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Information Processing in the Brain

Master’s thesis in Complex Adaptive Systems

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Gothenburg, Sweden 2018

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Cover: An image of a human brain on white background.

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Abstract

The topic of this master's thesis is information processing in the brain. The basic principles and mechanisms of the brains information processing are not known despite the wealth of knowledge about the brain.

By combining the insights from biology, computer science and other levels of science the problem can be approached from a different perspective.

The results of the analysis can be divided into two areas. The way neurons are organised together and the way neurons are organised internally. Together one way neurons are organised is in small groups that perform basic functions and interact with other groups. Internally there are two systems, one regular system in the dendrites that continuously process information and one meta information system in the soma that is used to update the regular system in the dendrites.

The conclusions are tentative but have support from the literature and show a substantial degree of internal cohesion. Further studies could shed more light on the topic.

Keywords: brain, group, neuron, information, computer, physics, biology

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Introduction

1.1 Background

There has been a vast effort to understand the brain, resulting in an extensive amount of understating and data. But the success in understating or even identifying the basic principles and mechanisms for information processing have so far been limited (Gallistel and King, 2009).

While the brain and its functions have been highly elucidated from some perspectives, for example the workings of neurons from cell biology (Alberts et al., 2002) or computational structures such as language from linguistics (Friederici, 2017), the information processing of the brain still eludes understanding (Gallistel and King, 2009). The following quote can illustrate the situation:

> ”[. . .] neuroscience still has not collected the key data because, to some extent, it is not known what that key data even is” (Gazzaniga, 2015, p. 190).

The basic principles of information processing defy understanding, but they ought to adhere to the findings of computer science. Basic computational-representational assumptions valid in the computer sciences ought to hold for the brain. There is also empirical backing for this, in for example the behaviour of various organisms (Gallistel and King, 2009) or the functioning of neurons (Trettenbrein, 2016). Furthermore advances in physics can possibly also become a part in the understanding of the brains fundamental principles (McFadden and Al-Khalili, 2016).

This master’s thesis combines the understanding from the biological and computational-representational levels with other levels of science in order to find mechanisms and principles that might explain the information processing in the brain in a more fundamental way. Given the current lack of fundamental understanding of the subject, there is no clear realisation of what is important and what is not. This state of affairs implies a need for caution in selecting a way forward for understanding the brain.

1.2 Aim

The aim of the report is to identify possible fundamental principles and mechanisms for information processing in the brain. Included in this, is the intent to investigate the feasibility of the principles and mechanisms, and if possible the interaction of them. Finally, the aim is to propose future research problems that can be addressed in order to further the understanding of the information processing in the brain.

1.3 Scope

The scope is limited to a general underlying of principles and mechanisms as part of basic science and not directed toward applied science.

1.4 Societal, Ethical and Environmental Aspects

Concerning societal, ethical and environmental aspects, two main effects appear to arise. First, the brain has, directly or indirectly, a central role in philosophy. Therefore the perspective taken by science regarding this topic can influence the philosophical thinking. Secondly, science, once applied tend to have a substantial impact on both the society and the environment, and raise fundamental ethical questions. Therefor a few questions, listed below, might be of importance to ask.

- Concerning the science itself, is this an ethical perspective to take on the human brain?
- What are the possible ethical outcomes from this research if it is successful?
    - What unethical forms of usage is there? And how could they be prevented?
    - What ethical forms of usage is there? And how could they be encouraged?

1.5 Thesis Structure

The thesis consists of the following main parts:

- Section 1, Introduction - introduces the topic and and the overall aim.
- Section 2, Perspective - provides the viewing point for the thesis.
- Section 3, Theory - contains the theories and data that enables the analysis.
- Section 4, Analysis - provides the reasoning behind the results.
- Section 5, Results - provides the results.
- Section 6, Discussion - questions the results, the reasoning and the ethics.
- Appendix A, Code - provides the software code used in the thesis.

2

Perspective

The inquiry centres on how information could be processed in the brain. This is answered by using the perspective and the theory in the analysis. The perspective attempts to give a frame for the choice of theory and to provide tentative support in the analysis. The perspective attempts to focus the investigation in such a way that it will become more fruitful than other approaches used for investigating the matter at hand.

There might be a need to introduce the perspective since it is not the standard perspective taken on the brain. The perspective is described in this section. The theories, observations and concepts are described in the theory section. The analysis and the presentation of the results is done in the analysis and results sections.

The view arrived at in this section is that the brain can be seen as a hardware-software system, where the hardware has a rich structure that underpins a rich software structure. A substantial part of the richness of the system can be derived from laws of nature and the genome. The basic principles of this system has to adhere to the understanding created in various areas of science and philosophy.

2.1 Perspective, Theory and the Analysis

The perspective clarifies what to look for in the selection of theories and what to aim for in the analysis. The theory consists of selected principles and theories from various areas of science. These modify the perspective and constitute the basis for the analysis. Finally the analysis is is based on the theory and the perspective and modifies them both, see figure 2.1.

The perspective attempts to confront the apparent lack of fundamental understanding of the information processing in the brain according to Gallistel et al. (2009). Other perspectives have provided openings into the brain by finding some basic principles and mechanisms. For example, cell biology has given deep insights into the workings of the cells in the brain (Alberts et al., 2002) and linguistics has provided insights about the computational structures themselves (Friederici, 2017). But the information processing of the brain is still not understood (Gallistel and King, 2009).

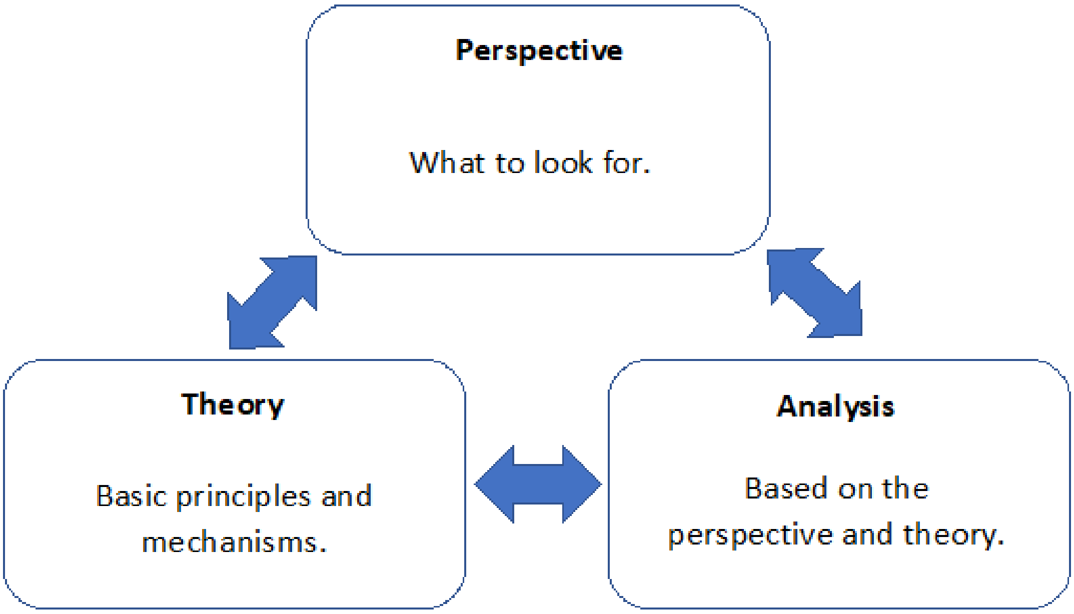

Figure 2.1: The connections between perspective, theory and the analysis. The perspective is used to select the theories and for tentative support in the analysis. The theory modifies the perspective and is a basis for the analysis. Finally the analysis modifies the perspective and effects the choice of theory.

Furthermore, there are two unfortunate tendencies that the perspective tries to combat. One tendency is the forgetting of past insights, where previously obvious ideas has to be painfully rediscovered. Another tendency is the lack of interactions between different disciplines, resulting in not only a lack of knowledge of the understanding generated elsewhere, but it also risks the creation of an overall misleading perspective and starting point for future attempts of understanding.

The perspective combines the history of the subject, the history of the sciences, philosophical investigations and arrives at a view of the brain. The history of the subject indicates the lack of basic principles and mechanisms that have been found but also indicates possible future developments. The philosophical investigations concerns some fundamental conceptual and empirical observations that need to be addressed by an understanding of the brain.

2.2 History of the Topic

The attempts to understand the brain and the human cognitive ability has a long history. Early successes where made already before modern scientific attempts, but lately success has been more elusive.

2.2.1 Early Practical Success

Figure 2.2: The Edwin Smith papyrus from ancient Egypt is a 3700 years old documentation of neurological health problems and treatments (Gross, 1999). Image from: Jeff Dahl (2007).

Already stone age cultures could treat some cranial injuries by for example drilling holes in the cranium in order to regulate the pressure or removing bone fractures and contamination (Alt et al., 1997). The first known use of the word for "brain" is from ancient Egypt and dates to around 1700 BCE. It appears in what seems to be an instruction manual for battlefield medicine and contains symptoms and sophisticated realistic treatments and procedures, see figure 2.2. It includes for example the understanding that the right side of the brain controls the left side of the body and vice versa (Gross, 1999).

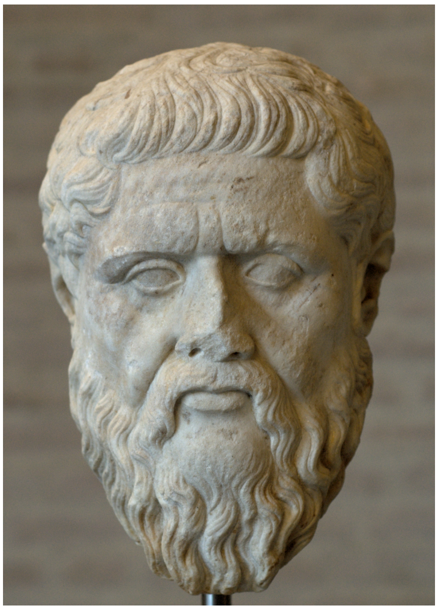

Figure 2.3: A roman copy of an ancient Greek statue of Plato. Image from: Boehringer Collection (2007).

2.2.2 The First Known Realistic Theoretical Speculations

In ancient Greece the pre-Socratic natural philosopher Alcmaeon of Croton, alive around the 5th century BCE (Stanford Encyclopedia of Philosophy, 2017a), made some insightful remarks about the brain.

> ”the seat of sensations is in the brain. This contains the governing faculty. All the senses are connected in some way with the brain; consequently they are incapable of action if the brain is disturbed [...] the power of the brain to synthesise sensations makes it also the seat of thought: The storing up of perceptions gives memory and belief and when these are stabilised you get knowledge” (Gross, 1999, p. 843).

The current understanding of the mind could be a refined version of this statement, despite the wealth of understanding that has been achieved, how this comes about is still fundamentally mysterious (Chatterjee and Sinha, 2007). This might be the case since “[...] neuroscience still has not collected the key data because, to some extent, it is not known what that key data even is” (Gazzaniga, 2015, p. 190).

While having different ideas about the brain, some ideas similar to associationism (see section 2.2.3) were proposed by Aristotle in which memories were associated with each other in time and the recollection of one memory could lead to the recollection of another (Aristotle, 1904). Plato, see figure 2.3, on the other hand claimed that innate explanations where central. For example is mathematics an innate idea and the process of learning is rather a process of remembering knowledge humans are born with (Bluck, 1961).

2.2.3 Associationism

In 17th century England the philosopher and medical researcher John Locke (1632 - 1704) (Stanford Encyclopedia of Philosophy, 2017b) argued that thoughts were created through associations between “ideas” (Locke, 1690).

The word “idea” was used both for the simple sensations from the senses like “red” and complex concepts such as “motherhood”. The person would learn by observing the world. First the simple sensations where aroused, and then combined when they repeatedly occurred together, into more complex concepts (Locke, 1690).

From this process, the whole mental capacity would be learned over time following a few simple general mental rules (Locke, 1690). This reasoning was called associationism and was part of the empiricist tradition.

On the other hand, there was the rationalist tradition which emphasise innate capacities (Buckle, 1999). A leading proponent of rationalism was the philosopher and “universal genius” Gottfried Leibnitz (1646 – 1716) (Stanford Encyclopedia of Philosophy, 2013) who stated that “Nihil est in intelleciu quod non fuerit in sensu; excipe, nisi ipse intellectus” (Leibniz, 1921, p. 70) – “Nothing is in the intellect that was not first in the sense, except the intellect itself.” (Mercer, 2004, p. 245).

2.2.4 Pavlovian

Around the end of the 19th century the Russian physiologist Ivan Pavlov (1849 - 1936) investigated the creation of learned reflexes in animals (Nobel Media AB, 2014a). The animals created saliva, not just when eating the food they were served, but also when receiving signals that had previously preceded the serving of food (Pavlov, 1897). Pavlov used the concept of learning by association to formulate a physiological hypothesis, that the temporal proximity of the simulations caused the animals to learn.

Pavlov knew that the strength of association between two ideas depended on a combination of several experimental aspects. But this is mathematically a many-one function which makes it mathematically impossible to conclude from the strength of the association the value of the parameters that caused it (Gallistel and King, 2009).

The approach can be reconstructed into something that creates associations if there are multiple associations and every association has a different mapping rule, but this would undermine Pavlov’s intention of a single principle for learning (Gallistel and King, 2009).

2.2.5 Behaviourism

Building on the work of Pavlov the American psychologist Burrhus Skinner (1904 - 1990) (Smith and Woodward, 1996) concluded that humans had no nature, did not think and simply displayed a behaviour created by condition and response (Skinner, 1990).

Animals were successfully trained according to this method of rewarded behaviour. But it was discovered that the continuous training of animals after some time lead to "instinctual drift", where the linear improvement in response to training predicted by behaviourism, after continued training disappeared and was replaced with an instinctual behaviour. This apparent reversion to instinctual behaviour was so strong that animals would start to starve, because they stopped doing the behaviour that they would receive a reward for (Breland and Breland, 1961).

The conclusions of Pavlov and Skinner were furthermore questioned by the linguist Noam Chomsky (1928 -) (Nationalencyklopedin, 2017) who meant that cognitive processes require an innate component since raw data alone would not provide sufficient information for the organism (Chomsky, 1980).

2.2.6 Synapses and Statistical Optimisation Methods

Around the end of the 19th century Ramón y Cajal showed that neurons can be connected to each other but remain separate cells. The contact between the cells was termed “synapses” by Charles Sherrington (Glickstein, 2014). In the middle of the 20th century the Canadian psychologist Donald Hebb (1904 – 1985) (Royal Society, 1996) built on this discovery and Associationism, Behaviourism and Pavlovian ideas and assumed that neurons are the basic computational units when he stated that:

> ”The general idea is an old one, that any two cells or systems of cells that are repeatedly active at the same time will tend to become ’associated’, so that activity in one facilitates activity in the other” (Hebb, 1949, p. 70).

But now Hebb (1949) added a mathematical component to this that could perform computations, see equation 2.1. The output from one neuron y_j equals the product of the output from the other neurons x_i and an adjustable wight of the respective inputs w_{ij}.

$$y_j = \sum_i w_{ij} x_i \tag{2.1}$$

The weights of the neurons are then updated according to equation 2.2. Where Δw_{ij} is the change of a synaptic weight, as a product of the learning rate η times the input x_i times the postsynaptic response y_j.

$$\Delta w_{ij} = \eta x_i y_j \tag{2.2}$$

The synaptic weight determines the influence of one neuron on another and as the network of neurons proceeds, more optimal neural relationships are reached. Various forms of randomness are then introduced in order to optimise the search over the space of possible weights $\mathrm{w_{ij}}$.

This is a stochastic optimisation method and was the beginning of artificial neural networks (ANN) and have since been developed further (Hertz, Krogh, and Palmer, 1991). But criticism has been raised, to begin with, there are several stochastic optimisation techniques and there is no reason to chose ANN a priori over the other ones, or stochastic over non-stochastic theories (Chomsky, 2000).

The biological plausibility of ANN:s has also been questioned; for example the way they learn is different than what has been observed in the brain, that all the neurons in some ANN:s are connected with each other which is not the case in brains and the non-localised distribution of functions is not observed in brains (Fulcher, 1991).

The neurons of an organism also continue to be active when they are not stimulated by any data, indicating internal sources of activation (Major and Tank, 2004). Furthermore, the number of neurons needed in an ANN in order to perform only one aspect of insect navigation is so large that it is not biologically realistic (Gallistel and King, 2009).

The studies on synapses have so far not seen the indicated connection from the interaction between neurons and the strength of the synapses. The interaction between two neurons has to be unusually frequent to correlate with any change in the strength of the synapses, and furthermore this strong interaction can lead to either a decrease or an increase in the synaptic connection, undermining the premise of the perspective (Markram et al., 1997).

Furthermore, the sole focus on synapses can have been misleading, every neuron performs a stereotypical computational operation on its input (Kandel E. R., 2013) which along with other data indicates that most information processing occurs in the cell body (soma) of the neuron (Trettenbrein, 2016).

2.2.7 The State of Brain Science Today

In the second half of the 20^{th} century, the state of understanding, was summarised by the recipient of the Nobel prize in Physiology or Medicine, Sydney Brenner (1927 -) (Nobel Media AB, 2014b).

> ”Behavior is the result of a complex and ill-understood set of computations performed by nervous systems and it seems essential to decompose the problem into two: one concerned with the question of the genetic

> specification of the nervous system and the other with the way nervous systems work to produce behavior” (Brenner, 1974, p. 72).

The current dominant perspective on information processing in the brain tend to be associationist. But associationist models are insufficient for understanding Nematodes, the simplest understood nervous system consisting of only 302 neurons, since they abstract too far from the observed data (Rockland, 1989). And the problem of understanding the connection between organisms behaviour and their neural networks behaviour still persists (Chatterjee and Sinha, 2007).

Cognitive neuroscience has had another approach to understanding the brain than associationism. And several conceptual insufficiencies with the associationist approach have been pointed out by Gallistel et al. (2009) and Gallistel et al. (2013). And Gallistel et al. (2014) have been arguing for a paradigm shift from the point of view of biology.

An approach with some success is the cognitive-representational in for example the study of language and a path for future discoveries might be to unify the cognitive-representational level with other levels of science, just as for example the “optical”, “electrical” and “chemical” have been united in the past (Chomsky, 2000).

2.3 History of the Unification of the Scientific Disciplines

Since this perspective is based on the unification of various branches of science, a revealing topic might be what has happened previously when branches of science has united. Furthermore, since there are attempts to unify different branches of science that are relevant for the topic at hand, for example quantum mechanics and biology (Lloyd, 2008), the consequences of such unifications in the past might give indications for the future development of the topic. In general these unifications have often occurred together with major breakthroughs in understanding and conceptual leaps (Chomsky, 2000).

Around year 1680 the leading science of the day was the "mechanical philosophy". It was based on a mechanism consisting of contact between physical objects and was considered self evident. But it had at the time not been unified with Kepler’s well established laws of motions for the planets. The conflict was resolved by Newton who replaced the direct contact between objects with action at a distance and brought together physics and astronomy (Chomsky, 2000).

Another example is classical physics that was seen as an almost complete understanding of nature around year 1900. It was continuous and deterministic and seen as self evident. It was in conflict with a discrete chemistry that was based on substantial empirical data. The conflict was resolved with a radically changed discrete physics partially based on randomness, and physics and chemistry was finally united with Linus Pauling's account of the chemical bond (Chomsky, 2000).

Figure 2.4: An artists rendition of DNA, the macromolecule that united parts of chemistry and biology. Image from: publicdomainpictures (2018).

In 1953 chemistry and biology, both well established, where partially unified with the discovery of a macromolecule capable of storing and copying information, DNA, see figure 2.4. Both fields where well established and the new discovery left the fields in many ways intact (Chomsky, 2000).

Currently there are several levels of science that are not completely combined. Several of these concern the brain. The brain for example has to fulfil basic computational-representational assumptions in order to adhere to the basic insights arrived at by the computer sciences. This is also supported by empirical data such as the behaviour of various organisms (Gallistel and King, 2009) and the activity of neurons (Trettenbrein, 2016).

Furthermore, the brain has to adhere to the insights generated in linguistics (Chomsky, 2000), and potentially other branches of science such as quantum physics (McFadden and Al-Khalili, 2016). How these levels of science can be combined with biology is still unknown.

Figure 2.5: René Descartes (1596–1650) proposed several ideas concerning the human mind (Stanford Encyclopedia of Philosophy, 2014). Image from: André Hatala (2007).

2.4 Philosophical Questions and the Brain

The brain has partially attracted direct attention from philosophers due to its apparent but surprising and unusually properties. Principal among these could be mentioned consciousness and free will. Some historical contributions have been highlighted by Chomsky (2000).

The problem of consciousness have been addressed in philosophy, and one approach proposed by Locke (1823) is that just as matter can create effects such as gravity, it could produce consciousness. Since no consciousness has been found so far outside of our own experience, this perspective is either wrong or indicates that important findings could possibly be expected in the future (Chomsky, 2000).

Another philosophical concern regards free will. According to Descartes (2013), see figure 2.5, humans have free will. This made Descartes (2013) propose a new substance that operated on the principle of free will and interacted with the substance of the physical world that obeys deterministic laws.

Unlike for the problem of consciousness, no convincing possible mechanisms for the free will or its interaction with determinism has been proposed, and Descartes et al. (1961) claimed that some questions will never be answered. But a causality based on randomness has been discovered in physics (Chomsky, 2000), leaving the door open for new forms of causality to be discovered.

The integration of consciousness and free will into a future understanding of the brain would seemingly require major breakthroughs in scientific understanding. This could perhaps be achieved through or from a unification of different scientific areas.

2.5 A Perspective on the Brain

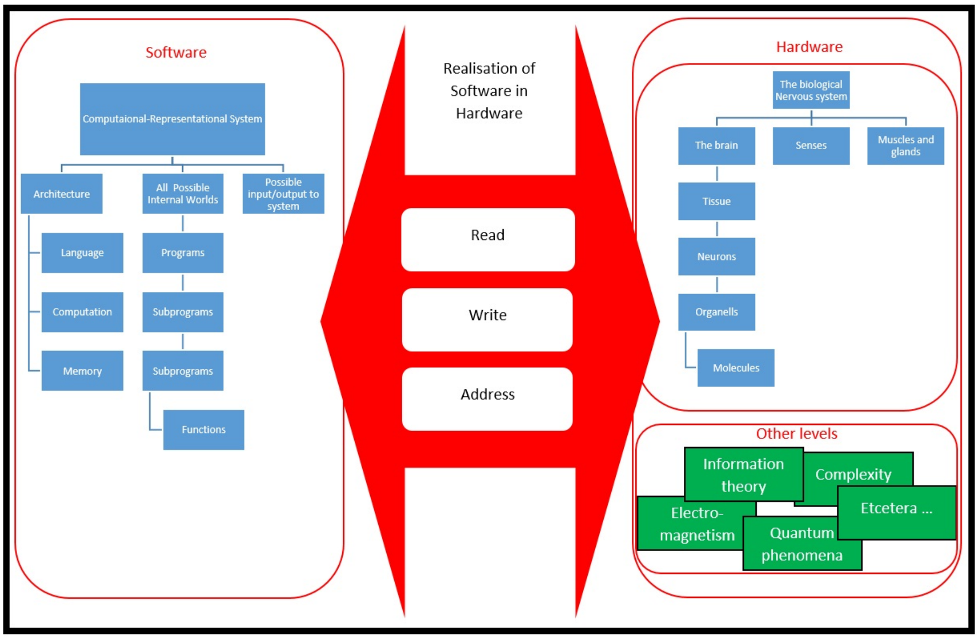

Figure 2.6: The information processing in the brain can be conceptualised as a software – hardware problem. The software would be the "programming language" and the "programs" of the brain with their possible in – and output. The hardware is the biological nervous system and other levels of science needed to realise the software. The software and hardware levels have to interact in such a way that information can be read, written and addressed.

