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ABSTRACT

In the ANNIE project - Applications of Neural Networks to Integrated Ergonomics - BE96-3433, a tool for integrating ergonomics into the design process is developed. This paper presents some features in the current ANNIE as applied to the design of car interiors. A variant of the ERGOMan mannequin with vision is controlled by a hybrid system for neuro-fuzzy simulation. It is trained by using an Elite system for registration of movements. An example of a trajectory generated by the system is shown. A fuzzy model is used for comfort evaluation. An experiment was performed to test its feasibility and it showed very promising results.

VIRTUAL REALITY IN ERGONOMICS PROTOTYPING

Some years ago the designer toolkit consisted of a piece of paper, a pen and a calculator, and the ergonomics tests were performed with real prototypes and in mock-ups. Time has changed and nowadays things are made in and with computers. Computer aided design (CAD) and to some extent virtual reality technologies (VR) are used. The automotive industry has followed this trend and today all the design process steps are more or less computerized, using from simple desktop models to advanced 'CAVE' systems.

Ergonomic analysis of the interior is one of the steps in the car design process. The first concepts produced in an early design phase can be simulated and evaluated from an ergonomic point of view in the computer, virtually. Less full scale testing is required. Simulations can be designed and repeated many times under more control and without any human consideration to the mannequin, a computerized human model. The mannequin will not be injured and will not be bored.

An advantage with the vr technique is its flexibility. Many design solutions can be created and visualized easily. A 3D visualization is easier to understand and contains more information than a 2D sketch, which may improve the evaluation. Changes to the design can be performed quickly. Testing and evaluation can be more effective. Using an intranet or an internet connection, several persons located on different places can work with or evaluate the product at the same time. All these positive characteristics of CAD/VR improve the ergonomic evaluation, reduce the design cost and decrease the development time.

With faster and less costly evaluations the number of ergonomic evaluations may be increased, more test subjects can be used or more potential concepts can be kept longer in the design process before they are excluded.

THE ANNIE-PROJECT

In the EC-project (Brite Euram), ANNIE - Application of Neural Networks to Integrated Ergonomics - the idea is to use the advantages of neural networks and CAD/vr-technology in order to improve the mannequin characteristics, especially motion control. The result will be a better tool for simulation and ergonomic analysis. To achieve this goal the ANNIE-partners are developing and training a set of neural networks (nn in table 1) for controlling the mannequin. Motion data to train the neural networks is collected from people performing tasks in real environments. The advantage of using trained neural networks is that the mannequin's movements will be more human and with a natural movement pattern i.e. limbs and joints will affect each other in a natural way when moving. Movement pattern will change with object properties e.g. cold-warm, robust-fragile, environment conditions e.g. dimension of working area, temperature and noise, and human conditions e.g. age, gender, and level of experience and stress. Within the project a standard mannequin with an appurtenant biomechanical model was designed. Complementary ergonomic evaluation methods were designed for the selected environments. The car interior was one of the environments, which was of interest in the project. A demonstrator for evaluating car interiors and control positions is under development and is presented in this paper.

In the future several options and combinations of the ANNIE product will be available. The complete ANNIE package contains trained neural networks, a mannequin and an ergonomic toolbox. If a mannequin already is available the trained neural networks and the toolbox potentially can be coupled to the existing human model. If somebody has a specific area of interest for which no neural networks are trained then it is possible to get untrained neural networks and train them with the same or similar techniques as used in the project and presented below.

MANNEQUINS AND COMPUTERIZED EVALUATION SOFTWARE AT THE MARKET

There are several mannequins and software packages on the market to which it is possible to import environments for evaluation. Examples are Transom Jack [1], SAMMIE [2], SAFEWORK [3], The McDonald Douglas Modeling system [4], RAMSIS [5] and ERGOman [6]. The mannequins mentioned above can represent a wide range of the population. In the simulation and evaluation programs it is mostly possible to choose stature, gender, age, nationality, and body configuration. In many programs it is also possible to design a mannequin of your own with unique lengths of the body segments. The anthropometric data are adopted from sources as Pheasant [7], Diffrient et al [8] and Reynolds [9]. In tests, the 5th percentile (female) and the 95th percentile (male) are the most used. This statement is based on the ergonomic guideline, "let the tallest person fit and shortest person reach". Unfortunately no mannequin mentioned above is a perfect replica of a person, neither in shape nor in motion control. In movement control the number of segments, number of joints and the number of degrees of freedom, DoF, in the mannequin are important factors together with the control mechanism. Today mannequins simulate a possible movement and the result can be far from the movement persons are likely to perform. Mannequins are mostly controlled by kinematics (kin in table 1) or inverse kinematics (I-kin in table 1) or a mixture. These methods produce solutions to the motion generation problem, but observing the mannequin it is easy to detect that the artificial movements differ from natural human movements, making the mannequin movements less useful for ergonomic evaluation. A mannequin is build up of body segments connected through joints. The polygon is the smallest construction piece in a mannequin, the cell. The types and the number of polygons used are critical factors for human likeness. For more realistic simulations limitations of human joint angels are used in some mannequins, sources are e.g. Diffrient et al [8] and Dempster [10]. Some increase the realism even more, when collision detection is implemented in the simulations to avoid that the mannequin can move limbs and objects through other compact objects.

