour, weight or location in time and space.

In between computational layers of machine learning, a computer engineer designs the method for the machine to build the specific representation. Physical substrates are similarly designed to attain certain representational properties that interact well with other physical (computational or non-computational) substrates. Common

138 Khemlani, Lachmi et al. »Intelligent representation for computer-aided building design.« Automation in Construction 8.1 (1998): 49-71.

139 Luyten, L., 2012. Structurally Informed Architectural Design. Chalmers University of Technology. P. 65

140 In natural consequence of Latour's Actor network theory.

to these two types of representation is that they are not targeted to humans, but to other actants in the loop. These can therefore be called *Non Anthropic Representations*. [141],[142]

In computer science, the inaccessible representations are referred to as Black Box. The current most prominent machine learning systems like the Deep neural network rely entirely on these black box representations. They should be discussed because they separate anthropic semantics from machine or artificial semantics. This separation could both turn into a great advantage, but also lead to more profound gaps between human and machine intelligence. In contrast to logic symbolic programs, Black Box can not easily be

»*...meaning is part of an object to the extent that it acts upon intelligence in a predictable way.*«[143] These black box representations are highly semantic, just not to humans—in many cases only to machines, as presented in figure 21.

The different non-anthropic representations in machine learning layers can be seen as condensed or refined meaning, and the algorithms used for stepping from one layer to the next could be considered the ontology—namely the binder between what is and how it is meaningfully described. Ontology in computer science is a crucial requirement for AI as a means to link machine and human knowledge[144] In that sense, ontology consist of a set of concepts, such as things, events, and their relations described in natural language, as well as formalized computationally in order to establish a semantical link from machine to human. Already a few computer languages has been proposed for this purpose, for example OWL[145] is currently dominant but has received much criticism for its limited capacity to describe concepts by other than syllogistic deduction.[146]

141 The problem of not clearly understanding the representations inside convolutional neural networks is discussed further by Yosinski, J., Clune, J., Nguyen, A., Fuchs, T. and Lipson, H., 2015. Understanding neural networks through deep visualization. arXiv preprint arXiv:1506.06579.

142 Deep architectures lead to abstract representations that can be more invariant to local changes of the input. Bengio, Yoshua, Aaron Courville, and Pascal Vincent. »Representation learning: A review and new perspectives.« IEEE transactions on pattern analysis and machine intelligence 35.8 (2013): 1798-1828. P.5

143 Hofstadter, Douglas R. »Godel escher bach.« New Society (1980).

144 »What is an Ontology?« 27 Jan. 2016 <http://www-ksl.stanford.edu/kst/what-is-an-ontology.html>

145 Web Ontology Language

146 Gärdenfors, Peter. »How to make the semantic web more semantic.« Formal Ontology in Information Systems. 2004.

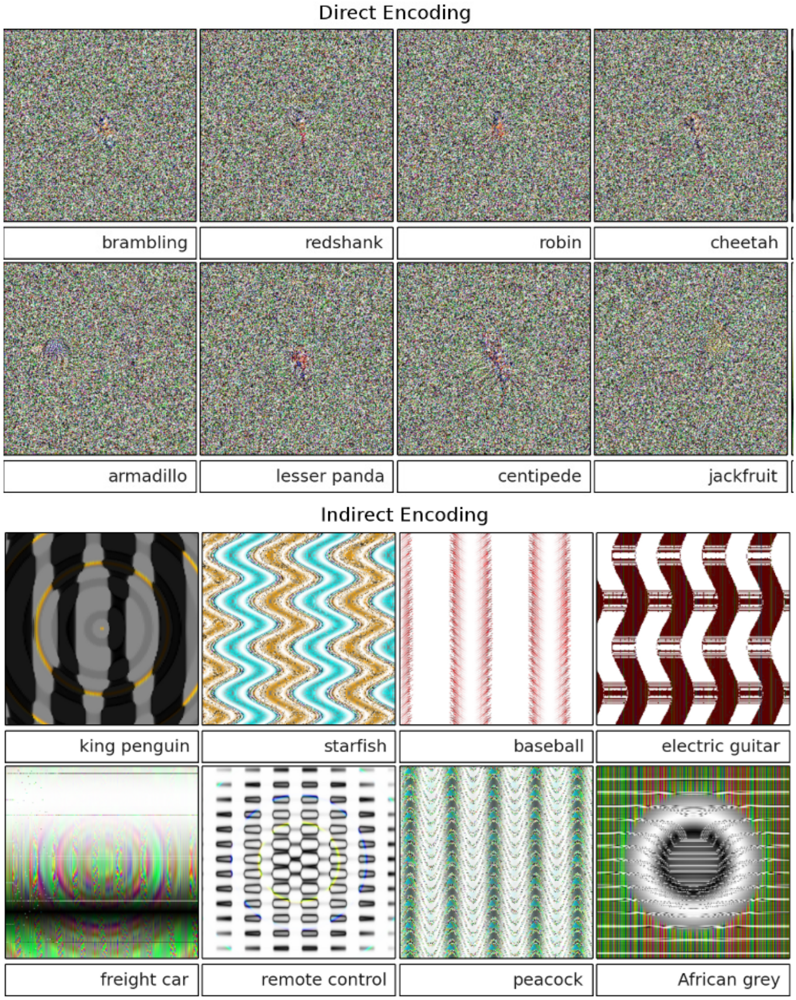


Figure 21. The images from the paper »Deep neural networks are easily fooled: High confidence predictions for unrecognizable images.« show how a deep neural network trained on Image Net training data can be fooled to recognize nonsense images with high confidence. The divergent Images are generated by evolutionary creation and selection using MAP-elites where the evolutionary success criteria is the DNN recognition score of the original concept (class name), named below each image in the figure 147. In other words, an EA algorithm creates an image that fits the non-anthropic semantics well, however the image has no association with the human semantical meaning of the word given. Given an expression, the algorithms are not able to create content that fit both human and machine semantics, despite the fact that the DNN in the first place is trained on human semantics. The study also shows how non-anthropic semantics quickly diverge from human semantics.

147 Nguyen, A., Yosinski, J. and Clune, J., 2015, June. »Deep neural networks are easily fooled: High confidence predictions for unrecognizable images.« InComputer Vision and Pattern Recognition (CVPR), 2015 IEEE Conference on(pp. 427-436). IEEE.

In results from Google's multilingual ANNs published in November 2016 the authors document how the model - which we can see as the non anthropic representation - can benefit in performance from learning multiple language pairs instead of the conventional approach of training separate models for each language pair. The interesting aspect in this regard is their visual analysis of these models to which they ask: "*Is the network learning some sort of shared representation, in which sentences with same meaning are represented in similar ways regardless of language?*" *and* "*Do sentences with similar meanings cluster, regardless of language?*".[148]

The planes of each language are connected through these representations, and the study show that independent of the direction of projection meaning can be transferred.

The models act no more just as representations between languages, but can act between meaning and language, relationships that has been studied intensely by linguistics researchers earlier.

Ferdinand de Saussure tried to order concepts through semiology and linguistics, and later Hjelmslev wrote 'omkring sprogteoriernes grundlæggelse'[149] which, in the awareness of Saussure's attempt to make sense of linguistic systems (*signifier* and *signified*[150]), instead described language as an open ordered system with close dependency on *context*. Hjelmslev, similarly to Gärdenfors, takes a topological approach. He describes *expression plane* and *content plane* as alternative to signifier and signified. The terms express the dependency on context upon which they are projected.

Expression plane and content plane are each other's opposite in the sense that the representation relation can be reversed, or that one can be seen as representation for the other. Physical as a consequence of the activities or the activities as consequence of the physical. A highly embodied relation between representation and the physical can facilitate just this. Hjelmslev makes clear that there is no justification for calling one the expression and the other content.[151]

Activities and the environment in which they take place has that same representational relation as the content and expression, being isomorphisms mutually influencing each other with modification and information. Deleuze and Guattari also underline that there is no distinction between a content and expression plane as they are each other's reciprocal presupposition.[152] As embodiment is achieved there is no need for additional ontologies.

148 Johnson, Melvin, et al. "*Google's Multilingual Neural Machine Translation System: Enabling Zero-Shot Translation.*" arXiv preprint arXiv:1611.04558, 2016.

149 Prolegomena to a Theory of Language

150 First defined by Vitruvius: Vitruvius, The Ten Books on Architecture, Morris Hicky Morgan (transl.), Cambridge, Massachusetts, 1914, New York 1960, pp. 5–16.

151 Louis Hjelmslev, Prolegomena to a Theory of Language, trans Francis J. Whitfield, Madison, University of Wisconsin Press, 1969, P. 60.

152 Deleuze, G. and Guattari, F., 1988. A thousand plateaus: Capitalism and schizophrenia. The Athlone Press Ltd, p.45.

6.0 EVENT SERIES PREDICTION

During the course of the thesis work it became necessary with a more general approach to the use of sensor data. In earlier chapters the generalization of sensor data has taken place through sensor fusion in the physical realm and sensor data was handled on a basis of the individual experiment. A versatile algorithmic and general approach to handling n-dimensional sensor data was the outset for the development of Event Series Prediction. The opportunity to also make a predictive system from ESP turned out during the construction of ESP the algorithm.

Firstly the detailed construction of ESP is explained in section 6.1, and in section 6.2 experiments that verify its applicability to certain environments will be described.

The purpose of the algorithm is to experience temporal landscapes through n-dimensional sensor data and constantly look within them the temporal landscape to recognize past series of events in order to predict the near future eventscape.

Stephen Grossberg introduced one of his first papers, from 1967, by writing: »*The theory provides a mathematical description of the following kind of experiment. An experiment E, confronted by a machine M, Presents M with a list of* »*letters*« *or* »*events*« *to be learned. Suppose for example, that E wishes to teach M the list of letters AB, or to predict the event B, given the event A. E does this by presenting A and then B to M several times. To find out if M has learned the list as a result of these list presentations, the letter A alone is then presented to M. If M responds with the letter B, and M does this whenever A alone is said, then we have a good evidence that M has indeed learned the list AB.*«.[153]

This basic concept of learning is what has since been developed widely, and also what the ESP(Event Series Prediction) composite algorithm achieves, although for ESP there is no difference between learning and ›examining.‹ In addition the ESP will only need to be trained once for every list of events, as every single one is unique.

153 Grossberg, Stephen. »Nonlinear difference-differential equations in prediction and learning theory.« Proceedings of the National Academy of Sciences 58.4 (1967): 1329-1334.

In 2004 Jeffrey Hawkins published the book On Intelligence, which outlines his theory on what he states is a technology: Hierarchical Temporal Memory. The theory accounts for its view on the brain as a 'Feedforward Hierarchical state machine.' with capability of learning.[154]

Merleau-Ponty on the other hand creates a nuanced view about the process of perception that deals with learning, memory, and recollection of memory, where he turns the order around. He describes perception as being conditioned by a landscape of memories or experiences. Only through this landscape can we perceive and thus make new memories. He describes the perception as ability to perceive only certain phenomena, then at a second stage learn. Humanity is thus restricted in two ways, both by the restriction given by our sensory organs, as well as this restriction to learn pre-conditionally. In turn this may be what the learning described by Grossman does, the capacity to predict on previously experienced patterns of experience. It may in fact depend whether perception is considered on the level of recollection or on the level of initial sensory perception.

Machines can be designed to understand profoundly differently from humans when decoupled from human semantics[155]. The condition of limited perception as result of experience presents a major challenge to the heterogeneities of cultures. If never experienced before, perception of signs and events can be misinterpreted or entirely missed. The condition becomes even more pertinent when attempting to design machines that have no preconditioned culture whatsoever. These machines must necessarily be kept decoupled from semantics, as they have no meaning to build upon. As these machines are designed to build their own non-anthropic representations without relying on human semantics, they will autonomously construct meaning different from a human sense of meaning, more closely and uniquely related to the environment they have sensed.

6.1 Constructing Event Series Prediction

Different sensors can trace different changes in the environment. Correlating these different dimensions of sensor information can take the information beyond the sum of the individual sensors. In previous sections of this dissertation we have discussed how sensor fusion and formal computation of information ensures a holistic picture of the events causing changes in the environment, whatever these events might be.

154 Hawkins, Jeff, and Sandra Blakeslee. On intelligence. Macmillan, 2007.

155 As discussed in section 5.8

To trace n-dimensional sensor data simultaneously, a sensor hub with various sensors was constructed. The hub is connected to a processor, which sends data to the computer, on which the formal computation takes place. The hub shown in figure 22 and provides around 25 hz of 8-dimensional sensor data information,equivalent to about 75 measurements over the course of the event of a hand moving palm down past the hub, and back again.[156] The hub is constructed to be small and fast, making it capable of detecting minute phenomena taking place in a small temporal and small spatial scale. The smaller scale allows for fast paced experimentation and focused study of the data processing code.

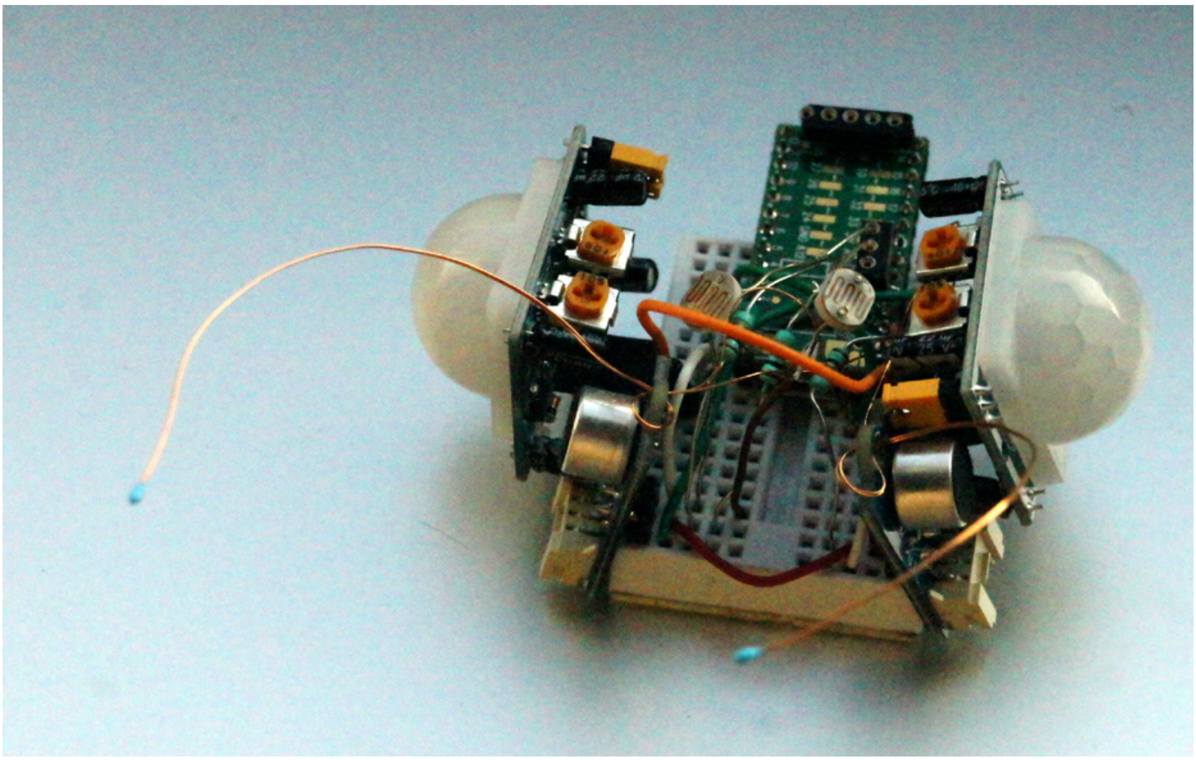


Figure 22. The sensor hub consists of a processor unit connected to multiple kinds of sensors; two motion sensors, two sound sensors, two light sensors and two temperature sensors. The processor unit connects via USB cable to the central workstation computer which runs the ESP algorithm.

156 This frequency is adjusted to the temporal eventscape in question, and both longer and shorter scales of eventscapes can be adjusted for easily.

