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A method for posture prediction of the upper trunk of video terminal operators

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ABSTRACT
This paper presents a method for posture prediction of the upper trunk of video terminal (VDT) operators, which is then verified by means of some test cases. The prediction of the upper trunk posture is, in fact, a very difficult task to carry out due mainly to the complexity of the anatomy of the spine and the surrounding muscles. The method being proposed in this paper is based on the integration of the knowledge which is obtained experimentally through the posture analysis of real cases into a configured human multi-body kinematic model which has been implemented in a commercial CAD system. A trained artificial neural network retains the knowledge concerning the VDT operator's postures detected in different working positions. The posture simulations obtained with the proposed method are subsequently compared with the real ones determined by a 3D scanner. The results obtained confirm the effectiveness of such a method, which is deemed promising to implement other anthropometric data and further human poses.

KEYWORDS
Posture prediction; ergonomics; multi-body virtual human models; artificial neural network

1. Introduction

Every individual assumes a posture (for the most part, without a conscious decision) when interacting with the surrounding workplace. Such adaptability is possible thanks to the complex anatomy of the musculoskeletal system, which allows of different degrees of freedom. However, not all of postures are necessarily correct. When a non-correct posture is adopted for a long period of time it may cause musculoskeletal injury; as an example, low levels of seating comfort often lead to musculoskeletal complaints such as low back pain (LBP) [15]. In order to correctly design the working place, human factor analysis is an activity that should not be disregarded. Human models for ergonomic design are implemented in many commercial CAD systems [11]. For one thing, using a Digital Human Model (*DHM*) in designing a new working place arrangement or industrial product may reduce both the costs and the time required to produce and test product prototypes ([3], [12] and [16]). Another reason for favoring the use of *DHM* has to do with the highly variable level of human performance and attributes, which necessarily require a greater number of tests for a complete analysis. The reliability of a human posture simulation, therefore, lies on the capability of the *DHM* to reproduce the human body performance, as well as the complex interactions between the subject and the external environment.

The spine, on its part, can be represented as a complex multi-joint structure whose configuration determines the upper-trunk posture. However, the considerable complexity of the articular system of the spine and its interaction with the head make it difficult to model the upper trunk without large approximations ([14] and [19]). Considering that there is not a unique relation between posture and human interaction with environment, but rather a complex one, which is determined by unpredictable kinematic constraints (such as the fibrous connective tissues that join the articular surfaces of bones), it follows that human pose, and hence spine configuration, are difficult to reproduce, due precisely to the postural attitudes of each individual and the voluntary human intents.

In order to solve the inverse kinematic model, each part of the human body can be described by a properly defined biomechanical equation which characterizes some aspects of human performance, such as discomfort or required energy [17]. In this sense, human posture is deduced by solving an equation system ([14], [9], [10], [8] and [18]). In the related literature, this approach is used in simple cases, for which few biomechanical equations are required, such as, for instance, the case of the right upper limb or arm. This affords a very limited number of degrees of freedom, though, especially if we bear in mind the fact that the articular system of the spine requires at least 24 DOF to be described.

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Another way of implementing a complex inverse kinematic model is by using artificial neural networks (ANN). Artificial neural networks, like biological neural networks, contain a collection of neuron units communicating with each other via axon connections. The memory of a neural network is included in the synaptic weights that are adaptively trained by a learning mechanism. A multilayer feed-forward neural network with an arbitrarily large number of units in hidden layers can approximate any real continuous function. It is for this reason that neural networks are also proposed to implement human biomechanical models ([11], [13] and [20]). Rezzoug and Gorce [13], on the one hand, present a technique based on neural networks that maps the fingertip 3D position and the corresponding joint angles so as to predict the hand and finger postures during grasping tasks. Zhang et al. [20], on the other hand, present the concept and the implementation of the ANN-based posture transformation methodology, which reconstructs the configuration of the human body, in arbitrary postures, through 27 landmarks. More recently, Bataineh et al. [2] have proposed the use of an ANN for predicting the upper-body posture for a 41-DOF human model. This is a preliminary work to test the capability of a neural network to reproduce the inverse kinematics model of a digital manikin. They do not introduce nothing news concerning the reproduction of a realistic posture.