Table 1. Characteristics for some mannequins on the market and for ERGOman with the ANNIE module (current version). A brief presentation of mannequin characteristics together with examples on ergonomic evaluation methods in the software packages.

	TRANSOM JACK	SAMMIE	SAFEWORK	RAMSIS	ANNIE
No of segments	69	19	99	56	11
No of joints	68	17	74	55	10
DoF	135	51	148	107	30
Motion control*	I-kin	kin	I-kin / kin	I-kin	nn
Reach envelopes	Yes	Yes	Yes	Yes	Yes
Field of vision	Yes	Yes	Yes	Yes	Yes
Comfort	Yes	Yes	Yes	Yes	Yes
Collision detection	Yes	Yes	Yes	Yes	Yes

* I-kin = Inverse kinematics. Kin = kinematics.
nn = neural networks

The mannequin must also be equipped with the right characteristics to be able to evaluate a specific product, e.g. a car interior. General designing requirements to consider when positioning controls are reachability as well as safe and easy handling. The control position must be safe and comfortable to minimize risks for traffic incidents and maximize comfort. A mannequin suitable for car interior evaluation is preferably equipped with a skeleton for biomechanic analysis, eyes for evaluation of the field of vision and a databank for subjective opinions about perceived comfort level [11]. Ergonomic evaluation methods which are used in the software packages mentioned above are for example RULA [12], OWAS [13] and the NIOSH lifting equation [14]. Databanks containing information about comfort zones and strength under different conditions are also used as reference. Comfort evaluations are frequently based on postures and joint angles. Comfort sources are for example Judic et al [15] and iso 6682 [16]. A general guideline is that the most comfortable position is within the middle third of the range of the joint motions [17]. Reach zones for human operation can be presented by envelopes. Data for comfortable and maximum handling are available, e.g. iso 3958 [18]. Strength data can be gathered from e.g. MIL-STD 1472D [19]. A lot of this information is adopted from the military investigations, from NASA, the US army and the French army.

In order to perform a good evaluation of the environment it is important to simulate natural movements. A "correct" head position is also of major importance in safety evaluation where the field of vision is of importance. Fields of vision are presented by cones showing the primary and secondary (periphery) zone [20]. In table 1 a number of mannequins on the market are listed with their characteristics. ramsis is a mannequin developed for the German automotive industry. Other mannequins are also used in the automotive industry, e.g. Transom Jack.

THE CAR EXPERIMENT

EQUIPMENT – In order to develop the simulation and evaluation demonstrator an experiment was performed. The experiment can be divided in two parts, one movement collection phase for recording training data to the neural networks and one comfort investigation phase in order to develop a comfort evaluation tool. The driver environment was a Volvo 850 automatic. In the interior, to the right from the steering wheel 31 control positions were defined onto two vertical planes at different heights and at different lateral positions. One plane in line with the center-console and the other in line with the navigation system, see figure 1.

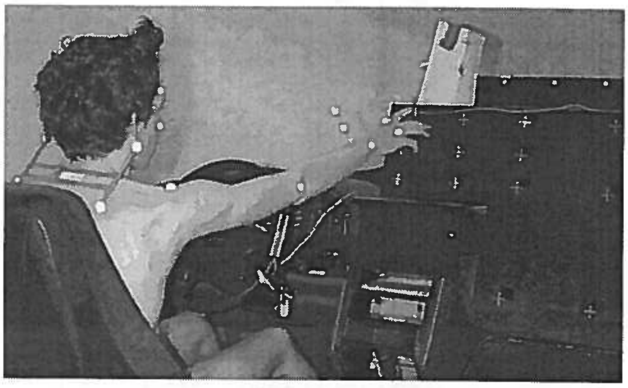

Figure 1. A test subject is driving in a mock-up. Reflective markers are attached to his body for movement recording. When driving he operates a control button. Afterwards the perceived comfort was ranked. Some of the control positions at the navigation system plane can be seen in the figure, marked with white crosses.

The control positions differed in x, y, and z directions. One electric pushbutton (size, 25x24 mm) was used. It was easily moved around to the different positions. The control position was changed randomly in order to avoid a 'progressive judgement' effect. The same position was never used twice. The ELITE system [21] with four ir-cameras was used for motion analysis. Subjects were equipped with 26 passive markers, applied on proper anatomical landmarks at the upper body. On the base of these markers, for each body segment a reference system for kinematic description was defined and applied to the biomechanical model. The positions of the marker were recorded by the ELITE-system using a sampling frequency of 50 Hz. Electrical switches were placed on the steering wheel and in the pushbutton for detection of start, stop and direction change of the hand. Switches were coupled to IR-diodes and ordinary diodes, recorded by the ELITE-system and a video. A side view of the subjects was video recorded.

SUBJECTS

Table 2. Personal and anthropometric information of the subjects, together with their driving experiences and the chosen seat positions. The three columns to the left shows data for subjects for which movements were recorded. Averages and standard deviations (in parentheses) data for the comfort groups are presented in the three columns to the right.