These multiple sensor data streams from the hub are firstly scaled and mapped into one common representation, as seen in figure 23. The graph plots the readings from left to right, creating a visualization of the n-dimensional data over time. The graph clearly represents different episodes or similar recurrent patterns in the information stream.

The graph representation in figure 23 and 24 shows sensor information from different instances of the event of a hand moving past the sensor hub. It is evident how a swipe of the left hand over the hub creates the same local eventscape again and again, but the same swipe of the right hand already creates a different event-scape. Video documentation for the hand-swipe is found at.[157]

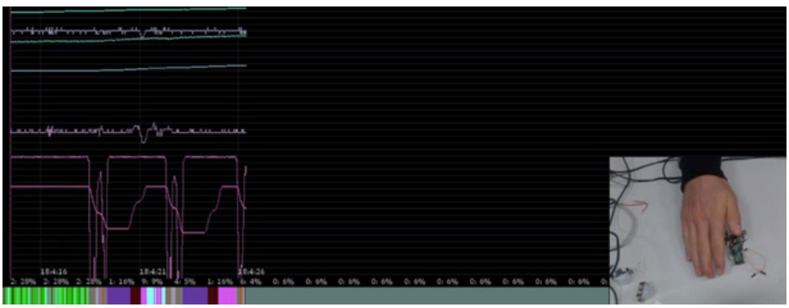


Figure 23. Data streams from the sensor hub plotted over time, Bottom shows time objects clustered and mapped on the time axis.

157 https://vimeo.com/stigantonnielsen/learning The lower part of the screen shows the internal representation of memory. It is worth noticing how this entire representation of earlier events is affected by new sensory experience. In this way new experience affect prior experience, making it something more than recording.

We as humans are able to recognize these recurring patterns when reading the graph. Provided a more thorough analysis, we could identify the number of each type of recurrent event (see figure 24). The objective is to enable the machine to do the same better and faster.

To achieve this, every timestep is treated as an object, with sensor data as its dimensions. The timesteps are clustered using the procedure for K-means and mapped back on the timeline, seen as the colored barcode in the bottom of figure 23 and in the middle of figure 24.

This barcode can now be computationally queried for recurring sequences. When a part of the barcode is found to have the same sequence as the most recent sequence, the sensor information is recurring, meaning the events in the environment are recurring.

A sequence of events could in this regard be the hand approaching the hub until the swipe is over, or a higher resolution of the sequence could describe discrete parts of the event: hand approach, hand above, hand moving past—stopping—moving back over.

Setting the machine to recognize discrete parts of each event allows for a quick, almost instantaneous recognition of the ongoing partial events.

The prediction is found through comparing the last few sensor information sequences to all past sequences. The sequences created by the hand approaching and the hand above the sensor hub can be searched for and the continuation of the similar previous sequence can be quickly retrieved. In this example, the continuation would be: hand moving away, stopping, moving back over. The machine is thus able to use the proceedings of a previously experienced event as prediction for the current events.

Although the system cannot predict sequences of events totally different from what it has experienced, it can construct partial predictions for recurrent sub sequences. It becomes a question of resolution.

Sequential pattern mining and recognition is a common approach to prediction within machine learning. The novelty lies in the embodiment of the prediction, and the combination of multiple real-time sensor streams, dimensionality reduction and sequential pattern mining.

The dimensionality reduction uses n-dimensions of a given moment to categorize a moment within all previously experienced similar moments. This category of similar moments is given a random name. In figure 24 these names are displayed as colours along the horizontal coloured barcode.

Once the states of previous moments are categorized, the sequence of past states can be compared to the sequence of events leading up to the current moment.

For every new moment, a 'new' non-categorized state may occur. However the system will instantly create a new category or re-calculate and rearrange the entire n-dimensional state-space to accommodate for that new state and henceforth create a new series of events. With this technique of constant re-evaluation of the n-dimensional experiential state-space the entire experiential sequence is affected by new experiences, thus constantly learning and adapting the experience. Figures 27 show the algorithm as a flow-chart.

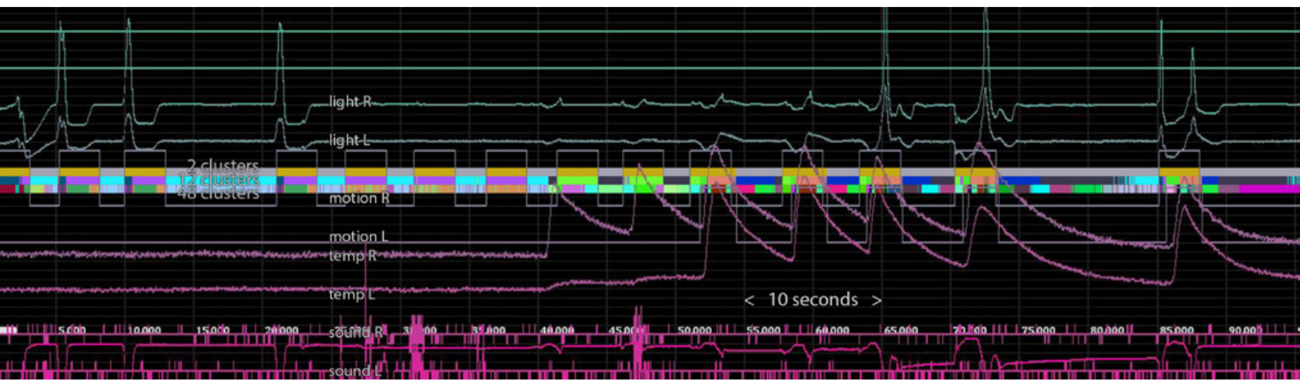


Figure 24. Sensor readings are plotted over the duration of about 100 seconds. The data is analyzed, and vertical time sections with similar sensor readings are clustered. The result is shown as the poly-colored bar across the middle. Same color time sections have similar sensor readings.

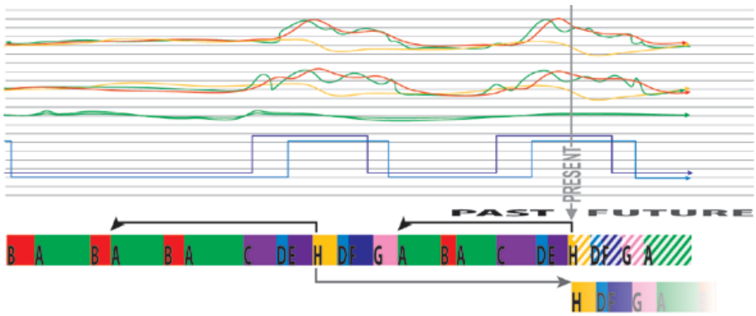


Figure 25. This diagram is designed to show how the ESP operates on the temporal data in order to fetch a prediction. As illustrated by the arrow 'PAST' the sequence (backwards) EDCABA is found earlier in the datastream, and the continuation (forward) HDFGA.. is brought up front as prediction of the future events.

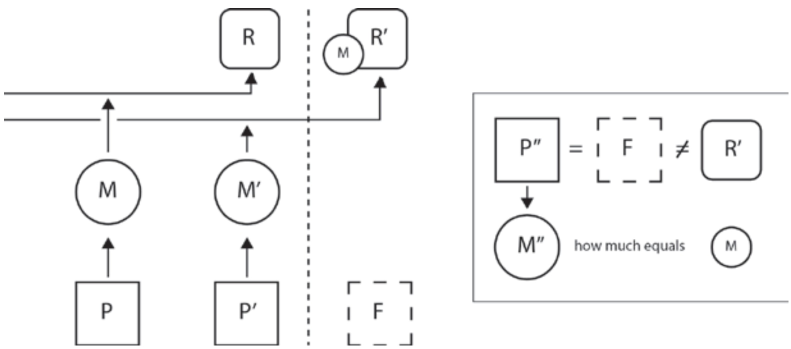


Figure 26. P being present F being future, and M being an abstract model or feature space given from P- the present. Finally R is the representation fetched from the memory, and projected to represent the future state F. M can be created from any P, and in hindsight P'' equals F, but it is difficult to compare P'' to R'. Therefore their models must be compared instead. As the prediction cannot be correct, we can only give an index of correctness through asking how much M'' equals m.

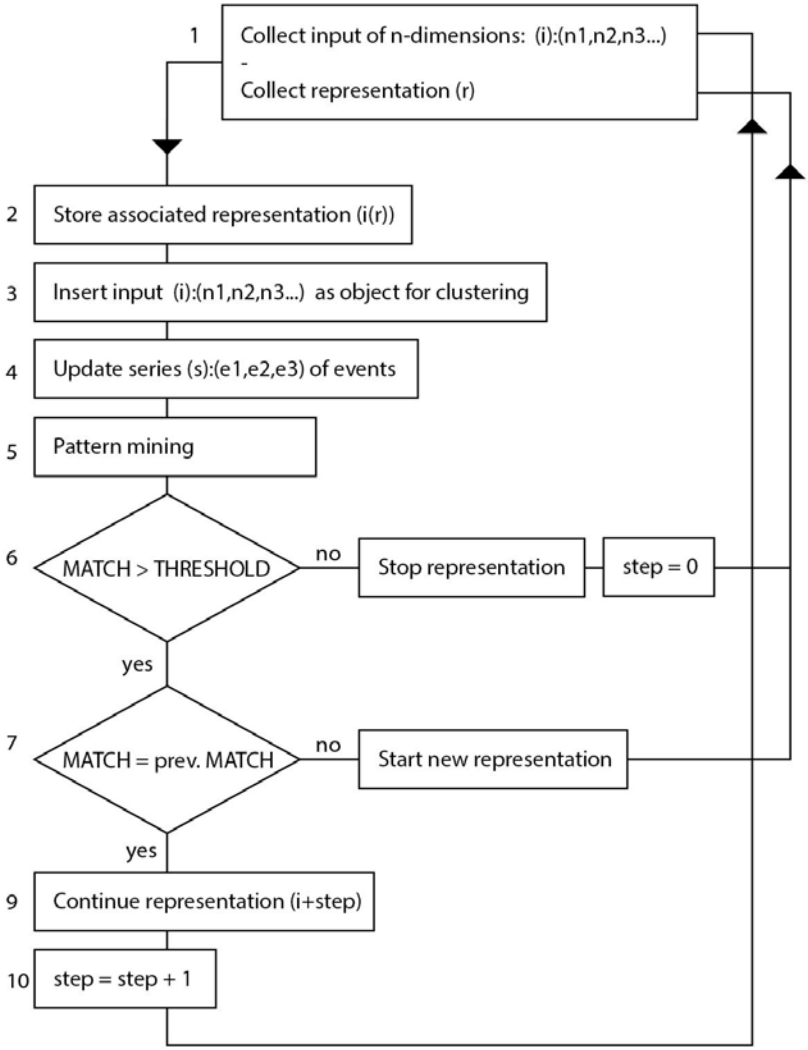


Figure 27. Flow chart of the ESP. Step 3,4 and 5 are expanded in the next figures. What makes this algorithm unique is the combination of dimensionality reduction in step 3 and and sequential pattern mining in step 5. It is also unconventional, in that it does not formalize results, but uses captured representations as results.

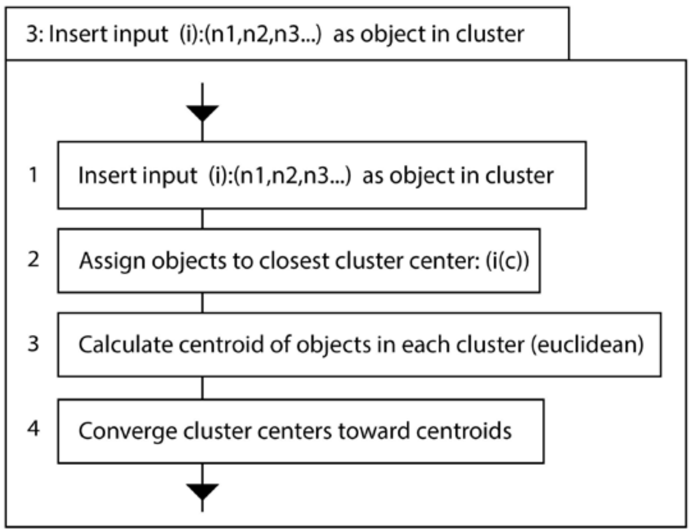


Figure 28. Step 3 is important as it captures and classifies each state-moment in relation to all experienced moments. The clusters of n-dimensional states are constantly reorganized as new states are inserted, new clusters will form, move and divide the existing ones. It is conventional K-means clustering, but could successfully be exchanged with another type of fast clustering algorithm.

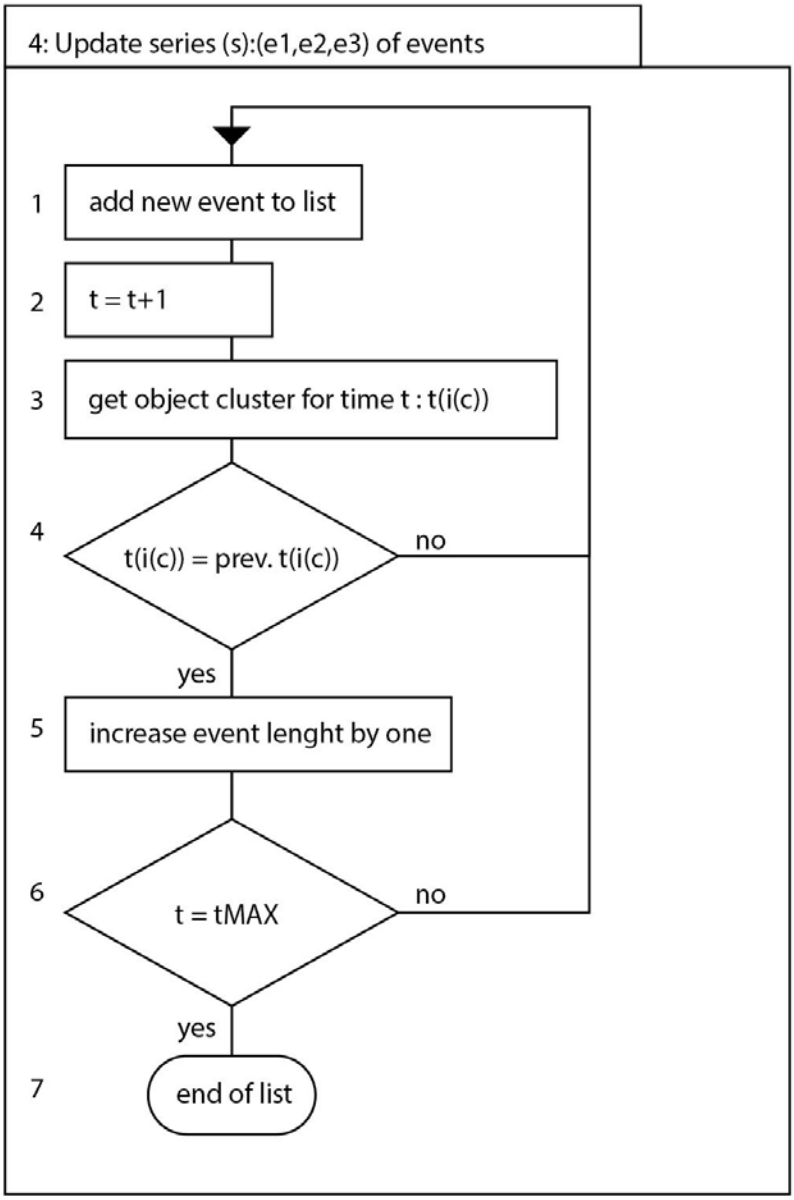


Figure 29. Step 4 creates a list of elements with a name and a length. Such a list can be represented with colors as names and size as length (as in center of figure 18). This list is rewritten every iteration as result of the shift in clustering of the states.