In order to perform an accurate prediction the upper-trunk posture of real video terminal operators, in this paper a new approach is proposed, which integrates the kinematic model of the spine with the knowledge about human postures. With the intent to survey the knowledge concerning human postures, who are somewhat constrained by the assigned working positions, an accurate method to detect the shape of the spine has been used. Then the data related to the environment interaction has been transformed into a map between upper trunk kinematic parameters and manikin interaction with the environment. This map defines the configuration of the multi-body structure representing a virtual manikin.

2. Trunk anatomy

The geometry of the lumbar spinal column plays an important role in determining human posture. It is a complex anatomical structure that interacts with the surrounding musculature and that is constrained by the position of arms, head and pelvis. The lumbar spine is a flexible structure composed of vertebrae, which are rigid elements. It consists of 24 vertebrae (figure 1): 5 in the lumbar part (l1÷l5), 12 in the thoracic part (t1÷t15), and 7 in the cervical part (c1÷c7). The trunk posture is mainly conditioned by the orientation of the lumbar and the thoracic vertebrae. The lumbar vertebrae form a curvature, called lordosis, which is posteriorly concave. The thoracic vertebrae, on their part, form a convex curvature, called kyphosis (figure 1). These curvatures are typical of the standing posture of any human being. In the sitting posture, on the contrary, the lordosis curvature generally tends to be less curved and, in some cases, may even disappear [5].

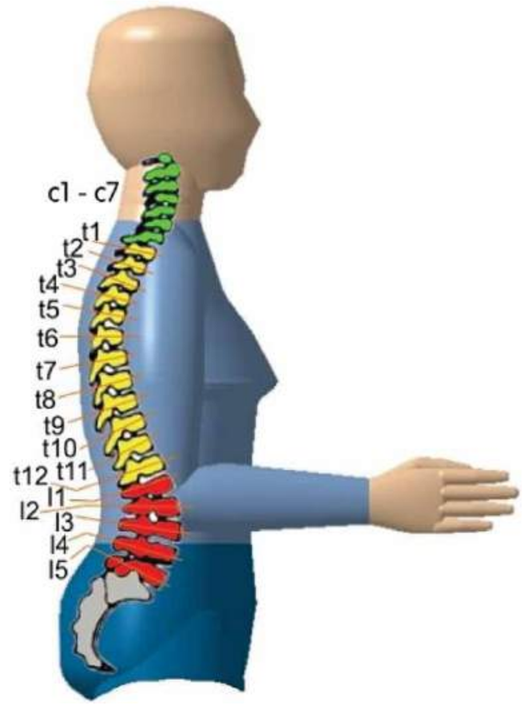

Figure 1. Human spine.

The trunk posture, therefore, can be defined in terms of the orientation of the motion segments and in terms of the orientation of the thorax with respect to the pelvis. The motion segments are the fundamental building blocks of the spine and consist of two vertebrae connected by intervertebral discs and by a number of ligaments. 24 motion segments which correspond to vertebrae can be identified in the human spine.

3. Enhanced digital human model

The method proposed in this paper is briefly described in the chart in figure 2. It performs an *Enhanced Digital Human Model* (*EDHM*), based on a classic kinematics model of the human body, in which the knowledge concerning the postural attitude is implemented by means of an *Artificial Neural Network* (*ANN*). The number of the degree of freedom of a manikin is greater than the constraints that a working plane can determine. So that, for a given manikin position, the redundancy of degrees