	5th percentile, female	50th percentile, male	95th percentile, male	5th percentile, group	50th percentile, group	95th percentile, group
Number of subjects	1	1	1	8	7	9
Personal information						
Age (years)	21	24	35	35 (11)	35 (11)	41 (13)
Weight (kg)	55	61	76	62 (10)	72 (9)	78 (9)
Anthropometric data						
Stature (mm)	1560	1760	1860	1598 (28)	1752 (29)	1856 (16)
Length arm (mm)	655	770	780	688 (17)	749 (18)	816 (19)
Hip height (mm)	825	920	950	921 (45)	1004 (33)	1053 (52)
Driving experience						
In/out city	in	in	both	in 6 both 2	in 3 out 3 n. a 1	in 4 out 3 both 2
Driving frequency	<1/m	1/m	d	<1/m 1 d 7	<1/m 1 1/m 1 d 5	2/w 2 d 7
Mock-up data						
Back rest inc. (°)	25	25	25	23 (2)	25 (0)	21 (3)

in = mainly driving in city traffic. out = mainly driving outside city. both = driving in and outside city equally. n.a = no answer. d = daily. 2/w = twice a week. 1/m = once a month. < 1/m = less than once a month

Twenty-four subjects were used for evaluating the comfort of the control handling. Three of the subjects, one 5th percentile female, one 50th percentile male and one 95th percentile male were also used for motion recording. Anthropometric estimates of stature for these groups are 154 cm, 174 cm, and 185 cm respectively [8]. Personal data (age and weight), anthropometric data (stature, hip height and shoulder to finger tip length and their mock-up adjustments (back inclination and driver seat position) can be seen in table 2. Information about driving experience was also recorded. Driving frequency was divided in five groups: 1) daily (d), 2) 2-3 times a week (2/w), 3) once a week (1/w), 4) once a month, (1/m), 5) less than that (< 1/m). Table codes are presented in brackets. The subjects experience of driving environment type was divided in 1) mainly city traffic (in) 2) mainly outside city (out) 3) both equal (both). In table 2 all data are presented in detail for the subjects taking part in the movement collection phase. Averages and standard deviations (in brackets) are presented for the percentile groups used for comfort investigation.

TESTING PROCEDURE – The subjects were asked to fill in a pre-questionnaire, containing person related questions e.g. about age, weight and driving experience. A number of anthropometric dimensions were also measured. The subjects were asked to sit in the car mock up after which the seat was adjusted to obtain a natural and comfortable driving position. For the three persons for which movements were recorded the back support inclination was fixed to 25 degrees. This seat inclination is in the middle of the comfort zone [15]. Subjects were informed about the testing procedure and were allowed to familiarize with the control and the set-up. A hand position "quarter-to-three" on the steering wheel was demanded. This hand position is recommended in Swedish driving schools to minimize risks of hand and arm injuries when airbags explode. During the simulated driving the drivers were asked to operate the pushbutton, in the 31 defined pushbutton positions. Movements, from the hand left the steering wheel until the hand was back at the steering wheel were recorded with an ELITE-system. The movements were repeated five to seven times for each control position. The other subjects not taking part in the motion recording part were controlling the start and the number of trials for each position by themselves. After each button position the subjects marked their comfort experience of the control handling on an open scale. The extremes were 'very uncomfortable handling' and 'very comfortable handling'.

CONTROL OF THE MANNEQUIN

BIOMECHANICAL MODEL AND STANDARDIZED MANNEQUIN – The mannequin developed for our purpose is based on an 11-segment biomechanical model, see figure 2. Each body segment is considered as a rigid body. All the segments are connected by joints: some have 3 and some have 2 or 1 DoF in order to match with corresponding human joint. The pelvis has 3 additional

DoF relative to the world coordinate system. The biomechanical model has in total 30 DoF. The root of the kinematic chain is the pelvis. The other segments are the trunk, the head, the clavicles, the upper arms, the forearms and the hands, giving a total of eleven rigid bodies. The lower limbs were excluded from the biomechanical model because of the main interest devoted to the sitting posture analysis. It means that in the mainframe of the project the objective of the ergonomic analysis tool is focused on a subject performing working tasks in the seated position.

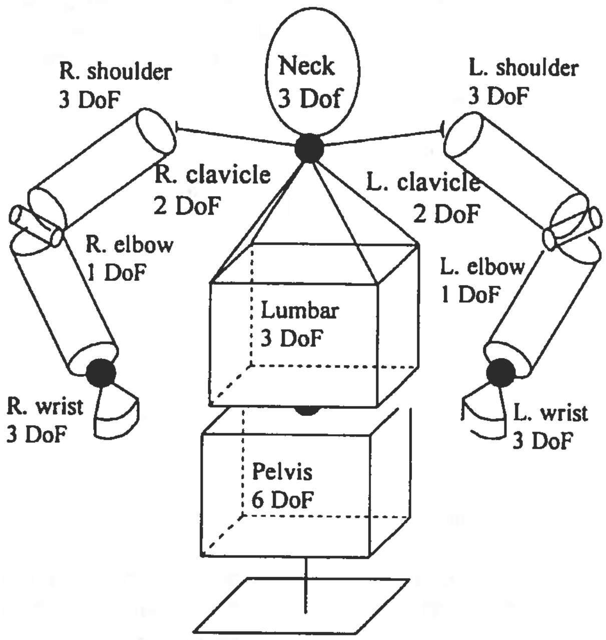

Figure 2. The ANNIE biomechanical model of the upper body consists of 11 segments, 10 joints with in total 30 degrees of freedom.