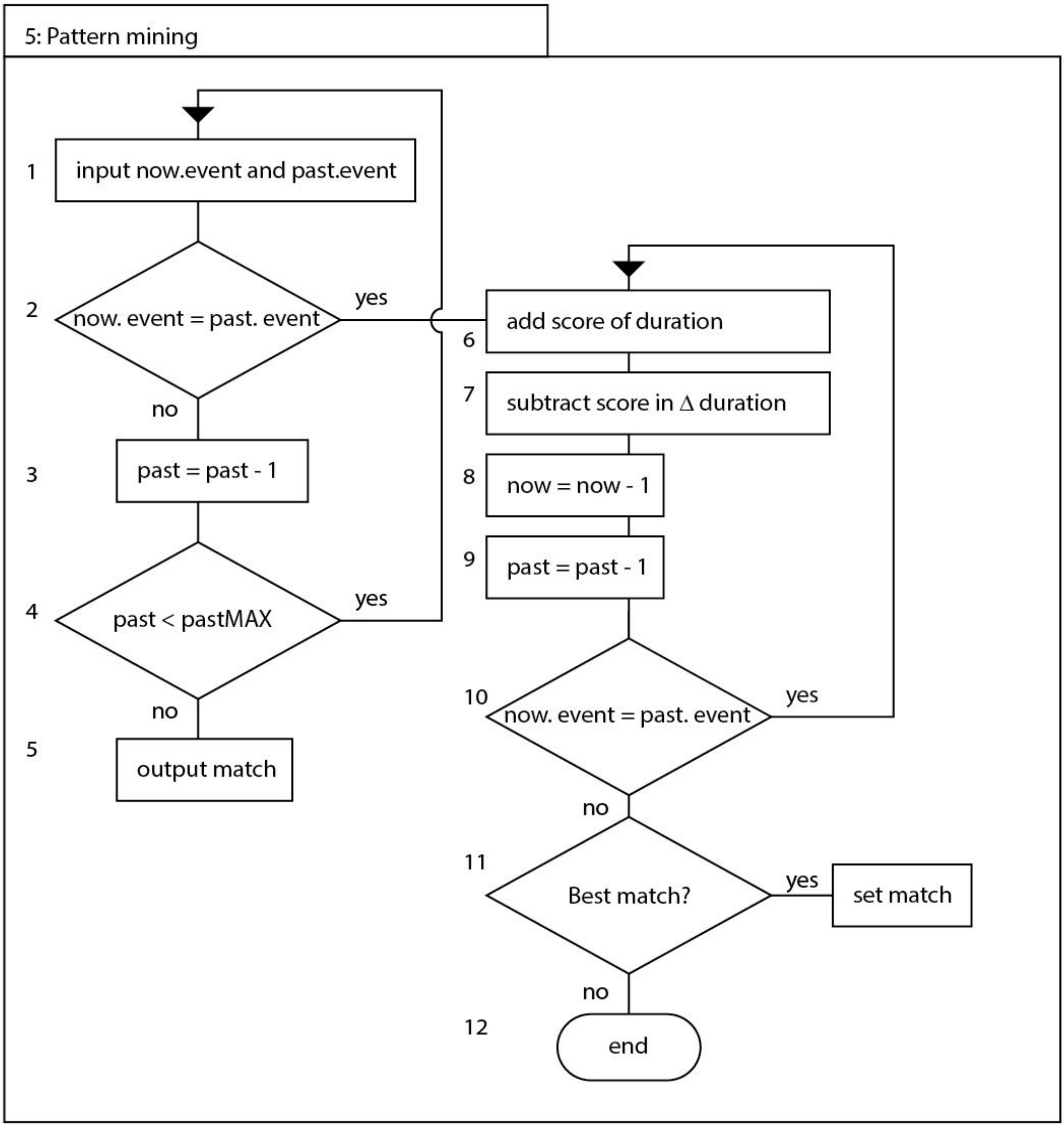


Figure 30. Step 5, Pattern mining can be done in different ways depending on the important features of the data being mined. Here the importance is the score of each match, which is given both by overall temporal length and matching length of each state. The mining still tolerates noise in form of non-matching states on both sides, such dissimilarity results in a setback on the score.

A specific working source code adapted for video input and image output can be found in the appendices.

6.2 Verifying Event Series Prediction

The ESP was developed using the JAVA programming language through the Processing interface.[158] In the first phase of development, a sensor hub (described in figure 22) provided sensor data as seen in figure 23 and 24. This graphical representation provides a robust verification between the 8-dimensional sensor data and the dimensionality reduction. However, insofar it offers no representation of the continuity of ongoing situations. This continuity being the prediction of any current situation. For this prediction ESP outputs a running timestamp of its best temporal match from a previous event.

This data required a representation, and we chose images from a webcam, associated with the timestamp and the 8-dimensional sensor data. This image becomes the onscreen representation for a prediction whenever one is found, but if no timestamp is found no image is shown. With this setup, the completion of a hand swipe would be represented the moment a hand swipe had begun, provided the algorithm had been trained for at least one hand swipe. After more training it would predict for particular hands and variations of the swipe.

Figure 31. The video on the right is the YouTube clip showing a food 3D-printer. The video clip is seen twice through a webcam while being analysed by ESP. When a prediction is found, the left frame shows the representation associated with that prediction.

158 »Processing is an open source programming language and integrated development environment (IDE) built for the electronic arts, new media art, and visual design communities with the purpose of teaching the fundamentals of computer programming in a visual context, and to serve as the foundation for electronic sketchbooks. The project was initiated in 2001 by Casey Reas and Benjamin Fry, both formerly of the Aesthetics and Computation Group at the MIT Media Lab« (https://en.wikipedia.org/wiki/Processing_(programming_language)

A number of experiments test and document the functionality of ESP. To test ESP on more complex situations, the incoming n-dimensional data was shifted from the sensor hub to pixels from the webcam. A scalable grid of pixels used the RGB code as input for ESP. ESP was firstly tested in deterministic situation of a video sequence repeating. The experiment comprised of a webcam placed in front of a computer monitor showing a YouTube video. The YouTube video is manually rewinded to allow ESP to recognize the video it has previously experienced. ESP correlates the information it presently experiences to data in its memory, and once a match is found it shows the representation of that memory on the monitor, cf. figure 31. The right image shows the current video, and the left shows the memory of ESP learned from watching the video once before. The3D printed dessert scene in the video is shown (from ESP's memory) with a lime added on the top of the dessert, before the lime is actually printed on the right side real-time video. The full documentation video can be found online.[159]

A second experiment was conducted using a dancer in the loop. The experiment is not a verification as such, but a test of the implications of interaction between humans and ESP.

ESP used the same video input dimensions from the camera's pixels, but the representation is shown in front of the dancer, projected on a screen. The screen is set up as if it was a mirror, only this "*mirror*"-showed the EPS movement predictions.

The dancer was given two different challenges. As the first challenge the dancer should follow the prediction on the screen. As the second challenge the dancer should avoid following the prediction.

As a consequence of the first challenge the dancer quickly went into a loop of motions, whereas with the second challenge the dancer got increasingly frustrated as the system learnt from her evasive moves and increasingly became able to better predict her moves. A part of the video material from the experiment can be found online.[160]

A third experiment was conducted with a musician in the loop. This experiment also explored the relation between improvisation and ESP's learning and prediction capabilities.

For this experiment, the input for ESP was changed to sound. A contact microphone attached to an instrument provided raw sound input. This sound is discretized to a number of dimensions using Fast Fourier Transform algorithm such that pitch is the value of each tonal segment. The tonal segments are dimensions given for each time-object.

159 https://vimeo.com/stigantonnielsen/videoprediction

160 https://vimeo.com/stigantonnielsen/dancer and https://vimeo.com/stigantonnielsen/dancer2

As the musician played the thumb piano contact microphones attached allowed for the isolated sound from the instrument to be sent to ESP. Using a contact microphone prevents the ESP system from taking input from its own predictions played over loudspeakers. The volume level of the predicted sound is set to match that of the instrument. This way the two sounds of equal intensity interacts in space and becomes inspiration for the musician, similar to the interplay between two musicians. The experiment is documented here in video and sound .[161]

Figure 32. Dancer in front of the semitransparent screen with the prediction projected from the back. Screen is between dancer and photographer

161 https://vimeo.com/stigantonnielsen/musician2

6.4 Further work on the algorithm ESP

To improve the Event Series Prediction a number of things could be done. Firstly better clustering capacity that autonomously can determine the relevant number of clusters by adaptation.[162]

Secondly the system could be constructed to forget only the unused memory while remembering the most reliable memories. This could be achieved through assigning reliability score to each memory object or sequence. These could be rated through the accuracy of each prediction sequence.

As sequences of events can recur in the same order, many events also take place in reverse. The algorithm could relatively easily be constructed to look for reversely similar events also.

As hardware optimization the code could run as separate processes on individual cores. One processor core running the basic feature extraction from input data, as well as the K-means adjustments while the other core could run the recursive sequential pattern mining. A third core could handle the stored representation from the memory. The three cores could exchange only relevant representations i.e. the series of events, and time of recognition.

As one of the main deductions from the discussion suggest, content and expression plane are the same. For further experimentation with ESP, this suggest a direct coupeling between input representation and output representation, turning these two into actuation. For an experimental system this would mean recording a track of known actuation, and use this directly as output instead of a representation.

162 This could be achieved through implementing the algorithms described by: Cabanes, Guénaël, and Younès Bennani. Learning the number of clusters in Self Organizing Map. INTECH Open Access Publisher, 2010.

7.0 CONCLUSION

To investigate the relationship between activities and the physical formation of the environment, I had first to explore the use of sensors and the computation of their information flows. As a next step, the relationship was explored through a number of experiments which examine principles of *embodiment* and *mixed substrate computation*.

The overall knowledge and experience from experiments have led to the design of a versatile algorithm that can be used for predicting on seemingly chaotic environments. The experimentation itself has led to a method that can best be coined as *Embodied Design Setups* and discussions on the experiments has led to a number of conclusions.

First, a close relationship between the environment and the models for design saves efforts on recontextualization, calibration and translation. The widening gap between digital models for design and the material world can be patched by achieving embodied computational systems consisting of sensors, material and other actants individually performing parts of the required computation.

These actants can be considered to exist on very different levels, and together the computational assemblage is coined *Mixed Substrate Computation*.

Second, Embedded, ingrained and external are various levels for which actants of sensory capacity can be considered. These can for example provide an immediate response to a designer in a design situation. But more abstractly they provide information—namely the change of particular dimensions—to other actants in an assemblage of *Mixed Substrate Computation*.

Third, Temporal models of a given environment can be created through correlating many of such dimensional changes from the environment. In this thesis these models have been defined as *Temporal Landscapes*. This term signifies the dimensional shift from the context of a design object to the temporal context in which the design object is described through its relationship with other actants, through activities over time. *Temporal Landscapes* are thus defined by scales of space and time, and consist of changes in multiple dimensions. I propose that recurrent n-dimensional changes can be considered phenomena and events of the environment, and that they can be detected and understood through such temporal models.

Fourth, The concept of *Mixed Substrate Computation* has been demonstrated through experiments and discussed in relation to a number of theories from past research within both philosophy and natural science.

The experiments are set up as *Embodied Design Setups*. This method provides a way to achieve higher degrees of embodiment which in turn leads to less formalization, simpler models, and reduced need for human semantics to close the gap from physical to formalized computation.

Fifth, the creation and handling of semantics is a core issue of *Mixed Substrate Computation*. Several machine learning techniques can be said to create their own form of semantics from data. However these semantics rely on the representational relationships between both actants and substrates.

Embodied representations are found between both digital representations and physical substrates. As such, every substrate can be said to share a representational relationship with the substrates it interacts with. Hence, the concept of a *Non Anthropic Representations* are defined as representations existing between substrates of computation as planes of both expression and content, concealed and incomprehensible to other substrates of the assemblage.

As an alternative to constructing simulated anthropic semantics for implementation between computational substrates, it seems more efficient to link anthropic and non-anthropic semantics directly through the environment, thus creating a relation of embodiment.

Sixth, By achieving a fully embodied design process, many aspects are maintained autonomously and computational capacity can come for free. Through embedded sensors insights to patterns of activity can be observed more accurately and in combination with the use of advanced computation these patterns can be analyzed. During experimentation the algorithm called *Event Series Prediction* was invented in order to make sense of these patterns in data. It turns out this algorithm can enhance the cognition of a given environment through sensor data and learn to predict occurrences before they recur, or more accurately, guess the continuation of recurring phenomena.

Seventh, Sensors detect change through the reaction of the environment caused by phenomena. This reaction can be considered a partial cognitive capacity of the environment which in turn is complemented by memory and recognition, through formal computation. As such, ESP provide some of the missing parts needed for a self-cognizant environment.

An artificial cognition is achieved in the assemblage of environment, phenomena, sensors and algorithmic operations, but it is a cognition built on its entirely own representations with context unique semantics. It can still be discussed whether this system behavior can be called semantics, but if so, it must cetrainly be considered *non-anthropic semantics*.

More specific conclusions on the experiments can be found in the appendix under the individual papers.

7.1 Predicting buildings

The capacity to predict activities in the built environment has the potential to change our approach to design, construction and modification. Presented with various possible outcomes of an ongoing design activity the design situation can engage with not just the physical embodied memory of the environment i.e. through present arrangement of matter, but also commence an interplay with the extended temporal landscape of the scene. Through such feed forward many past activities can contribute to decision making and provide the designer with more than his own intuitive grasp.

ESP has been shown to be able to provide context specific representations of future events. But the demonstration has taken place—for the sake of the argument here—in small spatial and short temporal scale.

In the experiment 'Dancer' the dancer is presented with alternative dance movements to inform the next movement and in the experiment 'Musician' the musician is provided context specific improvisational alternatives of tunes to continue playing.

But the applicability or extension of the ideas presented can be illustrated with a thought experiment; A small imaginary city-part is the scene where ESP is implemented to provide predictions of activities and modifications on two larger spatial and temporal scale levels.

At the longest temporal and largest spatial level of implementation the dimensions provided to ESP consists of demographic data as well as data on shops, bars and offices within the scene. The data is accurately traced through time as input for the ESP. The representation associated with the data patterns can be a map of refurbishments ranging from change in use of industry spaces, refurbishments of shops to division of shop spaces or from establishment of roof terraces to small apartment renovations.

With more training time, let's say even years, the model may effectively be able to predict what areas will be having renovations and changes and thus assist local governance to guide urban development ahead of time with better more specific urban regulations.

At a smaller scale, i.e individual refurbishment and modifications, ESP can be implemented as direct design and construction aid.

By delocalizing the individual modifications, the data consists only of refurbishments and modification, but at a highly detailed level. The concrete predictions design as well as construction steps.

The data recorded on similar past modifications throughout the city can provide designers and builders with predictions.

The use of ESP can not only help designers ability to envision design alternatives they did not envision themselves, but raise their awareness of constraints incorporated in past modifications.

With the capacity to foresee constraints they are enabled to think of alternatives in due time, capitalizing on experiences as well as contributing to experience with their own data and representations.

Thus through sharing knowledge and experience a collective experience is not only incrementally created and raised, but through feed forward knowledge and experience is directed to impact the most relevant situation before decision making. A condition which allow learning from incrementally smarter solutions.

This approach augments the design process and turns it into an interplay between temporal landscapes and design experience, rather than just the individual designers intuitive grasp.

8.0 SUMMARY OF PUBLICATIONS

A summary of each included paper is provided in this chapter. Additionally, the summary of conclusions drawn from the individual papers and the experients highlight how they each individually contribute to the overall thesis.

Figure 33. The refurbished house where the central shaft is blocked, resulting in lack of airflow on the lower levels.

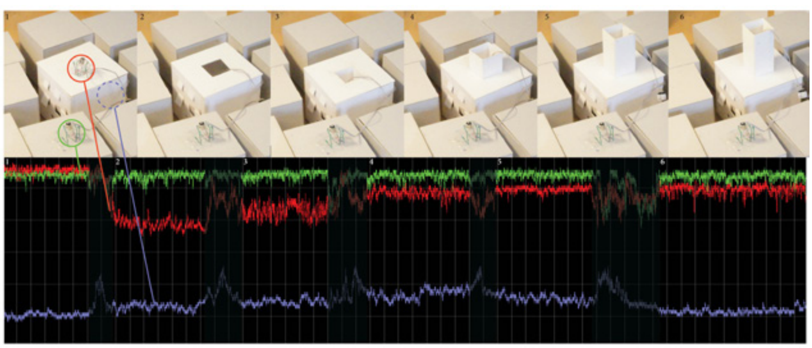


Figure 34. The model simulates the context and morphology of the Arabic houses and urban context from the first study, using openings and a constant airflow to create an intuition of how different shapes of shafts influence internal airflow in the model. Sensor chaining results can be read on the graph. Darker areas are measurements for changing shaft morphology.