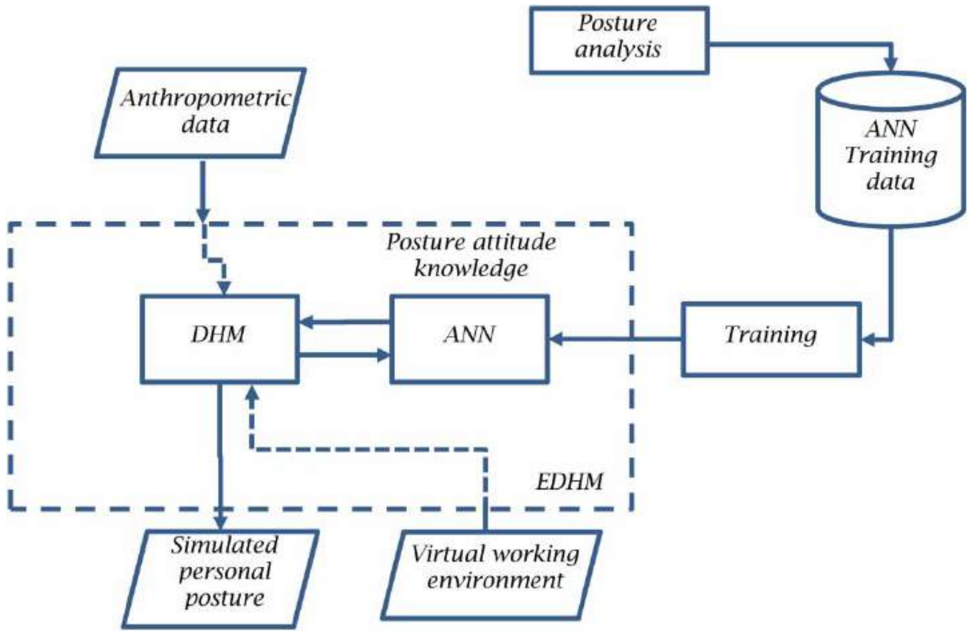

Figure 2. The proposed method chart.

of freedom (DOF) involves that alternative postures can be assumed. For each unconstrained articulation, it is known that there is a defined range of possible movements [1]; within this range, the specific value of these parameters determines a specific posture. The posture assumed by a specific subject can be described by a proper function which relates articular configuration with the tasks in the workplace, it is possible to say that this function describes the specific postural attitude of the subject. Typically in commercial *DHM*, the redundancy in kinematic parametric specification are solved according to a criterion which is generally unknown to the user. This criterion makes manikin postures rigid, un-personal and unnatural.

In the *Enhanced Digital Human Model*, here proposed, the under-determinate parameters of the kinematic model are furnished by a properly trained *Artificial Neural Network* that controls each kinematics segment when the manikin interacts with the working place. The *ANN* is, actually, the component of the model which retains the knowledge concerning the relations between environment interaction and body part configuration. In order to furnish the specific posture attitude of a real subject, some experiments have been performed in which the posture of VDT operators in action are analyzed. The *EDHM* consists in two main parts: the Digital *Human Model* (*DHM*) and the *Artificial Neural Network* which retains the specific postural attitude. When the anthropometric data are assigned, the *DHM* is configured to reproduce the dimension of a specific subject. The *ANN* is trained with the data concerning specific VDT operators which works performing a specific activity in a specific working place.

3.1. Posture attitude knowledge acquisition

In order to ascertain the postural attitude of VDT operators, some experiments have been conducted, and a pattern has been defined for setting up different working environment configurations. The number of postures which are necessary to identify the data to train the posture simulator grows factorially with the number of DOF. In this study, the posture simulator has been trained to reproduce postures that are defined in the *sagittal plane*; such is the case for the VDT operator. For this purpose, a configurable working environment has been reproduced in the laboratory (figure 3).

The working environment chosen consists of a seat with a footrest, a table and a target to be observed by the subject selected for the experiments. All the components of the simulated working environment may, nonetheless, be modified to define different working configurations. The environmental parameters used to design the experiment comply with EN ISO 9241 (2001); they are the following (figure 4):

- θ = angle between the line of view and the horizontal plane;
- a = distance between the buttocks and the table edge;
- b = height of the table with respect to the seat;
- c = height of the seat with respect to the footrest.