HYBRID NEURO-FUZZY SIMULATION OF HUMAN MOTION – One of the main goals of the ANNIE project is the development of a data-driven engine for the Realistic Simulation of Human Motion (RSHM), i.e. a tool that predicts the motion of a human operator during the execution of assigned tasks. This is done under the assumption that the relevant features of human motion are retained in the simplified description based on the bio-mechanical model and supplied by the previous data processing phase.

From an external viewpoint the RSHM engine receives as input the detailed description of the task to be performed along with some additional information about the initial state of the bio-mechanical model, and provides as output the corresponding expected sequence of states of the bio-mechanical model.

The sort of tasks users are interested in involves at most few "end effectors", i.e. specific anatomical segments and/or points on the body which are directly in charge of the accomplishment of the task itself. This suggested to separate the overall prediction in two subsequent stages:

- The first stage predicts the motion of the "end effector(s)" on the basis of the detailed description of the task to be performed along with the initial state of the specific anatomical segment(s) and/or point(s) on the body involved.
- The second stage predicts the sequence of states of the bio-mechanical model on the basis of the outcome of the preceding stage.

The effectiveness of the proposed architecture relies on the assumption that the details of the task to be performed influence the sequence of body postures mostly through the motion of the "end effector(s)". The second stage is in fact isolated from the detailed task description. As a result, the two parts of the neural system are characterized by different kinds of complexity. Namely:

- From the input side, the first stage receives the "meaning" of the movement, whose description may substantially vary from task to task and is likely to involve heterogeneous quantities. Therefore its design is strictly tied to the characteristics of the specific problem at hand and to the intricacies of each single experimental protocol. From the output side, it has to predict relatively few quantities.
- From the input side, the second stage receives the time evolution of quantities whose nature is shared by all the tasks involving the same end effector(s). Even though different tasks still require dedicated networks, its design can conform to quite general principles. From the output side, it has to predict far more quantities.

NEURAL ESTIMATION OF THE END EFFECTOR'S TRAJECTORY – One major point that has a profound impact on the first stage of the hybrid neuro-fuzzy system is task segmentation. On this side the detection of relevant events by means of infrared IR-diodes proved to be very useful, especially in comparison with the cumbersome (and sometimes misleading) analysis of velocity profiles previously employed in preliminary trials.

Movements acquired in the car experiment were thus segmented so as to assign the right sequences of frames to either of the following two elementary tasks:

- move the right hand from the rest position on the steering wheel so as to operate the specified pushbutton;
- move the right hand back to the rest position on the steering wheel.

Even though the pushbutton was actually operated by means of the forefinger tip, the role of end effector was played by the 2nd metacarpal head, since fingers are not included in the bio-mechanical model.

A separate neural network was trained for each elementary task. All such networks share the same general architecture shown in the following figure. Dark arrows indicate feed-forward connections, whereas light arrows indicate feedback connections.

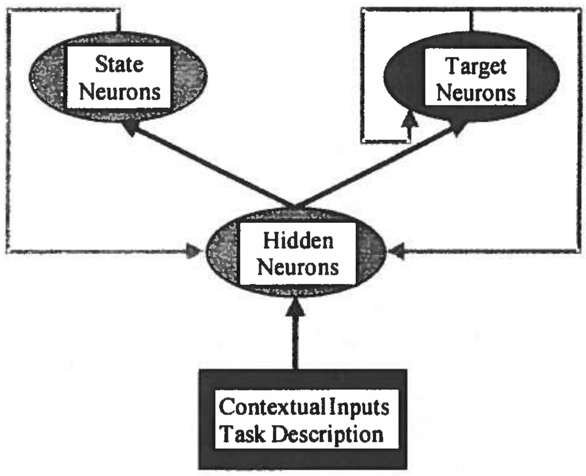

Figure 3. Architecture of the recurrent neural network for the prediction of the end effector's trajectory

The architecture actually implements a NARX (Non-linear Auto-Regressive with eXogenous inputs) model. That is, the position xright(t) of the right end effector at frame t – which is supplied by the target neurons – comes to depend on past positions and on the detailed specification of the task to be performed. While past positions are at their turn internally generated by the network itself until the beginning of the movement (thence the attribute "auto-regressive"), task specification has of course to be provided externally. It is made of the total number of frames T in the movement and of the locations and of the rightmost point on the steering wheel (xsw) and of the pushbutton (xpb), respectively. The initial position xright (1) of the right end effector is provided externally as well. In formulas, we have:

$$\begin{aligned}
&\forall t \in \{1,..,T\}, \\
&x_{right}(t+1) = f_{target}\left[x_{right}(t), x_{right}(t-1), u(t), u(t-1), I\right] \\
&u(t+1) = f_{state}\left[x_{right}(t), x_{right}(t-1), u(t), u(t-1), I\right] \\
&I = \left(T, x_{sw}^T, x_{pb}^T\right)^T \\
&x_{right}(0) \equiv x_{right}(1) \\
&u(0) \equiv u(1) \equiv 0
\end{aligned} \tag{1}$$

State neurons – whose outputs at frame are denoted as u(t) – are added in order to make the network able to learn even non time-invariant dynamics.

