A New Hybrid Methodology for Motion Emulation in Virtual Environments

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Abstract

Simulation of natural human movement has proven to be a challenging problem, difficult to be solved by more or less traditional bio-inspired strategies. To simulate human-like movements in a virtual environment a sample database of real movements has been first transformed into sequences of instantaneous states of an explicit biomechanical model. These are then associated to an anthropometrical class of reference in order to be interfaced with an artificial neural network, resulting in a new hybrid approach for data aggregation. Experimental tests have been performed on the upper part of the human body, in particular on the movements of arms and head with respect to the trunk. The analysis has been focused on three different tasks, chosen in assembly line, car interior and manufacturing environment.

Keywords*: Ergonomics, simulation, modelling, virtual humans, optimisation, neural networks.*

1. INTRODUCTION

Human interaction with such complex systems as working places, driving seats, or cockpits is more and more asking for designers to face both the human-machine compatibility ("industrial ergonomics"), and the efficiency of the overall engineering system. Because of the rising costs in product development, the market is issuing a growing demand for advanced ergonomic tools, capable to assist the product designer in evaluating the human behaviour under several perspectives. In particular, the correct simulation of pseudo-human movements in virtual environments could help designers to assess the suitable ergonomic variables and their influence on some product features. This gives the opportunity to avoid both the construction of physical mock-ups and the execution of long experimental runs on real people at an early design stage.

In opposition to several existing solutions, mainly based upon deterministic algorithms [7][8], a data-driven approach is presented herewith, which is able to grasp the natural essence of human movements. The work aims to propose a methodology based on the inference of each pseudo-human (i.e. virtual) movement, starting from a sample database of real ones, previously logged by means of any data acquisition system.

ANNs (Artificial Neural Networks) have shown their suitability in descriptive and predictive generalisation of complex systems. They offer the possibility to take real experimentally acquired kinematical data and to interpolate and extrapolate the movements into conditions that have not actually been recorded.

The nature of the problem suggested a two-step methodology.

In the first step, each real movement is transformed into a set (or sequence) of instantaneous states (or postures) of a parametric biomechanical model. This transformation procedure also allows estimating the uncertainty associated to the biomechanical model parameters.

In the second step an artificial neural network (ANN) has been adopted to learn the way humans perform elementary tasks.

In order to reduce the complexity of the second step, data related to different subjects, or different tasks, can be compared if these different cases are referred to a standard mannequin. Such data are obtained by sampling the movement of suitable checkpoints that, in the actual experiment made herewith, correspond to passive markers (fig. 1) attached to the human body and logged by a specific acquisition system - ELITE – developed at the "Politecnico di Milano" [12].

Therefore an anthropological classification, combined with a suitable data transformation procedure, is given in order to interface the network with a set of mannequins-independent data, representing a standard sequence of postures.

An application of this hybrid approach to a simple experimental case is presented, which proves that the proposed data analysis could be afforded without any underlying hypotheses about the human dynamics.

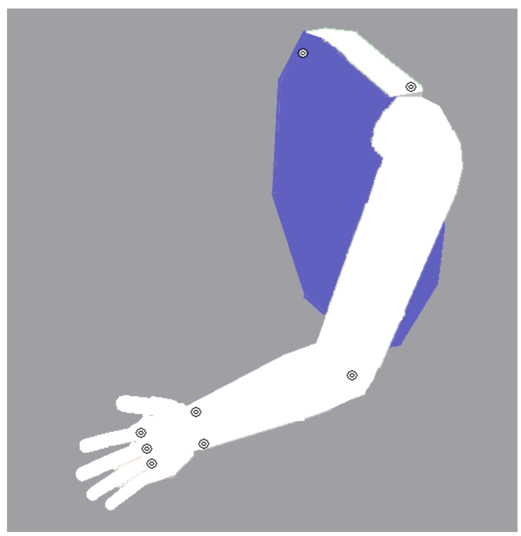

Figure 1: Example of marker position for detecting the movement of a human arm.