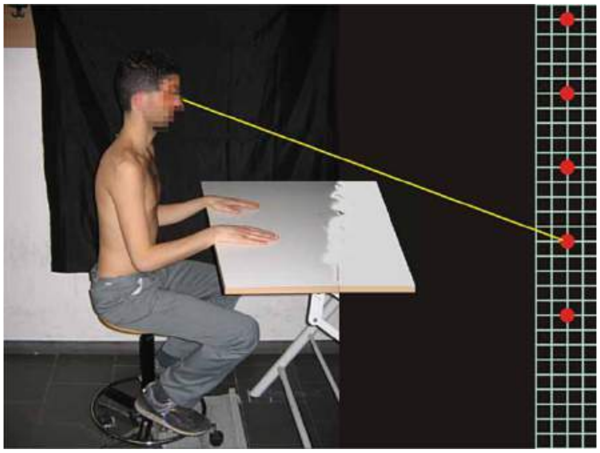

Figure 3. The experimental set-up.

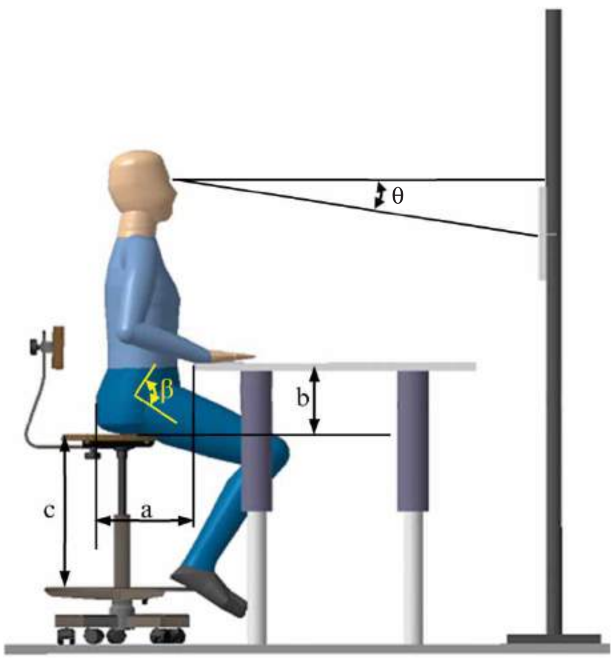

Figure 4. The four characteristic parameters of a VDT virtual working environment.

When the individual's anthropometric data and the parameter c are known, it is possible to calculate the angle β which measures the inclination between the femur and the base of the spine (L5) near the pelvis. The parameter β, through the pelvis configuration, greatly affects the sitting posture [5].

The geometry of the back must be acquired so that precise quantitative information can be taken. At this purpose, the geometry of the back is acquired by using a structured-light 3D scanner, which makes it possible to obtain the whole three-dimensional geometry of the back with a single scanning operation in a relatively short time with a density sampling of about 0.75 mm. The acquisition of the back needs to be complete and performed across the vertebral column. After the acquisition is completed, the point cloud is processed by a typical smoothing operation and then tessellated. This filtering process is useful to reduce outliers and large noise.

First of all, however, before scanning the geometry of the back, markers are placed on the individual in correspondence with the landmarks T1 and L5 of the spine column (figure 5a) so as to identify its beginning (vertebra T1) and its end (vertebra L5). Second, and with a view to detecting the vertebral column, a specific method to evaluate the *symmetry line* is used [6], which performs a 3D virtual reconstruction of the spine. Then, the typical human global reference frame is estimated, whose characteristic planes are *coronal* (Π_C), *transversal* (Π_T) and *sagittal* (Π_S).

For the type of postures which have been analysed, the *symmetry line* is nominally contained in the *sagittal plane*. In real cases, however, the *symmetry line* detected for a VDT operator is a curve which deviates from the *sagittal plane*. This deviation is, at any rate, limited, and, consequently, there is not a great difference between the 3D *symmetry line* and its projection onto the Π_S (figure 5).