The starting point of this report is a realisation of the lack of fundamental understanding of the topic. The perspective consists of the history of the topic, a share of the history of the sciences, some philosophical considerations and arrives at a perspective for the brain. This perspective is then used to choose and discard among theories, observations and concepts in order to do an analysis.

Currently, the major attempts to understand information processing in the brain tend to suffer from three problems. But these problems can be tentatively solved by adopting a different perspective.

A common thread in the larger historical attempts to understand the information processing in the brain is that the brain is not attributed a rich inner structure. It is characterised, as a reflection of the environment and its history. This is is not done for other biological objects such as arms or legs, or in the sciences generally. This might be a partial explanation of the lack of results when it comes to a basic understanding of the information processing in the brain.

Another problem with the approaches taken to understand the information processing in the brain is that different branches of science have not been sufficiently combined. For example, the laws of computation ought to be as important for understanding the brain as the laws of optics are for understanding the eye.

Therefor it might be fruitful to combine parts of cognitive neuroscience, biology, physics, computer science, the cognitive-representational models of language and other branches of science info a new framework. Given that previous combinations of branches of science has resulted in or been the result of major conceptual reformulations and discoveries this approach might yield such future advancements.

A third problem with the approaches to science is that there is a tendency to aim for explanations that in principle would close the door to addressing the central questions historically raised by philosophy concerning the brain. The questions might be wrong, but approaches that assume that they are has the additional problem of explaining why they are.

A perspective that incorporates these three problems and finds a potential solution to them can be made more concrete by identifying the parts of the various branches of science that enables the attribution of a rich inner structure to the brain. These parts can then be combined creating the possibility of allowing major discoveries that can address the philosophical concerns.

The various parts of theory that needs to be combined can be categorised as either software and hardware. The software would be the “programming language” and the “programs” of the mind with their possible in – and output. The hardware would be the biological nervous system and other levels of science needed to realise the software, see figure 2.6. The scientific problem is then to identify the software and the hardware and how these are related. Given the displayed richness of the software, there is presumably a need for a rich hardware to be found.

A rich structure of the brain does not only have to be innate, it can mostly be a property of its fundamental building blocks and natural law. The brain can then be seen as a puzzle consisting of the parts that nature have made available. Evolution recruited frequently present phenomena of physics, chemistry and biology and combined them in ways indicated in the genome in order to create computational structures beneficial to the species reproduction under environmental and internal constraints.

The fundamental understanding arrived at in the various disciplines needs to be combined in order to create a coherent framework for an analysis of the topic. An identification of the relevant basic principles and mechanisms in the disciplines can be done and these can then be combined to identify possible principles and mechanisms for the information processing in the brain. It might be well to bear in mind that according to Gallistel et al. (2009) all contemporary attempts to explain how computations are made in the brain are speculative.

3

Theory

The theory section consists of various literature that gives a more concrete framework than the perspective. This framework is then used in the analysis to arrive at the results.

The information processing in the brain can be seen as a software – hardware problem. The software is then the “programming language” and the “programs” of the brain with their potential in– and output. The hardware is the biological nervous system together with other levels of science needed to realise the software. The problem is to identify the software and the hardware and how these are related.

From an evolutionary perspective the evolution can be seen as having recruited frequently present phenomena of physics, chemistry and biology and combined them in ways described by the genome in order to create computational structures beneficial to the species reproduction under the environmental and internal constraints.

There are three main sub parts of this section, the biological level, other levels, and the computational-representational level. The "biological level" and the "other levels" constitute the hardware and the "computational-representational level" constitute the software. All of these levels have basic principles and mechanisms that provide a structure that the analysis has to adhere to in order to reach the results.

3.1 The Biological Level

Humans and other organisms with nervous system are biological creatures and their mental abilities are manifested and dependent on organs and biological subsystems. From a larger perspective, organisms and their structures depend on evolution and natural laws, and their internal organisation is partially hierarchical.

3.1.1 Evolution and the Hierarchy of Biological Systems

Life operates under evolution. The influence on life by evolution can be summarised in three principles (Griffiths, 2002):

- Variation, all populations have internal variation in morphology, physiology, and behaviour.
- Heredity, there is a higher similarity between offspring and their parents than other individuals.
- Selection, the ability to create reproductively successful offspring in a given environment is not uniform.

Biological organisms are organised in systems and subsystems. In a human this organisational hierarchy is as follows (OpenStax College, 2018):

- Organ system, which consist of a group of organs that perform a sufficiently distinct set of functions. For example the nervous system.
- Organ, is an anatomically separable system with one or more specific functions. It consists of two or more types of tissue. As an example can be mentioned the brain.
- Tissue, is a group of many similar or related cells, that work together for a specific function. For example grey matter, which partially consist of the cell bodies of neurons.
- Cell, is an enclosed structure common to all life, and almost all physiological functions of humans are performed or initiated in them. As an example, neurons.
- Organelles, cells consist of several components such as mitochondria or nucleus (Pearson Education, 2018).

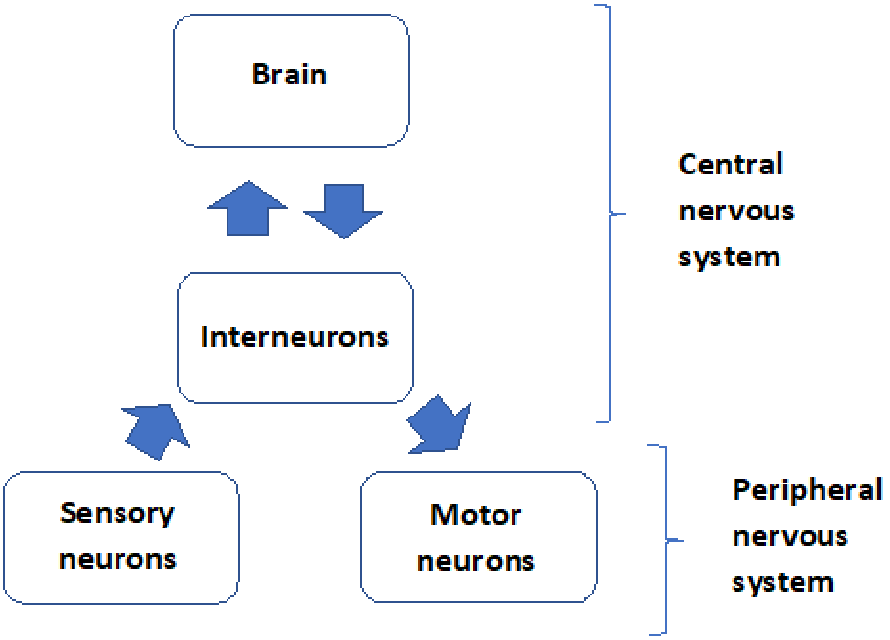

Figure 3.1: Conceptual outline of the nervous system (NS). The NS has two major parts, the central nervous system (CNS) and the peripheral nervous system (PNS). The CNS consists of the brain and interneurons. The PNS consists of sensory neurons and motor neurons. Signals flows from the sensory neurons, via the interneurons to the brain and then back via the interneurons to the motor neurons (Koeppen and Stanton, 2010).

3.1.2 The Nervous System

The general biological functions of the nervous system (NS) are to activate muscles and glands appropriately according to sensory inputs. It consists of two parts, the central nervous system (CNS) and the peripheral nervous system (PNS), see figure 3.1.

The CNS consists of the brain and the spinal cord and receives and relays information to the PNS as well as processes information. The peripheral nervous system consist of the rest of the nervous system and is distributed throughout the rest of the body and connects the central nervous system with the senses and the muscles and glands. The nervous system consists of interconnected neurons (Koeppen and Stanton, 2010).

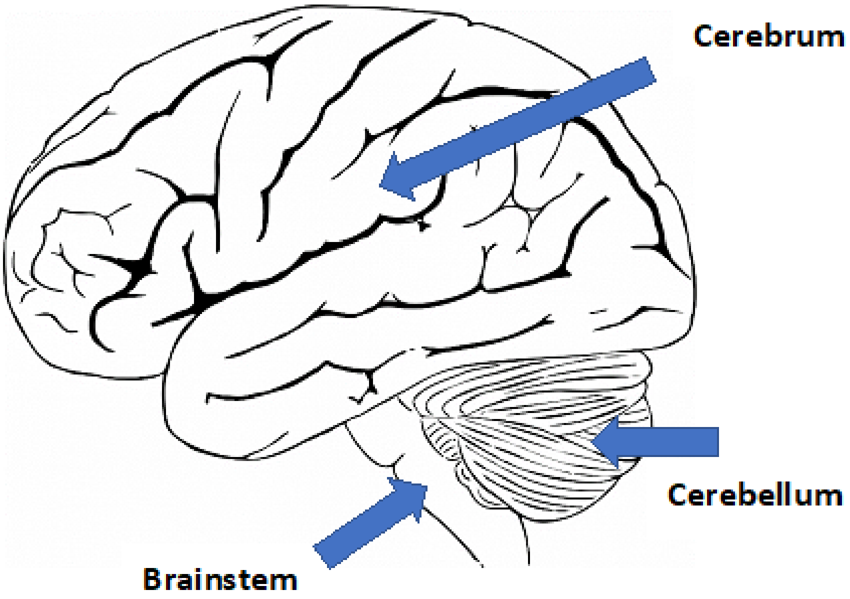

Figure 3.2: The human brain can be seen to consists of three major parts, the cerebrum, the cerebellum and the brainstem (Azevedo et al., 2009).

3.1.3 The Human Brain

The brain consists of three major parts: the cerebrum, the cerebellum and the brainstem, see figure 3.2 (Azevedo et al., 2009). The cerebral cortex has been divided into several functional areas for motor function, vision etcetera. These are then further subdivided into areas that are involved with more specific functions (Kolb and Whishaw, 2009).

The average volume of a human brain has been estimated to 1 202.4 cubic centimetres (given an equal distribution of men and women) (Allen, Damasio, and Grabowski, 2002). The average weight is estimated to 1 283.5 grams (given an equal distribution of men and women) (Pakkenberg and Voigt, 1964).

The mass of the brain is divided into 82 % in the cerebral cortex (42 % cerebral cortical gray matter and 40 % cerebral cortical white matter), 10 % in the cerebellum and 8 % in the brainstem.

The average adult brain (cerebral cortex and the cerebellum) contains on average 170.68 ± 13.86 billion cells, and of these are 86.06 ± 8.12 billion neurons and 84.61 ± 9.83 billion nonneural cells (Azevedo et al., 2009).

The cerebrum holds 16.34 ± 2.17 billion neurons (of which around 12 billion are in the cerebral cortex) and so represents only 19 % of all brain neurons but 72 % (or 60.84 ± 7.02 billion) of all nonneuronal cells in the brain. Whereas the cerebellum has 69.03 ± 6.65 billion neurons, or 80 % of all neurons in the human brain and 19 % of the nonneuronal cells (or 16.04 ± 2.17 billion).

Finally the brainstem has fever than 1 % of all neurons (which is probably an underestimation due to available methods) and holds 9 % (or 7.73 ± 1.45 billion) of all the nonneuronal cells in the brain (Azevedo et al., 2009). The estimation of the average number of synapses per neuron varies between studies, but has been estimated to around 20 000 per neuron by Dicke et al. (2016).

The cerebrum is covered by the thin cerebral cortex, with an average surface area of around 2 300 cm^2 (Toro et al., 2008). The cerebral cortex have been divided into 52 Brodmann areas in the cerebral cortex in each cerebral hemisphere (Brodmann, 1909), resulting in 104 areas in total. The share of neurons in each area can hence be approximated as roughly 1 % of the total, resulting in around $1.2 \cdot 10^8$ neurons per area.

The cranium normally has a blood volume of about 150 ml, with around two thirds in the venous system. The flow of blood to the brain is about 50 ml/100g/min totalling about 700 ml/minute, accounting for over 15 % of total cardiac output (Gilkes and Whitfield, 2007).

The energy usage of the brain can be estimated to be 20 % of the resting metabolic rate (Hrdina, 1996). The mean resting metabolic rate has been estimated to 0.863 kcal/kg/h (McMurray et al., 2014) resulting in 1 450 kcal/person/day assuming a weight of 70 kg. For the brain this is 290 kcal/person/day.

The brain is sensitive to fluctuations in heat but the ranges under which it can operate are unknow. Unknown is also the distribution of heat in the brain and the mechanisms for changing the temperature in the brain (Wang et al., 2014).

3.1.4 Neurons

The main cells that constitute the nervous system are neurons. They store information and transmit information between each other. The nervous system consists of connected neurons (Alberts et al., 2002).

3.1.4.1 Cell Structure

Multicellular organisms tend to have have eukaryotic cells. These tend to be 10 – 100 µm in diameter (Pearson Education, 2018) and are very complex structures containing around 10^{14} atoms (Helmenstine, 2018). In animal cells, they tend to contain the following components (Pearson Education, 2018):

- Nucleus, which contains most of the inherited generic information mostly stored in the form of DNA.
- Cytoplasm, which is the rest of the interior of the cell and it contains several structures.
  - The endomembrane system, consists of membranes that sort and transport RNA and proteins.
  - Cytoskeleton, which is composed of several interconnected linear structures which are used for internal transportation and sorting, keeping the internal structures of the cell ordered and for cell movement.
  - Ribosomes, which receives RNA transcribed from the DNA, and converts it to proteins.
  - Mitochondrion, which has some DNA of its own, produces energy for the cell by converting ADP to ATP. A cell usually has hundreds of Mitochondria.
- Plasma membrane, consists of a phospholipid bilayer and proteins which separates the cell from the environment and serves as a selective barrier for the import and export of molecules.

Cells furthermore consist of a few main macromolecules (Pearson Education, 2018):

- Nucleotides, which store information. They can be either DNA or RNA.
- Proteins, which form structures and guide chemical reactions.
- Phospholipid bilayer, which form enclosed structures, for example around organelles and around the whole cell itself.

The genome consists of complex data structures that enable a complex computational system that guides the development and operation of the organism (Gallistel and King, 2009). DNA is stored in the nucleus of almost every cell in an eukaryotic multicellular organism. This DNA is copied to RNA which is transported out from the nucleus out to the cell. There the RNA is transformed into a protein. In more detail the process is described below, with connections being made to the structure of a computer.

DNA can be seen as a memory written by bits on a double string in the form of adenine (A), cytosine (C), guanine (G) and thymine (T). In a computer, bits are organised into minimal computational elements, and in the DNA 3 adjacent bits on one string are a codon (Gallistel and King, 2009).

Every word in a computer has two functionally distinct parts, the word itself and its address. When the address is accessed then the memory is transcribed to a bus and transported for computation. The same can be said for the DNA where there is an operon that refers to a specific sequence to be read (Gallistel and King, 2009). The maximal reading rate of DNA is about 1 bit in 20 milliseconds (Maier, Bensimon, and Croquette, 2000).

The operon decides the frequency for how often the reading will take place, and can be enhanced or suppressed by macromolecules, transcription factors, that interact to form a system of logical gates. The read part of the DNA starts with a specific start codon, ends with a stop codon and the codons in between are transcribed by a macro molecule complex into an RNA sequence.

The RNA is basically a copy of the DNA, and is transported out of the nucleus. There the RNA sequence is read and translated into a protein by a ribosome. Proteins consist of amino acids according to a code that links codons to amino acids (Gallistel and King, 2009).

A protein is often a transcription factor and makes it possible to form hierarchical structures where for example one gene can be activated and initiate the formation of an eye by in turn activating other genes (Halder, Callaerts, and Gehring, 1995).

Proteins can change conformation, meaning that their mode of interacting with their environment changes. This can radically change their function in the context of the cell. A change in conformation can be done using only $1.7 \cdot 10^{-24}$ kcal (Seo et al., 2014). Furthermore protein have half-times in human cells of typically 20 ±5 hours (Boisvert et al., 2012).

As an example of a group of proteins, there is a group of proteins called kinesins that walks on “roads” called microtubule, with a payload of proteins kept in a “backpack” called liposome with a speed of 2 000 nanometres/second. These proteins can transport a substantial amount of molecules from and to exact locations in the cell (Howard, 2001).

In general neurons have a nucleus which is located in the soma, the cell body, see figure 3.3. The soma creates the cells components, enzymes and other chemical substances (Alberts et al., 2002). The location of the soma relative to the extrusions differ, and have a wide variety of shapes and sizes depending on their location and function (Kolb and Whishaw, 2006). From the soma there are branching protrusions, that receive electrical current called dendrites, and structures that send electrical currents called axons, see figure 3.3 (Koeppen and Stanton, 2010).

3.1.4.2 Communication Between Neurons

Neurons can communicate with other neurons and other cells. Neurons can transfer information to each other in diverse ways. Neurons can communicate with action potentials that travel as spike trains in fibres or with chemical signals in different systems such as the bloodstream (Alberts et al., 2002). This report, as most of the literature, focuses on the communication method that uses the fibres. There are two

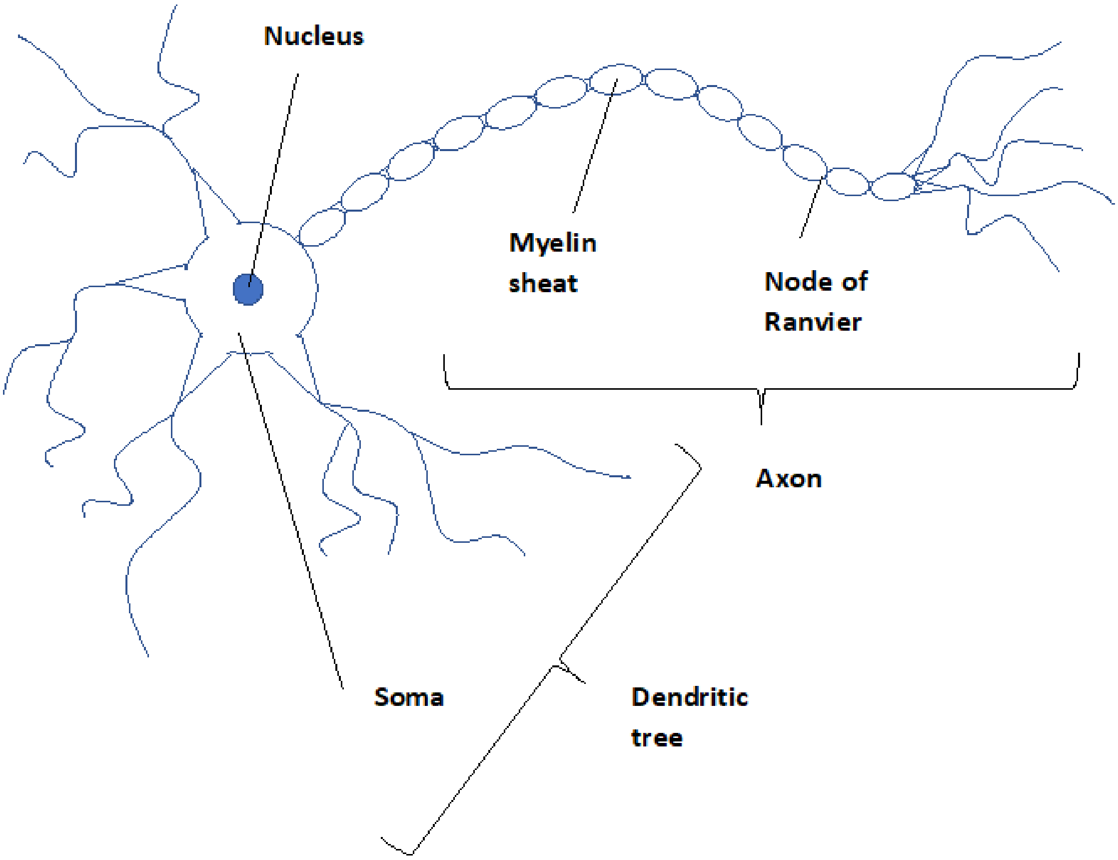

Figure 3.3: A neuron consists of the soma, an axon and a dendritic tree. The soma is where the cells components are produced and where the nucleus that contains most of the cells genome resides. The dendritic tree receives signals from other neurons and the axon send signals to other neurons (Alberts et al., 2002).

kinds of fibres:

- Gap-junctions with electrical gaps that are overcome by chemical transmissions.
- Non-gap synapses with fused neurons.

The main focus in the cell biology literature is on the fibres with gap-junctions, and this is also the focus in this report. Axons with gap-junctions have branches that end with axon terminals that harbour the synapses. Synapses transfer the signals to the next neuron via chemical substances. Axons transmit the spike by repeating the exchange of ions along its length to keep the current strong until it reaches the axon terminal (Koeppen and Stanton, 2010). There are two main types of axon (Alberts et al., 2002):

- Isolated.

- Non-isolated.

Isolated axons are covered in myelin sheath produced by Schwann´s cells. The sheets are interrupted along the axon by the nodes of Ranvier which regenerate the action potential. These constructions allow for saltatory conduction where the current can move from one node to another at a higher speed. This also reduces the energy need since the signal does not have to be regenerated continuously but rather at discreet distances along the way (Alberts et al., 2002) and (Kuhtz-Buschbeck et al., 2010).

The spikes are received by the dendritic tree of the next neuron. Dendrites constitute up to 90 % of the surface area of the neuron (Koeppen and Stanton, 2010). The dendrites can integrate the inputs from 100 000 other cells into a single neuron (Alberts et al., 2002). Gallistel et al. (2009) has proposed that the branches on dendrites are equipped with logical gates.

3.1.4.3 Membrane Potential

Fibres transport electrical signals from one neuron to another, but the electrical signal has first to be produced. In the neuron it is produced by an action potential. There are three main types of action potentials in animals (Alberts et al., 2002):

- Fast sodium mediated.
- Slow calcium mediated.
- A combination.

The neuron has a membrane potential at rest of around -70 mV. It is created by an asymmetric distribution of ions between the inside and outside of a neuron, see table 3.1, causing an electro chemical gradient. This asymmetry can be converted into an action potential (Alberts et al., 2002).

Table 3.1: The typical concentrations of ions involved in the creation of spike trains, inside and outside of neurons at rest (Alberts et al., 2002).

Ion	Extracellular (mM)	Intracellular (mM)
Na+	145	12
K+	4	155
Cl-	123	4.2

The imbalance at rest is created by active transport ion pumps (which consume energy), and is maintained by the cell membrane (Alberts et al., 2002). The action potential is initiated by stimulus from the surrounding to receptors that activate ion channels so ions are let through. This generates a flow of ions over the membrane and if it reduces the membrane potential to around -50 mV then all the passive ion transports are opened (Kolb and Whishaw, 2006).