2. THE HYBRID METHODOLOGY

In case of complex systems it is hard to assess all the system parameters by means of a set of direct and independent measurements, as the specific context could affect any identification methodology of the very parameters.

Specifically, collected data can be represented as a series of Cartesian trajectories of checkpoints (hereafter referred as raw data), measured in laboratory co-ordinates. In principle, raw data could be completely interpreted by means of an ANN: the latter could learn both the structural (i.e. anthropometrical) and dynamic relations among raw data and other ergonomic factors. Anyway the two faces of the same problem should better be de-coupled upon availability of an explicit model for structural relations only. This hybrid approach is justified by a set of reasons, listed below [3][4].

Since the biomechanical features of the person under test are known in advance, there is no use to make recourse to neural computation in order to determine those constraints imposed by geometric relations among the marker locations, which – in case of tests performed on a single person – are fixed throughout the whole set of experiments. Otherwise, the ANN would be indirectly charged with the target of modelling those time-invariant relations that have a different nature from other time-dependent relations and factors mentioned above.

In case of tests performed on more individuals, relative raw data cannot be directly compared and used to train the same ANN: as a matter of fact, the constraints imposed by geometric relations among the marker locations would be different from person to person, and would ask for further integration to the neural computation.

For both cases, given any other set of conditions, a demand for wider integration would negatively reflect on the total uncertainty of the ANN prediction.

Another reason arises from the fact that the ultimate purpose of this work is to reproduce a realistic simulation of human movement by means of a virtual mannequin, implemented in a CAD environment. The latter obviously imposes its own geometric relations, thus giving rise to unavoidable discrepancies between the mannequin movements and the information got back by the ANN (based on raw data, whatever real test they may represent).

As to what has been stated above the sampled raw data are first used to evaluate the parameters of an explicit model for the structural relations among marker locations. The fitting model is used to define a referring posture at every time step, which in its turn is identified by the set of model state variables (i.e. angular values of rotational joints). In such a way, raw data are transformed into a sequence of values for such variables, representing the information quota strictly related to the dynamic characteristics of human movements.

The proposed structural model, in its overall form, consists of a cinematic chain with *G* segments and *M* joints, and with a total number of *D* degrees of freedom (DoFs).

A *local reference system* is attached to each segment S_j in order to reconstruct its position and orientation in the space.

Denote with L_j and L_w the *local reference systems* of two consecutive segments, respectively S_j (descendent) and S_w (parent). If $\boldsymbol{P}_k^j$ is a column vector specifying the homogeneous co-ordinates of a generic point *k* in the local reference system L_j, the vector $\boldsymbol{P}_k^w$, specifying the homogeneous co-ordinates of the same point in the parent *local reference system* L_w can be calculated as

$$\boldsymbol{P}_k^w = \boldsymbol{A}_j^w \boldsymbol{P}_k^j = \begin{vmatrix} & \boldsymbol{R}_j^w & & \begin{matrix} x_j \\ y_j \\ z_j \end{matrix} \\ 0 & 0 & 0 & 1 \end{vmatrix} \boldsymbol{P}_k^j \quad (1)$$

where (x_j, y_j, z_j) are the co-ordinates of the origin of the local reference system L_j with respect to L_w and $\boldsymbol{R}_j^w$ is the rotation matrix of L_j with respect to L_w.

By identifying the origin of each *local reference system* with the rotation joint centre that links the current segment with its parent, the co-ordinates (x_j, y_j, z_j) allow for the straight recover of the distances between joint centres, that is the anthropometrical lengths or structural parameters of the biomechanical model.