The *symmetry line* evaluated by means of the method proposed in [5] is projected onto the *sagittal plane* and, then, approximated by using a polynomial parametric curve $\boldsymbol{c} = \boldsymbol{c}(t)$ of degree 3 (figure 5b). The interpolation of the points detected on the *symmetry line* is approximated by using a special kind of parameterization, in such a way that a linear map is defined between the value of the parameter t and the position of the column segments associated with the vertebrae. The value of t associated with *L5* is 0 and the value at the end of the column (*T1*) is 1. The approximation of the points $\mathbf{P}_\mathrm{i}$ is performed by the least-squares method, for which the best coefficients are those which minimize the sum of the squared deviations of the curve from the points $\mathbf{P}_\mathrm{i}$:

$$S = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \boldsymbol{P}_i - \boldsymbol{c}(t_i)^2} \qquad (3.1)$$

where the value of the parameter t_i associated with the point $\mathbf{P}_\mathrm{i}$ is evaluated as follows:

$$t_i = \frac{\sum_{j=1}^{i} \boldsymbol{P}_{j+1} - \boldsymbol{P}_j}{\sum_{j=1}^{n-1} \boldsymbol{P}_{j+1} - \boldsymbol{P}_j} \qquad (3.2)$$

This parameterization makes it possible to normalize the *symmetry line* with little deviation from the real value, regardless of the specific anthropometric characteristic of the analysed subject.

The spine is modeled as a multi-body kinematic structure comprising 17 motion segments (figure 6c). Each

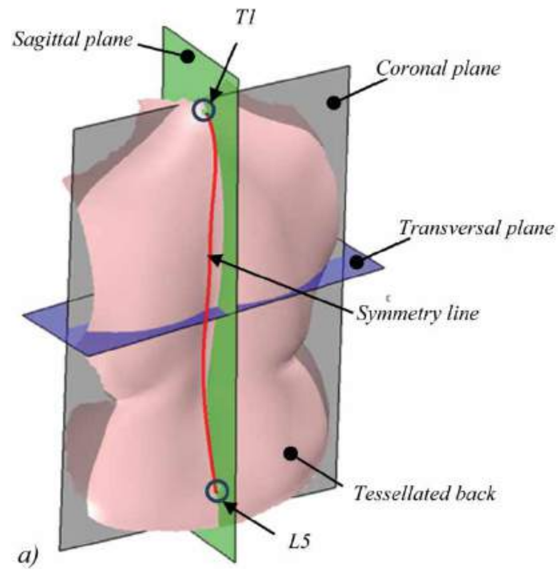

Figure 5. The point clouds acquired for the back of an individual, position markers and symmetry line.

motion segment of the lumbar spine is associated with a human vertebra and is defined as a rigid mechanical link. Thus the spine is modeled as an open kinematic chain in which each link is connected by ball-and-socket joints with both the previous and the subsequent vertebrae.

The dimension of each motion segment depends on the anthropometric characteristics which are chosen. The surveyed model of the spine, described by means of a polynomial function, is subdivided into 17 rectilinear segments whose lengths correspond to the links of the kinematic model. For this purpose, 17 intervals (t_i-t_{i+1} for i = 1, ...,18) of the parameter t of the curve $\boldsymbol{c}$ are identified, which correspond to the location and length of 17 vertebrae. The angle φ_i of the *i-th* link is evaluated as follows (figure 6 d):

$$\varphi_i = \arccos[\boldsymbol{x_i} \cdot \boldsymbol{x_{i-1}}] \tag{3.3}$$

where $\boldsymbol{x_i}$ is the direction of the *(i-1)th* link. The position and orientation of the end-effector of the i-th link is expressed, according to the Denavit-Hartenberg convention, in terms of the joint variables by the following transformation matrix ${}^{i}_{i-1}T$:

$${}^{i}_{i-1}T = \begin{bmatrix} \cos(\varphi_i) & -\sin(\varphi_i) & 0 & a_i \\ \sin(\varphi_i) & \cos(\varphi_i) & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3.4}$$

where a_i is the length of the link projected along $\boldsymbol{x_i}$. Therefore the position of the end-effector of the i-th link