The flow is produced by passive transport ion pumps (Alberts et al., 2002). This causes a reversal in membrane potential to +40 mV followed by a reversal to the resting potential (Kolb and Whishaw, 2006). The creation of the sodium mediated action potential can be divided into six steps (Kolb and Whishaw, 2006):

1. First the sodium channels are activated and opens which initiate the depolarisation.
2. Then the potassium channels open bringing the potential to +40 mV.
3. The sodium channels are inactivated.
4. The potassium leaves the cell which brings back the membrane resting potential.
5. The potassium channels are closed and the sodium channels are deactivated.
6. The potassium channels close slower than the sodium channels causing a temporary hyperpolarization - lower membrane potential - before it goes back to resting potential -70 mV.

3.1.4.4 The Speed of Communication

Close nerve cells are typically 100 microns apart (Gallistel and King, 2009), but some axons, in the spinal cord can be as long as 1 meter in humans. The speed of transportation along the chord varies, see table 3.2 (Tollison, Satterthwaite, and Tollison, 2002).

Table 3.2: The speeds of the spike train in various types of axons (Tollison, Satterthwaite, and Tollison, 2002).

Type of axon	Speed [m/s]
C-fibres (nociceptors). Thin, non-myelinated axons with a diameter of 0.3 - $1/\mu m$.	0.5 - 1
Aδ-fibers (nociceptors). Medium wide, thinly myelinated axons with a diameter of diameter 1 - 5 μm.	12 - 30
Aβ-fibers. Thick, heavily myelinated axons with a diameter of 5 - 15 μm.	40 - 70

The slowness of the communication between the neurons seem to contradict the observed speed of the mind. It takes action potentials on the order of 10 – 100 microseconds to travel 100 microns along axons, a typical distance separating neurons in a local circuit, this is slower than between similarly spaced electric circuits by a factor of 10^8 (Gallistel and King, 2009).

The transmission over the synaptic junctions is even slower, taking around 500 microseconds. And the postsynaptic polarization takes several milliseconds to return to normal. This is an eternity in a computer. How the brain is as fast as it is is a major mystery.

Gallistel et al. (2009) proposes that memory has to be molecular or sub molecular in order to make the information processing speeds observed in the brain possible given the slow transportation of information between cells.

The rate of firing is also limited. The maximal firing rate of a neuron has been estimated to 453 Hz meaning that the firing itself would require about 2.2 milliseconds (Wang et al., 2016). Neurons often fire in the 30 – 80 Hz region (Friederici, 2017).

This can be compared with the fastest enzymes which can catalyse one reaction in about 9.3 milliseconds (McCord, 1999). But conformational changes of proteins can occur in less than 1 millisecond (Gonzalez and Miksovska, 2014).

The substantially interconnected nature of neurons might contribute to the speed of the mind. Signals from a neuron can reach a lot of other neurons, since when axons branch the signal travels along both branches. The branching of axons and dendrites is massive (Sherrington, 1906) and could be utilised in the improvement of mental speed (Gallistel and King, 2009).

3.1.4.5 Memory Could Reside in the Soma

The neurobiological basis of learning and memory has been assumed to be synaptic plasticity. The idea of the synapse as the mechanism for learning has significant backing, see for example (Martin and Morris, 2002). But other perspectives as those by Dudai et al. (2015) and (Poo et al., 2016) are increasingly being recognised (Trettenbrein, 2016). The reasons for this are partially the reduced arguments for assuming the synapses to be the only location of memory and partially the increased arguments that the soma is a seat of memory. A quote can serve to illustrate part of the current situation:

> ”If we believe that memories are made of patterns of synaptic connections sculpted by experience, and if we know, behaviourally, that motor memories last a lifetime, then how can we explain the fact that individual synaptic spines are constantly turning over and that aggregate synaptic strengths are constantly fluctuating?” (Bizzi and Ajemian, 2015, p. 91).

To start with it is worth considering that synapses are generally built out of proteins known to have a short lifetime. That synapses might be rewired without any learning might therefore be expected (Trettenbrein, 2016). A study using two-photon microscopy of the rate of synaptic turnover and motor skill learning found that the rate of turnover continued to be high after the learning period. If memory was solely based in synapses this would eliminate the memory (Xu et al., 2009) and (Yang, Pan, and Gan, 2009).

The constant turnover of synapses in cortex has so far been observed in all parts of cortex which have been investigated using two-photon microscopy, see references cited by Yang et al. (2009). According to Trettenbrein (2016) this leaves two possibilities. Either memories are constantly remodeled or synapses is not the sole seat of memory.

Axons and dendrites seem to be close to the smallest possible length in the cortical column (Chklovskii, Schikorski, and Stevens, 2002) and (Chklovskii, 2004) and the same might hold globally (Cherniak et al., 2004) and (Lewis et al., 2012) and (Sporns, 2012). From this would follow that the idea of the synapse as the seat of memory is further undermined because:

> ”[. . .] an increased number of synapses could not be accommodated without degrading performance in some way because the cortex is already optimally wired in the sense that the number of synapses is already maximal” (Chklovskii, Schikorski, and Stevens, 2002, p. 345).

One of the further facts that underpins this scepticism has to do with how synaptic efficacy is regulated. The change of conductivity of a synapse require synchrony of pre- and postsynaptic action potentials of +10 to -10 milliseconds and a firing rate of 10 times per second (Markram et al., 1997) which is 10 times the normal rate (Gallistel and King, 2009).

Furthermore, the synchrony of pre- and postsynaptic action potentials can result in either a down or an up regulation in conductivity between the neurons (Markram et al., 1997) which would contradict the reason for a change in conductivity. Over all, this indicates that the mechanisms of changes in synaptic conductivity are different and more complicated than commonly assumed (Gallistel and King, 2009).

The synapses in the sea slug Aplysia have been shown to respond to change very differently than generally expected, with some not being very plastic at all (Kandel and Siegelbaum, 2013). Furthermore, according to studies on Aplysia motor and sensory neurons by Chen et al. (2014) the memory still persisted after the synapses had once been removed pharmacologically.

There is a mismatch between synaptic plasticity in Purkinje cells and learning in the cerebellum (Hesslow et al., 2013). The timing and responses in eye blink conditioning did not depend on temporally patterned input. The conclusion by the authors was that the timing and the memory was located in the cell stating that “[...] the data strongly suggest that the main timing mechanism is within the Purkinje cell and that its nature is cellular rather than a network property” (Johansson et al., 2014).

Furthermore, contradictory to the expectations of the authors, the changes in synaptic strength and density of dendritic spines are not related to the storage of new information in memory (Ryan et al., 2015). In the experiment, a protein involved in the strengthening of synapses and density of dendritic spines in the brain of mice was inhibited, resulting in the same synaptic strength and density of dendritic spines as before a learning event, but with the same ability to display the learned behaviour as a control group (Ryan et al., 2015).

It is still unclear how information is carried forward in time in the brain (Trettenbrein, 2016). If information is carried forward in time by synapses, then Gallistel et al. (2009) claims that several unanswered fundamental computational questions appears:

- How does the change in conductivity encode information?
- Is the utilised symbolisation compact?
- What is the quantitative relationship between the number of synapses and the size of the stored information? Linear, logarithmic or some other relationship?

These questions are unanswered (Gallistel and King, 2009), but on the other hand there are substantial indications that the memory is stored in the soma of the neuron. The questions according to Trettenbrein (2016) are what non-synaptic mechanisms on the sub-cellular level might be identified for memory and learning and how do they relate to the networks in which they are integrated?

A new and promising finding regarding the location of memory comes from Aplysia. Memory has been moved between two individuals of Aplysia by transferring RNA between them. This indicates that modulation of activity DNA plays a roll in memory (Bédécarrats et al., 2018).

Two proposed principles for the memory mechanism are that memory as other biological systems is highly domain-specific (Chomsky, 1975)) and (Gallistel, 2000), and an evolutionary argument might be constructed to support high conservation of the memory mechanism (Trettenbrein, 2016).

3.1.4.6 The Need to Separate Learning and Memory

It has been implicitly acknowledged in neuroscience literature that memory and learning might be separated, see for example (Bannerman et al., 1995) and (Saucier and Cain, 1995). The containment of the idea from other disciplines might be due to ambiguous experimental results (Martin and Morris, 2002). But this has not been interpreted as contradicting the sole synaptic mechanism for memory (Trettenbrein, 2016).

An example is spatial learning which relies on the hippocampus (Bannerman et al., 1995). The synaptic plasticity has been dependent on N-methyl-D-aspartate (NMDA) receptors of the postsynaptic neuron (Bruel-Jungerman, Davis, and Laroche, 2007). This indicates that blocking of these receptors would reduce or eliminate learning, and learning is impaired but in a peculiar way (Bannerman et al., 1995) and (Saucier and Cain, 1995).

Bannerman et al. (1995) and Saucier et al. (1995) have shown circumstances where there is no reduction in spatial learning capacity. When the animal is introduced to a new environment then there is a reduction in the ability to learn to navigate it, but if it is a modification to a previously encountered environment, then the ability to learn is unaffected. This might have several implications of which one is that a separation of memory and learning is needed (Gallistel and Matzel, 2013).

Trettenbrein (2016) recommends a distinction between memory and learning. Trettenbrein (2016) postulates that the relevant learning mechanism is only in part dependent on synaptic plasticity. The initial acquisition of the ability requires synaptic plasticity and neural reorganisation, but altering the details (such as updating or modifying stored memories) does not. Hence synaptic plasticity cannot solely constitute the brain's basic memory mechanism. This could explain why synapses change even when no new learning seems to take place.

Synapses might be the result of learning. Their role might be to ensure efficient connectivity and activity patterns within physical and developmental constraints. Perhaps the synaptic weights and connections regulate behaviours once learning has already occurred (Trettenbrein, 2016).

3.1.4.7 Spatial Structures

Axons and dendrites seem to be optimally organised with close to the smallest possible length in the cortical column (Chklovskii, Schikorski, and Stevens, 2002) and (Chklovskii, 2004) and the same might hold for the nervous system globally (Cherniak et al., 2004), (Lewis et al., 2012) and (Sporns, 2012). The degree of optimisation seems to be very high and could potentially explain why the brain is located in one end of the long thin bodies of animals.

Given how unsuited synapses are for the storage of symbols, the usage of them for memory might be less interesting, but given their ability to move information across space this might simply be their main role. And the changes in conductance and connectivity might ensure the proper function of the network (Trettenbrein, 2016).

It is possible that synapses could be seen as establishing points of access to information already stored in memory inside the cell (Ryan et al., 2015). Given this, memories could then be considered synapse-specific, in the sense that activating different synapses would elicit different memories from the cell (Ryan et al., 2015).

Some structures for organising cells have been found. There are cells in hippocampus that the mouse uses for orientation. One group of cells are place cells that gives the position of the mouse in a space. Another group of cells are grid cells that orient the mouse according to overlaying patterns of repeating triangles. In both groups of cells, the cell that signifies the current position of the mouse becomes active and fire signals (Moser, Kropff, and Moser, 2008).

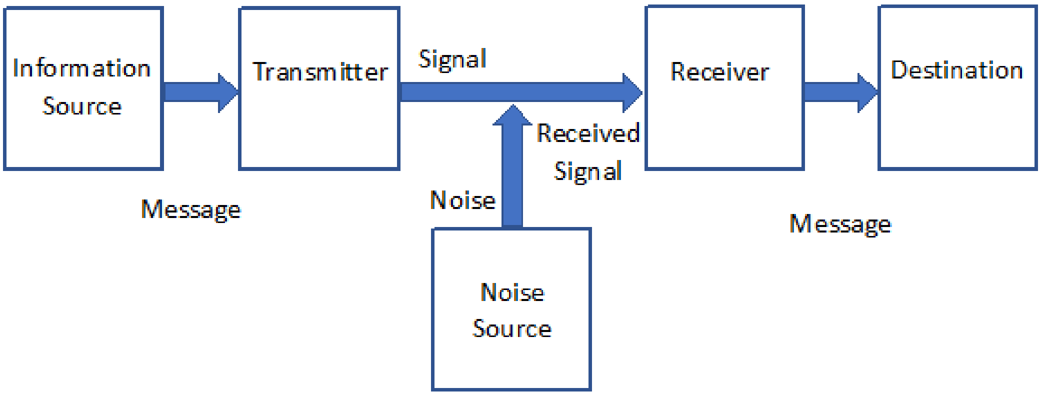

Figure 3.4: Conceptual overview of information theory. First the information originates at a source, and the massage is converted by a transmitter to a signal. The signal is sent to a receiver but is affected on the way by noise from a noise source. The received signal reaches the receiver and is converted to a message that reaches the destination (Shannon, 1948).

3.2 Other Levels

The understanding of the nervous systems ultimately have to be in accordance with theories concerning information and the behaviour of the molecules and sub-atomic elements in the cells. This section therefore contain information theory from a biologically relevant perspective and quantum mechanics in regards to biological systems.

3.2.1 Information Theory and Bayes theorem

The understanding of spike trains is dependent on Shannon's insights into information theory and subsequent work (Roddey, Girish, and Miller, 2000). Information can be viewed from the perspective of communication, the transmission of a message from an information source to a destination, see figure 3.4. Conceptually the information source sends the message to a transmitter that converts the message into transmitted signals (Shannon, 1948).

The signal is a fluctuation in a physical quantity that, after disturbance from a noise source, arrives as the received signal at a receiver which decodes it and sends the message to the destination. The mechanism that encodes the message in the transmitter is the encoder and the opposite mechanism in the receiver is the decoder (Shannon, 1948).

This could be translated in to an example for the nervous system. Starting with sensory input as the information source, what psychologist have termed the proximal stimulus. This is encoded in the relevant sensory apparatus into streams of spikes travelling in the axons of the sensory neurons (Gallistel and King, 2009).

Noise from biophysical sources distorts the spike train on its way to the brain. The sensory-processing components of the brain decodes the signal in two stages. First some aspects of the signal are turned into a representation, by psychologists known as a percept, and then this is coded into symbols (Gallistel and King, 2009).

These symbols constitute the message and are referred to as the distal stimulus by psychologists. The message is sent for succeeding processing in the brain. The combination of the proper processing of the symbols and the chain of communication that refers to them, turns the brain into a representational system (Gallistel and King, 2009).

It is possible to quantify the information communicated to the destination. This can be done from the perspective that reduction in uncertainty at the destination is information. With this definition of information, one way to measure it is to start with the prior probability of each message. Messages with low probability will contribute with higher amount of information, but those have smaller frequency (Shannon, 1948).

In discrete cases, the average uncertainty, the entropy H in bits, is the sum of contribution from all possible messages. The contribution from one message is the probability of that message pi $\mathrm{p_i}$, multiplied with the information gained from that message $\log \frac{1}{p_i}$, see equation 3.1 (Shannon, 1948).

$$H = \sum_{i} p_i \log_2 \left(\frac{1}{p_i} \right) \tag{3.1}$$

The average quantity of information that is communicated is the reduction of the average amount of uncertainty it caused at the destination. The mutual information, $\mathrm{H_{mutual}}$, is the sum of the entropies of two distributions minus the joint distribution, see equation 3.2 (Shannon, 1948).

$$H_{mutual} = \sum_{x \in X} \sum_{y \in Y} p(x,y) \log_2 \left(\frac{p(x,y)}{p(x)p(y)} \right) \tag{3.2}$$

If the two distributions are those for the source and the signal, then this is the fraction of the source information contained in the signal (Shannon, 1948).

Bayes' rule shows the general optimal relationship between the probabilities of the world before (prior probability) and after (posterior probability) receiving a signal and the probability of receiving that signal dependent on (marginal likelihood) and independent of the prior state of the world (the likelihood) (Jaynes, 2003).

The categorisation of it as a rule signifies that it follows directly from probabilistic definitions. And it adheres to and follows from common sense premises such as logical consistency, the need to take all evidence into account and the equal numerical value of the same amount of uncertainty. The derived relationship from these premises is Bayes theorem (Jaynes, 2003).

Bayes theorem claims that the posterior probability of the hypothesis p(h|s) equals the probability of the signal given the hypothesis p(s|h) multiplied with the prior probability of the hypothesis p(h) divided by the overall probability of the signal p(s|h), expressed in equation 3.3.

$$p(h|s) = p(s|h)\left(\frac{p(h)}{p(s|h)}\right) \tag{3.3}$$

Given this formula, the prior probability can be updated using new information (Jaynes, 2003).

Efficient communication presupposes that the destination has an a prior probability of each message. This can be used to create efficient codes where more likely messages have shorter codes. Thus, minimising the total amount of data that needs to be sent. Furthermore, the usage of codes where no coded entity is the prefix for another coded entity enables the construction of self-delimiting messages without the need for separation between the words (Shannon, 1948).

It appears to be well established that humans have a good estimate of the frequency of words in language, see for example (Hasher and Zacks, 1984), (Hulme et al., 1997) and (Jescheniak and Levelt, 1994). The computational-representational approach offers an explanation why this might be the case. The frequency would be constructed in the process of acquiring the language (Gallistel and King, 2009).

Based on information theory it has been possible to make estimates of the information transmitted between sensory neurons to the brain in flies and frogs. 7 bits of information can be transported with a single spike and a single axon can transmit 300 bits per second (Rieke, Bodnar, and Bialek, 1995). The rate of 300 bits per second inside the brain itself is considered controversial (Latham and Nirenberg, 2005).

An efficient encoding of words in the English language needs about 10 bits per word. This would mean that a single axon can transport 30 words per second to a speech centre. But this would require a knowledge of the statistical frequency of words. This is above the rate used by people in speech, 2 – 8 words (Gallistel and King, 2009).

Finally, it might be assumed that the brain uses a digital information system. This is in part due to that it reduces error, increases precision, enables the usage of compact symbols and makes two similar symbols distinguishable (Gallistel and King, 2009).

3.2.2 Quantum Mechanics

Figure 3.5: The European robin (Erithacus rubecula) appear to use sophisticated quantum mechanical effects in its eyes for its orientation in the earths magnetic field (Hein et al., 2011). Image from: © Francis C. Franklin (2014).

The idea of "quantum biology" has been around for decades for example in Schrodinger (1944), but was coined by Löwdin (1963). There is a substantial amount of uncertainty of the actual role of more powerful quantum mechanical effects in biology.

It is now well established that quantum effects are important for "small-scale" biological and chemical processes (Mershin and Nanopoulos, 2008) such as the tunnelling of the π electrons over all bonds in the benzene molecule (Al-Khalili and McFadden, 2008). But how far and in what way quantum effects extends into larger scale objects and processes is not clarified. Demonstrations of dynamical tunnelling by Hensinger et al. (2001) indicate that the understanding of quantum coherence is far from complete.

One paradoxical way of enabling coherent superposition and entanglement is to allow for high degree of compelling in certain degrees of freedom in order to reduce it in others in the context of neutrino oscillations in a medium (Bell et al., 2002). Regarding biological systems there are indications that the interplay between coherence and incoherence might provide an efficient basis for biological functions (Streltsov, Adesso, and Plenio, 2017).

Starting with organic molecules, there are some indications of the possibility of quantum effects playing a role. The superconductivity of doped fullerene (C60) molecules at 117 K by Margadonna et al. (2002) and proton tunnelling in a hydrogen bounded network by Horsewill et al. (2001) indicates that quantum superpositions of organic molecules might be possible.

Extending into macromolecules, several possible discoveries have been made. Quantum tunnelling of electrons and protons has been proposed as a mechanism in several enzyme reactions (Scrutton, 1999). Proton tunnelling has been indicated as the dominant source to the rate acceleration by the enzyme aromatic amine dehydrogenase (Masgrau et al., 2006). And it has recently been indicated that charges along the DNA molecule are transported through quantum tunnelling (Giese et al., 2001). This would indicate the ability of biological organisms to interact with quantum mechanical effects even at the earliest evolutionary time.

Even the effect of chiral induced spin selectivity (CISS) has been demonstrated for several biological molecules including DNA and peptides (Bloom et al., 2016). This might account for some of the energy efficiency of biological systems and their ability to not over heat (Benjamin et al., 2014).

The central reaction for plants, photosynthesis has been proposed to be based on quantum tunnelling. And the elements involved in this has even been proposed to be used for the construction of quantum logic gates (Hitchcock, 2001).

Vision is based on quantified energy where light signals are converted into action potentials by phototransduction. In that process, the enzyme chromophore interacts with a photon. The enzyme then undergoes photoisomerisation, which changes its structure. This change changes the structure of the photoreceptor which leads to the transmission of the signal. The speed of the photoisomerisation, under 200 femtoseconds (Johnson et al., 2017), with high yield, indicates the usage of quantum effects for the creation of the ground and excited states (Schoenlein et al., 1991).

The sense of smell in humans might use the quantum vibrations of molecules to identify them. The quantum vibrations of molecules rather than their structure would be used to categorise them by the sensory neurons (Gane et al., 2013).

Magnetoreception is the ability of animals to navigate using the earths magnetic fields inclination (Hore and Mouritsen, 2016). One attempt to explain this is by the usage of a radical pair mechanism (Schulten, Swenberg, and Weller, 1978) and (Kominis, 2015). Radical pairs are established as a mechanism in spin chemistry (Rodgers, 2009).

The mechanism works by having two molecules form a radical pair. This pair can then exist in either a quantum entangled singlet or a possibly quantum entangled triplet state. The direction of the magnetic field determines the probability of the two states. If the singlet state is favoured then then radical pair will tend to revert back to two molecules. But if the triplet state is favoured then it leads to a different product. The amount of this other final product can be detected by a cell (Hore and Mouritsen, 2016).

Schulten et al. (1978) proposed that this mechanism might be used in organisms. And the molecule assumed responsible is Cryptochrome. The European robin (Erithacus rubecula) appear to have this ability in its eyes, see figure 3.5 (Hein et al., 2011). Laboratory evidence have been found that a radical pair can function as a chemical compass (Maeda et al., 2008). But the proposed protein appear to have an insufficient coherence time when it is isolated. A possibility is that it functions differently in the cell environment (Kattnig, Solov'yov, and Hore, 2016).

It has been proposed that anaesthetics might work by changing electric spin to enable electrical signalling between molecules. This underlines the possibility of quantum mechanics being central to the nervous system (Turin, Skoulakis, and Horsfield, 2014). Quantum mechanics is digital (Lloyd, 2008) which also is the assumed structure for the mental computational representational system by (Gallistel and King, 2009).

An investigation into bees serves as a possible connection between the programs of the brain and sub-atomic quantum mechanical effects. The spatial patterns of the dance of bees have been discovered to be the same as a two dimensional projection of the probability distribution of a specific quantum mechanical particle. The difference in the dance between different species of bees can be explained with a variation in one variable in the projection, and the change of the dance depending on the message being communicated can be explained in a similar way. This gives a speculative connection between physics and the programs in the brain (Frank, 1997).

3.3 Computational Representational Level

Within what might be called the “classical" cognitive science the assumption has always been that the brain is a computational-representational system (Piattelli-Palmarini, 2001) even if there has not been universal agreement, see for example (Fodor and Pylyshyn, 1988). It has somewhat gone out of fashion (Gallistel and King, 2009) but in the last decade a substantial literature have renewed this position, see for example Gallistel et al. (2009) and Gallistel et al. (2013) and Gallistel et al. (2014).

An organ as computationally fast and capable as the brain ought to be constructed in an optimal way from a computational point of view following the logic of coding and compact procedures (Gallistel and King, 2009). The brain ought therefor prima facie adhere to the discoveries of computer science.

A further argument that the brain might be a computational-representational organ is that a seemingly far simpler system, the genetic system, is computational-representational. The system stores vast amounts of data in a small space and computes how to use the data appropriately in a given situation (Gallistel and King, 2009).