Paper 1 »Physical Form Finding by Embedded Sensors«

explores sensors as an architectural design tool in different spatial and temporal scales. The focus is on how sensors are able to operate in a constantly shifting environment, and how they can support the intuition of otherwise non perceivable aspects within the built environment. This is showcased through two experimental scenarios.

The first scenario is a comparison between the onsite sensor reading of the performance of an classical Arabic house and one of a refurbished Arabic house. The refurbished house has had the central ventilation shaft blocked to increase usable square meters, while the other is renovated and inhabited in a traditional manner. This part of the study is at large spatial and temporal scale. The designer's perception is augmented by sensors on site, but they do not provide data in real time. In the second scenario the performance of the same Arabic house typology is tested at a considerably smaller spatial and temporal scale. This study showed how large scale architecture can be investigated through the use of sensor chaining, and how simple sensors can be implemented in a design task in order to augment the cognitive capacity and intuition of the designer about certain aspects of performance in the design iterations in real time.

Conclusions:

This paper supports on the main arguments of the thesis, namely the use of sensor fusion for an augmented perception of the built environment. This initial experiment with the use of sensors was made using rather simple sensor setups where each type of sensor manages its own distinct aspect or dimension of the system. However, when dealing with multiple performative aspects simultaneously, there must be a strategy for the interaction between the individual computational parts, material as well as formal. These interactions are investigated in the following experiments and papers. There is a discussion on how to achieve a more general sensor strategy, one which describe how sensors successfully can be chained and thereby normalized against each other providing locally relative information. Conclusively it is suggested that sensors may be used for augmenting cognition of unknown temporal landscapes and environments. A notion leading to the idea of using several types of sensors to trace ongoing phenomena: »*... tools consisting of integrated computation, sensory devices and user interfaces can nurture our creative potential, and in particular help our intuitive understanding of causal relations in our physical environment.*«[163] The sections 5.1, 5.2, 5.3, 5.4 discuss the preceding work and considerations on these topics in the light of the full thesis work.

163 Nielsen, Stig Anton. »Physical Form Finding by Embedded Sensors: Using 'sensor chaining' in various temporal and spatial scales.« eCAADe 2013: Computation and Performance–Proceedings of the 31st International Conference on Education and research in Computer Aided Architectural Design in Europe, Delft, The Netherlands, September 18-20, 2013 18 Sep. 2013.

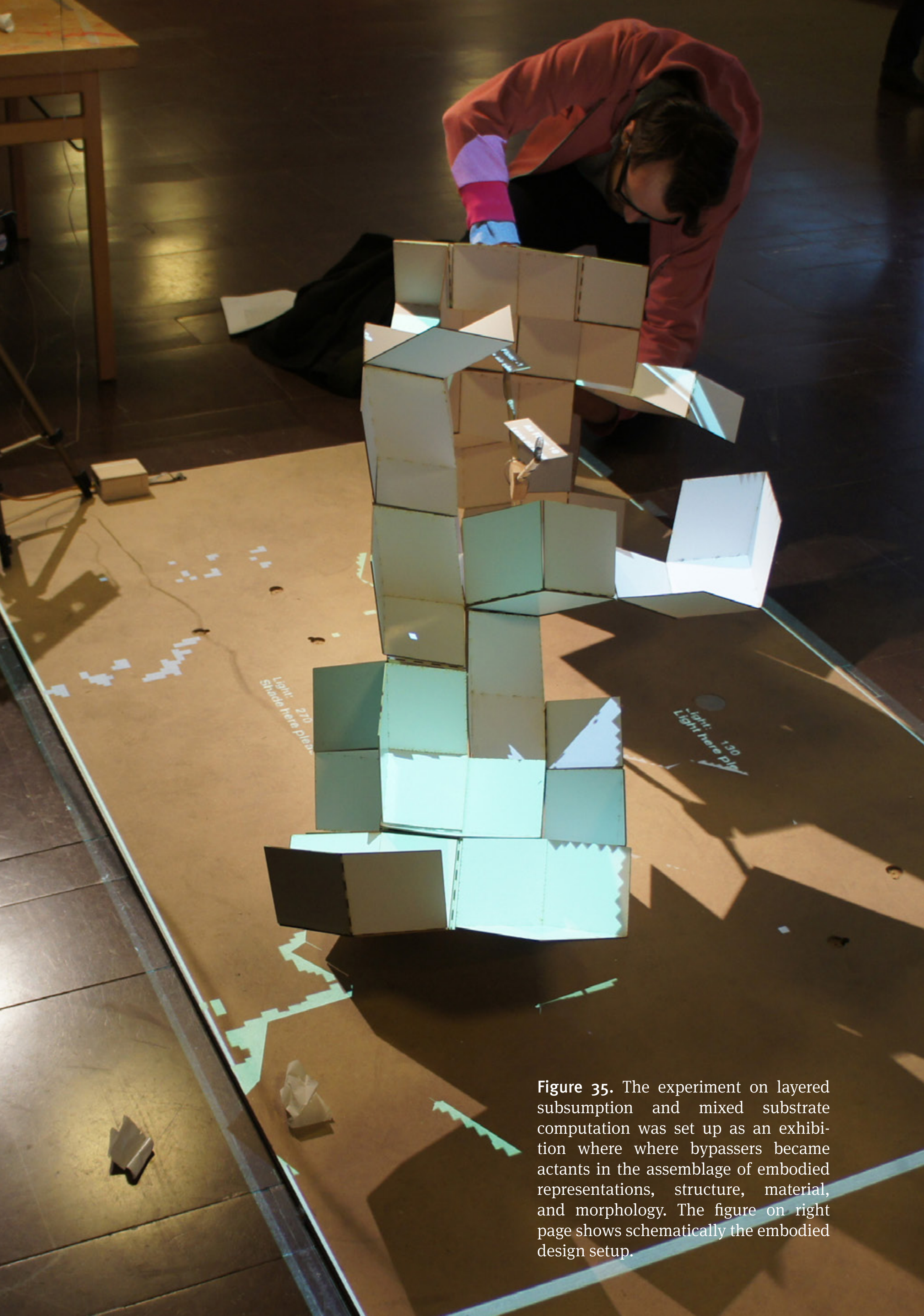


Figure 35. The experiment on layered subsumption and mixed substrate computation was set up as an exhibition where where bypassers became actants in the assemblage of embodied representations, structure, material, and morphology. The figure on right page shows schematically the embodied design setup.

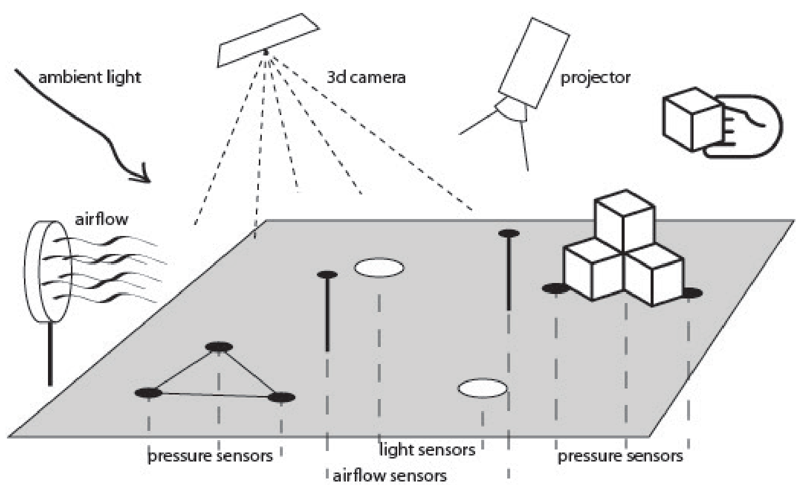
Paper 2 »Layered subsumption in intelligent material building systems«

discusses how layered subsumption can be used as a robust linkage between environment and actions, acting both digitally and through functionality embodied in the material of a building system. Layered Subsumption—as invented by Rodney Brooks—is a computational approach for interaction between low-level control mechanisms in robots. We describe a building system with embodied computational control over the building process. Demonstrated here is a building system where embodied computation is seamlessly shared between the digital and the physical computational substrate of the system. With reference to John Fraser's book (»*An Evolutionary Architecture*« from 1995) this experiment successfully demonstrates a construction system where users, environment, morphology, and materiality interacted and resulted in a physical structure balanced according to multiple criteria. In the conclusion we asked two relevant questions:

- Is it likely that these materially aggregated systems have certain 'layers' working solely in physical reality through morphologic and material dependency?
- Can these digital/physical building processes be seen as artificial, intelligent and creative processes?

Conclusions:

The paper exemplifies the important concept of mixed substrate computation— here balancing elegantly criteria such as airflow, structure, and light. It is a good example of a fully embodied design setup. These topics are further discussed in sections 5.1, 5.2, 5.3 and 5.7.



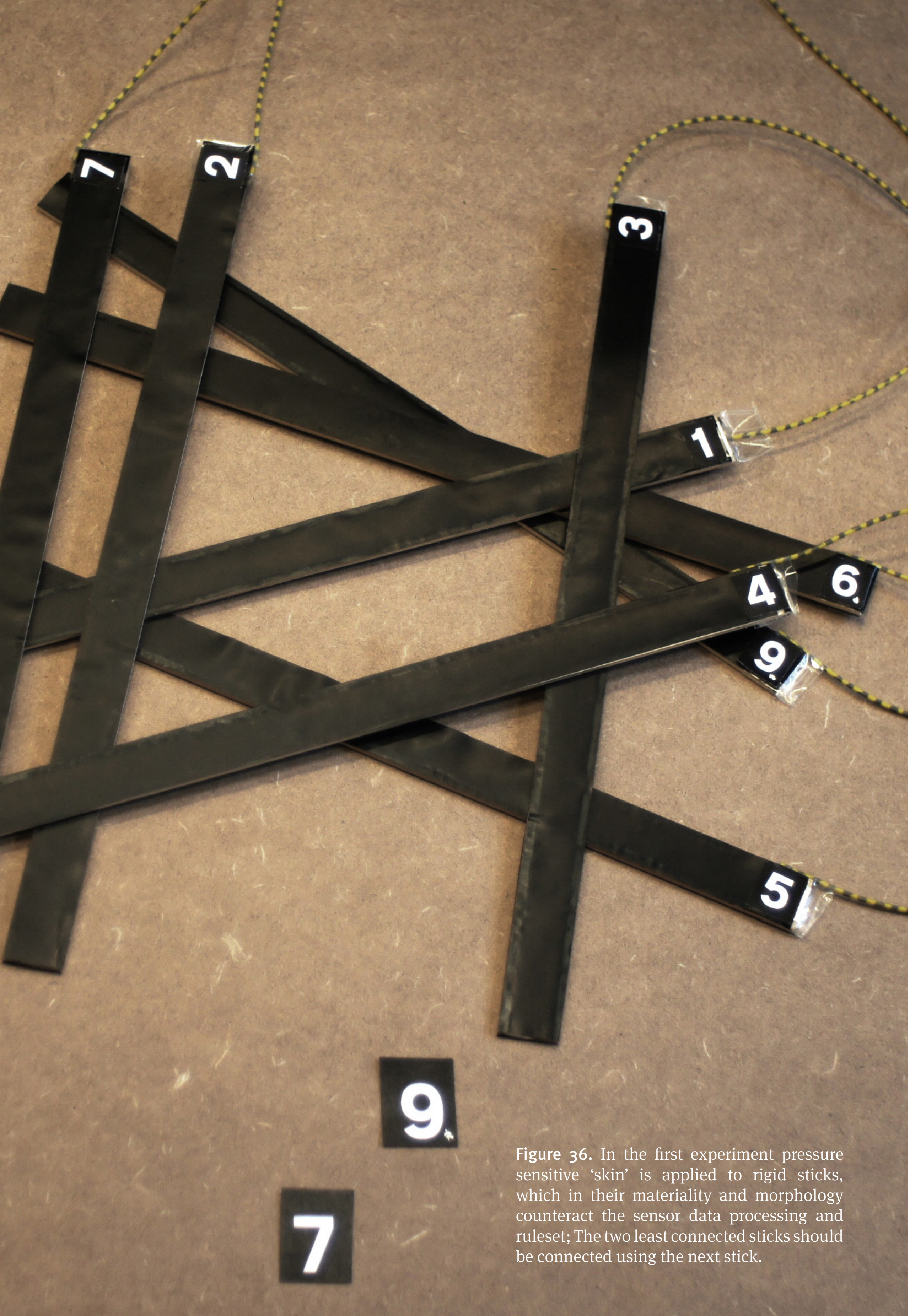


Figure 36. In the first experiment pressure sensitive 'skin' is applied to rigid sticks, which in their materiality and morphology counteract the sensor data processing and ruleset; The two least connected sticks should be connected using the next stick.

Paper 3 »A process where performance drives the physical design« investigates the consequences of information flowing from the material architecture to virtual models. This is shown with two different design setups that mix substrates of computation such as morphology, material, and formalized sensor data.

The first experiment deals with sticks of a certain morphology and material performativity used according to a somewhat contradictory ruleset. These three performative aspects of the experiment can be considered actants of a rhizome assemblage, where only their individual enactment on the others allows for the assemblage to play out.

The second experiment works with external sensors and a higher dependence on formal computation. More actants were in play, but again the individual object contained several actants with one of them being parallel—for example the morphology is present in all building blocks.

The paper explores the distinction between 'embedded sensors' and 'external sensors' and outlines the differences inherent to the two strategies, cf. section 5.1. This paper further describes a sensor strategy that requires only a minimum of calibration to navigate emanating environments where pre-calibration is not possible.

Conclusions from these experiments leads to the important realisation that sensor data does not need semantic grounding before being applied, but rather that meaning is inherent to the data itself and can be extracted from it.

The experiments also explore the close relation between morphology, materiality, and computation, and thereby the concept of embodiment, cf section 3.4, 5.2 and 5.3.