During the training phase, for each movement the basic architecture shown above is unfolded in time so as to build up a giant feed-forward network with partial connectivity and massive weight sharing, whose depth grows linearly with T [22]. Error signals are generated from the observed differences between the outputs of target neurons and the corresponding experimental data, and then propagated backwards throughout the unfolded network. The procedure is repeated on all the training movements in order to compute the sensitivity of the global cost (in this case, just the sum of squared differences) with respect to the weights, i.e. the strengths of synaptic connections. These are updated in an iterative fashion so as to minimize the global cost. Among the very many updating schemes available, we made use of the RPROP algorithm [23] because of its extreme robustness against the numerical problems induced by the huge depth of the unfolded network on the back-propagation of error signals.

NEURAL NETWORKS AND FUZZY CLUSTERING – Let the motion of the biomechanical model of the mannequin be formally described by the nonlinear functions

direct (forward) task:

$$x_{l,r} = \begin{pmatrix} x_{left} \\ x_{right} \end{pmatrix} = f_{l,r}(q) \tag{2}$$

inverse task:

$$q = g(x_{left}, x_{right}) \tag{3}$$

where

$x_{l,r} = (x_{left}, x_{right})^T$ - (6 x 1) vector

q - (36 x 1) vector,

$f_{l,r}$, g - nonlinear functions.

In most cases the inverse function g is difficult to determine while the function $f_{l,r}$ is normally analytically known. There are, however, ways to learn the inverse task from examples (from input-output data)

Two basic methods have been used for modeling the motion of the mannequin: i) the so-called joint density estimation ii) the approximation with local linear (affine) systems.

Joint density estimation – The first developed approach relies mainly on the performed right-hand point-to-point experiments.

Let q be the vector of joint angles and x_{left} the spatial coordinates of the left end-effector. Let, furthermore, z=(q, x_{left}) be the corresponding product space. In the first step the joint density p(z) is modeled in the product space z=(q,x_{left}) with the help of the sampled data and a kernel density approach using Gaussian kernels [24].

$$p(z) = C \cdot \sum_{j=1}^{M} P(j) \cdot \exp\left(-\frac{1}{2}(z-\mu_j)^T \Sigma_j^{-1} (z-\mu_j)\right) \tag{4}$$

where Σ_j are diagonal covariance matrices, M is the number of kernels, P(j) are the prior probabilities that a certain z was generated by the j-th kernel, μ_j are mean values.

The density's parameters were learned using the well known EM-Algorithm (EM: Expectation minimization) [24]. In a second step, this joint density is used to calculate the joint angles q from a given left hand end-effector trajectory by means of conditional expectation $E[q|x_{left}]$ taking Bayes' theorem into account. The patented approach is described in [25].

Further experiments revealed, however, that the achieved accuracy of the required trajectory was less than expected. Therefore another approach was tested based on local linear (affine) systems.

Approximation of the inverse kinematics with local linear (affine) systems

Basic principle – Since there exists an analytical model of the forward kinematics of the biomechanical model it is feasible to compute the position of any end-effector for a given link configuration. It is much more difficult to find the solution of the inverse task: Given a point in world coordinates. Determine the corresponding joint angles. This task is not uniquely solvable since there are much more degrees of freedom in the links than in Cartesian world coordinates. Since there are many different link configurations leading to the same end-effector position the inverse task is redundant and for the given kinematics not uniquely to determine. Furthermore, both the forward and the inverse kinematics are highly nonlinear functions between the joint angles and an end-effector position. Therefore, the inverse kinematics will not be analytically computed but determined by learning by examples.

The learning procedure is based on local linear mapping between link coordinates and effector coordinates where the global mapping remains nonlinear. Learning of the inverse kinematics is done by fuzzy clustering and local linear (affine) fuzzy models being smoothly connected [26, 27, 28].

Although the learning procedure used here results in a full nonlinear model it is of advantage to calculate the differential kinematics which is a mapping of the velocities or coordinate differences, respectively [29, 30]. This enables us to make a correction of the already computed joint vector with the help of the direct analytical coordinate transformation. Moreover, it becomes feasible to put well defined restrictions on joint angles and even on contributing joint torques.

Finally, the introduction of a simple operator dynamics in the kinematical model takes delays in the operator's movement into account and considers the effect of weight in the end-effector on the behavior of the links [31].