Now denote with $S_0\, S_x\, S_y \ldots\ S_w\, S_j$ the polygonal that belongs to the cinematic chain starting from the root, up to the segment S_j, where the elements of the polygonal are selected according to the topology of the current chain. The laboratory homogeneous co-ordinates $\mathbf{T}_k$ of a checkpoint *k* integral to the anatomical segment S_j can be recovered starting from its local homogeneous co-ordinates $\boldsymbol{P}_k^j$ with respect to L_j as follows:

$$\mathbf{T}_k = \boldsymbol{A}_x^0 \boldsymbol{A}_y^x \ldots \boldsymbol{A}_j^w \boldsymbol{P}_k^j \qquad (2)$$

where the elements of eq. (2) are again selected according to the topology of the current chain. From the homogeneous co-ordinates $\mathbf{T}_k$ it's easy to obtain the laboratory co-ordinates $\mathbf{t}_k$ by selecting the first three elements of the array.

The biomechanical model establishes clear-cut hypotheses as to the nature of raw data before processing takes place. That is:

1. All the checkpoint positions measured on the same individual during the same experimental session derive from the same instance of the biomechanical model, which means that the model structural parameters are time-invariant.
2. All the checkpoint positions that belong to the same posture derive from an instantaneous state of that instance (i.e. not only the structural parameters, but also the DoFs are fixed).
3. Discrepancies between the measured raw data and checkpoint positions arise because the formers are affected by noise.

Of course the biomechanical model is not perfectly faithful. Strictly speaking there exist no "true" values of its structural parameters and DoFs. However "optimal" (i.e. maximum likelihood) values can be found through a suitable fitting procedure provided that a noise model is given.

3. MODEL FITTING

The model is characterised by *G* free structural parameters h_j (segments lengths: pelvis, trunk, clavicles, arms, legs,…), *M* joints and *D* degrees of freedom $\omega_{i,l}$ (rotation computed for *G* reference systems angles and translation co-ordinates of the *local reference system* attached to the root with respect to the laboratory system). Further unknowns are the locations $\mathbf{p}_k$ of the checkpoints with respect to the local reference systems.

The functional form (2) depends on the above-mentioned structural parameters whose values have to be determined to see the model practically behaving as a human emulator. So identification is necessary. The simplest way to proceed in this identification is to measure them with independent procedures for each frame starting by the marker positions registered by ELITE (intra-frame procedure). The estimates of the anthropometrical lengths are the mean values of the obtained samples. This way to identify the parameters is the simplest, but it can be criticised for two reasons:

- it is based on hypotheses about the locations $\mathbf{p}_k$ of the checkpoints with respect to the local reference systems.
- it doesn't provide the optimal estimate of the model

parameters.

A statistical estimation technique can overcome these inconveniences.

By denoting:

- i as the posture index,
- k as the marker index,
- $t_{i,k}$ as the laboratory co-ordinates of a checkpoint k in the posture i, calculated by means of eq. (2),

the expected value $E(y_{i,k})$ of the measured data $y_{i,k}$ is related to the quantity $t_{i,k}$ as follows:

$$E(\boldsymbol{y}_{i,k}) = \boldsymbol{t}_{i,k} \qquad (3)$$

It has been assumed that the errors $(\boldsymbol{y}_{i,k} - \boldsymbol{t}_{i,k})$ are independent and normally distributed, with a standard deviation $\sigma_{i,k}$, which expresses the uncertainty of the measured data $\mathbf{y}_{i,k}$,

In this way the statistical process can be stated as an optimisation of the likelihood function expressed by the following relationship:

$$L = \frac{1}{\prod_{i,k} \sqrt{2\pi} \cdot \sigma_{i,k}} \cdot \exp\left(- \frac{\sum_i \sum_k \left\| \mathbf{y}_{i,k} - \mathbf{t}_{i,k} \right\|^2}{2\sigma_{i,k}^2} \right)$$

Three kinds of parameters (i.e. quantities whose optimal values have to be found through the fitting procedure) are included therein:

- Lengths of anatomical segments h_j.
- Checkpoint positions $\mathbf{p}_k$ in each local reference system.
- Rotation angles and translation co-ordinates $\omega_{i,l}$.

The fitting procedure performs an inter-frame estimation treating each movement as a whole. By denoting with λ_i a generic parameter included in the previous listed class (hereafter denoted with Λ), the set of values $\Lambda^o = \lambda_1^o, \ldots, \lambda_i^o, \ldots, \lambda_n^o$ that maximise the cost function L represent the set of maximum likelihood estimates for the set of parameters Λ.