Following the discovery of the DNA molecule, biologists realised that it was a truly symbolic molecule, with unlimited abilities to code any information without chemical constraints. The DNA molecule was complemented with a complex machinery for copying and reading the data. All of these realisations gave rise to a new discipline, molecular biology (Jacob, 1993) and (Freeland, 1979). The core of the new discipline was the coding and processing of information, concepts that the biochemistry of the time was unable to include (Gallistel and King, 2009).

If brains are computational-representational system then this would hold true for animal brains too. A frequent example is the occurrence of representation of numbers in animals. Several animals including fish, birds, lions and monkeys have some ability to count (Butterworth, Gallistel, and Vallortigara, 2018). There is furthermore overwhelming behavioural evidence that animals represent numbers, times, locations, distances and angels and uses them for navigation. For this there are several examples even from insects such as ants (Collett, Collett, and Wehner, 2001), butterflies (Shlizerman et al., 2016) and bees (Gould, 1986). If insects can perform these behaviours without performing something homomorphic to vector addition and other sophisticated mathematical operations, then mathematics will have to be profoundly modified (Gallistel and King, 2009).

An understanding of a computational-representational system is based on how information is represented in physical symbols and the operations on them that make them have relevant causal efficacy (Gallistel and King, 2009). This section explains some of the relevant concepts the brain has to adhere to.

3.3.1 Architecture

An “[a]rchitecture describes the internal organisation of a computer in an abstract way; that is, it defines the capabilities of the computer and its programming model”. It is possible to have “two computers that have been constructed in different ways with different technologies but with the same architecture" (Clements, 2006, p. 1).

Complex computational systems can be seen as consisting of components configured in a particular way. A reasonably capable architecture needs read/write memory (Gallistel and King, 2009). Starting from the simplest structure and adding complexity progressively.

3.3.1.1 One-Dimensional Look-Up Tables

It was pointed out by Sherrington (1906) that a machine needed three things to react when it was given a different input: receptors, effectors, and conductors.

- Receptors register the state of the world and converts it to signals.
- Conductors transport these signals to the appropriate effectors.
- Effectors receives the signal and converts it into action.

Sherrington (1906) summarised the idea as “[f]rom the point of view of its office as the integrator of the animal mechanism, the whole function of the nervous system can be summed up in one word, conduction” (Sherrington, 1906, p. 9). This would in computational terminology be equivalent to, that the nervous system is only a one-dimensional look-up table. Gallistel et al. (2009) means that while look-up tables are important in computation, it is not the only mechanism of the nervous system, because it would lack a memory of past events.

3.3.1.2 State Memory

Memory can be introduced by bringing in the capacity of the computing machinery to enter different stable states. The machinery can then respond differently to the same input given what state the memory is in. This memory has a very limited ability to remember long sequences since the resources needed grow exponentially. Furthermore, the response to all possible stimuli have to be explicitly saved in the memory, leading to exponential growth in the size of memory (Gallistel and King, 2009).

The brain is of finite size but the possible inputs and memories are practically infinite, they quickly become more than the estimated number of atoms in the observable universe 10^{80}. Hence it would cause what can be termed a combinatorial explosion. The nervous system must be designed to avoid this problem (Gallistel and King, 2009).

It can be mentioned that there is a need for logical operators that together can perform the basic operations in logical propositions, for example AND, OR and NOT. This enables the construction of n-dimensional look-up tables, many-one functions and arithmetic. Although there are more computationally optimal ways to construct many of these functions than by combinations of local gates, state memories would offer the theoretical possibility (Gallistel and King, 2009).

3.3.1.3 Register Memory

A read/write memory can record memories with a symbol. Hence only the actual memory needs to be recorded and the combinatorial explosion can be avoided. Such a memory needs a modifiable structure that can symbolise the relevant symbols and an ability to read and write such symbols to and from the structure (Gallistel and King, 2009).

The computational machinery and the memory structures as well as the programs that run on them and the specific ways programs are run is a complicated interplay. The optimisation of these features from a chosen point of view is demanding (Gallistel and King, 2009).

3.3.1.4 Realising Functions Physically

In order for functions in the brain to be biologically possible they have to be computable. Computable procedures can be implemented by an abstract purely mechanical device. A category of such devises are commonly referred to as Turing machines. A Turing machine is itself a procedure that realises a function that maps from symbols to symbols. For this, functions have to be expressed as algorithms (Gallistel and King, 2009).

An algorithm is an unambiguous and clear method that allows a person to robotically transform the input of a function to the output. This is achieved by breaking the function down into a step-by-step recipe with a list of distinct states. The state decides what to do at any given moment, based on the current situation, during which the method proceeds. An algorithm can thus be seen as a set of embedded functions with later steps depending on earlier outputs. In order to create such a machine, functions have to be expressed as procedures and be physically realised (Gallistel and King, 2009).

In order to realise the functions physically they have to be instantiated as a physical system that acts on incoming symbols and produces outgoing symbols. This constitutes an efficient procedure, or in abbreviated form, a procedure. The physical running of a procedure is called a computation (Gallistel and King, 2009).

There is no general method to decide the procedure given the function. But, the compositional usage of a small set of procedural primitives appears sufficient to perform any computation (Gallistel and King, 2009).

3.3.1.5 Computation

There is a symmetric disconnection between the formation of a function and the possibility to determine the output from a given input. In some instances, the mapping of inputs to outputs might be known but the function itself is not, this is typically the state science is in since it aims to find representational systems for natural systems. In other instances, the function is known but the mapping is either know to be impossible in theory, understood to be impossible in this universe, realised to be too resource expensive to be performed or it has not been determined whether it falls into one of these categories yet (Gallistel and King, 2009).

To find the procedures for a function, even if possible, might be hard and there exist well defined functions what have avoided attempts to find a procedure to compute them (Gallistel and King, 2009).

Well defined notions of computation have been produced, under which it has been proven that no procedures exist, these functions are termed uncomputable (Gallistel and King, 2009).

Some functions have procedures that mathematically could compute them, but the quantity of physical resources or time need renders the procedures impractical, these are termed intractable functions. The distinction between tractable and intractable is conventionally made based on if the resources needed has a polynomial growth to the number of bits required to encode the input compactly. This categorisation has not been achieved for a large set of important functions, referred to as NP-Complete. It is currently not known if procedures could be found for these functions which would move them into the tractable category (Gallistel and King, 2009).

3.3.1.6 Compact Procedures

Gallistel et el. (2009) creates two categories of procedures. One category is implemented using look-up tables and the other is implemented using only the necessary instructions. A look up table will in general contain substantially more information then will ever be utilised. The compact procedure on the other hand can practically extract hundreds of orders of more information than the size in number of bits required to specify the retrieving procedure itself.

Furthermore, the number of bits needed to specify look-up tables grows exponentially with the size of the usable domain and codomain, while the bits needed for the compact procedure is usually independent of the size of the usable domain and codomain (Gallistel and King, 2009).

Beyond the distinction, there are two further advantageous properties of the compact procedure in relation to look-up tables: the avoidance of a combinatorial explosion and extensive pre-specification. Combinatorial explosion results from the high number of calculations needed to find the entry in the look-up table. The problem with extensive pre-specification arises from the need to specify all entries in the look-up table (Gallistel and King, 2009).

The compact procedures efficiency is dependent upon the symbols it uses. If the number of nominal symbols is large then distinguishing between them becomes impractical. On the other hand, the distinction between encoding symbols can be done using procedures. If symbols encode their referents systematically then it is often possible to use efficient procedures. All useful functions need nominal symbols to operate on since nominal symbols lack a systematic composition (Gallistel and King, 2009).

All procedures need some state memory and some pre-determined structure that is not the result of experience. The need for pre-specification of some structure before any input is given reflects the need for an a priori representation of possible messages (Gallistel and King, 2009).

The procedure and the coding are interconnected. The usage of a code that represents the size of a quantity by the number of 1s has a simple procedure. But the encoding is made impractical since the usage of resources would be growing fast as the numbers increases. The encoding of the brain ought to be highly efficient since it seems to be able to represent distances and timescales ranging over several orders of magnitude (Gallistel and King, 2009).

3.3.1.7 The Turing Machine

An abstract mechanical device capable of computation is based on the ability to proceed through a step-by-step recipe that ends in the desired result, given a specific input. In order for an abstract mechanical device to be able to compute differently depending on previous input it needs the ability to shift between a finite number of stable states (finite in order to be physically realisable). This is a finite-state machine but it cannot make its state accessible to other computational states. In order to have this capacity a read/write memory can be added where symbols can be stored, read and written. An example of such a machine is the Turing machine. The Turing machine consist of three basic components (Turing, 1937):

- A long “tape” that constitute the symbolic memory and the input and output for each machine.
- Read/write head that reads and writes on the memory.

- Finite-state processor, that takes on one of a finite list of predetermined states based on previous steps specified in a transition table.

Furthermore, the atomic symbolic data is specified for each machine. It is enough with just two atomic data but more can be added (Turing, 1937).

The tape is the symbolic memory and the input and output of the procedure. The tape is linear and organised into discrete cells each containing exactly one of the possible symbols. The tape can mathematically be infinitely long (Turing, 1937).

The read/write head can read or write symbols (also over write) and stand still or move up or down the tape. The combination of these capacities makes it possible for the head to potentially read from and write on every cell on the tape (Turing, 1937).

The processor determines what direction the head moves in (or stands still) and if it reads or writes (and what it writes). The processor has a finite number of predetermined states that it moves between as a consequence of previous input to the head and what the stated responses in those states are. At each state the heads perform an action (including standing still) and based on the input and the state a next action is chosen by the processor (Turing, 1937).

The machine starts in a specified state, termed the start state, and ends in a specific state, denoted the halt state (Turing, 1937).

As the machine computes, there are three possible actions at each step. It can write (a specified symbol), move a specified direction (including standing still) and transition to another state (Turing, 1937):

- Writing with the head any or none of the specified symbols on the tape.
- Moving, after the writing is complete it can move or remain standing.
- Transitioning, once it has moved, the processor changes state (or remains in the same state).

3.3.1.8 Universal Turing Machines

By symbolising transition rules for the processor on the tape, it is possible to store the transition table on the tape. When this is done it is possible to construct a universal Turing machine, a machine that can simulate any other Turing machine. The possible actions of this machine are specified with strings of “0” and “1” on the tape (Gallistel and King, 2009).

This means that a program can treat another program as data and the conditions for modification of the original program can be specified. If a set of instructions can create any Turing machine then it is Turing complete. A machine containing this meta program structures are termed von Neumann machine and its principles are used for the reading of the genetic code in cells (Gallistel and King, 2009).

Modern computers are modified realisations of the von Neumann machine. In order to increase the efficiency of computers (with sufficiently known usage) about 100 common elementary operations have been built in to save time, space and energy (Gallistel and King, 2009).

So far no computable procedure have been found that a Turing machine cannot compute. There does not exist any rigorous definition of computable and the machine is therefore the modern understating of computation (Gallistel and King, 2009). The thesis that the Turing machine can compute all computable functions is termed the Church-Turing thesis (Stephen, 1967).

There do exist problems which do not need a symbolic memory and could be solved with a finite state mechanism. But animals in nature routinely solve problems that require Turing machines in order to be solved by a finite and physically possible machine. It might be the case that brain can perform computations that Universal Turing machines cannot but if so then this remains to be discovered (Gallistel and King, 2009).

The Turing machine needs a read/write memory. Hence the problem of transporting symbols to the computational machinery (read), storing symbols in memory (write) and locating symbols in memory (address) has to be confronted (Gallistel and King, 2009).

3.3.2 Memory

Data structures are complex symbols and consist of symbols encoded in their topological relationships in memory structures. As an example of a minimal data structure can be mentioned a binary number. In order for an architecture to provide unrestricted access to a memory there needs to be a read/write memory that can be located, read from and written to. This means that it is capable of symbolising the locations of memory (addresses) with encoding symbols by having a representation of the memory locations. This enables the construction of relationships between memories and the creation of more complex and new symbols (Gallistel and King, 2009).

Data structures within computers typically consists of 32 or 64 bits, forming a "word". When the computational machinery needs a word it is transported on a bus from the memory. While this might be inefficient it only needs to be addressed once in order for a message that can be one of 2^{64} possible messages to be read. In practice, this leads to significantly improved computational performance. Once delivered to the computational machinery, the individual bits are free to be manipulated in order to perform the relevant operations such as arithmetic (Gallistel and King, 2009).

The bus consists of two fields. One part transports the address and the other the value it refers to. The address code, termed the “signal”, is placed on the bus, and finds the data. The data is transported on the bus and only the data is accessible to computations in the computational machinery (Gallistel and King, 2009).

The efficient usage of symbols for memory requires the ability of the computational machinery to find the memory. This makes the memory addressable. The address of a memory specifies the location of the symbol in memory. The extent of temporal and spatial variation of the referent of the symbol places constraints on the design of memory capable of representing it accurately.

Some referents are static, such as the value for π. These can be built directly into the computational machinery. This kind of memory is termed a “literal” by computer scientists. Literals cannot be directly accessible outside of the computational machinery. As an example, the memory in the transition table of a finite-state processor in a Turing machine.

3.3.2.1 Variables

When the value of a referent is dependent on information in an information theoretic sense then its value varies. There is a practical infinity of such possible referents, for example the position of the sun in the sky. The memory contains the address referring to the location of the value, and the address is termed a “variable” by computer scientists (Gallistel and King, 2009).

The problem of constructing a device capable of handling variables is called, variable binding. Two problems arise (Gallistel and King, 2009):

- How is the value associated with a variable stored in order to facilitate transport to and usage of the computational machinery?
- How is the value associated with a variable updated?

This is solved with the usage of an addressable read/write memory. The variable decouples the past from present and decouples the information extraction process from the process of using the information. It makes it possible to share a value between different computational processes, the value of the memory can be changed while leaving the structure intact and the value only needs to change once for the whole representing system (Gallistel and King, 2009).

Different computational processes can therefore communicate and use the results of their different computations and the architecture needs not to be rewritten in the process of operating the system. This makes learning independent of modifications in the architecture. This machine can learn by updating the values (Gallistel and King, 2009).

This memory allows random accessing and can therefor access any memory in any order. This makes it a more suitable form of memory than a Turing machine that requires sequential access of the tape. The capacity of random access memory could plausibly be so powerful that there is theoretically no need for the brain to forget, potentially reducing the problem with deleting memory (Gallistel and King, 2009).

Since the existence of some variables are contingent on brain external factors, there is a need for a system capable of using indirect addressing. For example, the existence of a compass direction for a flower from a bee hive is dependent on the existence of a set of external circumstances. A system dealing with this need to be able to create new variables (Gallistel and King, 2009).

Contingent variables can be categorised for for example the location of a food source. These can be stored in an array. An array is a structure with a repeating substructure. Arrays can be addressed by using indirect addressing. The addressing consists of the array variable that specifies the first address in a sequence of addresses and a second command that specifies the number of the specific memory in the array (Gallistel and King, 2009).

At the first address, there is an array internal number stored, the pointer. The pointer and the number of the specific memory in the array can be added by the indirect addressing command and the symbol at the specific location in the array can be retrieved. This symbol can in turn be a variable containing the address to the desired data (Gallistel and King, 2009).

Arrays allows for the memory to only contain the space needed to store the actually stored data. Otherwise the brain would have to come equipped with all possible locations for all possible data. With arrays only the address of the array needs to be pre-stored. Arrays allow for the systematic creation of complex hierarchical data structures such as “person”, containing “eye colour” and "hair colour” (Gallistel and King, 2009).

Since addresses mathematically are strictly ordered set, the next data point can be found even if the physical location of the memory need not be sequential. An example of an animal with apparently extreme usage of arrays is a bird that remembers tens of thousands of instances of stored food (Gallistel and King, 2009).

There is an interdependence between computation and memory. In order to function and to function efficiently there is a need for them to work together. The complexity can grow fast and the design of algorithms and suitable data structures can be demanding (Gallistel and King, 2009).

3.3.3 Language

Using the ideas about genetic language by Patel (2008) as an analogue for the computational language it can be said that brains use knowledge. And that knowledge equals information plus interpretation.

Language is needed to communicate knowledge, and it uses a set of building blocks with fixed meaning that can be arranged in various ways that can be interpreted using rules. A useful language takes into account criteria for efficiency. This means that it has to find an optimal position between the often conflicting principles of minimising error and reduce the usage of resources such as space, time and energy (Patel, 2008).

The questions then, according to Patel (2008), are if there is an optimal language given the constraints? And if so, how can it be found? If the brain is a representational system it must contain unconscious symbols and rules for manipulating them with syntax and semantics (Fodor, 1975).

3.3.3.1 Representations

There is a communication between the world and the brain. It is a mapping between the states of the world and representations of those states. Inside the brain the computational operations map their respective inputs to their outputs. The world and the brain together with the functions between them constitute a representation if (Gallistel and King, 2009):

- Changes in the world can cause changes in the represented system.
- The functions are structure preserving, meaning that possible mappings in the mind are mirroring possible mappings in the world. Mental symbols have to choose suitable referents in the world and operations on the symbols have to map to suitable non-symbolic relations.
- The mappings inside the mind sometimes create effective behaviour.

The mappings inside the brain would have to be functions (Gallistel and King, 2009). A function is a relation that deterministically maps elements from one domain to another (the codomain) (Halmos, 2017). Having a function with multiple outputs will not increase the expressive power. And by combing functions they all only need two inputs each in order to be able to perform all calculations together (Gallistel and King, 2009). According to Gallistel et al. (2009) there are some basic questions about functions and the brain that arises:

- Is there a small set of elementary functions in the brain's computational machinery, from which the large set of complex functions that brains implement are realised by composition?
    - If such a small set exists, what is it?
- At what level is it structurally implemented?

  - By systems-level structures (neural circuits)?
  - By cellular-level structures, such as synapses?
  - By molecular structures, such as microRNAs?
- In what way is the composition of the functions achieved?
  - What is the mechanism for memory which facilitates the composition over indefinite intervals of time? This is essential given the indefinite amount of time between the production of output in one function and the usage of that data as input in another.

3.3.3.2 Symbols

The assumption that there are symbols in the mind has substantial representation within the mainline cognitive science, see for example (Chomsky, 1975) and (Fodor, 1975). There are two kinds of symbols, nominal and encoding. Encoding symbols are constructed according to some rules that relate it to what it refers to while nominal symbols are just stipulated (Gallistel and King, 2009).

The input symbols to a function must be distinguished by their syntax, meaning their form and spatial and temporal context. This has to be done independently of the referents which the symbols only refer to. Symbols differ from their referents in that they are constituted of the same components, meaning that they are easier to use as elements in computations than the referents themselves. In the brain, this can be exemplified by spike train which can convey information from all senses and between all parts of the brain (Gallistel and King, 2009).

In this context, symbols can be defined as physical entities realised in a physically realised representational system. The systems effectiveness is strongly dependent on what symbols it is based on and their properties. Symbols that might result in efficient representational systems have to qualify according to the following criteria: distinguishable, constructable, compact and efficacious (Gallistel and King, 2009).

The need to be able to distinguish one symbol from another arises from the needed to treat differently symbols differently in the information processing. The memory of a conventional computer distinguishes symbols primarily based on their location rather than their form. This is recognised in neuroscience and the principle is termed place coding (Gallistel and King, 2009).

Symbols will have to be able to be constructed. This is based on the contradiction that the brain is finite, and can only contain a finite number of symbols, but that there is a practical infinitude of possible worlds that needs to be represented in the mind. This contradiction is possible to resolve if symbols can be generated (Gallistel and King, 2009).

The limited size of the brain compared to the aspects of the world that it represents requires that symbols are compact. If for example a symbol grew linearly in size with the quantity it represented, then a whole human brain might be needed to store a single large number in memory, and numbers like 10^{80} (the estimated number of particles in the visible universe) would be too large for humans to be able to think about. Compact symbols on the other hand could be constructed to grown logarithmically with the represented number (Gallistel and King, 2009).

Spike trains could be encoded using rate code, which would grow linearly with the symbolised quantity. Another form of coding is time coding, which would be able to distinguish between to forms of distance between spikes, this would create a digital signal. A reasonable amount of spikes per axon per second might be 50, if the programming is linear then this can transport 50 distinct messages, but the digital structure could transport $2^{50} = 10^{15}$ messages per second (Gallistel and King, 2009).

Symbols need to be physically efficacious within the computational mechanism. This means that the output needs to be determined by the input (Gallistel and King, 2009).

The irreducible physical forms that the symbols are constituted of are atomic data. They can be information bearing symbols alone or collectively. In order to do this they need a referent and to be constrained to a specific computational role. Common atomic data is the bit values of computers, the 4 nucleotides in DNA, the Indo-Arabic numeral system or the letters of the alphabet (Gallistel and King, 2009).

A sequence of atomic data is a sequence of one or more atomic elements. These can also be ordered in more complex non-linear structures with more complex topology. To order the atomic elements allows for more compact symbols. There seems unavoidable that there is a mechanism that constructs the symbols from atomic elements. In general, the fewer atomic symbols the better since the simpler the computational mechanism can be (Gallistel and King, 2009).

3.3.3.3 Programs in the Brain

Given that programs can be imagined in the brain, the question arises of what they ought to look like. A very simple program from the perspective of the computational-representational perspective has been described by Gallistel et al. (2009). Messages originating from two different neurons can be distinguished, they can be termed a and b. Different characteristics of the flow of previous combinations of a and b can be coded for. These codes can for example symbolise if an even number of a's have been used or if the sub sequence aab have been used.

This categorisation can be the basis for actions. If certain categories are activated then this will lead to a specific behaviour. The structure will be built of functional components defined by their input-output characteristics. These have to be able to be realised physically. Turing machines are not hard to construct physically.

These components have to be combined in such a way as to make it possible for two symbols that are needed at one place to be available a that place (Gallistel and King, 2009).

3.3.4 Programs

Approaching the human brain from a software-hardware perspective raises the question of what can be said about these programs in general. One proposed principles for the brain is that just as for other biological systems it is highly domain-specific (Chomsky, 1975)) and (Gallistel, 2000).

An indication of the domain-specific nature of the programs of the brain would be to compare the capacity of the brain of humans and chimpanzees. While the human brain is generally supposed to be more capable than that of a chimpanzee, an investigation of specific capacities can show that this is not always the case. For example chimpanzees are remarkably more capable at remembering random strings of numbers than grown up and mathematically educated humans (Inoue and Matsuzawa, 2007).

As a further indication can can be mentioned the various discovered mental abilities of insects for orientation which surpass that of humans (Gallistel and King, 2009). This indicate that the brain is a highly heterogeneous system with several programs and subprograms working together.

This introduces the question, which "programs" do the human brain have? Several such programs have been investigated, for example in vision, motion and language.

For vision there is for example Ullman's "structure from motion" theorem which describes which innate restrictions are needed in order to infer the 3-d shape of an object from its motion on a 2-d surface. The innate restrictions constrain the possible interpretations from infinity to 2 (Ullman, 1979).

Concerning bodily motion there has been significant investigations concerning what is termed Fitt's law. The law states that the time to perform a bodily movement depends on the amount information, in an information theoretic sense, that needs to be transmitted from the brain to the muscles (Fitts, 1954).

In regards to language there has been an attempt to reduce the essential features of human language to the mathematical operation of set formation (Chomsky and Collins, 2001). This has been the attempt of a part of modern linguistics.