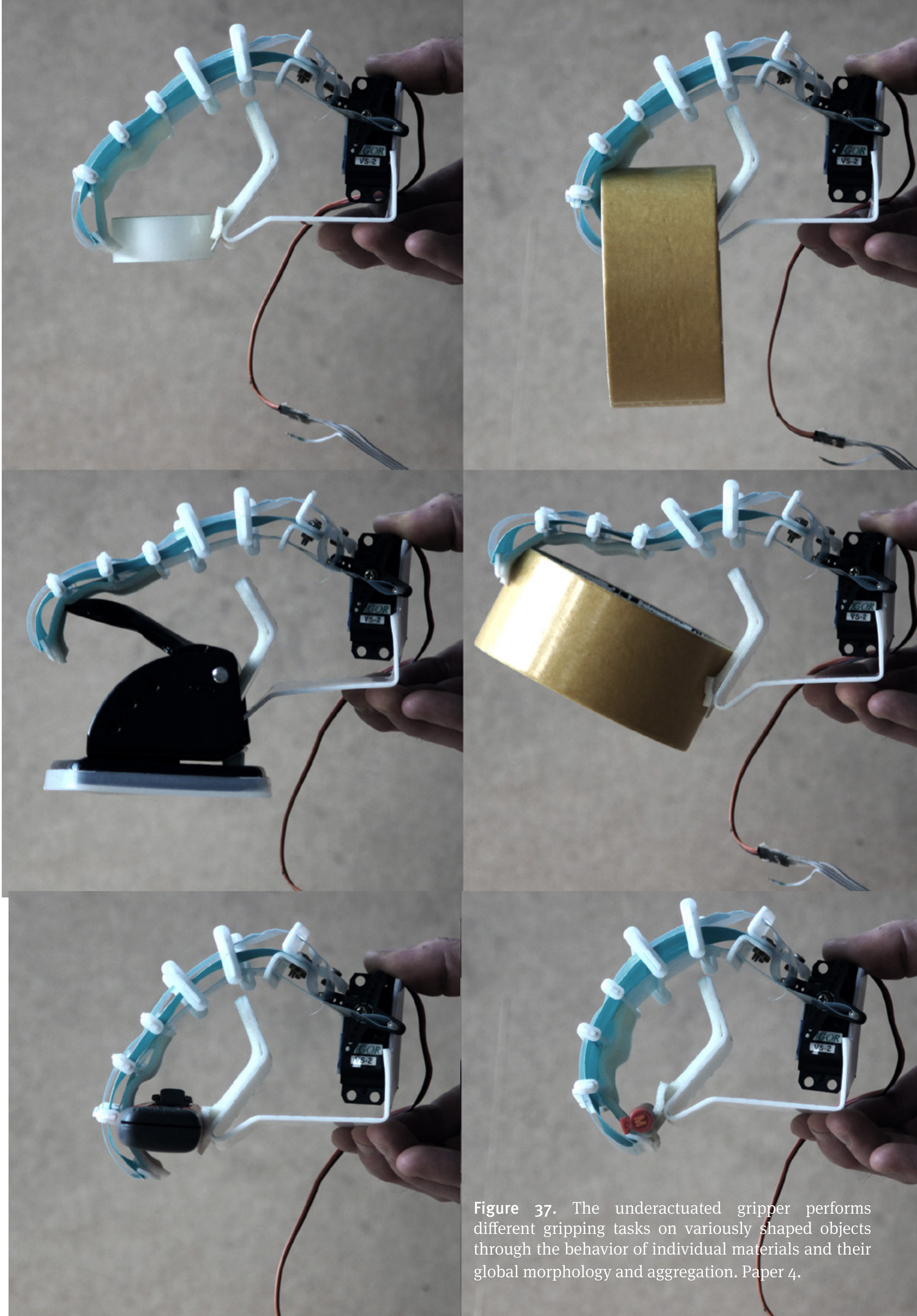


Figure 37. The underactuated gripper performs different gripping tasks on variously shaped objects through the behavior of individual materials and their global morphology and aggregation. Paper 4.

Paper 4 »Embodied computation in soft gripper«

presents an underactuated soft gripper able to hold everyday objects of various shapes and sizes without the use of sensors and control algorithms.

The design combines sheets of flexible plastic materials and a single servo motor attached to a material aggregate instead of using sensors for providing information to a central processing unit. This is to show that an aggregate structure – by virtue of material composition and aggregate behavior – is able to compute form and force just through its own material composition and aggregate behavior. Thus the prototype is able to perform various complex gripping operations through its self-contained material system

The paper discusses how embodied computation can be programmed into a material aggregate by tuning and balancing its exact morphology and material properties. It is discussed what parts of the material aggregate, material properties, and morphology are needed in order to robustly perform small computational tasks for adaptation. Cf section 3.4.

Conclusions:

In the conclusion it is summed up that: »*It seems relevant to let material properties compute active aspects like pressure and collision*«.

Similar underactuated material aggregate grippers has been suggested earlier, where the interplay between local environment and objects has been documented in similar ways.[164]

The papers provides an important example for the thesis that mixed substrate computation takes place without the presence of formal computation or embodied representation—the representation of the computation is both expression and content simultaneously.

164 Dr. Rudolf Bannasch, Presentation at Design Modelling Symposium Berlin 2013

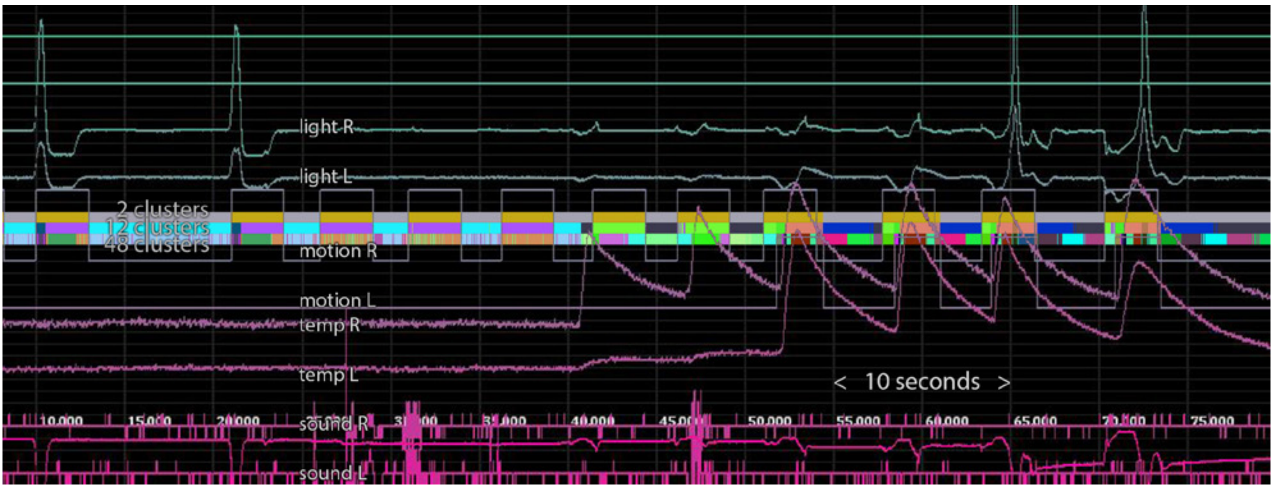


Figure 38. A k-means algorithm reducing the n-dimensional sensor data stream to a sequence of states. In the illustration the data readings are mapped on the timeline in temporal correspondance with the sequence of states as a proof of concept. Changing the number of clusters (2, 12, 48) changes the resolution of the state sequence.

Paper 5 »Propositional Architecture Using Induced Representations«

describes experiments on the use of sensor data, machine-learning, and pattern recognition — in order to guide and enhance design and modification processes of the built environment.

The proposed method; Induced Representation, consist of a number of steps identified as crucial to any approach of modification. Step A is: Data collection from the environment. Step B is: Machine cognition, learning, prediction. Step C is: Proposition, visualization, and embodied representations for quick implementation.

The paper outlines the theoretical basis for this approach, and presents and discuss three experiments that separately deals with either A, B or C.

Through this approach, the steps can be individually explored and advantages and disadvantages can be identified.

Conclusions:

Experiment A exemplify the concept of n-dimensional data capture and shows how formal computation can be used for dimensionality reduction from which in turn patterns are traced. This suggests that patterns can be considered traces of the phenomena having taken place in the scene. This experiment constitute the first half of ESP, but the second half, which identify and compare sequences was not yet constructed at the time of this experiment, leaving the actual patterns in data undetected computationally, but merely recognized graphically.

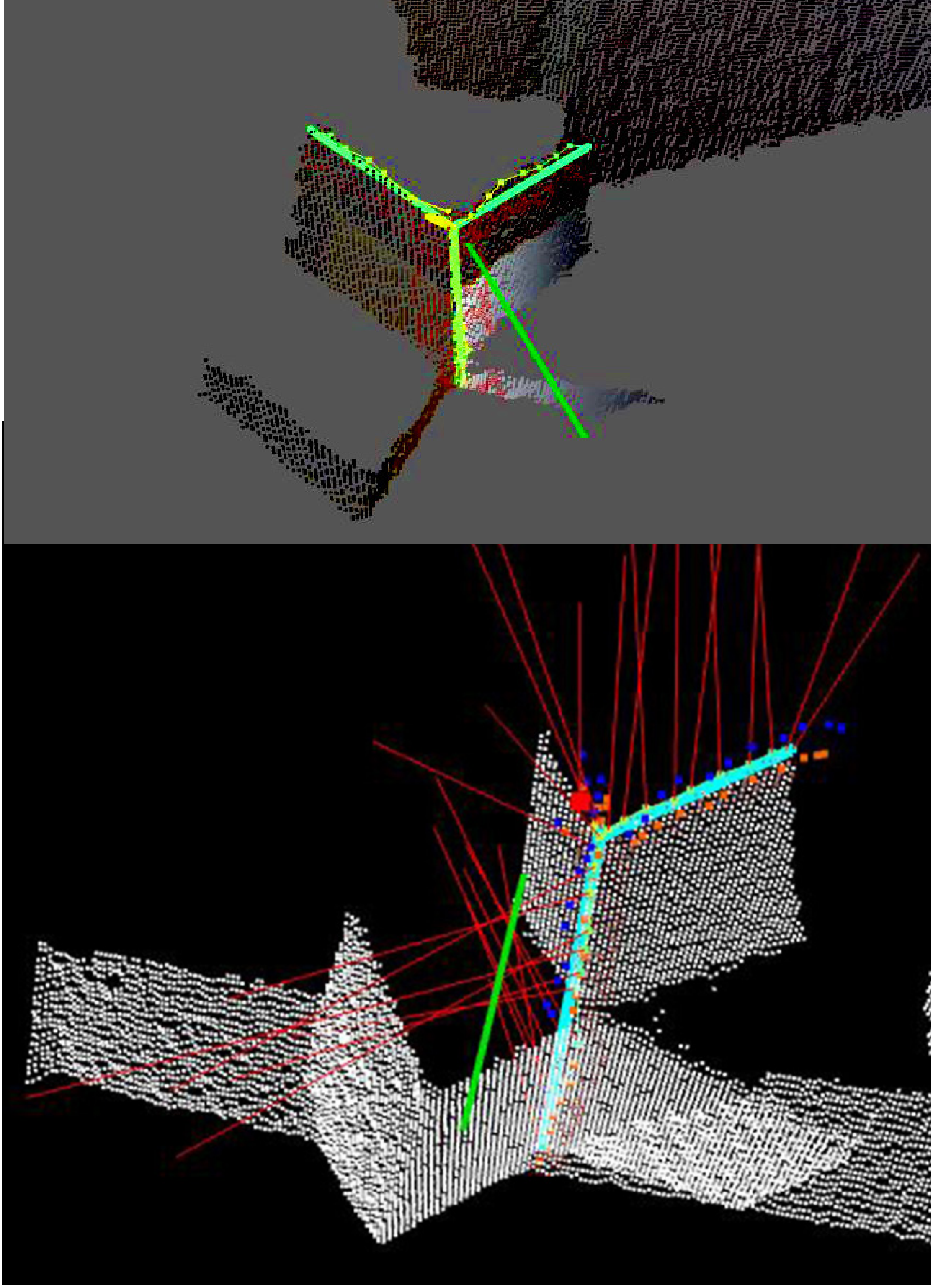


Figure 39. The algorithm specifically written for this experiment uses recursion to trace edges in the 3-dimensional point cloud. However this approach somewhat contradicts the later discovery that features of sensor-data does not need anthropic semantics to act meaningfully. After retrieving the edges as 3d vectors, new plates for construction can be created for use in experiment C.

Experiment C demonstrates how a 3D sensor can retrieve edges from the built structure. An algorithm using recursion was written for this purpose. Edges are used for constructing new custom building block elements.

Experiment C demonstrates how formal computation from experiment A and B is linked back to the physical structure.

Experiment C, uses an Augmented reality application[165] for and aligning the virtually proposed model to the real physical environment. This way no secondary representation is needed when it comes to assembly of the emergent and constantly recalculated structure.

Conclusions:

The full experiment where the three parts should be combined was never realized as one embodied design setup due to its complexity lack of time available. A very important lesson, in that the more specific and less general and versatile the individual system became, the more difficult they were to combine through representational relationships.

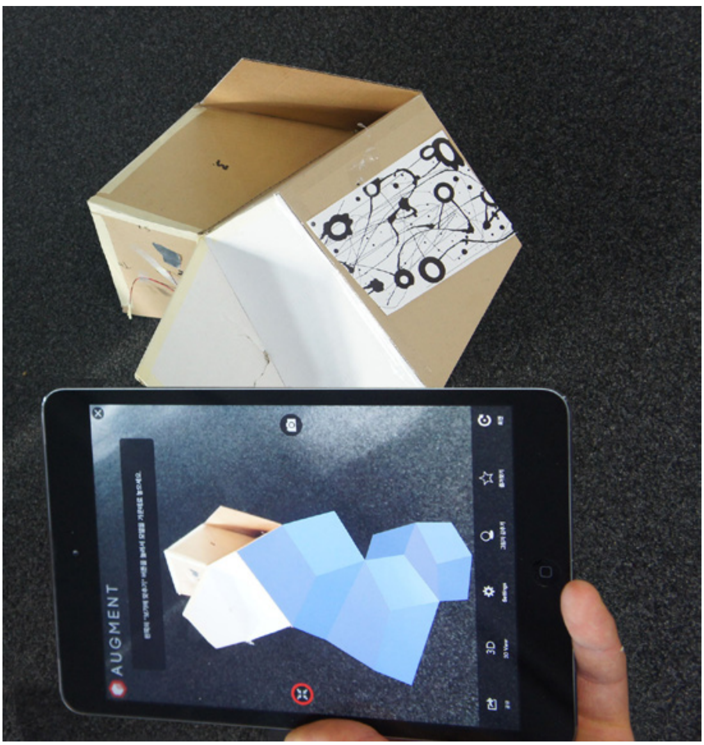


Figure 40. Augmenting the representation of the next series of building blocks via pattern recognition and augmentation software.

165 Augment: http://www.augment.com/

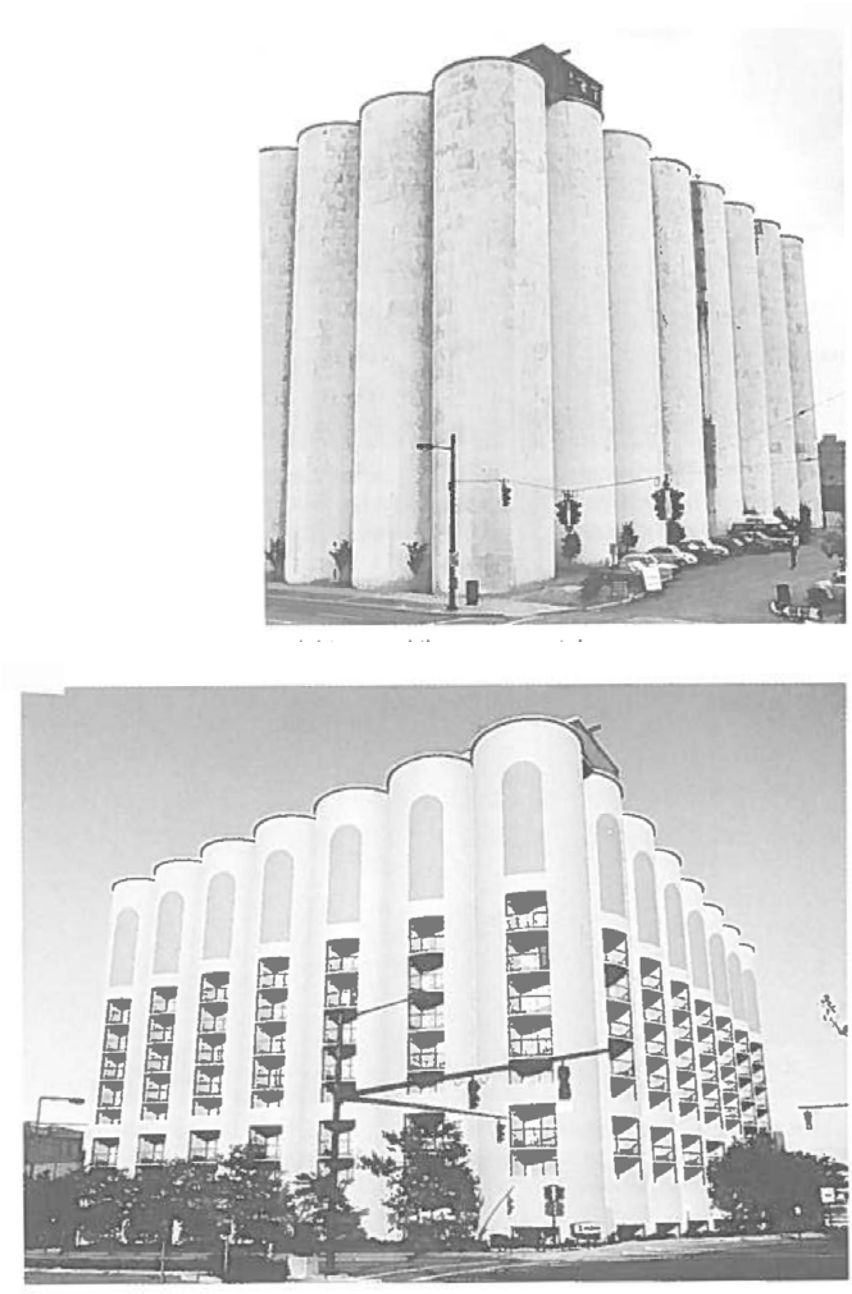


Figure: As the downtown Akron, Ohio, grew closer to the grain silos of the Quaker Oats Company, it was decided to transform the structures into a hotel. Now known as the Quaker Hilton. Figures from Brand, Stewart. (1995) How buildings learn: What happens after they're built. Penguin.