No hypothesis about the locations $\mathbf{p}_k$ of the checkpoints is needed. The fact we leave free these parameters can permit an estimate of the positions of the markers, which do not enter as an input in our identification procedure, therefore permitting a better fit with experimental data.

However, most elements of the roto-translation matrices are set in advance. Their values fix additional structural constraints. For example, some joints have less than 3 associated DoFs. Moreover, some critical checkpoints are used to identify reference frames of relative reference systems. In this way such critical frames - associated to critical checkpoints - are time-invariant. Provided that such critical checkpoints are carefully positioned on the body, the same "physical" meaning of joint angles could be preserved also across different individuals.

After the fitting phase checkpoint positions loose their usefulness. The relevant informations inherited from the original experimental evidence together with the structural hypotheses are summarised into the optimal values of all the other parameters.

Denoting with λ_r, λ_s two generic parameters belonging to the set Λ, it's possible to define the elements of Fisher's matrix F as follows:

$$F_{r,s} = -E\left(\ell''_{r,s}\right) \qquad (6)$$

where:

$\ell = \ln(L)$ is the logarithmic likelihood function

and

$\ell''_{r,s} = \dfrac{\partial^2 \ell}{\partial \lambda_r \partial \lambda_s}$ are second derivatives of ℓ computed in the maximum likelihood point Λ^o, $\forall \lambda_r, \lambda_s \in \Lambda$.

Using asymptotic properties of maximum likelihood estimators [11] the covariance matrix of the estimates can be expressed as:

$$\mathbf{C} = \mathbf{F}^{-1} \qquad (7)$$

where:

- $c_{i,k} = \mathrm{cov}(\lambda_i, \lambda_k)$ is the covariance between the estimated parameters λ_i and λ_k;
- $c_{i,i} = \sigma^2(\lambda_i)$ is the variance of the estimated parameter λ_i

The calculus of the covariance matrix $\mathbf{C} = \mathbf{F}^{-1}$ has been performed by means LU decomposition. In this way we took advantage of the properties of the matrix **F,** which is symmetric and positive definite, then it has a special, more efficient, triangular decomposition, i.e. the Cholesky decomposition that is about a factor of two faster than alternative methods for solving linear equations [10]. Instead of seeking arbitrary lower and upper triangular factors, Cholesky decomposition constructs a lower triangular matrix whose transpose can itself serve as the upper triangular part.

4. THE NEURAL NETWORK

Contrary to previous works, which rely on explicit assumptions about some relevant features of movement [5][6][7], our neural model is essentially based on the mere description of the problem itself.

In this methodology it's supposed that the execution of a determined sub-task is strongly dependent from the behaviour of one anatomical district called effector (e.g. the forefinger tip during a reaching movement, the rotation DoF of the hand in a screwing task, etc.); therefore the values of its state variables are taken into account both in the task description and in the joint angles prediction. This suggested separating the overall prediction in two subsequent stages:

- The first stage predicts the motion of the "task effectors" on the basis of the detailed description of the task to be performed along with the initial state of the specific anatomical segment(s) involved [1][2].
- The second stage predicts the sequence of states of the biomechanical model on the basis of the outcome of the preceding stage [13][14].

Even though we focus here on the first step, the meaning of the pre-processing procedure can be fully understood only if we consider the overall system.

We can represent the behaviour of the first stage as a discrete-time mapping:

$$\mathbf{x}_n = \mathrm{F}(\mathbf{x}_{n-1}, \mathbf{x}_{n-2}, \ldots, \mathbf{x}_{n-i}, \mathbf{y})$$

being $\mathbf{x}_n$ the position of the anatomical point of interest at the *n*-th time step, F a generic non-linear function; i the number of previous positions to be taken into account; $\mathbf{y}$ the set of “exogenous" inputs that describe the task to be performed; that is, for reaching movement, the desired initial and final positions of the forefinger tip, together with the duration T of the movement of the effector.