Forward kinematics – The biomechanical model can be seen in figure 2. The biomechanical model has two end-effectors, one for the right and one for the left arm. A general formulation of the direct coordinate transformation of the biomechanical model for the left and the right arm is equation 2.

q is a vector of joint angles. x_{left} and x_{right} are 3 x 1 vectors of spatial world coordinates, $f_{l,r}(q)$ reflects the nonlinear kinematic relationships between q and x_{left} and x_{right}, respectively. A further approach is to linearize (2) around q which results in a differential coordinate transformation

$$\dot{x}_{l,r} = J_{l,r}\dot{q} \tag{5}$$

where $J_{l,r}(q) = \dfrac{\partial x_{l,r}}{\partial q}$ is a Jacobian.

Inverse kinematics – The knowledge of the inverse kinematics is needed when the technological task is defined in world coordinates and an appropriate joint angle vector has to be found to perform the task. The inverse task can formally be defined as follows. Given the end-effector positions x_{left} and x_{right}, find a corresponding joint vector q. Hence, formally the inverse kinematics is given by some function

$$q = g(x_{left}, x_{right}) \tag{6}$$

Because of the redundancy of the biomechanical model it is obvious that there does not exist a unique solution. Therefore, a set of additional restrictions on the joint angles concerning end positions, singularities, and bounds on the working space enables us to compute one of the infinite possible solutions.

However, to find an analytical solution (6) from (2) remains a difficult task. Thus it is easier to calculate the inverse kinematics in the differential way by inversion of (5). The corresponding differential solution is

$$\dot{q} = G_{l,r}\dot{x}_{l,r} \tag{7}$$

Approximation of the inverse kinematics with local linear (affine) systems – Since the highly nonlinear inverse kinematics is difficult to find in an analytical way, the solution implemented here is based on the assumption that (6) can be approximated by a finite number of local linear (affine) systems

$$q = G^i \cdot x + b^i \tag{8}$$

G^i is a 36 x 6 matrix, b^i is a 36 x 1 vector, i is the number of the i-th local linear (affine) model. The local models are obtained from a collection of (x,q) data pairs which are derived from training experiments of the human operator. Normally, the (x,q) data pairs have the property to form clusters (condense) around some centers. From the data belonging to a specific center a local model (8) for that center can be derived. The weighted sum of all local models yields an approximation of the nonlinear function (6).

$$q = \sum_{i=1}^{c} w_i(x)(G^i \cdot x + b^i) \tag{9}$$

From (9) one directly obtain an approximation by local differential models:

$$\dot{q} \approx \sum_{i=1}^{c} w_i(x) \cdot G^i \cdot \dot{x} \tag{10}$$

<u>Clustering algorithm</u> – The main steps of clustering and subsequent modeling are:

- Clustering of the (x,q) data pairs in the <u>product</u> space using c-elliptotype clusters.
- Projection of the clusters onto the input space and changing of the projected clusters into Gustavson-Kessel clusters (GK).
- Computing of local linear (affine) models in the product space using the GK clusters from step 2.

Figure 4 shows a 3D example where the product space is defined by $(x1, x2, x3) \in \Re^3$. The input space is defined by $(x1, x2) \in \Re^2$. Details of this clustering algorithm can be obtained from [26], [27], and [28].

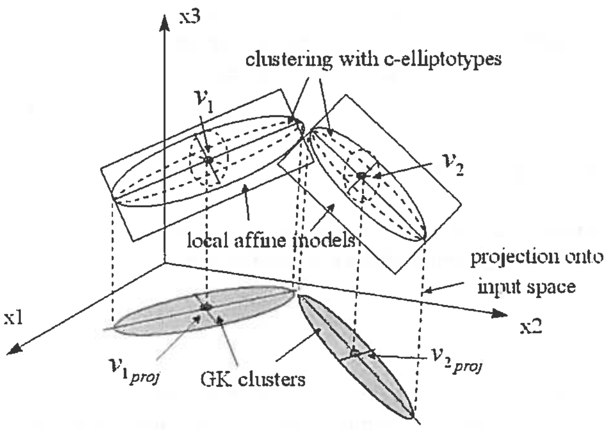

Figure 4. Clustering and model computation

Correction of the differential inverse kinematics – Experiments show that the use of (10) may cause errors because of the integration of lineariziation errors and approximation errors. In order to avoid large errors an optimization loop corrects the output from the differential coordinate transformation using the forward kinematics of the biomechanical model.

The correction algorithm is presented in figure 5. x_d is a desired point of a trajectory which has to be transformed into the joint space. The difference $x_d - \tilde{x}$ between a desired and an actual position vector multiplied by a diagonal matrix K is transformed by (10) into some change dq. The differences dq are integrated and fed into the forward kinematics of the biomechanical model. The resulting output $\tilde{x}$ is then fed back and subtracted from x_d.