3.3.4.1 Linguistics

To a first approximation the overall human language system can be seen to consist of three parts. A conceptual-intentional system, an externalisation-perception system and a system that translates between the two parts.

The conceptual-intentional system creates hierarchical mental structures that are sent to the translations system. The externalisation system appear to only be able to receive linear instructions, so the translation system converts the hierarchical structure to a linear structure of words. This linearization process can be seen as a mathematical operation with many possible solutions, hence making different languages possible and at least one arbitrary language necessary (Chomsky and Collins, 2001).

The central subprogram of the overall human language is the translation system. The creation of the sentences of human language can be understood as the subprogram that takes a word-like object (according to instructions in the form of the mental creations of the conceptual-intentional system) and its own previous output and creates an unordered set containing both.

Table 3.3: Tasks in the language system and the number of possible outputs (Friederici, 2017).

Task	Number of possible outputs
Identify syllables	circa 100
Identify possible word	-
Identify word category	circa 10
Identify actual word	circa 5000 per word category?
Collect word information	-
Construct small phrases	>4
Send information to semantic processing	-
Send information to syntax processing	-
Semantic processing	-
Syntax processing	infinite
Send information further	-

This process is then repeated until a hierarchical sentence is created. In order to send the created hierarchical sentence to the muscular apparatus a process of lineraization according to language specific rules takes place. In the case of the perception of a sentence the process takes place in the opposite direction (Chomsky and Collins, 2001).

When a sentence is uttered by one person and received by another then several brain regions seem to be involved in a stereotypical and rapid process in order to comprehend the sentence. This can be observed using fMRI scanning. The scans of subjects hearing a sentence show that the areas concerned progress from "simpler tasks" such as hearing and identifying words, to reconstructing the structure and content (Friederici, 2017).

The whole stereotypical process is fast and is done well within one second. There are several steps, mostly ordered sequentially. As an indication of the time needed, to investigate whether the syntactical structure is correct is done within 200 milliseconds and in the following 200 milliseconds the meaning of the words are investigated. Just identifying the word category requires about 120 - 150 milliseconds (Friederici, 2017).

Several of the minor identified tasks performed consists of categorising the input, and they therefor have a maximal number of possible outputs. A temporally ordered list (when a sentence is received) of the tasks performed and the number of possible outputs (if applicable) are displayed in table 3.3.

4

Analysis

The analysis attempts to arrive at answers to the the aim introduced in the introduction. The questions revolve around how information could be processed in the brain. The primary method used is to combine various parts of the literature resulting in various forms of equations. These equations then lead to sets of values which in turn are related to each other and other values from the literature. From this tentative conclusions are reached.

The analysis as a whole is divided into two areas. One is to investigate the combined structure of multiple neurons and the other is to investigate the internal structure of a single neuron. The combined structure of multiple neurons explains how neurons could relate to each other. The internal structure shows the hypothetical internal workings of the neuron.

The analysis of the external structure arrives at the possibility of organising neurons in small groups. These small groups are preferred to be small from an information processing perspective, but can be larger from an algorithmic task solving perspective.

The internal structure of the neurons arrives at the possibility of having two systems. One "regular" system for direct appropriate responses to the environment and one "meta" system for updating the regular system, in order to make it respond more appropriately to the environment. The meta system can be seen as a system for learning.

The MATLAB code used in the analysis is displayed in appendix A.

4.1 The Combined Structure of Many Neurons

Neurons are connected in the brain, and this section addresses how neurons can be connected and why. The connection between neurons is assumed to be central for the functioning of the brain.

4.1.1 How Could Neurons be Connected to Each Other?

There could be many ways that neurons are connected to each other. There are reasons indicating that a common way to organise neurons is in small groups. These reasons are the way other biological structures are organised (see section 3.1.1), the occurrences of such small groups for the categorisation of spatial questions (see section 3.1.4), the appearance of categorisation and other simple tasks in central aspects of the workings of language (see section 3.3.4) and finally from the computational needs of any sophisticated biological computational system (see section 3.3).

4.1.1.1 Larger Structures

There is an often-occurring circumstance in biology of having the tasks performed by a system being divided up by the systems components which solve a subset of the task when seen as a part of the whole system (see section 3.1.1). Expressed in another way, a modular system organised in a form of hierarchy.

The neurons in the cerebral cortex have been categorised in a hierarchy of layers (see section 3.1.3) with the task of smaller areas being a more specialised "subtask" of the task of the larger area that they are part of. In principle this pattern could continue further with smaller and smaller areas.

4.1.1.2 For Identifying Space

Tiny groups of neurons have been found in the brain of mice for the animal’s orientation in space (see section 3.1.4). A system of a few neurons categorises position in space according to a specific space and geometry. In general, cells organised in groups that classify information according to a schema could account for some aspects of the brains functioning.

It could be done by specific groups of cells. In the simplest form, and for a categorising system, the group could consist of the same number of neurons as the number of possible outputs. Parallel groups with similar categorisation could exist to increase reliability while also categorising from a slightly different perspective hence increasing the power of the information available at the next level.

4.1.1.3 For Comprehending Language

The overall language system in the brain have several "subtasks" based on categorisations (see section 3.3.4), these could be done by specific groups of cells. Other "subtasks" than categorisation are the collection of information, sending information and set formation.

This could be an indication that there are groups that categorise, others that perform more administrative computation tasks such as collecting or sending information and furthermore groups that do basic computations such as the basic operations of set theory. This is not too unrelated to the instruction set architecture of a computer (see section 3.3). This would mean that this set of tasks is at least partially organised at this level, groups of cells, in the brains computer architecture.

The reason for there being such a large number of neurons in the various areas, on the order of 0.1 - 1 % of the total neurons of the cerebral cortex, when only a small group is needed for the central task that the whole area performs, could partially be that a lot of input from other systems might be needed in order for the central categorisation, administration or computation to be done optimally.

The difficult part might not be the specific task in itself, but to do it in a way that maximises the biological utility. The surrounding area would then consist of groups that feed the central group(s) with relevant data in order to make it function more appropriately. An overview over some of the possible sizes of the central groups based on the number of possible outputs is given in table 4.1.

Table 4.1: Tasks and kind of tasks in the language system and the number of possible outputs.

Task	Type of task	Number of possible outputs
Identify syllables	categorisation	circa 100
Identify possible word	simple rule	-
Identify word category	categorisation	circa 10
Identify actual word	categorisation	circa 5000 per word category?
Collect word information	collection	-
Construct small phrases	categorisation	>4
Send information to semantic processing	sending	-
Send information to syntax processing	sending	-
Semantic processing	-	-
Syntax processing	set formation	infinite
Send information further	sending	-

4.1.1.4 Computationally Needed

From a computational perspective there is a fundamental need to categorise information (see section 3.3). And any system with a sufficient storage of accessible information needs to do administrative tasks to direct the information to the place where it is needed. Furthermore, in order for a system to use the potential of its components, it needs to be able to perform basic computational operations on its components in order to combine them into new and appropriate combinations. These are problems that could be solved in an infinity of possible ways, but it might be so central that it is optimal to solve the problem head on with groups that perform the task.

Focusing on categorisation, categorisation is a way to increase the power of the information. Raw data is in itself useless, in itself it says nothing about the world. For example, the blur of colours of varying intensity that hits the human retina, it in itself says close to nothing about the world (but it might be noticed that the eye organises the data in several ways simply by using the “laws of optics”).

The brain ought to organise data even more than the eye does. Categorised data where the categories are related to each other in a representational system has the possibility of being extremely powerful. Finding the relations between the categories makes the data useful. This is why learning and understanding matters, if data was sufficient, then no discoveries would be made, or alternatively, everything would be a discovery.

The step from the data such as sight, to grammar, concepts or emotions, as in reading, is massive and there is nothing about the data of a written page that says that it could be used in such a way. Furthermore, the smallness of the amount of data that is needed in order to create huge consequences also speaks of the power of a system. For example, the grade in a university course can be written with one letter but a rich system will be able to draw major conclusions from this.

The power of a computational system could partially be seen as the ability to go from one point to the seemingly most unrelated point using the least amount of information in a biologically relevant way, as in the examples above. Connected groups of neurons that categorise information might be an efficient way to do this. For a biological system this needs to be done in a biologically relevant way.

4.1.1.5 Tentative Conclusion About Groups

The assumption that groups are a significant aspect of how the brain is organised can be motivated from several directions. And this way of organising the brain can provide several suggestions about the workings of the brain.

Groups can be used to categorise information according to an internal "space". This space can be more or less abstract and sophisticated. Sensory nerves can serve as one less abstract clue to the structure of such spaces and their evolutionary origins. Sensory cells are placed in the body in a structure which means that the computational space for categorising information is "outsourced" to the external structure of the body. The degree of sophistication of the internal space can be quite substantial for example in the case of the eye.

The organising of neurons in groups lends itself to an explanation of the evolutionary and embryonic development of the brain. In principle the brain can start with one group performing one task. This group can then expand and split into parallel and sequential groups. A possibility would therefore be that for example hearing would start with one small group identifying loud sounds, which the organism could use as a clue to move from the current position. This group could split into a sequential group that can rudimentary categorise these sounds as dangerous or not, increasing the potential for identifying which sounds actually are dangerous, hence increasing the evolutionary chance of survival. A potential way to test part of this would be to genetically mark one dividing nerve cell in a developing organism and identify the pattern that the succeeding neurons form.

Assuming that groups have a role as one of possibly many fundamental ways of organising neurons, what ought then be their characteristics? What are their size and their relations to information, computation etcetera? More concretely:

- What is the relation between groups and firing?
- What is the relation between group size and information?
- What is the relation between groups and computations?

4.1.2 What is the Relation Between Groups and Firing?

There are on average around 12 billion neurons in the cerebral cortex. They have been divided into 52 Brodmann areas in the cerebral cortex in each cerebral hemisphere, resulting in 104 areas in total. The share of neurons in each area can hence be approximated as roughly 1 % of the total, resulting in $120 \cdot 10^6$ neurons per area (see section 3.1.3).

Assuming that a neuron can either fire a signal or not and that the firing of one neuron only activates the previously "unfired" but connected neurons, a cascade of firing will occur. If these firings are done at synchronised moments in time then then the cumulative number of firing neurons will increase in discrete steps.

Assuming in there separate cases that each neuron is connected to 10 000, 20 000 or 100 000 neurons respectively, that have not yet fired, then the cascade will accelerate rapidly, see figure 4.1. As can be seen, the cascade would soon activate the whole human brain. If the neurons have random connections instead of only connections to neurons that have not fired then the development on this scale would have been similar.

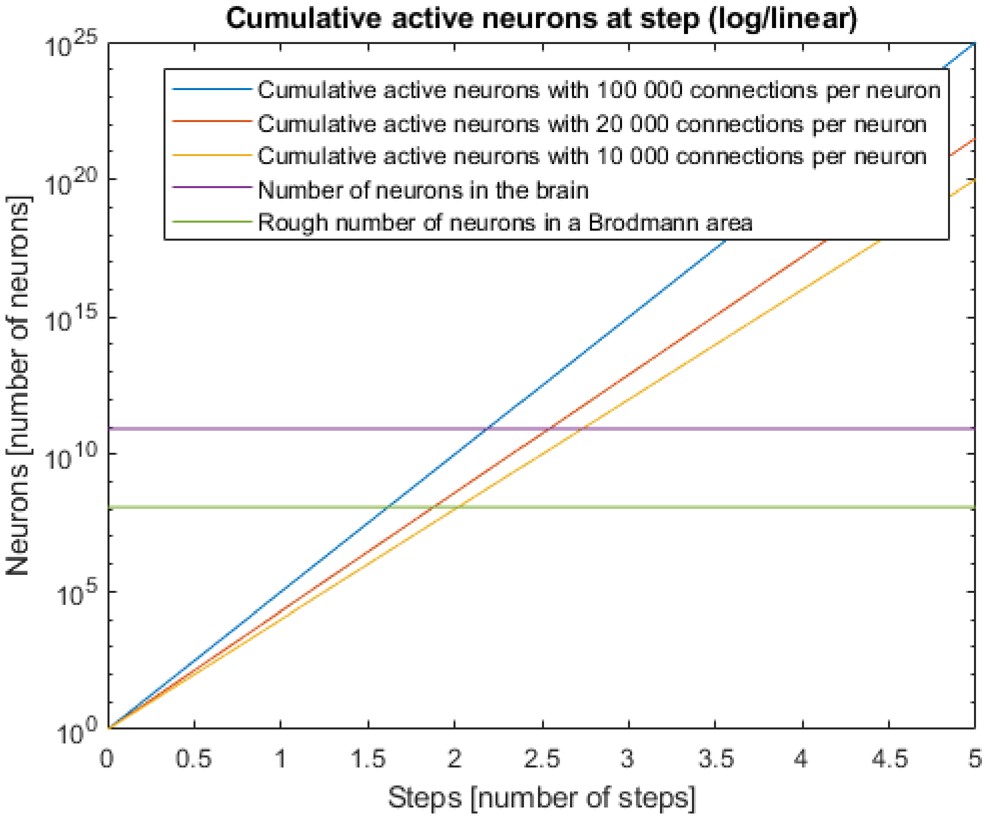

Figure 4.1: The cumulative number of neurons that have fired at a step for different number of connections per neuron (blue (100 000), red (20 000) and yellow (10 000)) compared with the number of neurons in the brain (purple) and the rough number of neurons in one Brodmann area (green), (see section A.1).

The relationship can be summarised in equation 4.1 where C is connections per neuron, N is Number of steps of firings and F_c is cumulative number of neurons that have fired.

$$C^N = F_c \tag{4.1}$$

The number of firings needed to fill the brain is increased as a consequence of introducing groups that categorise. Mainly this is because most of the connected neurons do not fire and the effective number of connections per neuron is divided by the size of the group. The total number of potentially activated neurons in the brain is also divided by the number in each group. But since the growth is still exponential the smaller growth per step is the dominant factor, see figure 4.2.

Equation 4.2 summarises the relationship at each group size with C as connections per neuron, G is the size of groups, N_b is the number of neurons in the brain and S is the number of steps.

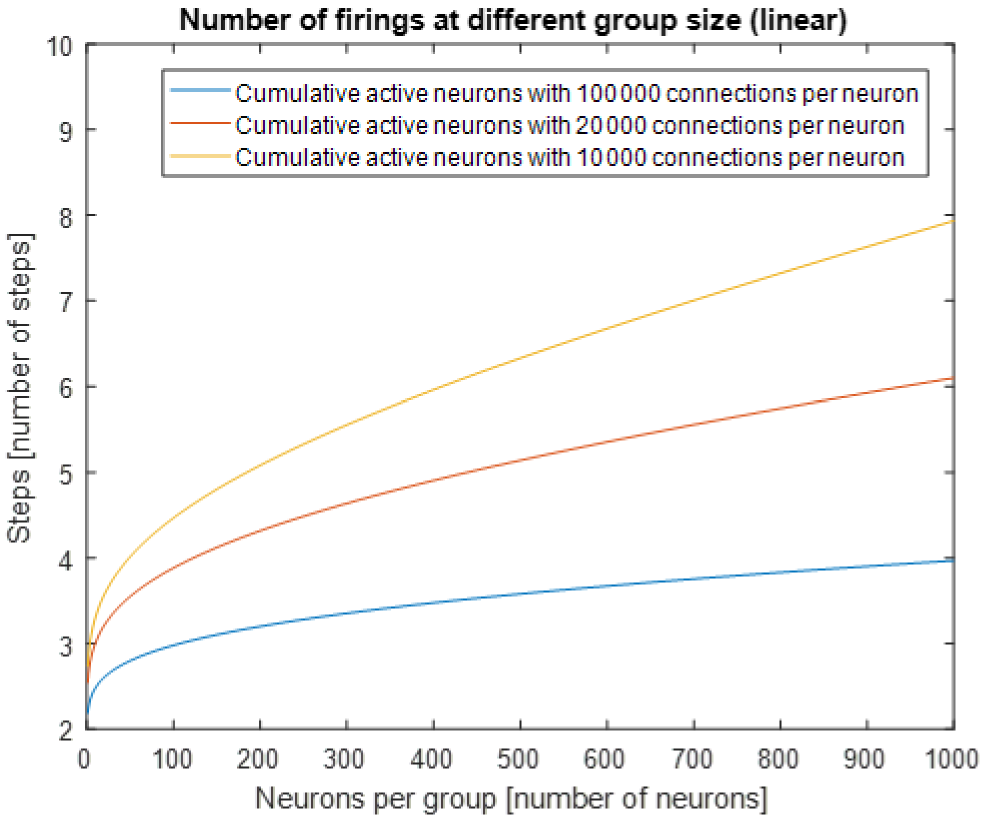

Figure 4.2: The number of steps needed to fire all groups once in the brain increases as the size of the groups increases. This is due to the number of connections that will result in the propagation of the firing is divided by the size of the groups. The exponential growth is thereby reduced. But since the growth is still exponential there is not much effect from dividing of the number of total neurons by the size of the groups (see section A.2).

$$\left(\frac{C}{G}\right)^{S} = \frac{N_b}{G} \tag{4.2}$$

It follows that a mechanism or structure is needed to prevent the whole brain from being constantly active. This can either be done by having groups that does not fire despite being activated, having groups structured in a non-random way or both. If the first solution is applied and the goal is to keep the number of firings constant, then on average one group can only make one other group fire. This would result in the share of groups that always fire ($\mathrm{F_{saf}}$) can be described as equation 4.3.

$$\frac{G}{C} \geq F_{saf} \tag{4.3}$$

Given that this set contains several different kinds of groups, including groups that categorise, administer and compute, then the respective share of them would have to be even smaller. In the second solution then the structure of the groups can be such that the problem is avoided. In general, the massive parallelism of neurons could need to be compensated by a substantial linearity in the connections between the neurons in the brain. Such a structure could for example be series of parallel groups that as a whole perform tasks linearly with only limited connections outside the linear flow. Such a structure would then be limited to only having a few groups in parallel according to equation 4.4, where P is the number of parallel groups, if all connections are internal to the structure.

$$\frac{C}{G} = P \tag{4.4}$$

Any firing outside of the parallel structure would increase the share of firing in the brain, but if every external group that is made to fire is compensated by one of the parallel groups that does not fire then the balance is kept. But since this is repeated at the coming steps of the linear structure then this repetition needs to be limited to the number of parallel structures at each step of the linear structure, as displayed in equation 5.3 where $\mathrm{F_o}$ is the number of firings to groups outside the linear structure.

$$F_o = P \tag{4.5}$$

This is in accordance with the observations for the sequence of larger brain areas that process understanding of language. There appear to be a linear sequence of parallel Brodmann areas that do this task (see section 3.3.4.1).

Since the structure can be more complicated than repeating layers of groups there can be significant deviations from the stated equations. And local deviation might be desirable but needs to be compensated by the opposite deviation in order to balance the average. But such deviations have to be organised (even more than a repeating structure of parallel groups have to be). For this there is a need for mechanisms, and such mechanisms need instructions. If such instructions are biologically or evolutionarily costly in relation to their utility then simple structures would be expected to be prominent.

4.1.3 What is the Relation Between Group Size and Information?

In a linear structure of parallel firing groups there are information theoretic relationships between the size of the groups and various information theoretic variables (see section 3.2.1). The relationships are displayed in figure 4.3 and the calculations are based on 20 000 neurons in each layer organised in identically sized groups all firing to the next level.

As group size increases from 1 there is a rapid increase in all variables. The information gain is largest for groups of size 3 (blue) and the prior uncertainty is largest for groups of size 2 (red). If the model included stochastic effects then the mutual information would be maximised with smaller groups since more neurons per group would increase the probability of error. From an information theoretic standpoint, one would expect the size of groups to be 3 or smaller. Deviations indicate that other variables are more important.

Several of the possible category groups for language could be close to the information theoretically optimal range (see section 4.1.1.3). There are groups for language that seems to be larger, some much larger. The groups for space are larger. This could reflect the needs of the classification task at hand, there is mathematically no way to solve the task with fewer cells, a smaller group would not be able to perform the necessary classification. Hence the this would indicate that the size required to perform the task always takes precedence over the information theoretic needs.

If that is the case then the brain would be optimised to perform certain tasks and only secondarily to do them in an optimal way. But there would be a pressure to find the algorithms that approximates a combination of the principles by finding ways to organise groups that are as close to the information theoretically optimal size as possible. Since this size is small anyway, this effect might be confounded with other optimisation criteria.

In a linear structure of parallel groups whiteout interactions with the surrounding groups outside of the structure, the improvement from an information theoretic standpoint would increase linearly with the length of the structure. This might indicate the that these kinds of pure structures are not optimal from an information theoretic point of view.

4.1.4 What is the Relation Between Groups and Computations?

Given certain assumptions it is possible to estimate the maximal number of calculations needed perform a task. Given that the task of identifying word category requires 120 – 150 milliseconds and assuming that the neurons fire in the 30 – 80 Hz region (see section 3.1.4). Then each individual group would perform a maximum of between 3.6 and 12 firings per second.

Furthermore, assume that one permille of the neurons of the cerebral cortex are involved then the maximal total amount of firing can be estimated using equation 4.6 where $\mathrm{T_r}$ is time required by region, F is frequency, $\mathrm{N_r}$ is number of neurons in region and $\mathrm{F_r}$ is firings in region. The estimates from equation 4.6 are displayed in figure 4.4.

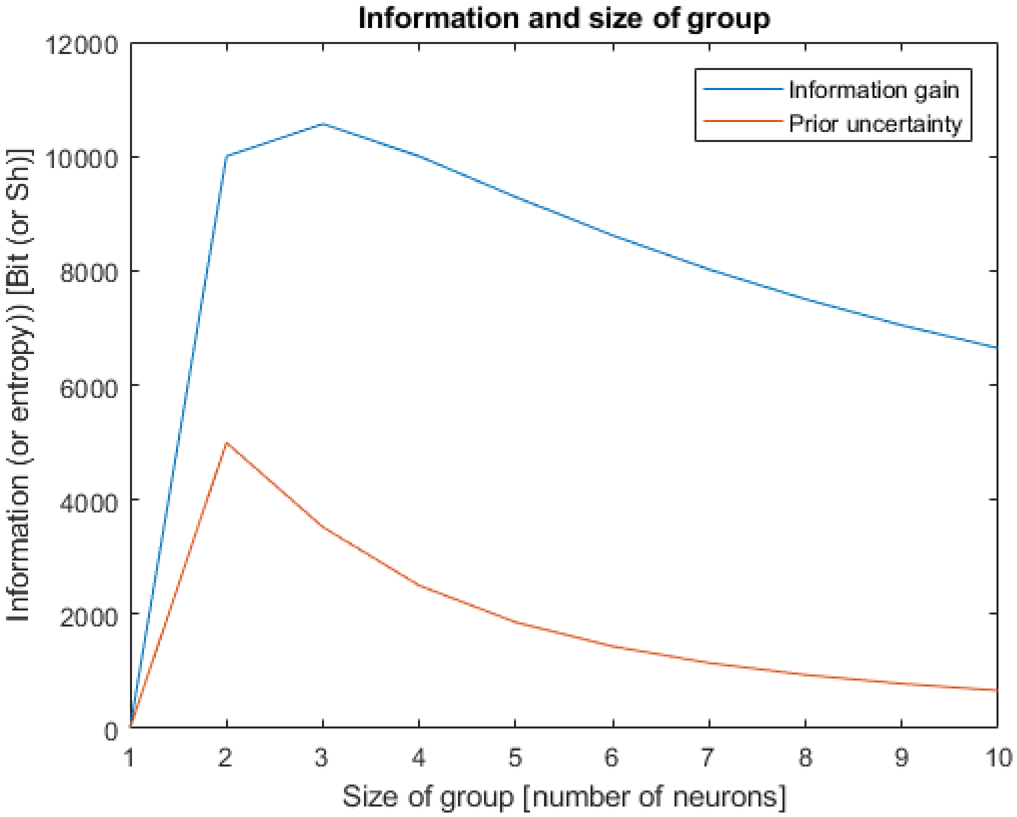

Figure 4.3: The change in information for each step in a parallel structure of firing groups. The information gain is largest for groups of size 3 (blue) and the prior uncertainty is largest for groups of size 2 (blue). The calculations are based on 20 000 neurons in each layer organised in identically sized groups all firing to the next level (see section A.3).

$$\frac{T_r F N_r}{G} = F_r \tag{4.6}$$

Assuming that the firing of a neuron is energy demanding and that energy is to be conserved, then the largest possible group is optimal. But since the increase in energy efficiency decreases significantly when the groups are larger than about 3 then other constraints might be interesting. Such other constraints might be the energy need to produce and maintain the cell or the waste of not using a neuron sufficiently. A guesstimate of the optimal group size given these constrains would be around 4 – 5 neurons. This is lower than many of the possible observed values, indicating that other principles would be of larger importance.