In this way we allow the network to learn how duration affects the shape of the trajectory as well as the velocity profile. This reformulation of the problem, that is the determination of the appropriate mapping F, finds its immediate neural counterpart in a recurrent auto-regressive network. Supervised training can then be accomplished by means of - for instance - the popular Back-Propagation Through Time (BPTT) algorithm [15]. A second-order regression scheme (i.e. with $i = 2$) allows the network to “sense" both the velocity and the acceleration of the checkpoint. This leads to an almost complete definition of the outer architecture. The insertion of a single hidden layer with full connectivity simply meet a parsimony requisite (fig. 2).

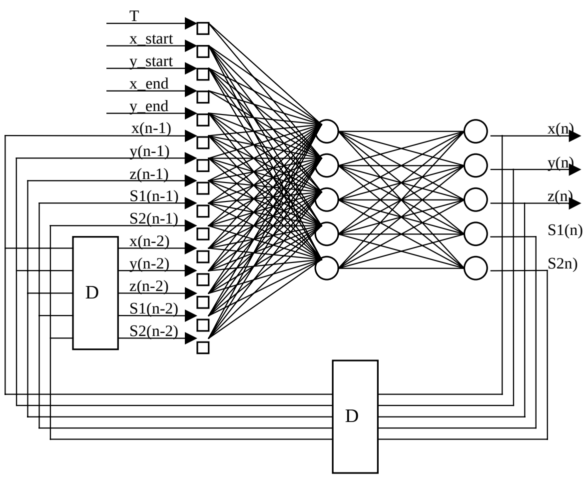

Figure 2. Neural network topology

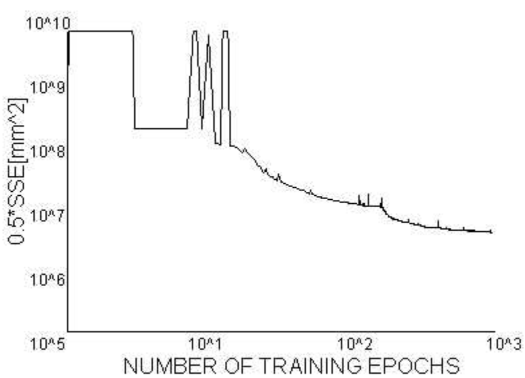

Figure 3. Cost function versus number of epochs

This kind of network could easily be extended to learn more general (i.e. non time-invariant) mappings. To this purpose some “floating" state neurones are added to the output layer**;** their responses are fed back to the hidden layer according to the same second-order scheme.

During the training phase the recurrent network has to be unfolded in time in order to compute the error signals coming from all the points of the trajectory. It therefore becomes like a huge *multi-layer perceptron* with massive weight sharing, whose depth depends on the duration of the movement. Because of that gradient components are likely to span a very large dynamic range both across weights and training epochs.

The training process, supported with the Davidon-Fletcher-Powell algorithm [16][17], represents the first step of quantitative validation of the network capabilities. The fig. 3 shows the cost function versus the number of training epochs in a manufacturing press experiment. The total square error (SSE) in a point to point lifting movement, after 1000 epochs, leads to a RMS error on the single trajectory point about equal to 39 mm. Starting from random weight values, it can be noticed that the function decreases about 2 orders of quantity in magnitude. Fluctuations take in evidence the “line-search” phase, in other words the research of the direction along which the function value is minimised.

5. SOME RESULTS

The experimental tests have been performed on the upper part of the human body, in particular on the movements of arms and head with respect to the trunk. The analysis has been focused on three different tasks, chosen for their industrial relevance, in three different environments:

- *Workbench tasks*, assembly line environment
- *Driver operating controls*, car interior environment
- *Mechanical press tasks*, manufacturing environment

performed by individuals belonging to 5th, 50th and 95th percentile.