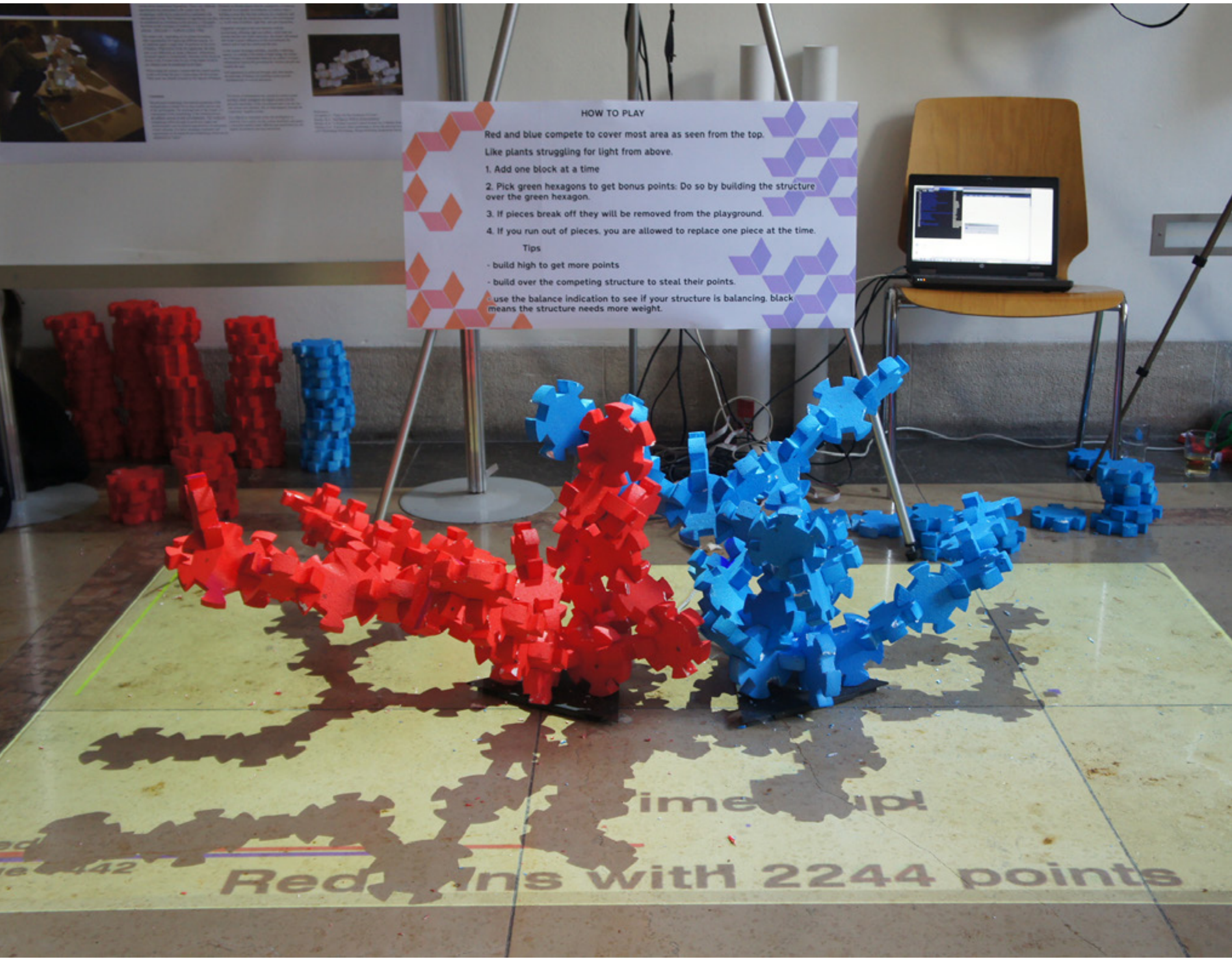
Paper 6: »Propositional Architecture and the paradox of prediction«

Tries to answer the question: What if we could predict trends, rising phenomena, and future necessities in our built environment? If we could trace behaviors and forecast the needs for the future? If we had tools for proposing architecture able to point out potentialities and suggest additions, subtractions, and modifications?

The algorithm, called *Event Series Prediction* (short ESP) is capable of making predicitions in unstructured environments.

The paper not only describes the basis and theory of the algorithm. The discussion also focuses on possible applications for this new tool, and the paradox of prediction is debated. Further more, improvements to the computational system are proposed.

Figure: This simple robust structure from 1924 was serving initially as garage, but has since been modified to fit several different needs.Through 80's and the 90's the building has served as a shop for outdoor apparel. Figures from Brand, Stewart. (1995) How buildings learn: What happens after they're built. Penguin.


HOW TO PLAY
Red and blue compete to cover most area as seen from the top.
Like plants struggling for light from above.
1. Add one block at a time
2. Pick green hexagons to get bonus points: Do so by building the structure over the green hexagon.
3. If pieces break off they will be removed from the playground.
4. If you run out of pieces, you are allowed to replace one piece at the time.
Tips
- build high to get more points
- build over the competing structure to steal their points.
- use the balance indication to see if your structure is balancing. black means the structure needs more weight.
with 2244 points

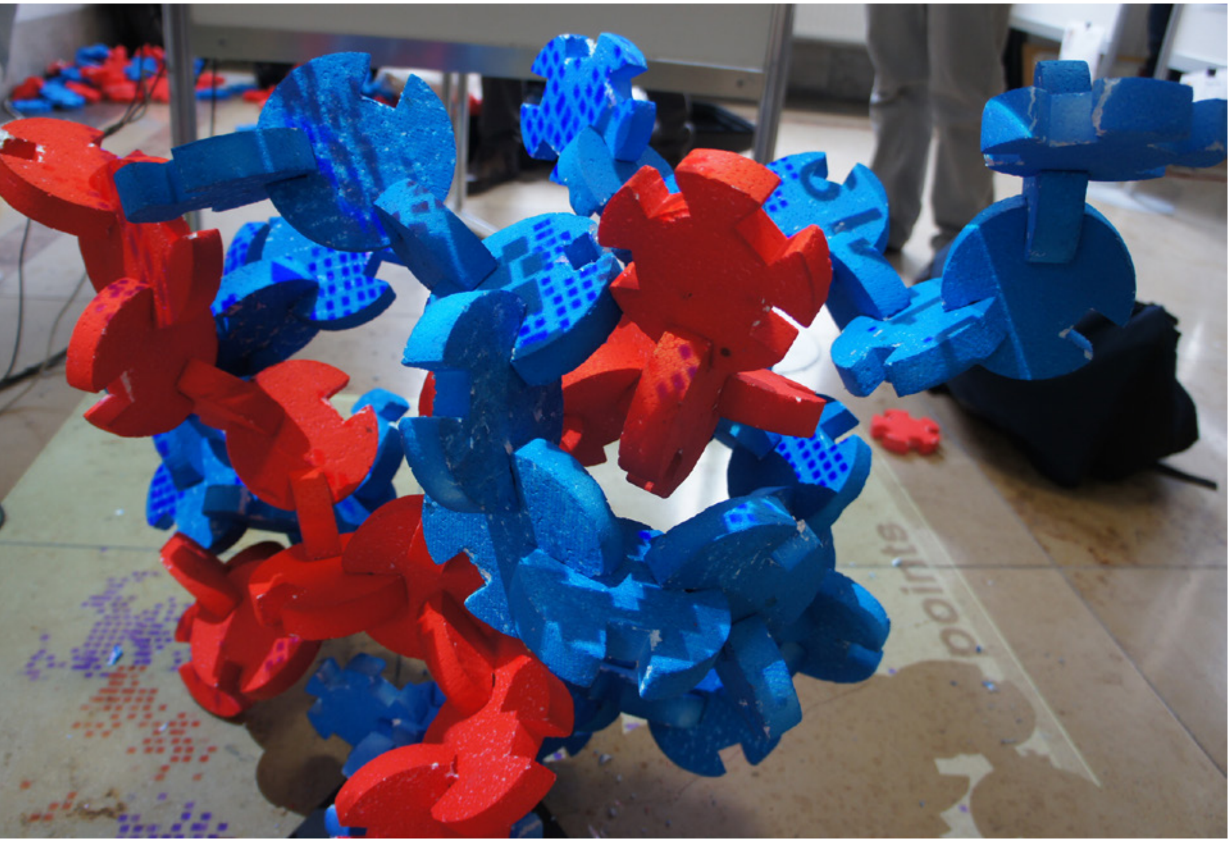
Paper 7: »Emergent Interfaces«

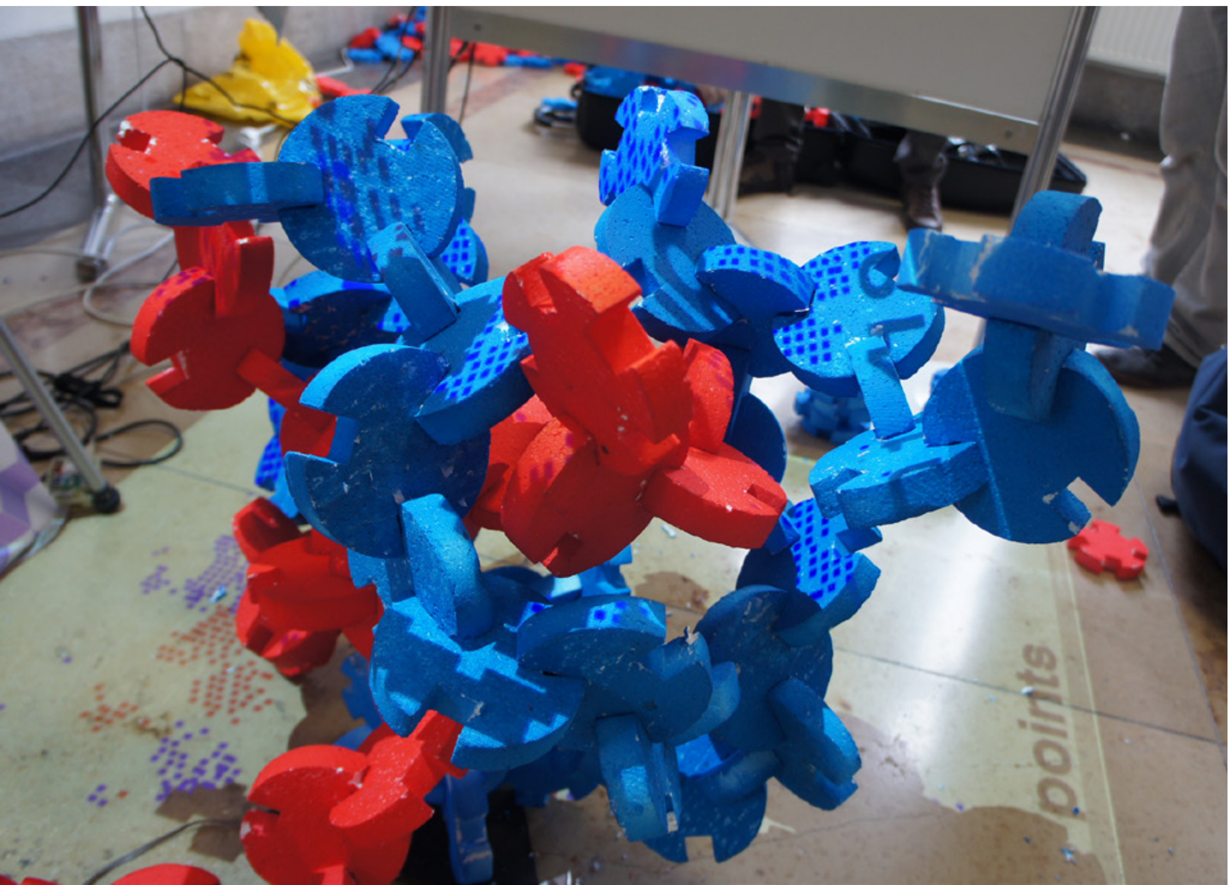
Investigates how constructive assemblies can emerge through a form finding process resembling growth. The synthetic growth is achieved through the assembly of identical foam blocks assembled by two competing users. A family of differently shaped blocks were tested in turn. Each block type gives rise to different morphologies during each assembly session depending on the user and the environment which is augmented through projection onto and sensors under the emergent structures. The resulting system is described as a digitally augmented tangible interface, and it is evaluated by professionals and students in interaction design. The concept of Emergent Interfaces (EI) introduced here, harnesses the interplay between various actants. The EI are charcterized by in-determinism, temporal design, and self-organization. This work contributes to organic user interfaces and morphogenetic engineering.

Conclusions:

The structures emerge in the assemblage between the individual type of morphology, the competing users, the rulset of the game, as well as sensors, computation and representations. As such, the setup is exemplary for *Mixed Substrate Computation*.

Figure 41. Left column shows the elements in order of number of connection slots 3-7. The structures (right) shows examples of the conglomerate structures built from each of those typical elements. Most significant is the difference between type 3 and type 4 slots, where 3 becomes very dense and 4 becomes very orthogonal.


points


points

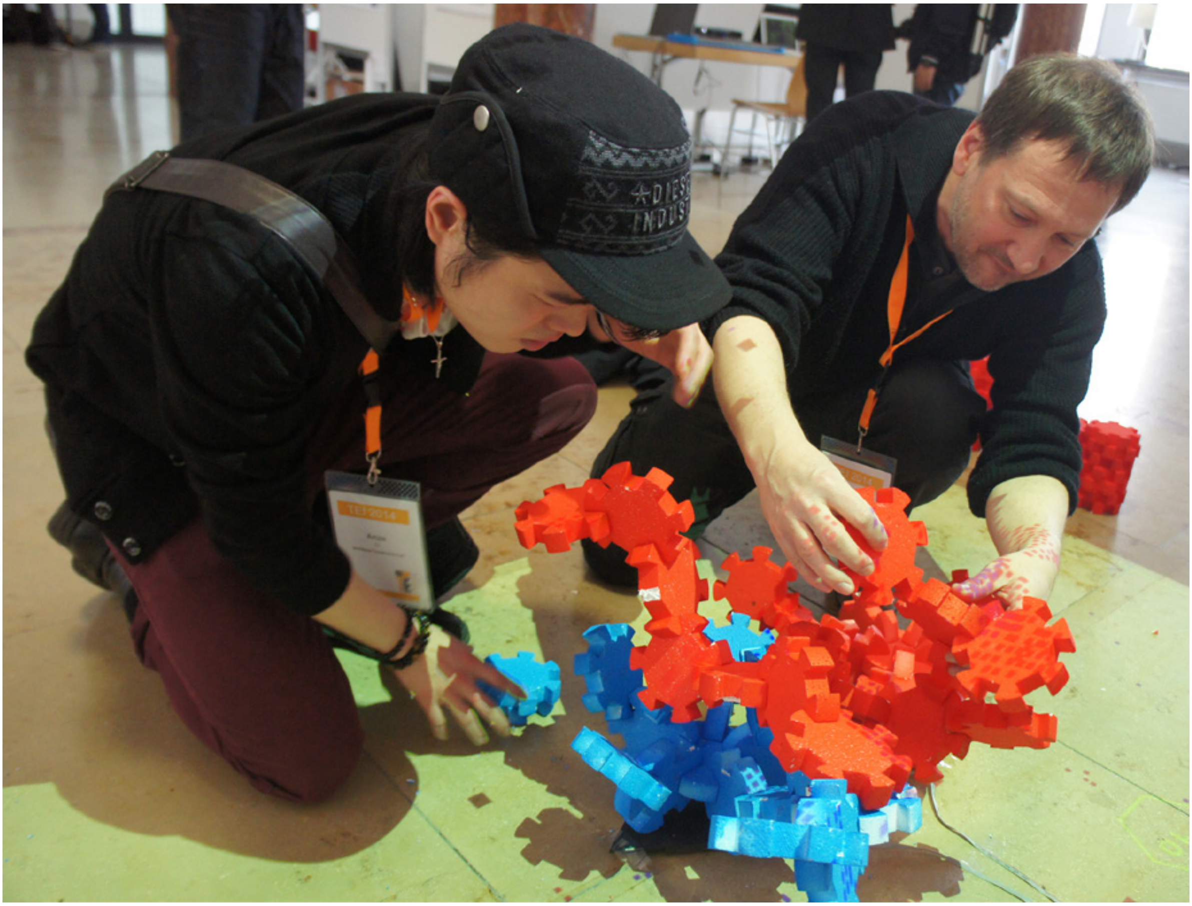


Figure 42. Demonstration and experimentation of the gamified construction system at Tangible, Embedded and Embodied Interactions conference in Munich 2014.