An interesting question is to investigate possible "simple" geometries of parallel and sequential groups that would be expected to exist in the brain, guided by the equations and conclusions in this section.

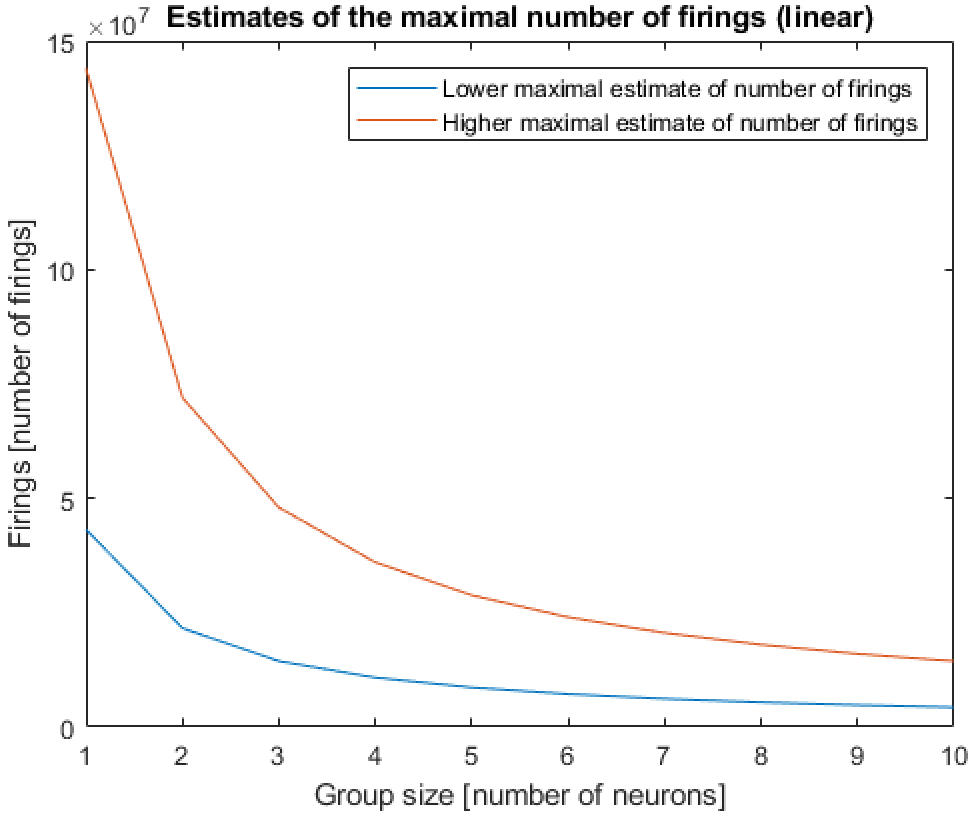

Figure 4.4: The maximal estimates of the number of firings required in one area for performing the task of identifying word category. Given that neurons operate at a frequency of 30 - 80 Hz and requires 120 – 150 milliseconds and the region involved constitutes one permille of the cerebral cortex (see section A.4).

4.2 Information Processing in Individual Cells

Inside the cells there is a need for a suitable structure that can create the desired output for the group. The demands on the cell and possible ways to satisfy them are presented in this section.

4.2.1 What are the Time Constrains for Information Processing in a Neuron?

Assuming that the neurons operate in the 30 - 80 Hz frequency (see section 3.1.4) then this means that a cell will have to decide whether to fire or not in about 0.0125 - 0.0333 seconds. This time also includes the time needed for the signal to travel between the cells.

Given an average surface area of the cerebral cortex is around 2 300 cm^2 (see section 3.1.3). Each Brodmann area would then average 23 cm^2, corresponding to a rectangle with sides of about 4.8 cm. For a region guesstimated to represent one tenth of a Brodmann area the corresponding numbers would be 2.3 cm^2 and 1.5 cm. Given that between 3.6 to 12 firings were performed and assuming the signal has to travel 1.5 cm then each firing has to travel around 0.125 to 0.4 cm in about 10 – 42 milliseconds. Myelination varies from 0.5 to 100 m/s, resulting in time intervals required for travel of 2.5 to 8 for the slow speeds and 0.012 5 to 0.04 milliseconds for the faster speeds.

If a calculation is done in the neuron then this would have to be done within between 7.5 to 42 milliseconds (assuming a travel time of 2.5 or 0.0125 milliseconds respectively and a total time of 10 – 42 milliseconds). The maximal firing rate of a neuron has been estimated to once every 2.2 milliseconds meaning that the firing itself would require about 2.2 milliseconds. This leaves about 5.3 to 39.8 milliseconds for computations inside the neuron.

A neuron has around 20 000 connections to other cells which can receive input (see section 3.1.3). The received inputs could be seen as a string of bits that could be fed into a Turing machine. Each reading of the data would require between 0.000 27 to 0.002 milliseconds.

The maximal reading rate of DNA is about 1 bit in 20 milliseconds. Assuming that the DNA machinery represents the biologically optimal possibility of a chemical system for reading massive amounts of information then this kind of process appear prima facie to be insufficient (although there might be ways around this).

4.2.2 Two Information Processing Systems

Another possibility is that the processes of the neurons can be divided into two kinds, regular information processing and meta information processing. The regular information processing would receive or create data as appropriate to the situation of the organism, and the meta information processing would serve to update the regular information processing in order to make it respond more appropriately to future situations, see figure 4.5. This could be a partial explanation for the intense activity of neurons despite that an organism performs no actions or receive any data (see section 2.2).

4.2.3 Regular Information Processing

It has been proposed that the branches on dendrites are equipped with logical gates (see section 3.3), this could be used for the regular information processing. At the splitting of the branches there could exist state memories that integrate a few data and give a 0 or 1 as output. This would separate the information and the information processing on several parallel units and they only need to read a few bits resulting in faster computations, see figure 4.6.

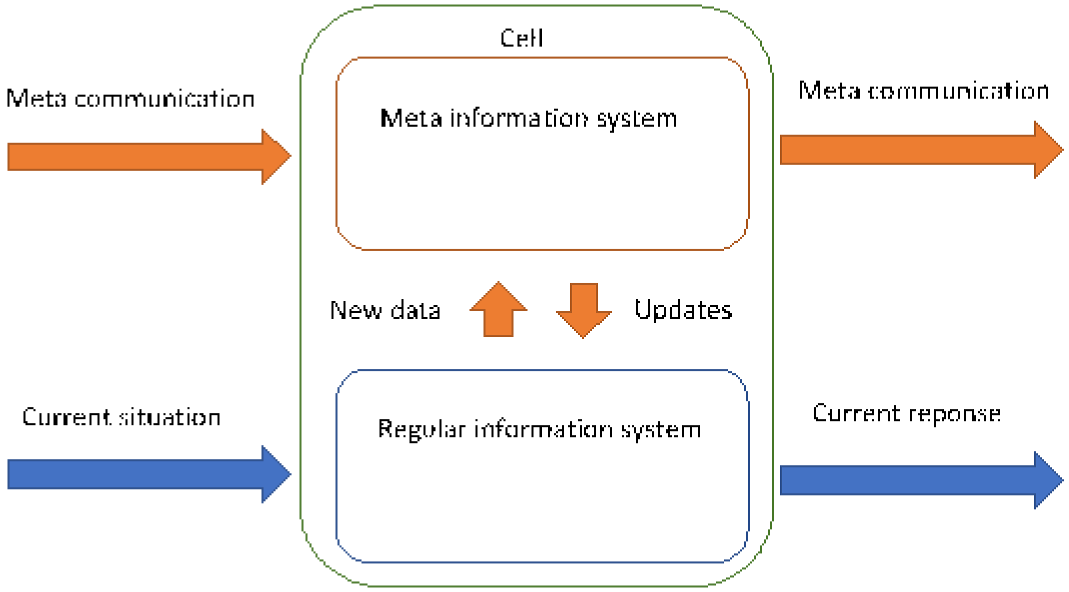

Figure 4.5: Schematic overview of the two information systems. The information that encodes the current situation enters the cell and exits the cell appropriately according to fast internal calculations. The meta information system also receives new data from this process and also receives meta information from other neurons. From this the meta information system updates the response of the fast regular information process system.

Assuming that the branches of the dendrite split in two at all places then the total number of state memories needed and the number needed in sequence as a function of the number of dendrite connections C can be displayed in figure 4.7. The number of state memories needed in sequence ($\mathrm{M_s}$) is displayed in equation 4.7.

$$M_s = \frac{\log C}{\log 2} \tag{4.7}$$

Whereas the total number of state memories needed ($\mathrm{M_t}$) is expressed in equation 4.8.

$$M_t = 2M_s - 1 \tag{4.8}$$

The state memory system appears to be most efficient when number of dendrite connections exceeds about 10 000. Dendrites tend to have about 10 000 connections or more (see section 3.1.3), indicating the possibility of a connection.

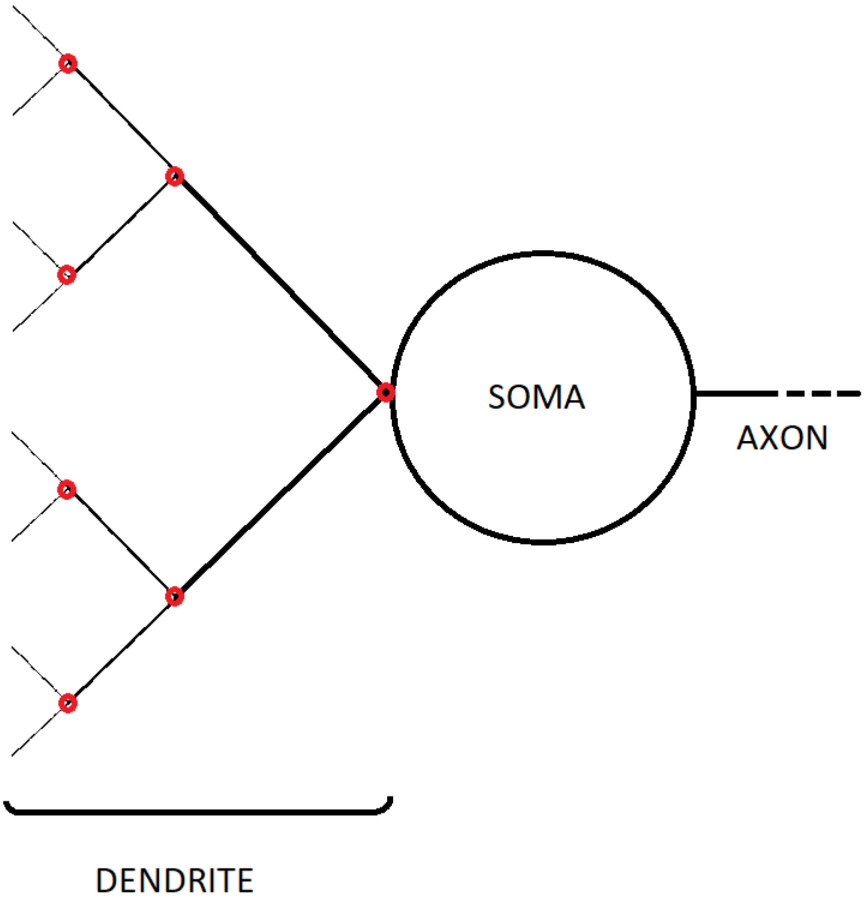

Figure 4.6: Schematic figure of nerve cell with dendrite, soma and axon with the position of state memories represented with red circles. The signals enter the end points of the dendrite on the left and travels thought some of the state memories to the soma where the signal, if it is a 1 is reinforced and sent in further via the axon.

If these state memories are as fast as the DNA reading process then reading 2 bits would take 40 milliseconds, and the whole process would need around $40 \cdot 15$ milliseconds equalling 600 milliseconds. Which is significantly more that than 5.3 to 39.8 milliseconds available to a neuron. If however the process can be faster since it can be specialised to only read two inputs, then it would need to read one bit in 0.17 to 1.32 milliseconds. This would be faster than the reaction rate of the fastest enzymes which can catalyse one reaction in about 9.3 milliseconds. But it is within the range of conformational changes of proteins that can occur in less than 1 millisecond (see section 3.1.4).

The state memories could in the ideal case be designed as logical gates for two inputs meaning that only four possible logical gates are necessary. These could be proteins or protein complexes placed at the place where the dendrite branches and undergo conformational change based on the input resulting in possible further transmission of the signal to its next branch. Proteins are continuously recycled in cells meaning

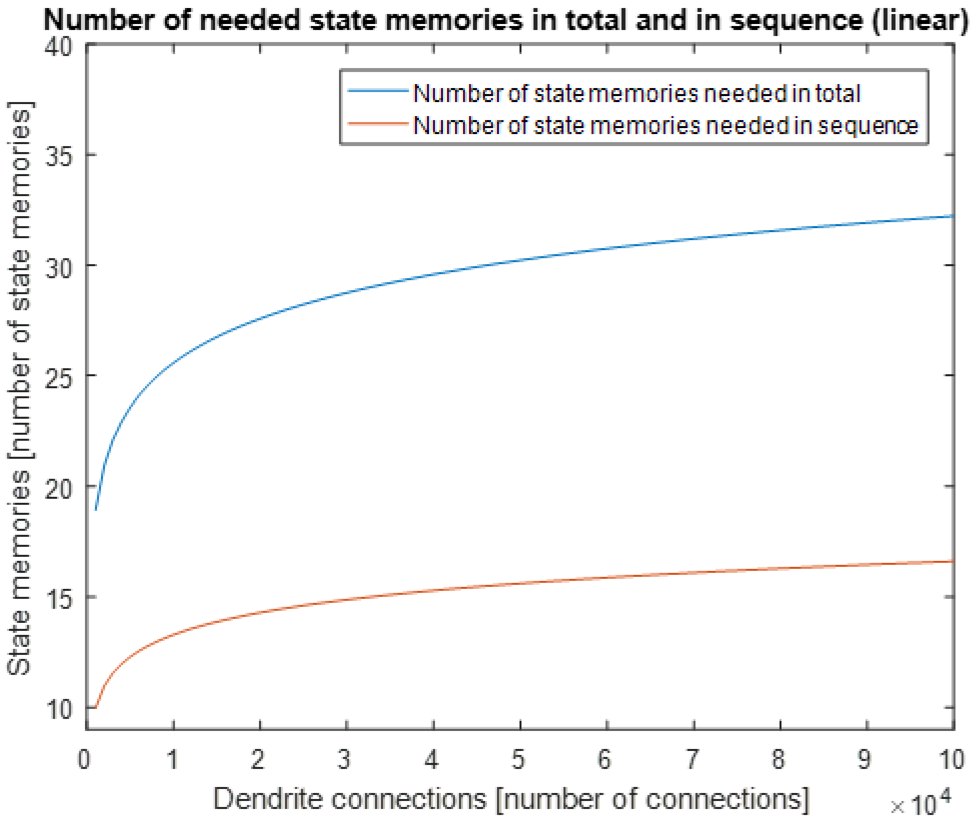

Figure 4.7: The number of state memories needed in a cell as a function of the number of dendrite connections to the cell (see section A.5).

that the previous state memory could be updated representing a form of learning.

The protein also needs to be able take two “inputs” directly or indirectly in the form of electricity, and undergo conformational changes that will have to lead to two distinct outcomes one for 0 and one for 1. The protein also needs to be able to be produced in four different forms, perhaps by the usage of alternative splicing in the production of the protein. It is conceivable that the energy needed for the conformational change could partially be supplied by the electricity, reducing the need to transport energy to the dendrites from the soma.

From the point of view of the brain, computational capacity of this system might be approximated to one reading of a bit in 1.32 - 2.7 milliseconds. For 86 billion neurons this would be the capacity to read about $6.53 \cdot 10^{13}$ bits per second. In a somewhat forced comparison, a 1 Ghz 64-bit CPU can move $64 \cdot 10^{9}$ bits per second. This would mean that the brain is faster by 3 orders of magnitude. Hence the brain, at its theoretical limits, would be about as fast as a desktop computer, hence the capacity of the brain could not be explained by the speed alone, rather the software has to account for a significant part of the difference in function between the two systems.

The energy usage of the brain can be estimated to be 20 % of the resting metabolic rate. The mean resting metabolic rate has been estimated to 0.863 kcal/kg/h resulting in 1 450 kcal/person/day assuming a weight of 70 kg. For the brain this is 290 kcal/person/day (see section 3.1.3). This would result in a consumption per protein conformational change of circa $5.3 \cdot 10^{-17}$ kcal as a maximum. Proteins can change conformation using only $1.7 \cdot 10^{-24}$ kcal (see section 3.1.4) making this a possible energy efficient mechanism.

The size of the memory can be estimated. Each state memory is one of four possible requiring four bits to specify which one is chosen. Assuming there are about 30 state memories there will be a storage of 120 bits per neuron. In a brain this would amount to $120 \cdot 86 \cdot 10^9$ bits equalling circa $1.032 \cdot 10^{13}$ bits. In a somewhat misleading comparison, in a 1 gigabyte computer memory there are $8 \cdot 10^9$ bits. The brain would then have a memory larger by a factor of three, once again placing the brain on par with a desktop computer. Counting with an average volume of 1 202.4 cubic centimetres, this leads to a memory density of $8.58 \cdot 10^9$ bits/cubic centimetres.

But the comparison is deceiving, the system is still a massive lock up table and itself incapable of change and if all possible future situations are accounted for then there is no room for learning. In order to reach the possibility to classify infinite amounts of data there is a need for a sophisticated computational architecture.

4.2.4 The Meta Information Processing System

The learning in the ideal case needs to select the correct protein of four possible at about 30 different places. This requires a mechanism that can estimate the ideal combination, store the information about the choice (which is in line with that memory seems to be stored in the soma (see section 3.1.4)) and finally perform the physical updating of the state memories (see section 3.3). Since this is a slower system, there is a need for short term memory and a way to communicate with this short-term memory. What are the quantitative demands on such a system?

The number of possible inputs is up to about $2^{100\ 000}$ in a cell with inputs from 100 000 other cells (this is circa $10^{30\ 103}$ possible inputs) (see section 3.1.4). This is a gigantic number for the computational capacity of a cell, and while having fewer cells connected will reduce the number substantially, it will still be gigantic. There might be an upper limit to this capacity, and the question whether the size of the soma correlates with the number of connections for the neuron might shed some light on the workings of this information system in the cell. Since the volume of a cell only grows with the cube of the radius, the possible growth of the volume can only explain a minor fraction of the increase in computational needs.

If the soma organised the information processing using a look up table (see section 3.3), solely this information, would need about $10^{30\ 103}$ entities. Is this feasible? Given that the number of atoms in a cell is around 10^{14} (see section 3.1.4) and that there is about 70 atoms per “bit” in the human DNA there is a need to compress the data by a factor of about $1.4 \cdot 10^{30\ 087}$ if it is organised on the level of large molecules. The hypothetical possibilities would only grow by a few orders of magnitude if subatomic levels were allowed. Hence the data needs to be stored in an abstract way.

This indicates that the system that encodes the data has to be very abstract if it has just the slightest variation of answers, in proportion to the possible number of them, to the incoming data. This vast space of possible answers will have to be searched in a limited time and with limited resources. The system also has to be abstract in the sense that it is a representational system with symbols, that have a significantly non-trivial relationship to the data it receives. This can according to the current understanding of computational machines only be done with a sophisticated computer architecture with random access memory and Turing machines (see section 3.3). Such a system will allow for the systematic application of rules on theoretically an infinity of data and memory while at the same time provide the answers to the questions posed to the cells.

The theoretical infinity will however be limited by constraints of space, time, energy etcetera. The apparent maximum of about 100 000 dendritic connections per cell might arise from the inability to construct a neuron capable of giving sufficiently differentiated answers to more possible inputs.

A soma is typically spherical which is the physical form that minimises the distance between all objects inside it. Since the computational system would have to be fast it requires the minimal distance between computation, memory etcetera. The drastic difference in form between it and the dendrite and axon could in part be that in the soma the information is flowing in all directions leading to that a sphere minimises distance, while in a dendrite and axon the distance travels linearly leading to the shape of a line being the optimal. An interesting question is whether organisms with less spherical somas or less linear dendrites or axons are reduced in their computational capacity. The difference between the two regions could also be caused by other factors such as that cells are spherical due to reducing surface tension and a way to keep the material need for axons minimal is to keep them as thin as possible.

What possibly could be said about the computational system and proteins, is that is has to be able to translate its output into a choice of protein from four possible ones and specify its destination. Furthermore protein have half-times in human cells of typically 20 ±5 hours (see section 3.1.4). This would somewhat correspond to the possibility that proteins are exchanged during sleep and the brain is “updated” with the experiences and meta processing from the day. This hints to the possibility that the meta system is connected to the cell clock and has a 24 hour “schedule”, with a program that is followed. This might include the elimination of unnecessary memory during sleep and repeated periods of "meta processing" during the day and night.

The time for a protein to be transported from soma to the destination depends on the speed and the distance. There is a group of proteins called kinesins that walks on "roads" called microtubule, with a payload of proteins kept in a "backpack" called liposome with a speed of 2 000 nanometres/second (see section 3.1.4) these could transport the proteins to their destinations. Assuming that the protein needs to move between 1.5 cm/12 = 0.125 0 cm and 1.5 cm/3.6 = 0.416 7 cm this would take between 625 seconds and 2 084 seconds for a neuron and might represent a recurring time slot in the possible 24 hour schedule.

The differentiation between axon and dendrite might depend on the desire to keep the updating time short for this while the axon might be much longer than the dendrite since it is not so sensitive to receiving the any updates as the dendrite is. Investigating what proteins are transported to the dendrites, their half times and which proteins are present at the branching of the dendrites might shed some light on the situation.

Furthermore, there is a general computational need for an architecture that is capable of dealing with an infinity of possibilities (see section 3.3). A system that is capable of dealing with the problems of a huge memory or infinities is well suited to deal with both of them. A potentially simple way to get an infinity of answers in a small space is to introduce an analogue instead if digital systems. Such a system could depend on the strength of force fields or the distribution of a particles probability distribution. In both there cases using unknown, if existing, mechanisms.