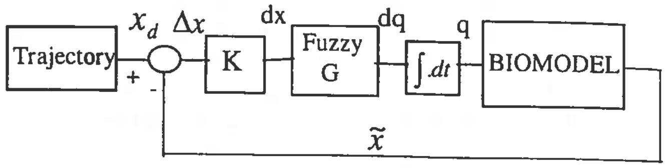

Figure 5. Block scheme of the differential inverse coordinate transformation with correction

The optimization loop runs in "virtual time". When $|\Delta x|$ is less than a predefined error or a given optimization step number is reached then the optimization stops and the next point in x-space will be approached. K is chosen as the unity matrix times a sufficiently small constant such that the algorithm converges. Figures 6 and 7 shows results with and without correction of the inverse model.

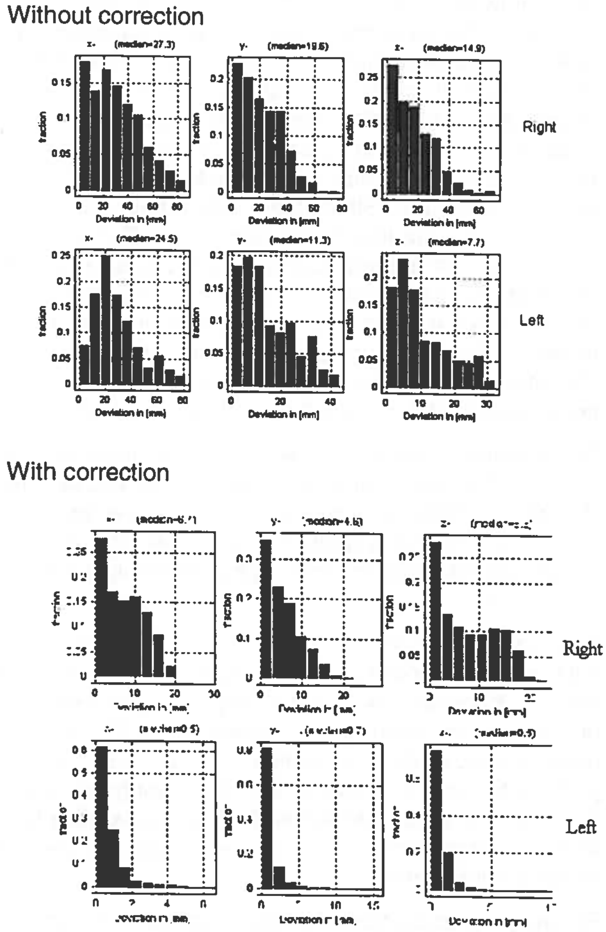

Figure 6. Histogram results without (top) and with (lower) correction from the analytical biomechanical model. Note the scale differences on the axis.

The accuracy has been improved by a factor of 3.5 compared to the non-corrected case.

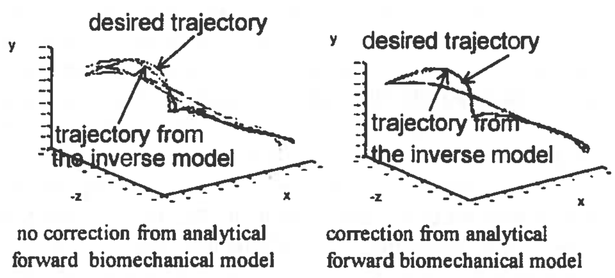

Figure 7. Results with and without correction from the analytical biomechanical model. In the right figure (without correction) the model trajectory coincides with desired trajectory. In the left figure (without correction) can a small difference between the model and desired trajectory be seen.

THE COMFORT EVALUATION SYSTEM

Perceived comfort when handling control buttons in a specific position was recorded in the car experiment. 15 other variables, a combination of personal and car environment information, which can affect the comfort opinion, were recorded too. It is supposed that comfort (y) is a non-linear function of the input variables x in terms of local affine models as was described in one of the previous sections. The available data set of 744 samples is randomly separated into two sets of equal size. The first set is used for the determination of the model's parameters. The second set serves for testing its performance. A mathematical and a subjective evaluation of the variables resulted in that four of them were used as input in the model. Figure 8 shows the result.

The rates from the open comfort scale were transformed into numbers (0=very uncomfortable and 100 very comfortable). The original comfort values have been sorted (monotonous line) in ascending order. The noisy looking line is the output of the fuzzy model. While the upper part is the model's response to the training data, the lower part of the figure is the result of the model when the test data are applied. It can be seen that the variance with regard to the test data is bigger than the variance on the training data. The model, however, is able to follow the trend in comfort. Unfortunately, high comfort values are systematically estimated too low by the model. Furthermore, some samples of the test data result in strong differences compared to the targets (e.g. samples no. 48 and 302) on the test set.

The performance can be further improved if a data analysis is performed first and data are sorted out. Doing this, just 544 samples remain. Splitting these into a training and a test set and repeating the modeling the corresponding result is shown in the following figure 9. As can be seen, the variance is mainly reduced on both sets now. High comfort levels are fairly good modeled even on the test data. Furthermore, training a model with the data removed by data analysis results in a poor performance. This indicates that the data removed seem to be in contradiction to the bulk of the data with regard to comfort interpretation.