Paper 8: »Event Series Prediction as Decision Support System at Fast Paced Processes«

This paper investigates how prediction – as used in science, technology and daily life – can be used to influence fast paced creative processes.

The setup of the experiments here employs actants performing creatively while being influenced by Event Series Prediction.

The experiments are evaluated and the participants report on their experiences. Based on the experiences from these three types of processes, the article discuss how a design or modification process may be guided by predictions.

The representations provided by ESP achieve clear similarities with the near future events in the environment. However, changing the environment based on such prediction will in turn change the outcome of events in the environment. These consequences are sought to be demonstrated through these fast-paced processes which take place near to human scales of perception.

In turn the goal is to scale the temporal dimension to challenging, time-consuming tasks such as modifying built environment which are normally outside of human cognitive capacity.

Paper 9: »Sensitive Assembly: Gamifying the design and assembly of façade wall prototypes«

The paper describes the demonstration of an *Embodied Design Setup* at the digital design festival NODE15. The installation consists of a wall made of stacked cardboard cubes that are from one side traced by 3d sensor[166] and from the other side modified by two human players.

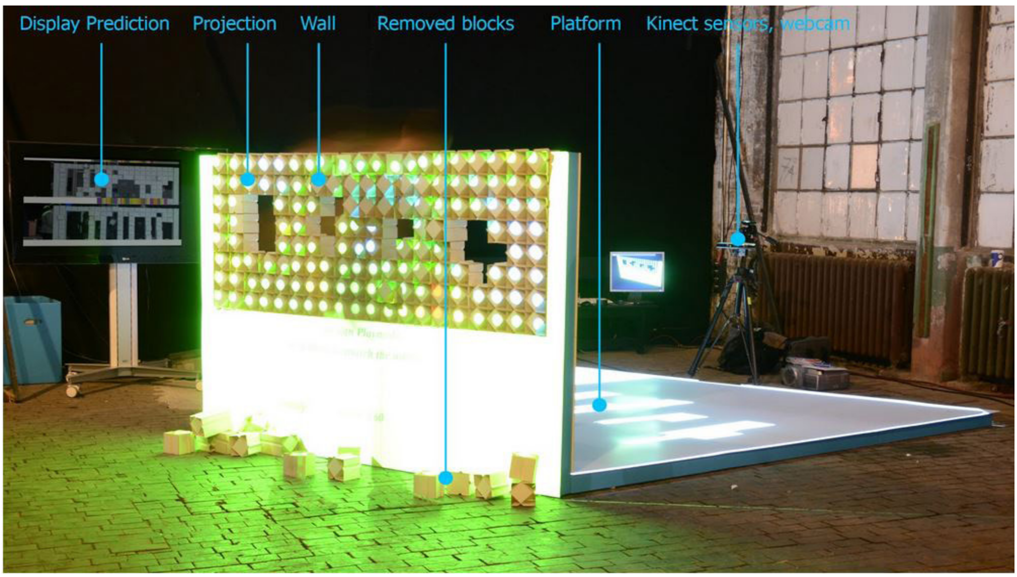


Figure 43. The installation Sensitive Assembly here referred to as SWall. The wall in the foreground, kinect sensor and camera on the right, and the prediction representation on the monitor to the left.

The players compete in a game similar to Jenga, and the winner is the player who removes the last cube without causing the collapse of the wall. One system observes the wall and analyzes the structural integrity via conventional finite element analysis, the other system uses ESP to make prediction of the wall activity. The main idea of using ESP is predicting when the wall collapses.

166 Kinect 3d for x-box 360

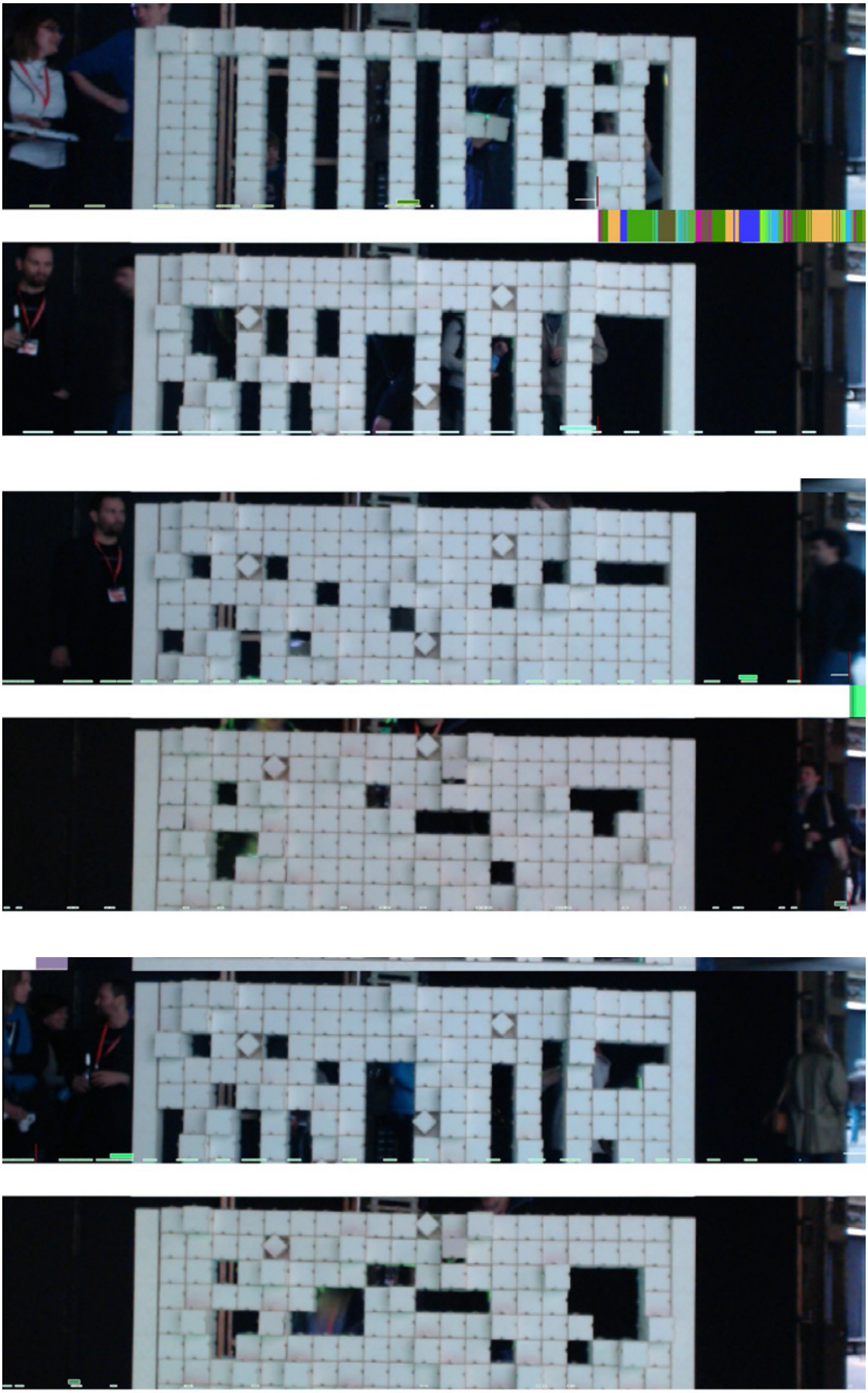


Figure 45. Two examples of game similarities found by ESP. Left side shows some larger holes in both top and bottom case, right side show two games where the wall is more perforated with one larger opening.

ESP is given data from the 3D sensor. The data goes through a pre-processing or filtering operations, which extract a set of features from the raw 3D data points. The filters extract features which are for association called porosity, edginess, and coherency. They are filtered out both in the horizontal and vertical directions and assigned to each 3D data point, making the data invariant to XY-position and instead variant to the topological character of the wall.

The features are not directly related to structural integrity, but they all together establish a nuanced representation of the state of the wall. As each player removes a cube, the state is recorded to create a temporal landscape, as training data for ESP. The prediction is displayed on a monitor next to the wall.

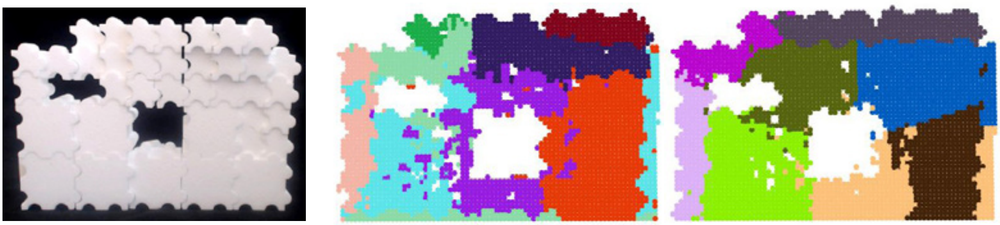


Figure 44. Middle and right display the filtered features after a clustering operation. Topologically different areas of the wall becomes the perception for ESP of the wall. This prototype wall was used for testing before implementation at the installation in Frankfurt. The prototype wall is shown on the left.

The installation ran for 7 days and 65 games. Initially, ESP was not able to predict correctly due to lack of experience, but during the last days ESP several times successfully predicted the collapse 3-5 turns ahead. Often players were far more optimistic in their own predictions.

The interesting aspect of this paper in regards to the discussion above is the semantical foundation for prediction. The dimensions used in the algorithm are not directly related to structural integrity of the wall, but still the experience built up over many games provides ESP with a certain understanding of the wall and its performance over time or in this case, gameplay.

APPENDICES

ESP Java Source code

The source code running Event Series Prediction with video input and video output as described in section 6.2 is separated into a few parts. The distinction between parts is somewhat similar in distribution as what is shown in Figure 27 (page 100).

The first part is the main setup and continuous loop. This continuous control loop addresses the other parts when needed. I will not go in details explaining the individual lines of code, but just refer the parts of code to figure 27, and also mention what the individual parts do.

Code Part 1 Control loop

This part is the overall control loop. This would be the entire flow chart of figure 27 (page 100).

```
/////////////////////////////////////////////////////////////////////////////////////DRAW
void draw () {
  frame.setTitle("Prediction Video Overlay"+ (int)frameRate + " fps");
  background(0);

  //////////////////////////////////////READING DATA FROM WEBCAM  // AND
///////////////////////Recording
  m.read();
  m.loadPixels();
  /////////////////////////////////////////////////////DISPLAYING THE IMAGE RETURNED

  for (int j=1; j<480; j++) { //y direction horizontal collumns
    for (int i=1; i<640; i++) {          //for 10 images from the display image and
forward
      memImg[frameCnt][i+(j*640)] = m.pixels[i+(j*640)];
      //compare specific fixel from each image
        set((1280-i*2)+1, (j*2)+1, memImg[frameCnt][i+(j*640)]);
        set((1280-i*2)+1, (j*2), memImg[frameCnt][i+(j*640)]);
        set((1280-i*2), (j*2)+1, memImg[frameCnt][i+(j*640)]);
      set((1280-i*2), (j*2), memImg[frameCnt][i+(j*640)]);

      if (displayImage>0 && displayImage<1280-forecastPiece-step) {
        color ptColNow= memImg[(displayImage+step)][i+(j*640)];
        int redNow = (ptColNow >> 16) & 0xFF;
        int greNow = (ptColNow >> 8) & 0xFF;
        int bluNow = ptColNow & 0xFF;
           set((1280-i*2)+1, (j*2)+1, memImg[(displayImage+step)][i+(j*640)]);
          set((1280-i*2), (j*2), memImg[(displayImage+step)][i+(j*640)]);

        for (int k=0; k<greenTail; k=k+2) {
          color ptColMem= memImg[(displayImage+step+k)][i+(j*640)];
          int redMem = (ptColMem >> 16) & 0xFF;
          int greMem = (ptColMem >> 8) & 0xFF;
          int bluMem = ptColMem & 0xFF;

          if (redMem<redNow-tol || redNow+tol<redMem ){//|| greMem<greNow-tol||gre-
Now+tol<greMem-tol || bluMem<bluNow-tol||bluNow+tol<bluMem) {
            set(1280-i*2, j*2+1, green );
            set(1280-i*2, j*2, green );
          }
          //compare the same pixel
        }
      }
    }
  }
  /////////////////////MOVED under
  if ( displayImage == displayImageOld && step < longestEvent*3) { // && step <
longestEvent*3
    //step=+2;
    step++;
    stroke(255, 0, 0);
    if (showMemory)line((displayImage+forecastPiece+step), height-80, displayImage+-
forecastPiece+step, height-50);
    noStroke();
  } else {
    displayImageOld=displayImage;
    displayImage=0;
    step=0;
  }
  //updatePixels();
  ///////////////////////////////////////////////

  InsertDim();
```

```
  calcKmeans();
  Sequence();
  Forecast();

  frameCnt++;

  if (frameCnt >= datasize) {
    frameCnt = 0;
    dataIsFull=true;
  } //move framecnt to the start of the screen
}
```

Code Part 2 InsertDim

This part inserts the dimensions as input data in a data array for later use. This part is shown as step 1 in figure 27.

```
void InsertDim() {
  int d=0;
  color ptCol=memImg[frameCnt][30000]; //jsut setting to someanycolor...
  for (int j=sampleDistFromTop; j<480; j=j+sampleHeightSpacing) { //y direction
horizontal collumns
    for (int i=30; i<640; i=i+sampleWidthSpacing) { //x direction vertical rows
      memImg[frameCnt][i+(j*640)] = m.pixels[i+(j*640)];
      // pixels[i+(j*640)] = img[i+(j*640)];
      // if (j%60==30 && i%60==30 && d<dim-2) { //there are three times as many
dimensions as samplepoints //%int((307200/samplePoints)
      if (d<dim-2) {
        //fill(memImg[frameCnt][640-i+(j*640)]);
        fill(255);
        if (samplesOnOff==true) {
          rect(i*2-5, j*2-5, 10, 10);
        }

        ptCol= memImg[frameCnt][640-i+(j*640)];
        dataset[frameCnt][d]   = (ptCol >> 16) & 0xFF;
        dataset[frameCnt][d+1] = (ptCol >> 8) & 0xFF;
        dataset[frameCnt][d+2] = ptCol & 0xFF;
        d=d+3;
      }
    }
  }
  updatePixels();
}
```