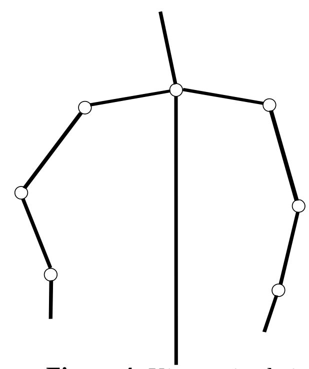

Figure 4: Kinematic chain

The adopted structural model consists of a kinematical chain with 11 segments and 8 nodes (fig. 4) for a total number of 30 DoFs, arranged as follows:

- Pelvis: The pelvis has 6 degrees of freedom to define its position and orientation with respect to the laboratory reference system.
- Trunk: The trunk has 3 degrees of freedom to define its orientation with respect to the pelvis.
- Head: The 3 DoFs describe the head orientation with respect to the trunk.
- Clavicles: The 2 DoFs approximately describe each clavicle orientation with respect to the trunk. The rotation of the clavicle along its longitudinal axis has been neglected.
- Arms: The 3 DoFs describe each arm orientation with respect to the clavicles.

- Forearms: The single DoFs describes each forearm orientation with respect to the arms. It's the rotation angle of the forearm with respect to the arm along the normal around to the plane defined by the longitudinal axis of both the arm and the forearm.
- Hands: The 3 DoFs describe each hand orientation with respect to the forearms.

Roughly speaking, the set of hypotheses on the structural model can be possibly disproved by evaluating the residual discrepancies, i.e. the three-dimensional distances $d_{i,k}=\left\| \boldsymbol{y}_{i,k} - \boldsymbol{t}_{i,k} \right\|$ between the actual marker positions and those derived from the model (virtual markers).

In particular, the inter-frame process has carried out a mean value of the this set of distances about equal to 3.5 mm, approximately 10 times less than the correspondent intra-frame value.

However, the validation process has remarked some criticism on the pelvis marker, probably due to the skin motion on the Great Trochanters. This phenomenon, particularly present in a car driving experiment (*driver operating controls)*, has led to a maximum distance from the measures about equal to 15 mm.

The obtained mean value of the whole set of distances $d_{i,k}$ is about 5 mm, which is an acceptable value for the scope of this work.

The tables 1 and 2 show the results for some anthropometrical measures and for the angular positions of the rotational joints.

	μ (cm)	σ (cm)
Clavicle	20.1	5e-01
Arm	33	1
Forearm	27	1

Table 1. Maximum likelihood values for the average and variance estimates of the anthropometrical lengths

	ψ (°)	θ (°)	φ (°)
Trunk	3	1	2
Head	2	4	3
Clavicle	4	3	-
Arm	5	3	2
Forearm	-	1	-
Hand	2	2	3

Table 2. Mean values of the uncertainties for the Eulero's angles estimates (φ_j, θ_j, ψ_j)

The following architecture has been validated: 7 inputs, 5 hidden neurones, 2 state neurones and 3 target neurones. To take into account the dependence by the past positions, a feedback of 2nd order mechanism has been introduced, on the state and on the output, by means of 4 and 6 supplemental neurones.

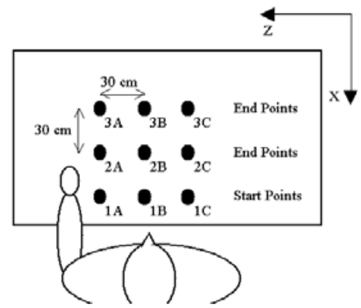

Figure 5: Experimental set-up

An extrapolation protocol has been developed to achieve this goal. A right- handed subject, belonging to the 50th male percentile, has been experimentally surveyed in reaching point to point movements of the right arm among 9 points on to the same plane (fig. 5). Considering the whole task formally composed by the forward and the backward action, 460 complete movements have been acquired and processed at a sample rate of 50 Hz. The figure sketches the experimental set-up.