The connection between the computational system and DNA could be that DNA in some sense has to specify which of these natural algorithms that are allowed to arise, liming the computational space of the organism. But this limitation of the computational space also enables it to function evolutionary appropriately since the ability to do X at a specific situation requires the potential ability to do X, but to do X at a certain instance also requires the inability to do Y if Y is an alternative choice to X. This inability to do the evolutionarily inappropriately action might be central to the relationship between DNA and the computational system.

This level of sophistication of a single neuron might be surprising, but it is line with that neurons have been identified that can classify the position of the organism in space and other such discoveries also seem to have been made (see section 3.1.4). This indicates a rich schema for the neuron where the properties needed to classify data according to some abstract schema is part of the cell soma since that is where the information seems to be stored. This is in line with the groups that appear to be manifestations of optimal algorithms spread out on a limited number of neurons. The cells also have to know what algorithm they are looking for, since this is not available from external data, it would be an argument for that there are "natural algorithms" that arises from the interaction of subatomic entities.

The presence of optimal algorithms in the brain ought not to be surprising given the presence of a sophisticated information system with a one meter long code in every human cell, the DNA. And that this codes for the management of the cell and the encoding of offspring. The source of the algorithms might to a substantial degree be natural law. This is because the input in itself is not rich enough to provide the instructions needed. And the data cannot say which instructions are “needed”. An example of the importance of natural law is that cells in general are round which does not have to be encoded by the DNA, but is rather a consequence of energy minimisation in the cell surface.

Similarly, as energy minimising structures can arise, computation minimising structures can also be envisioned. The question is if chemistry can allow rich enough structures to arise at a small enough level. Assuming the possibility of optimality, there is a possibility that subatomic structures might contain even richer structures than are easily available at larger scales. Smaller systems might in some sense be richer than the larger ones that they are part of.

This would then have the advantage that the combination of these smaller subatomic structures will be smaller than the combination of possible larger atomic structures, keeping size, energy consumption and algorithm construction optimal. Quantum biology as a field is still emerging (see section 3.2), but given that such effects have been fruitfully investigated in “simple” plant cells indicates that they could exist even more in humans “sophisticated” neurons. And the retina neurons of some birds and the olfactory neurons of humans (see section 3.2.2) seem to indicate that there are quantum processes in the “simpler” sensory neurons, indicating their possible presence at what could be more "sophisticated" neurons in the cerebral cortex.

This is starting to give some hints on how optimality might arise spontaneously in sub atomic optimal systems. Analogously to an understanding of the properties of water and fat molecules can explain how close to “perfect” spheres can arise spontaneously.

One more reason why sub atomic structures might be of interest is that no large molecules that perform the computation and memory tasks needed appear to have been found so far. While DNA and RNA are involved with memory (see section 3.1.4) they appear to operate at speeds and memory requirements below the need for neurons. One possibility is that the information of the logical tables for the dendritic spines is stored in the DNA. This information could then use the massive and seemingly unused parts of DNA to regulate the individual neurons interaction between the DNA and the subatomic elements. Allowing the subatomic elements to solve the storage and computational problem of the meta system. An example would then be the apparent subatomic computations and memory storage of European robin in parts of its orientation system (see section 3.2.2).

There is a need to communicate with the temporary memory. For this there is a need for a “language” between the cells. Also, there is a need to communicate with other neurons beyond the ones which the neuron is currently connected in order to exchange data that might improve the reaction on the input. In order to be able to address anyone of the 86 billion neurons in the brain is a need for an address. If this address is written in binary with the firing of a signal as one then the address will be at least 36 bits long, statistically requiring 18 firings. This possible (see section 3.3) but will be very cumbersome.

The conceptually simple solution to the “language problem” is that a spike from a neuron contains not 1 and the absence of a spike contains a 0. Rather a spike would contain an encoded message itself consisting of several 0s and 1s. There is a possibility that there are two parallel languages, one simple and fast for regular usage with one 0 or 1 per spike and a more sophisticated but slower language for the more sophisticated meta system. The difference between these spikes might be seen in the frequencies and amplitudes between different spikes, both as a whole and internally to the spike. Investigating whether there is a possibility to categories spikes might therefor be interesting.

The “language” would have to essentially be the same between sender and receiver in order to be efficient, opening up the possibility of a language of the mind. If there is such a language then it would either be essentially the same as the internal system of each cell or different. If it is the same then what could be said about one of them could be said about both. There are then questions about how the language is encoded and on what entities. Since the electrical spikes appear central to the information processing of the brain then this would be one form, but the form would have to be able to change into other forms such as electrical (but not spikes), chemical, protein based, atomic, subatomic etcetera.

The so far known “languages” in a cell are all discrete such as the language for DNA, RNA and proteins and the translation between them. Other systems of “equal sophistication” such as the production of energy at the mitochondrion membrane is not discrete. This indicates the ability of cells to produce both discrete and analogue systems but that discrete seems to be preferred for information systems. Since DNA is discrete there is reason to suspect that the information systems that DNA code for will be discrete too in order for the DNA to be able to give exact instructions for the system. Likewise, digital systems might be expected to arise from the interactions of elementary particles. But the forces and probability distributions of elementary particles appear to be analogue and could hence contribute with analogue information systems (see section 3.2.2).

Another possibility is that the slow system does not use electrical systems to communicate, but rather uses slower chemical systems of communication. This system could then transport DNA or RNA between cells in a way to exchange information. This would still mean that each neuron needs an address. This kind of communication could take place by either placing major amounts of information in a vesicle with a nucleotide address tag or sent as a complex of macromolecules arranged around a nucleotide chain of either DNA or RNA. This communication could use either open spaces, specific vessels or specialised cells, such as nonneural cells to facilitate the movement and sorting of the data packages. Investigating the content released from and received by neurons could provide insights into the matter.

The problem of how the language, the programs in the brain etcetera could have arisen evolutionary would also be reduced if subatomic structures would create a limited space of opportunities.

5

Results

The results attempts to answer the problems presented in the introduction. The problems revolve around how information could be processed in the brain.

The results sections as a whole is divided into two areas. One concerns the combined structure of multiple neurons and the other the structure of a single neuron. The combined structure of multiple neurons explains how neurons could relate to each other. The internal structure shows the hypothetical internal workings of the neuron.

The analysis of the external structure arrives at the possibility of organising neurons in small groups. These small groups are preferred to be small from an information processing perspective, but can be larger from an algorithmic task solving perspective.

The internal structure of the neurons arrives at the possibility of having two systems. One "regular" system for direct appropriate responses to the environment and one "meta" system for updating the regular system, in order to make it respond more appropriately to the environment. The meta system can be seen as a system for learning.

5.1 The Combined Structure of Many Neurons

Neurons are connected in the brain, and this section addresses how neurons can be connected and why. The connection between neurons is assumed to be central for the functioning of the brain.

5.1.1 How Could Neurons be Connected to Each Other?

Neurons could be connected to each other in many different ways. But there are reasons indicating that a common way to organise neurons is in small groups. An example of some possible small groups are listed in table 5.1.

Table 5.1: Tasks and kind of tasks in the language system and the number of possible outputs.

Task	Type of task	Number of possible outputs
Identify syllables	categorisation	circa 100
Identify possible word	simple rule	-
Identify word category	categorisation	circa 10
Identify actual word	categorisation	circa 5000 per word category?
Collect word information	collection	-
Construct small phrases	categorisation	>4
Send information to semantic processing	sending	-
Send information to syntax processing	sending	-
Semantic processing	-	-
Syntax processing	set formation	infinite
Send information further	sending	-

In general, groups can be used to categorise information according to an internal "space". This space can be more or less abstract and sophisticated. Sensory nerves can serve as one less abstract clue to the structure of such spaces and their evolutionary origins. Sensory cells are placed in the body in a structure which means that the computational space for categorising information is "outsourced" to the external structure of the body. The degree of sophistication of the internal space can be quite substantial for example in the case of the eye.

The organising of neurons in groups furthermore lends itself to an explanation of the evolutionary and embryonic development of the brain. In principle the brain can start with one group performing one task. This group can then expand and split into parallel and sequential groups. A possibility would therefore be that for example hearing would start with one small group identifying loud sounds, which the organism could use as a clue to move from the current position. This group could split into a sequential group that can rudimentary categorise these sounds as dangerous or not, increasing the potential for identifying which sounds actually are dangerous, hence increasing the evolutionary chance of survival. A potential way to test part of this would be to genetically mark one dividing nerve cell in a developing organism and identify the pattern that the succeeding neurons form.

5.1.2 What is the Relation Between Groups and Firing?

If all the groups are connected randomly then the share of groups that always fire ($\mathrm{F}_{\mathrm{saf}}$) where C is connections per neuron and G is the size of groups, would be described by equation 5.1. This means that a low share of the groups can be categorising information or performing similar tasks which always produces an output.

$$\frac{G}{C} \geq F_{saf} \tag{5.1}$$

Given that this set contains several different kinds of groups, including groups that categorise, administer and compute, then the share of them respectively would have to be even smaller. But the structure of the groups can be such that the problem is avoided. In general, the massive parallelism of neurons could be compensated by a substantial linearity in the connections between the neurons in the brain. Such a structure could for example be series of parallel groups that as a whole perform tasks linearly with only limited connections outside the linear flow. Such a structure would then be limited to only having a few groups in parallel according to equation 5.2, where P is the number of parallel groups, if all connections are internal to the structure.

$$\frac{C}{G} = P \tag{5.2}$$

Any firing outside of the parallel structure would increase the share of firing in the brain, but if every external group that is made to fire is compensated by one of the parallel groups that does not fire then the balance is kept. But since this is repeated at the coming steps of the linear structure then this repetition needs to be limited to the number of parallel structures at each step of the linear structure, as displayed in equation 5.3 where F_{o} is the number of firings to groups outside the linear structure.

$$F_o = P \tag{5.3}$$

Since the structure can be more complicated than repeating layers of groups there can be significant deviations from the stated equations. And local deviation might be desirable but needs to be compensated by the opposite deviation in order to balance the average. But such deviations have to be organised (even more than a repeating structure of parallel groups have to be). For this there is a need for mechanisms, and such mechanisms need instructions. If such instructions are biologically or evolutionarily costly in relation to their utility then simple structures would be expected to be prominent.

5.1.3 What is the Relation Between Group Size and Information?

As group size increases from 1 there is a rapid increase in information but the values then decreases, see figure 5.1. The information gain is largest for groups of size 3 (blue) and the prior uncertainty is largest for groups of size 2 (blue). If the interaction between the groups has random errors, then the mutual information is also decreased as the number of neurons per groups increases due to the increased probability of error. From an information theoretic standpoint, one would expect the size of groups to be 3 or smaller.

Several of the possible category groups seem to be significantly larger than is the case indicating that the brain would be optimised to perform certain tasks and only secondarily to do them in an optimal way. But there would be a pressure to find the algorithms that approximates a combination of the principles by finding ways to organise groups that are as close to the information theoretically optimal size as possible. Since this size is small anyway, this effect might be confounded with other optimisation criteria.

In a linear structure of parallel groups without interactions with the surrounding groups outside of the structure, the improvement from an information theoretic standpoint would increase linearly with the length of the structure. This might indicate the that these kinds of pure structures are not optimal from an information theoretic point of view.

5.1.4 What is the Relation Between Groups and Computations?

Assuming that the firing of a neuron is energy demanding and that energy is to be conserved, then the largest possible group is optimal, see figure 5.2. But since the increase in energy efficiency decreases significantly when the groups are larger than about 3 then other constraints might be interesting. Such other constraints might be the energy need to produce and maintain the cell or the waste of not using a neuron sufficiently. A guesstimate of the optimal group size given these constrains would be around 4 – 5 neurons. This is lower than many of the possible observed values, indicating that other principles would be of larger importance.

An interesting question is to investigate possible "simple" geometries of parallel and sequential groups that would be expected to exist in the brain, guided by the equations and conclusions in this chapter.

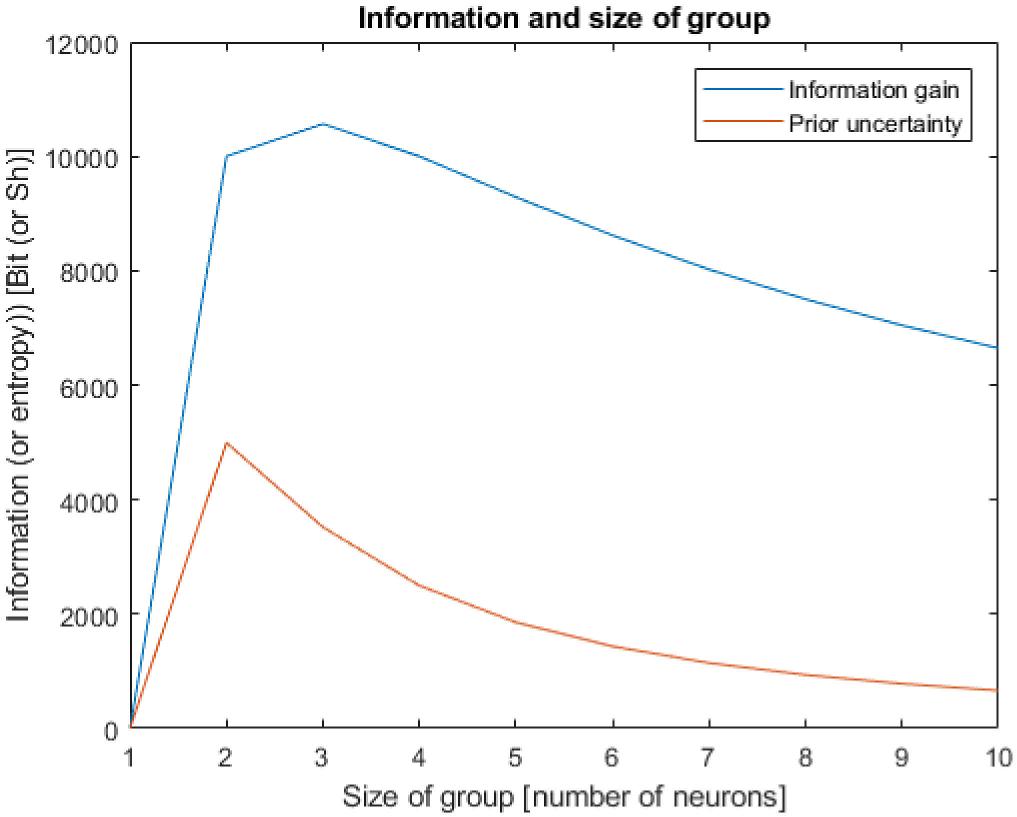

Figure 5.1: The change in information for each step in a parallel structure of firing groups. The information gain is largest for groups of size 3 (yellow), the prior uncertainty is largest for groups of size 4 (blue) and the reduction in entropy is largest for groups of size 6 (orange). The calculations are based on 20 000 neurons in each layer organised in identically sized groups all firing to the next level (see section A.3).

5.2 Information Processing in Individual Cells

Inside the cells there is a need for a suitable structure that can create the desired output for the group. The demands on the cell and possible ways to satisfy them are presented in this section.

5.2.1 What are the Time Constrains for Information Processing in a Neuron?

The DNA machinery appear prima facie to be to slow to deal with the information demands of the cell insufficient (although there might be ways around this).

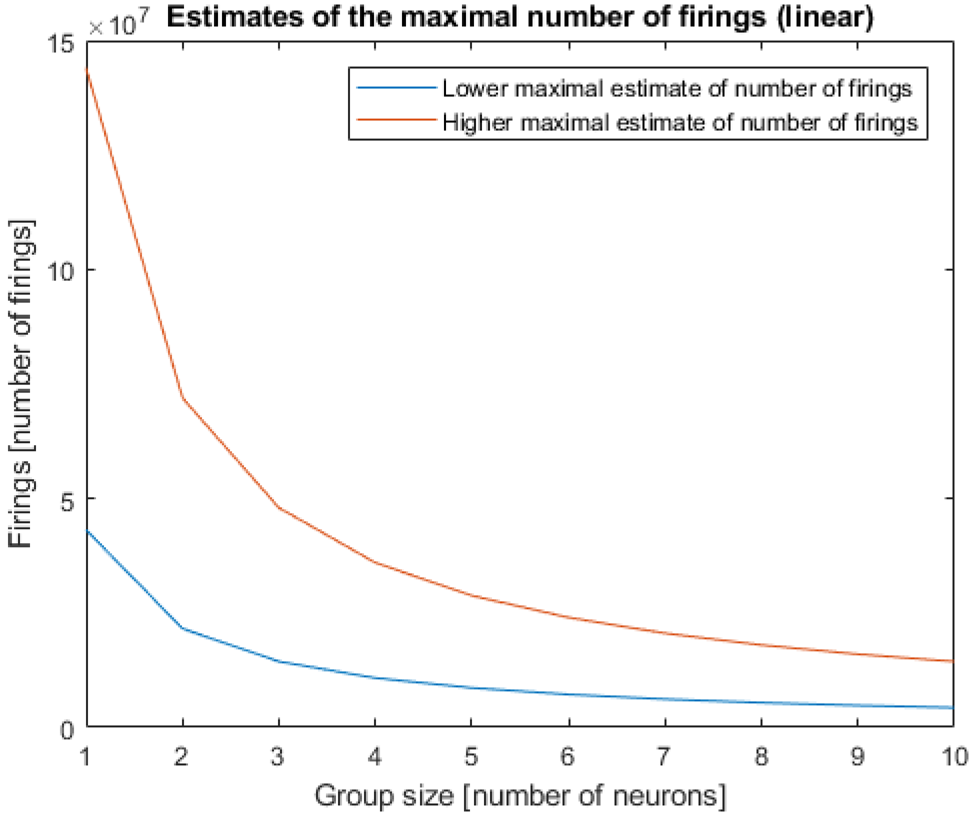

Figure 5.2: The maximal estimates of the number of firings required in one area for performing the task of identifying word category. Given that neurons operate at a frequency of 30 - 80 Hz and requires 120 – 150 milliseconds and the region involved constitutes one permille of the cerebral cortex (see section A.4).

5.2.2 Two Information Processing Systems

Information processing could be divided into two kinds, regular information processing and meta information processing. The regular information processing would receive or create data as appropriate to the situation of the organism, and the meta information processing would serve to update the regular information processing in order to make it respond more appropriately to future situations, see figure 5.3.

5.2.3 Regular Information Processing

The branches of the dendrite split in two at all places, see figure 5.4, so the total number of state memories needed and the number needed in sequence as a function of the number of dendrite connections can be displayed in figure 5.5. The number of state memories needed in sequence (M_s) in relation to the number of connections per neuron C is displayed in equation 5.4.

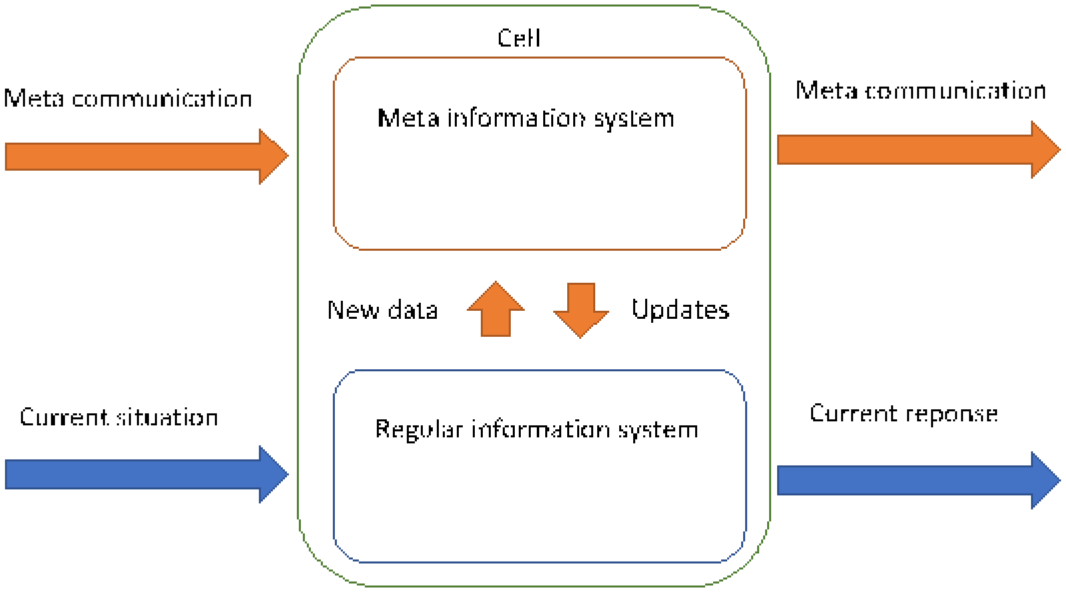

Figure 5.3: Schematic overview of the two information systems. The information that encodes the current situation enters the cell and exits the cell appropriately according to fast internal calculations. The meta information system also receives new data from this process and also receives meta information from other neurons. From this the meta information system updates the response of the fast regular information process system.

$$M_s = \frac{\log C}{\log 2} \tag{5.4}$$

Whereas the total number of state memories needed ($\mathrm{M_t}$) is expressed in equation 5.5.

$$M_t = 2M_s - 1 \tag{5.5}$$

The state memory system appears to be most efficient when number of dendrite connections exceeds about 10 000. Dendrites tend to have about 10 000 connections or more, indicating the possibility of being a tree of logical gates.

The operations could be done with conformational changes of proteins that can occur in less than 1 millisecond. The state memories could in the ideal case be designed as logical gates for two inputs meaning that only four possible logical gates are necessary.

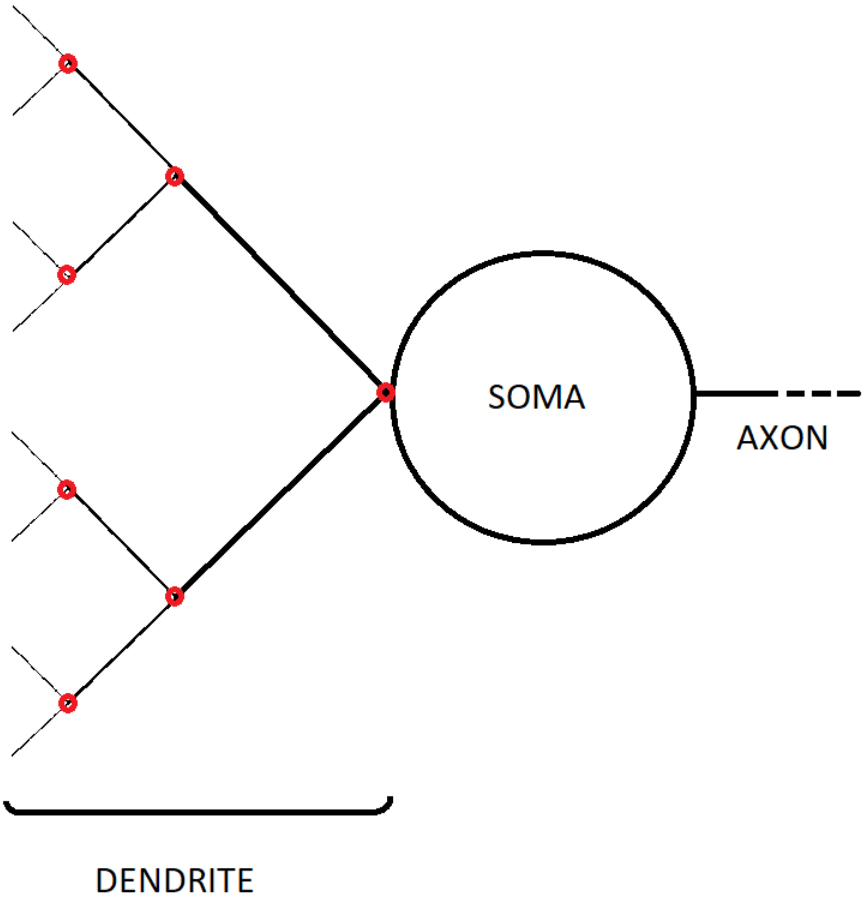

Figure 5.4: Schematic figure of nerve cell with dendrite, soma and axon with the position of state memories represented in red. The signals enter the end points of the dendrite on the left and travels thought some of the state memories to the soma where the signal, if it is a 1 is reinforced and sent in further via the axon.