Code Part 3 calcKmeans

This part runs one iteration of the K-means algorithm on the n-dimensional data points. This part is show as step 4 in figure 27.

```
void calcKmeans()
{
  for (int i=0; i<clusters; i++) {
    for (int d=0; d<dim; d++) {
      centroids[i][d] = centroids_new[i][d];
    }
  }
  RecomputeCentroids();
  AssignPointstoClusters();
  CalculateClusterMembers();
}
////////////////////////////////////////////CALCULATE MEMBERS
void CalculateClusterMembers () {
  numActiveClusters=0;
  for (int i=0; i<clusters; i++) {
    if (clusterMembers[i]>0)
```

```
      numActiveClusters++;
    clusterMembers[i]=0;
  }
  for (int i=0; i<datasize; i++) {
    clusterMembers[indices[i]]++;
  }
}

///////////////////////////////////////////SEEDGENERATOR
void SeedGenerators()
{
  for (int i=0; i<clusters; i++) {
    startData = int(random (0, datasize-1));
    for (int d=0; d<dim; d++) {
      centroids[i][d] = dataset[startData][d];   ///////////////_new
    }
  }
}
///////////////////////////////////////////ASSIGN TO CLUSTERS
void AssignPointstoClusters()
{
  float min_dist;
  float max_dist;
  float cent_dist;
  float sumDist;
  max_dist =0;
  for (int i=0; i<datasize; i++) {
    min_dist = 999999;

    for (int j=0; j<clusters; j++) {
      sumDist=0;
      for (int d=0; d<dim; d++) {
        sumDist=sumDist+ ( (centroids[j][d]-dataset[i][d])*(centroids[j][d]-dataset[i]
[d]) );
      }
      cent_dist=sqrt(sumDist);

      if (cent_dist <= min_dist) {
        min_dist = cent_dist;
        indices[i]=j;
      }
      if (cent_dist >= max_dist) {
        max_dist=cent_dist;
        startData=i;
      }
    }
  }
}
///////////////////////////////////////////////RECOMPUTE CLUSTER CENTERS
void RecomputeCentroids()
{
  float[][] mean = new float[clusters][dim];
  float [] count = new float[clusters];
  for (int i=0; i<datasize; i++) {  //looking at all data
    for (int j=0; j<clusters; j++) { //for each cluster
      if (indices[i]==j) {          //for each member
        for (int d=0; d<dim; d++) {  //each dimention
          mean[j][d]+=dataset[i][d];  //add data to mean value
        }
        count[j]+=1;                //count how many are added to each mean value
      }
    }
  }
  for (int i=0; i<clusters; i++) {

    for (int d=0; d<dim; d++) {
      if (count[i]>0) {
        centroids[i][d] = mean[i][d]/(count[i]);
      } else {
        //if(true) { //cluster has no members
```

```
        centroids[i][d] =dataset[startData][d];
        //print(".");
      }
    }//}
  }
}
```

Code Part 4 Recursive sequence pattern mining

This part is shown as step 6 and 7 in figure 27. This is where the sequences from 'now' is compared to all previous events.

```
void recur(int origin, int first, int lookAt, int next) {
  //origin is the last color value
  //lookAt is the next same found backwards
  //'first' and 'next' steps backwards to see if there is sequence and the calls the
recur
  eventPart eventLook = (eventPart) sequence.get(lookAt);
  eventPart eventFirst = (eventPart) sequence.get(first);
  eventPart eventNext = (eventPart) sequence.get(next);

  eventLook.totalLgt = eventLook.totalLgt + eventNext.lgt; //adding up the total
length of the sequence
  eventLook.totalDif = eventLook.totalDif + abs((eventFirst.lgt-eventNext.lgt)/event-
Next.lgt)*eventKonst;
  eventLook.members++;

  first--;
  next--;

   ///////////////CALL THE RECUR IF:

  if (next>0 && sequenceData[first] == sequenceData[next])  {
    CalculateLongest(0, 0, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first, lookAt, next);
  }

  else if (next>frameCnt+1 && noiseTolerance>1 && sequenceData[first] == sequence-
Data[next-1])
  {
    CalculateLongest(1, 1, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first, lookAt, next-1);
  }
  else if (next>frameCnt+1 && noiseTolerance>1 && sequenceData[first-1] == sequence-
Data[next]) {
    CalculateLongest(0, 1, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first-1, lookAt, next);
  }
  else if (next>frameCnt+2 && noiseTolerance>2 && sequenceData[first] == sequence-
Data[next-2]) {
    CalculateLongest(1, 2, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first, lookAt, next-2);
  }
  else if (next>frameCnt+2 && noiseTolerance>2 && sequenceData[first-2] == sequence-
Data[next]) {
    CalculateLongest(0, 2, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first-2, lookAt, next);
  }
  else if (next>frameCnt+3 && noiseTolerance>3 && sequenceData[first] == sequence-
Data[next-3]) {
    CalculateLongest(1, 3, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first, lookAt, next-3);
```

```
  }
  else if (next>frameCnt+3 && noiseTolerance>3 && sequenceData[first-3] == sequence-
Data[next]) {
    CalculateLongest(0, 3, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first-3, lookAt, next);
  }
  else if (next>frameCnt+4 && noiseTolerance>4 && sequenceData[first] == sequence-
Data[next-4]) {
    CalculateLongest(1, 4, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first, lookAt, next-4);
  }
  else if (next>frameCnt+4 && noiseTolerance>4 && sequenceData[first-4] == sequence-
Data[next]) {
     CalculateLongest(0, 4, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first-4, lookAt, next);
  }
  else if (next>frameCnt+5 && noiseTolerance>5 && sequenceData[first] == sequence-
Data[next-5]) {
     CalculateLongest(1, 5, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first, lookAt, next-5);
  }
  else if (next>frameCnt+5 && noiseTolerance>5 && sequenceData[first-5] == sequence-
Data[next]) {
     CalculateLongest(0, 5, eventLook.totalLgt-eventLook.totalDif, first, next, event-
Look.pos, eventLook.num);
    recur(origin, first-5, lookAt, next);
  }
}

void CalculateLongest(int firstOrNext, int num, float total, int first, int next,int
lookPos,int lookNum) {

  eventPart eventJump = (eventPart) sequence.get(1); //not yet used but

  for (int i=0; i<num; i++)
  {
    if (firstOrNext==0)
       eventJump = (eventPart) sequence.get(first-i); //getting the eventpart that was
jumped.
    else
       eventJump = (eventPart) sequence.get(next-i); //getting the eventpart that was
jumped.

    total=total - eventJump.lgt;
  }
   if (total> longest) {
    longest=total;
    displayImage=lookPos;//eventLook.pos
    longestEvent=lookNum;//eventLook.num
  }


  if (longest<showTolerance) {
    displayImage =0;
  }

  //accordance of the sequence size
  rect(lookPos, height-55, -longest, -2);
}
```

Code Part 5 Forecast

This part takes the best matching sequence and jumps forward to the representation from that time.

```
void Forecast() {////////////////////////////////////////////the FORECAST/////the FORECAST/////
the FORECAST/////the FORECAST/////the FORECAST
  longestEvent=0;
  longest=0;
  cntRecur=0;  //TOTAL recursions per runthrough.
  //println(sequence.size());
  if (frameCnt>12) { //just to not start too early
    eventPart eventNow = (eventPart) sequence.get(sequence.size()-1); //getting the
last member of sequence
    for (int i=sequence.size ()-noiseTolerance-1; i>0; i--) {   //going through each
datapiece
      eventPart eventLook = (eventPart) sequence.get(i);  //get the latest
      if (eventNow.name == eventLook.name) { //count down/backward and see if the
seqData(color) is the same
        recur(eventNow.num, eventNow.num, eventLook.num, eventLook.num);  //void
recur(int origin,int first, int next, int addup, int cnt)
        rect(eventNow.pos, height-65, -longest-2, -1);
      }
    }
    eventPart eventLongest = (eventPart) sequence.get(longestEvent);
    rect(eventLongest.pos, height-65, -eventLongest.totalLgt, 6);
  }


  //display the piece being forecast
  stroke(255, 0, 0);
  line(frameCnt+1, height-55, frameCnt+1, height-100);
  stroke(0);
  line(frameCnt, height-55, frameCnt, height-100);
  noStroke();
}
```

Code Part 6 eventPart

This is a class establishing the event parts as objects having a position, length and other parameters used when finding the best match.

```
class eventPart {
  // states
  int num;
  int name;
  int pos;
  float lgt;
  float totalLgt;
  int members;
  float totalDif;
  // constructor
  eventPart(int eventNumber, int eventPartName, int eventPartPos, float eventPartLgt,
float eventTotalLgt, int eventMembers,float eventTotalDif) {

    num= eventNumber;
    name = eventPartName ;
    pos= eventPartPos  ;
    lgt= eventPartLgt ;
    totalLgt= eventTotalLgt ;
    members= eventMembers ;
    totalDif= eventTotalDif;
  }
}
```

Code Part 7 Sequence

This part constructs a sequence based on the clustered time objects. This sequence is what is used in Code Part 4.

```
void Sequence() {
  sequence.clear();
  int lengthCnt=0;     ///counter for the length of each event part
  int nameOld=666;
  int eventNum=0;     //counter for the number of color bars - event parts' index
  int drawUpTo=0;
  if (dataIsFull) drawUpTo=datasize;
  else drawUpTo=frameCnt;
  if (showMemory) {
    for (int i=0; i<drawUpTo; i++) {
      fill(palette[indices[i]]);
      rect(i, height-50, 2, 48);
    }
  }
 for (int i=0; i<drawUpTo; i++) {

    lengthCnt++;
    if (indices[i]==nameOld) {
      sequenceData[eventNum-1]=nameOld;
      sequence.set(eventNum-1, new eventPart(eventNum-1, nameOld, i, lengthCnt, 0, 0,
0) );
      //print(", addingTo"+eventNum);
    } else {
      sequenceData[eventNum]=indices[i];
      sequence.add(new eventPart(eventNum, indices[i], i, lengthCnt, 0, 0, 0));
      eventNum++;
      lengthCnt=0;
      nameOld=indices[i];
    }
  }
}
```

Code Part 8 GUI

This part creates a control interface that allows the user to change some settings regarding the performance of the code while it is running.

```
// global variables
int frameRateSet=10;
int forecastPiece=0;
float eventKonst=.9;
int showTolerance =5;
int noiseTolerance=5;
int sampleDistFromTop=100;
int sampleHeightSpacing=45;
int sampleWidthSpacing=24;
boolean samplesOnOff = true;
boolean showMemory = true;
int see =3;
int greenTail=11;
////////////////////////////////////
void keyPressed() {
  if (key=='c') {
    for (int i=0; i<clusters; i++) palette[i] = color(random(5, 250), random(5, 250),
random(5, 250));
  }
  if (key=='s') {
    saveFrame("pred"+day()+"_"+hour()+"_"+minute()+"_"+second());
  }
  if (key=='k') {
    calcKmeans();
  }
}
////////////////////CLASS FRAME
ControlFrame addControlFrame(String theName, int theWidth, int theHeight) {
  Frame cpf = new Frame(theName);
```

```
  ControlFrame p = new ControlFrame(this, theWidth, theHeight);
  cpf.add(p);
  p.init();
  cpf.setTitle(theName);
  cpf.setSize(p.w, p.h);
  cpf.setLocation(100, 100);
  cpf.setResizable(false);
  cpf.setVisible(true);
  return p;
}
// the ControlFrame class extends PApplet, so we
// are creating a new processing applet inside a
// new frame with a controlP5 object loaded
public class ControlFrame extends PApplet {
  int w, h;

  // int abc = 100;
  Textlabel explainA;
  Textlabel explainB;
  Textlabel explainC;
  Textlabel explainD;
  Textlabel explainE;
  Textlabel explainF;
  Textlabel explainG;

  public void setup() {

    size(w, h);
    frameRate(25);
    forecastPiece=2;
    eventKonst=.9;
    showTolerance =15;
    noiseTolerance=5;
    cp5 = new ControlP5(this);
    int space=0;

    explainA = cp5.addTextlabel("labelA").setText("speed/length of memory, and fluidity
of projection").setPosition(10, space).setColorValue(0xffffff00);
    space=space+10;
    cp5.addSlider("frameRateSet").setValue(21).plugTo(parent, "frameRateSet").se-
tRange(0, 88).setPosition(10, space);
    space=space+10;

    space=space+10;
    cp5.addSlider("dim").setValue(270).plugTo(parent, "dim").setRange(100, 400).setPo-
sition(10, space);
    space=space+10;
    space=space+10;
    cp5.addSlider("greenTail").setValue(0).plugTo(parent, "greenTail").setRange(0, 40).
setPosition(10, space);
    space=space+10;
    space=space+10;
    cp5.addSlider("see").setValue(2).plugTo(parent, "see").setRange(0, 5).setNumber-
OfTickMarks(5).setSliderMode(Slider.FLEXIBLE).setPosition(35, space); //.setSliderMod-
e(Slider.FLEXIBLE)
    space=space+10;
    explainB = cp5.addTextlabel("labelB").setText("Mirror
Forecast").setPosition(0, space).setColorValue(0xffffff00);

    space=space+10;
    cp5.addSlider("forecastPiece").setValue(0).plugTo(parent, "forecastPiece").
setRange(0, 88).setPosition(10, space);
    space=space+10;
    space=space+10;
    cp5.addSlider("clusters").setValue(10).plugTo(parent, "clusters").setRange(0, 88).
setPosition(10, space);
    space=space+10;
    space=space+10;
    cp5.addSlider("eventKonst").setValue(.9).plugTo(parent, "eventKonst").setRange(0,
10).setPosition(10, space);
```

```
    space=space+10;
    explainD = cp5.addTextlabel("labelD").setText("sequence minimum length to/not 
show").setPosition(10, space).setColorValue(0xffffff00);
    space=space+10;
    cp5.addSlider("showTolerance").setValue(12).plugTo(parent, "showTolerance").
setRange(2, 30).setPosition(10, space);
    space=space+10;
    explainC = cp5.addTextlabel("labelC").setText("The higher the more tolerant").
setPosition(10, space).setColorValue(0xffffff00);
    space=space+10;
    cp5.addSlider("noiseTolerance").setValue(5).plugTo(parent, "noiseTolerance").
setRange(0, 6).setNumberOfTickMarks(6).setPosition(10, space);
    space=space+10;
    space=space+10;
    explainE = cp5.addTextlabel("labelE").setText("next 4: set the samples to fit the 
'dance space'").setPosition(10, space).setColorValue(0xffffff00);
    space=space+10;
    cp5.addSlider("sampleDistFromTop").setValue(60).plugTo(parent, "sampleDistFrom-
Top").setRange(1, 250).setPosition(10, space);
    space=space+10;
    space=space+10;
    cp5.addSlider("sampleHeightSpacing").setValue(45).plugTo(parent, "sampleHeight-
Spacing").setRange(1, 90).setPosition(10, space);
    space=space+10;
    space=space+10;
    cp5.addSlider("sampleWidthSpacing").setValue(45).plugTo(parent, "sampleWidthSpac-
ing").setRange(1, 60).setPosition(10, space);
    space=space+10;
    space=space+10;

    cp5.addToggle("samplesOnOff").setPosition(10, space).setValue(true).setSize(20, 
15).plugTo(parent, "samplesOnOff");
    cp5.addToggle("showMemory").setPosition(80, space).setValue(true).setSize(20, 15).
plugTo(parent, "showMemory");

    space=space+10;
    space=space+10;
    space=space+10;
    space=space+10;

    explainF = cp5.addTextlabel("labelF").setText("Please do not publish or share this 
sourcecode just yet").setPosition(5, space).setColorValue(0xffffff00);
    space=space+10;
    explainG = cp5.addTextlabel("labelG").setText("Author: Stig Anton Nielsen").setPo-
sition(5, space).setColorValue(0xffffff00);
    space=space+10;
  }

  public void draw() {
    background(0);
  }

  public ControlFrame() {
  }

  public ControlFrame(Object theParent, int theWidth, int theHeight) {
    parent = theParent;
    w = theWidth;
    h = theHeight;
  }

  public ControlP5 control() {
    return cp5;
  }

  ControlP5 cp5;
  Object parent;
}
```