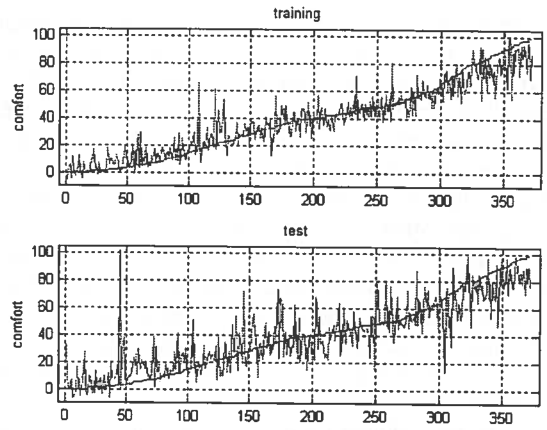

Figure 8. Fuzzy model results compared to input with the training set and the test set. All comfort data is used. The y-axis shows the perceived comfort (0=very uncomfortable and 100 very comfortable) and the x-axis sample index.

The experiment performed is encouraging and is a first step into the direction of modeling perception in terms of comfort. The next step is to use such a model in order to determine e.g. positions of the button which results in a high comfort for most of its input variables. The approach is described in a patent application [32] and is part of a demonstrator realized within the ANNIE project.

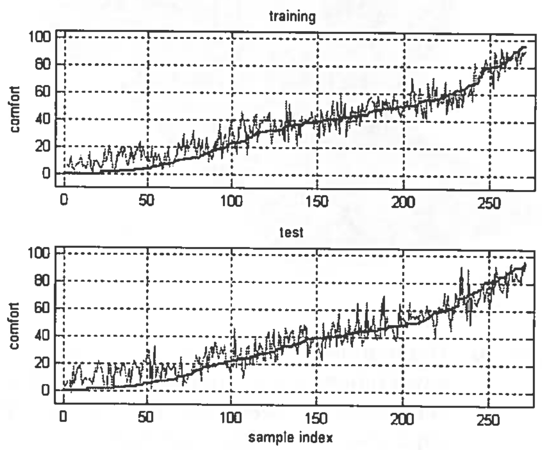

Figure 9. Fuzzy model results compared to input with the training set and the test set. Selected data is used. The y-axis shows the perceived comfort (0=very uncomfortable and 100 very comfortable) and the x-axis sample index.

CAR INTERIOR EVALUTION WITH THE ANNIE TOOL

The tool is based on parts of the simulation program ERGOman and uses the ANNIE biomechanical model, a variation of the ERGOman model. In the simulation program files of designed interiors can be imported. It is also possible to construct a new interior and make modifications in an old interior. The movement of the new improved ERGOman is controlled by the ANNIE neural networks. The net is trained to simulate short females and average as well as tall men driving and pushing a control placed at the center stack or the dashboard. Scaling of the mannequins' body proportions is possible. After and during simulation of the movement different tests can be performed. A small toolbox with ergonomic and safety methods suitable for interior evaluation was designed. The toolbox contains new developed methods and methods from the original ergoman mannequin. The comfort evaluation and the dynamic biomechanical tool are the new methods. The original ERGOman mannequin was able to simulate reach envelopes and field of vision. These features have been implemented in the toolbox. Figure 10 shows the mannequin seated in a car interior together with a visualization of the maximum reach zone without body assistance.

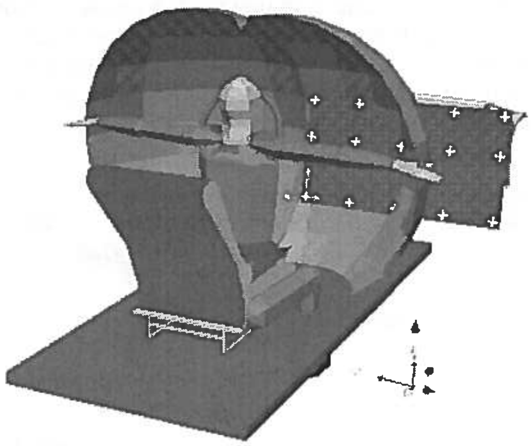

Figure 10. The mannequin is seated in a vehicle environment. Neural networks control the mannequin's movements. The software allow ergonomics evaluation, the figure shows reach envelopes as an example.

A typical working procedure with the annie/ergoman can be as follows. A designer imports a car interior environment. Environment parameters which influence the movement are specified, e.g. dimensions, temperature, noise etc. The new control button is positioned on the dashboard or the center stack. The object characteristics which affect the movements are defined, e.g. button size. The second step is to import the mannequin and position it in the environment in a natural seat position. The mannequin characteristics and qualifications are defined, e.g. anthropometric data, gender, motivation and experience of the task. Finally the task is described in a code based on the MTM-language. Codes as 'apply pressure', 'move' and 'reach' are used. On a command from the designer, the mannequin simulates the control handling, pushing the button naturally dependent on the environment, the object and the human characteristics. During the movement and afterwards it is possible to evaluate the movement, both for safety (by field of vision) and for comfort (operating comfort, biomechanical analysis). The designer gets in this way an idea in the early design phase how to modify the conceptual interior to better fulfil the design requirements and desires.

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