These could be proteins or protein complexes placed at the place where the dendrite branches and undergo conformational change based on the input resulting in possible further transmission of the signal to its next branch. Proteins can change conformation using only $1.7 \cdot 10^{-24}$ kcal (see section 3.1.4) making this a possible energy efficient mechanism.

Proteins are continuously recycled in cells meaning that the previous state memory could be updated representing a form of learning. It is conceivable that the energy needed for the conformational change could partially be supplied by the electricity, reducing the need to transport energy to the dendrites from the soma.

For 86 billion neurons this would be the capacity to read about $6.53 \cdot 10^{13}$ bits per second. In a somewhat forced comparison, a 1 Ghz 64-bit CPU can move $64 \cdot 10^{9}$ bits per second. This would mean that the brain is faster by 3 orders of magnitude. Hence the brain, at its theoretical limits, would be about as fast as a desktop

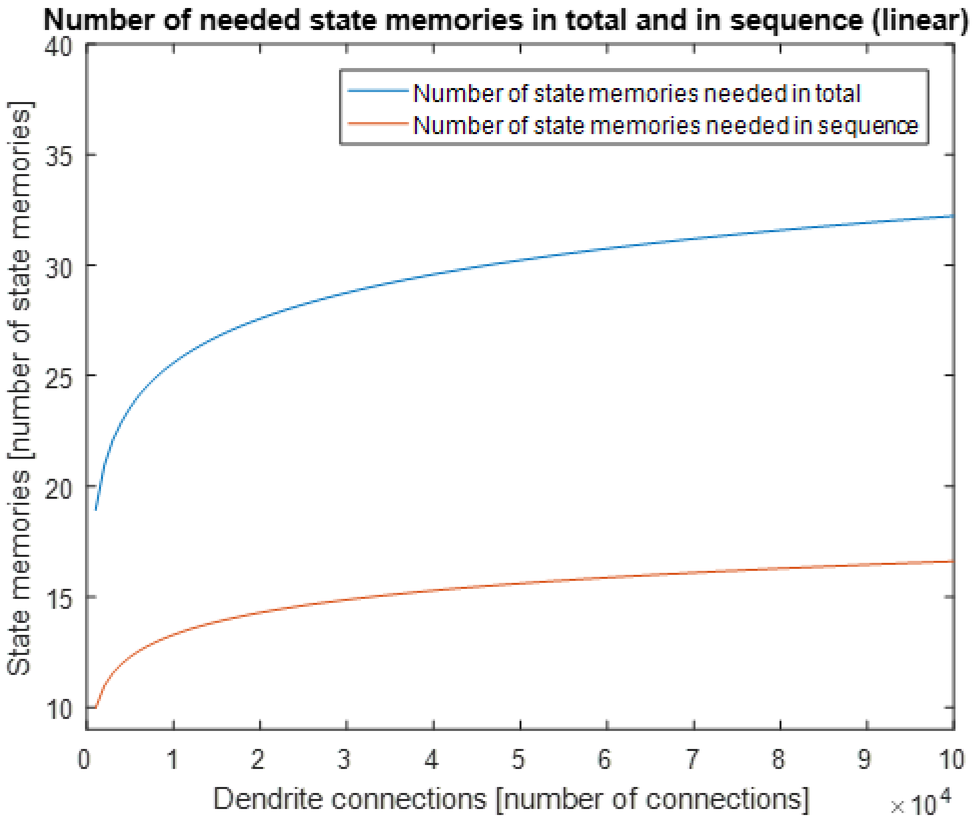

Figure 5.5: The number of state memories needed in a cell as a function of the number of dendrite connections to the cell (see section A.5).

computer, hence the capacity of the brain could not be explained by the speed alone, rather the software has to account for a significant part of the difference in function between the two systems.

In a brain there would be $120 \cdot 86 \cdot 10^9$ bits, circa $1.032 \cdot 10^{13}$ bits in the regular information system with a memory density of $8.58 \cdot 10^9$ bits/cubic centimetres. In a somewhat misleading comparison, in a 1 gigabyte computer memory there are $8 \cdot 10^9$ bits. The brain would then have a memory larger by a factor of three, once again placing the brain on par with a desktop computer.

But the comparison is deceiving, the system is still a massive lock up table and itself incapable of change and if all possible future situations are accounted for then there is no room for learning. In order to reach the possibility to classify infinite amounts of data there is a need for a sophisticated computational architecture.

5.2.4 The Meta Information Processing System

There is a need to compress the data in neurons by a factor of about $1.4 \cdot 10^{30\,087}$ if it is organised on the level of large molecules. The hypothetical possibilities would only grow by a few orders of magnitude if subatomic levels were allowed. Hence the data needs to be stored in an abstract way. The apparent maximum of about 100 000 dendritic connections per cell might arise from the inability to construct a neuron capable of giving sufficiently differentiated answers to more possible inputs.

This indicates that the system that encodes the data has to be very abstract if it has just the slightest variation of answers, in proportion to the possible number of them, to the incoming data. This vast space of possible answers will have to be searched in a limited time and with limited resources.

The system also has to be abstract in the sense that it is a representational system with symbols, that have a significantly non-trivial relationship to the data it receives. This can according to the current understanding of computational machines only be done with a sophisticated computer architecture with random access memory and Turing machines (see section 3.3).

Such a system will allow for the systematic application of rules on theoretically an infinity of data and memory while at the same time provide the answers to the questions posed to the cells.

This hints to the possibility that the meta system could be is connected to the cell clock with 24 hour “schedule”, with a program that is followed. This might include the elimination of unnecessary memory during sleep and repeated periods of "meta processing" during the day and night. The updating could be done within a few minutes. The time for a protein to be transported from soma to the destination depends on the speed and the distance. This could be done with kinesins within a maximum of between 625 seconds and 2 084 seconds.

The differentiation between axon and dendrite might depend on the desire to keep the updating time short for this while the axon might be much longer than the dendrite since it is not so sensitive to receiving the any updates as the dendrite is. Investigating what proteins are transported to the dendrites, their half times and which proteins are present at the branching of the dendrites might shed some light on the situation.

There is a general computational need for an architecture that is capable of dealing with an infinity of possibilities (see section 3.3). A system that is capable of dealing with the problems of a huge memory or infinities is well suited to deal with both of them.

A potentially simple way to get an infinity of answers in a small space is to introduce an analogue instead if digital systems. Such a system could depend on the strength of force fields or the distribution of a particles probability distribution. In both there cases using unknown, if existing, mechanisms. These mechanisms needs to be understood if the architecture of the neuron is to be understood.

A naturally arising optimality is needed in neurons in order for them to contain the algorithms and architecture needed. These abilities might arise spontaneously in sub atomic optimal systems. And the situation in the cell might give clues to how this is done.

The connection between the computational system and DNA could be that DNA in some sense has to specify which of these natural algorithms that are allowed to arise, liming the computational space of the organism. But this limitation of the computational space also enables it to function evolutionary appropriately since the ability to do X at a specific situation requires the potential ability to do X, but to do X at a certain instance requires also requires the inability to do Y if Y is an alternative choice to X. This inability to do the evolutionarily inappropriately action might be central to the relationship between DNA and the computational system.

The conceptually simple solution to the “language problem” between neurons in the meta system is that a spike from a neuron contains not 1 and the absence of a spike contains a 0. Rather a spike would contain an encoded message itself consisting of several 0s and 1s.

There is a possibility that there are two parallel languages, one simple and fast for regular usage with one 0 or 1 per spike and a more sophisticated but slower language for the more sophisticated meta system. The difference between these spikes might be seen in the frequencies and amplitudes between different spikes, both as a whole and internally to the spike. Investigating whether there is a possibility to categories spikes might therefor be interesting.

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If it is the same then what could be said about one of them could be said about both. There are then questions about how the language is encoded and on what entities. Since the electrical spikes appear central to the information processing of the brain then this would be one form, but the form would have to be able to change into other forms such as electrical (but not spikes), chemical, protein based, atomic, subatomic etcetera.

The so far known “languages” in a cell are all discrete such as the language for DNA, RNA and proteins and the translation between them. Other systems of “equal sophistication” such as the production of energy at the mitochondrion membrane is not discrete. This indicates the ability of cells to produce both discrete and analogue systems but that discrete seems to be preferred for information systems.

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Another possibility is that the slow system does not use electrical systems to communicate, but rather uses slower chemical systems of communication. This system could then transport DNA or RNA between cells in a way to exchange information. This would still mean that each neuron needs an address.

This kind of communication could take place by either placing major amounts of information in a vesicle with a nucleotide address tag or sent as a complex of macromolecules arranged around a nucleotide chain of either DNA or RNA. This communication could use either open spaces, specific vessels or specialised cells, such as nonneural cells to facilitate the movement and sorting of the data packages. Investigating the content released from and received by neurons could provide insights into the matter.

The problem of how the language, the programs in the brain etcetera could have arisen evolutionary would also be reduced if subatomic structures would create a limited space of opportunities.

6

Discussion

The discussion attempts to evaluate the strengths of the results and evaluate societal, ethical and environmental aspects. The results attempts to address the aim in the introduction, which revolve around how information could be processed in the brain.

6.1 The Robustness and Reasonableness of the Results

How robust are the results? The applied approach to the brain might be a fruitful way to understand the brain. While the findings are tentative they are in line with a substantial amount of literature and the various results tend to strengthen each other.

What are the major weaknesses of the results? As stated, the findings are tentative, hence they are weak in themselves. What is needed is empirical findings that makes the findings more firmly rooted. To some extent such findings have already been made, from several directions, and there seem to be an accelerating trend of such findings.

If these findings are robust, why have they not been found before? The perspective assumed in the report is not sufficiently investigated, leading to a situation with relatively low hanging fruit. The difficulty is not making the findings in themselves but rather finding a perspective that guides inquiry into areas with the possibility of rich findings.

6.2 The Thinking Behind the Principles and Mechanisms

Is a sufficient understanding of the literature acquired? The literature about the brain and related fields is wast, and beyond the capacity of an individual to investigate. This is partially why a broad effort is needed to investigate broad topics. Furthermore, there is a need to constrain the possible literature to the most relevant literature. This can be done with a perspective. A perspective limits the field of view but can be justified if it allows for the picking out of the relevant parts.

Can the specific perspective be justified? In general, literature from various fields are used and combined, and this ought to rise the level of the conclusions since the demands from the various fields constrains the possible consistent solutions to a smaller area. This constraining also makes possible the creation of an analysis since the number of paths of analysis are reduced leading to the possibility to create an analysis that proceeds in several steps with the support of literature along the way. But only sub-sets of the total literature have been used, resulting in a limited basis for the conclusions. This can be motivated if the consistency and results of the combination of concepts and literature is judged to exceed the level deemed necessary by the reader.

Is the relevant theory used? The theory follows from the perspective and is used to attempt to create a more concrete basis for the analysis. In itself the theory is hence needed but the choice of theory can be criticised. The theory was selected from two points of view: if it needed according to the perspective and if it is needed to facilitate the reasoning in the analysis.

How far does the constrains carry the analysis? The analysis of the groups and the system in the dendrites is more constrained by the literature and hence gives rise to more specific results. The literature offers less guidance concerning the prevalence of groups and the possible kinds, and it offers less guidance regarding the meta system in the soma.

Are the important problems confronted or hidden? The assumption that dendrites plays a major role in the regular information processing is to some extent a way to use a more known structure in order to constrain the analysis. The dendrites offer a more structured geometry than the soma which is close to a sphere. But the main reasons is the simple connections between the soma and the computational needs and capacities of the neuron. The meta information system could be seen as a way of just isolating the harder problems in a black box, but the distinction between a simpler system and a more sophisticated one appear to arise from the analysis and offers insight.

Is anything new and surprising discovered? The value of the discoveries is subjective, but if they are substantially on the right track then they help open up a new and fruitful field of science.

6.3 The Principles and Mechanisms in Themselves

The proposed mechanisms and structures have the potential capacity to explain the brain. They also appear to work well together and show a high degree of internal cohesion. But they are in many instances to vague to provide the level of detail desired.

6.4 Societal, Ethical and Environmental Aspects

What can be said about the societal, ethical and environmental aspects? Considering the questions raised in the introduction some tentative conclusions can be mentioned.

6.4.1 Concerning the Science Itself, is This an Ethical Perspective to Take on the Human Brain?

The science can effect the thinking in other areas of society for good or bad. A major cornerstone in a broad set of philosophical views is that humans have value. Does this perspective undermine this premise? If so, then the perspective could be criticised as degrading and immoral, whether scientifically right or wrong.

To start of, this perspective attributes a rich and capable system to the brain which would mean that it is in line with that humans have a value even in a strict economic sense. A common principle for the value of animals is that they have feelings, hence consciousness. This perspective does not rule out that possibility, it rather keeps it as a future possible discovery. A central moral dilemma attributed to humans is free will, and this perspective keeps the possibility of free will as a possibility. Hence the perspective is not clear enough and not sufficiently developed to answer the question, but it leaves the possibility open for a development according to these moral concerns.

6.4.2 What are the Possible Ethical Outcomes From This Research if it is Successful?

Assuming that the perspective will be so successful that it will lead to the creation of applied science and technology, it will have consequences. In general, in order to ensure an ethical usage of the technology, there is a need to make sure that the wisdom regarding the technology develops faster among the general population than the technical understanding of the technology develops in the sciences and in the industry.

6.4.2.1 What Unethical Forms of Usage is There? And How Could they be Prevented?

The understanding of the brain could lead to the possibility of controlling people. Hence undermining the possibility of a free society, this could be considered highly unethical. During less dramatic circumstances two more realistic problems might arise. There might be an unequal access to the advantages of the technology leading to a situation where the more successfully the technology is the more unequal the society will be. Even if the technology is available to all, a situation might arise where people feel pressured to adopt it against their will, for example to be competitive members of the workforce. Even in the case where these two problems do not arise, an environmental problem might occur if the technology is costly in terms of energy or matter or creates a substantial amount of waste and pollution.

6.4.2.2 What Ethical Forms of Usage is There? And How Could they be Encouraged?

The potential health benefits might range from curing diseases such as dementia to improving the capacity of the brain beyond that of healthy individuals today. The societal impacts of a healthy population might in general be assumed to be positive.

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A

Code

For some calculations in the analysis MATLAB code has been used, it is displayed in this appendix.

A.1 Cumulative Active Neurons at Step

```
% --- Cumulative active neurons at step (log/linear)"

% % % % % %  PRE PROGRAM  % % % % % %

disp('Cumulative active neurons at step (log/linear)')

% % % % % %  COMPUTE  % % % % % %

numberOfSteps = 5;
brainNeurons  = 86000000000;
cortexNeurons = 12000000000;
cumulativeNeuronsAtStep1 = zeros(1,numberOfSteps+1);
cumulativeNeuronsAtStep2 = zeros(1,numberOfSteps+1);
cumulativeNeuronsAtStep3 = zeros(1,numberOfSteps+1);
neurons1 = 1;
neurons2 = 1;
neurons3 = 1;
cumulativeNeuronsAtStep1(1,1) = neurons1;
cumulativeNeuronsAtStep2(1,1) = neurons2;
cumulativeNeuronsAtStep3(1,1) = neurons3;
connectionsPerNeuron1 = 100000;
connectionsPerNeuron2 = 20000;
connectionsPerNeuron3 = 10000;
for index = 1:numberOfSteps
    neurons1 = neurons1*connectionsPerNeuron1;
    neurons2 = neurons2*connectionsPerNeuron2;
```

```
    neurons3 = neurons3*connectionsPerNeuron3;
    cumulativeNeuronsAtStep1(1,index+1) = neurons1;
    cumulativeNeuronsAtStep2(1,index+1) = neurons2;
    cumulativeNeuronsAtStep3(1,index+1) = neurons3;
end

% % % % % %  PLOT  % % % % % %

x = 0:numberOfSteps;
y1 = cumulativeNeuronsAtStep1;
y2 = cumulativeNeuronsAtStep2;
y3 = cumulativeNeuronsAtStep3;
y4 = ones(1,numberOfSteps+1)*brainNeurons;
y5 = ones(1,numberOfSteps+1)*cortexNeurons/100;
figure
semilogy(x,y1,x,y2,x,y3,x,y4,x,y5)
legend('Cumulative active neurons with 100 000 connections per neuron',...
'Cumulative active neurons with 20 000 connections per neuron',...
'Cumulative active neurons with 10 000 connections per neuron',...
'Number of neurons in the brain',...
'Rough number of neurons in a Brodmann area')
title('Cumulative active neurons at step (log/linear)')
xlabel('Steps [number of steps]')
ylabel('Neurons [number of neurons]')

% % % % % %  END  % % % % % %

disp(' ')
disp('end')
```

A.2 Number of Fierings From Group Size

```
% --- Number of fierings from group size

% % % % % %  PRE PROGRAM  % % % % % %

disp('Number of fierings from group size')

% % % % % %  COMPUTE  % % % % % %

numberOfSteps = 1000;
cortexNeurons = 86000000000;
```

```
    numberOfFirings1 = zeros(1,numberOfSteps);
    numberOfFirings2 = zeros(1,numberOfSteps);
    numberOfFirings3 = zeros(1,numberOfSteps);
    connectionsPerNeuron1 = 100000;
    connectionsPerNeuron2 = 20000;
    connectionsPerNeuron3 = 10000;
    for index = 1:numberOfSteps
        grouppSize = index
        syms x
        eqn = (connectionsPerNeuron1/grouppSize)^x == ...
            (cortexNeurons/grouppSize);
        numberOfFirings1(1,index) = double(solve(eqn,x));
        syms x
        eqn = (connectionsPerNeuron2/grouppSize)^x == ...
            (cortexNeurons/grouppSize);
        numberOfFirings2(1,index) = double(solve(eqn,x));
        syms x
        eqn = (connectionsPerNeuron3/grouppSize)^x == ...
            (cortexNeurons/grouppSize);
        numberOfFirings3(1,index) = double(solve(eqn,x));
    end

    % % % % % %  PLOT  % % % % % %

    x = 1:numberOfSteps;
    y1 = numberOfFirings1;
    y2 = numberOfFirings2;
    y3 = numberOfFirings3;
    figure
    plot(x,y1,x,y2,x,y3)
    axis([0 numberOfSteps 2 10])
    legend('Cumulative active neurons with 100 000 connections per neuron',...
        'Cumulative active neurons with 20 000 connections per neuron',...
        'Cumulative active neurons with 10 000 connections per neuron')
    title('Number of firings at different group size (linear)')
    xlabel('Neurons per group [number of neurons]')
    ylabel('Steps [number of steps]')

    % % % % % %  END  % % % % % %

    disp(' ')
    disp('end')
```

A.3 Information and Size of Group

```matlab
% --- Information and size of group --- %

% % % % % %  PRE PROGRAM  % % % % % %

disp('Information and size of group')

% % % % % %  COMPUTE  % % % % % %

max = 10;
min = 1;
jumps = 1;
numberOfSizes = ((max-min)/jumps)+1;

x = zeros(1,numberOfSizes);
y1 = zeros(1,numberOfSizes);
y2 = zeros(1,numberOfSizes);
y3 = zeros(1,numberOfSizes);
step = 1;
for index = min:jumps:max
    numberOfNeurons = 20000;
    sizeOfGroup = index;
    numberOfGroups = round(numberOfNeurons/sizeOfGroup);
    priorUncertainty = -((1/sizeOfGroup)*...
        log2(1/sizeOfGroup))*numberOfGroups;
    informationGain = log2(sizeOfGroup)*numberOfGroups;
    x(1,step) = index;
    y1(1,step) = priorUncertainty;
    y2(1,step) = informationGain;
    step = step + 1;
end

% % % % % %  PLOT  % % % % % %

figure
x = 1:numberOfSizes;
plot(x,y2)
hold on
plot(x,y1)
hold on

title('Information and size of group')
legend('Information gain','Prior uncertainty')
```

```
xlabel('Size of group [number of neurons]')
ylabel('Information (or entropy)) [Bit (or Sh)]')

% % % % % %  END  % % % % % %

disp(' ')
disp('end')
```

A.4 Estimates of the Maximal Number of Firings

```
% --- Estimates of the maximal number of firings

% % % % % %  PRE PROGRAM  % % % % % %

disp('Estimates of the maximal number of firings')

% % % % % %  COMPUTE  % % % % % %

numberOfSteps = 10;
cortexNeurons = 12000000000;
fierings1 = zeros(1,numberOfSteps);
fierings2 = zeros(1,numberOfSteps);
for index = 1:numberOfSteps
    groupSize = index;
    fierings1(1,index) = ((0.120/(1/30))*(cortexNeurons/1000))/...
        groupSize;
    fierings2(1,index) = ((0.150/(1/80))*(cortexNeurons/1000))/...
        groupSize;
end

% % % % % %  PLOT  % % % % % %

x = 1:numberOfSteps;
y1 = fierings1;
y2 = fierings2;
figure
plot(x,y1,x,y2)
legend('Lower maximal estimate of number of firings',...
    'Higher maximal estimate of number of firings')
title('Estimates of the maximal number of firings (linear)')
xlabel('Group size [number of neurons]')
ylabel('Firings [number of firings]')
```

```

    % % % % % %  END  % % % % % %

    disp(' ')
    disp('end')
```

A.5 Number of Needed State Memories in Total and in Sequence

```
    % --- Number of needed state memories in total and in sequence (linear)  ---

    % % % % % %  PRE PROGRAM  % % % % % %

    disp('Number of needed state memories in total and in sequence (linear)')

    % % % % % %  COMPUTE  % % % % % %

    numberOfSteps = 100;
    fierings1 = zeros(1,numberOfSteps);
    fierings2 = zeros(1,numberOfSteps);
    for index = 1:numberOfSteps
        numberOfConnections = index*1000;
        numberOfStateMemories = log(numberOfConnections)/log(2);
        fierings1(1,index) = numberOfStateMemories;
        fierings2(1,index) = (numberOfStateMemories*2)-1;
    end

    % % % % % %  PLOT  % % % % % %

    x = (1:numberOfSteps)*1000;
    y1 = fierings1;
    y2 = fierings2;
    figure
    plot(x,y2,x,y1)
    axis([0 numberOfSteps*1000 9 40])
    legend('Number of state memories needed in total',...
        'Number of state memories needed in sequence')
    title('Number of needed state memories in total and in sequence (linear)')
    xlabel('Dendrite connections [number of connections]')
    ylabel('State memories [number of state memories]')

    % % % % % %  END  % % % % % %
```

```

    disp(' ')
    disp('end')
```