Leave one out procedure has been performed on the neural architecture implemented to support simulation in assembly, car driving and press environments. One movement at time is extracted from the training set, the network and its response is then compared with the left-out item. The fig. 6 and 7 show an example of this test performed on the hand effector net, both for the forward and for the backward movement, in 24 experimental trials of the same movement. We extracted the movement from the boundary of the training set region (in particular from the upper-left corner) in order to test the extrapolation capabilities of the network.

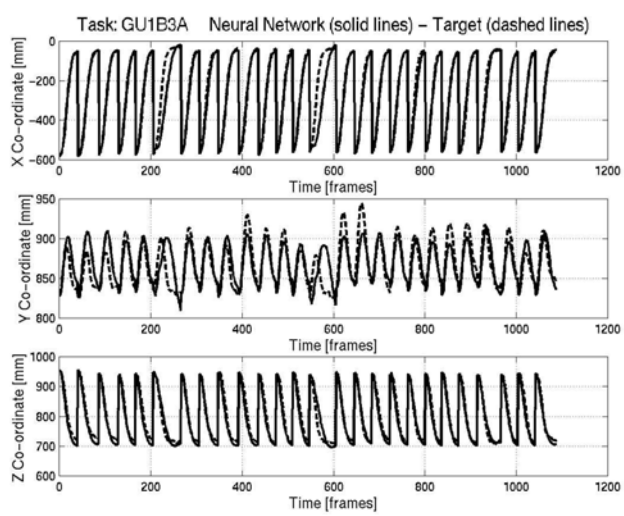

Figure 6: Hand effector net for the backward movement

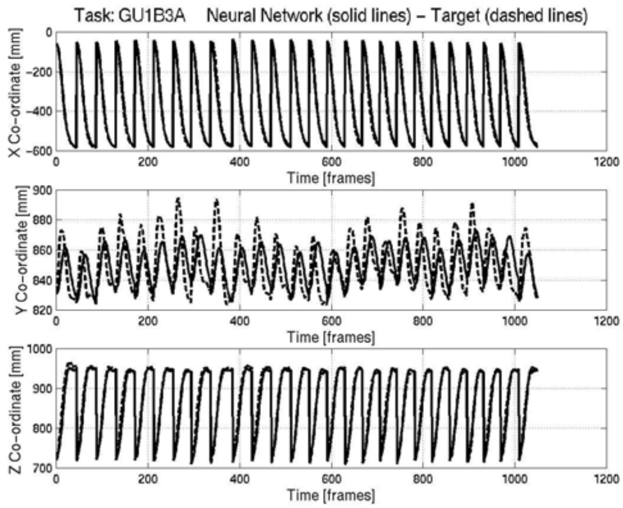

Figure 7: Hand effector net for the forward movement

In qualitative terms, the predicted trajectory appears very smooth and regular, even if training data coming from the identification procedure have also fitted measure noise. Moreover, also temporal features seem to be learned.

The results intended as discrepancy between neural prediction and data left out from the training process, have been expressed in terms of average value of the RMS error on the repetitions of the same task. For the forward movement it varies from 6.28 to 48.51 mm on the single co-ordinate. In the other case it is from 6.55 to 50.08 mm. These values appear quite plausible with respect to the intrinsic variability of the movement, intended as the discrepancy among different trials of the same task, performed by the same subject.

6. CONCLUSIONS AND FUTURE DEVELOPMENTS

Previous paragraphs show the reliability of our ANN data-driven approach to human movement generation. We fixed a methodology tailored to relieve ANN core from the burden of any kind of structural identification. This method appears more flexible and no model is embedded.

We use MLPs, checking the predictability of the movement in term of expectations. The validation procedure demonstrated the reliability of the architecture in learning and simulating the human movement in tasks, chosen for their industrial relevance, in three different environments. In particular, encouraging results arise from extrapolation capabilities also in tasks not explicitly taken into account during the design.

New involved aspects about the simulation of the postural behaviour became visible. The possibility of learning kinematical time sequences of clustered individuals, weighted by their joined uncertainties, appears very interesting.

7. ACKNOWLEDGEMENTS

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