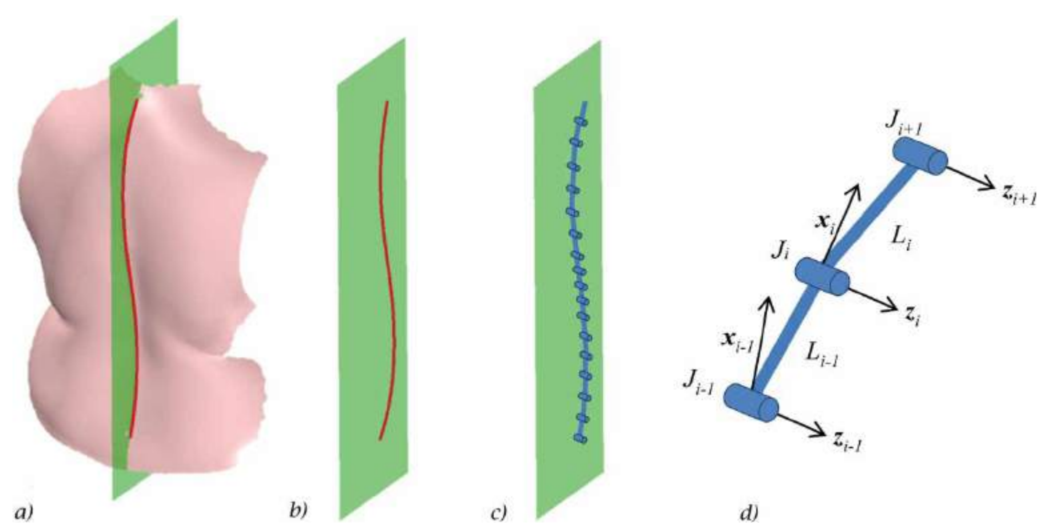

Figure 6. The multi-body kinematic structure modeling the spine.

in homogeneous coordinates ($\widetilde{P}_i$), as a function of the origin of the kinematic chain ($\widetilde{P}_0$), can be expressed as:

$$\widetilde{P}_i = \left(\prod_{j=1}^{i} {}^{j}_{j-1}T\right) \cdot \widetilde{P}_0 \tag{3.5}$$

4. Software and tests

The proposed method has been developed in a commercial CAD environment (CATIA V5 R12), by using the Visual Basic Developer environment, which implements the Safework® virtual manikin (DASSAULT SYSTEMS, 2014). Safework® provides a digital geometric representation of humans and permits the analysis of the interactions between the working place and the user. The skeletal structure of the human model comprises 100 independent elements and the complete model has 148 degrees of freedom, which are enough to ensure realistic joint movement capability. The spine is modeled with 17 elements (5 lumbar vertebrae + 12 thoracic vertebrae) and the neck is defined as a single rigid piece. It is a fully articulated spine that can be configured by setting the values of the angles between the 17 elements. The postures and movements of the Safework virtual manikin can be simulated by assigning control commands following a direct kinematic approach or an inverse kinematic approach. The direct-kinematic control commands make it possible to set the degree of freedom of each manikin component and assign its posture. Those direct control commands are generated by the trained neural network and presented to Safework®.

The neural network which has been used is of a back-propagation type and has been implemented in the MATLab platform. It consists of 4 nodes in the input layer, 144 and 72 nodes in the two hidden layers and 17 nodes in the output layer. The four nodes in the input layer are associated with the environment configuration parameters and each node in the output layer provides the inclination angle between two connected links (Figure 7). The activation functions used are sigmoid – tangent for the hidden layers and linear functions for the output layer.

In order to be able to generalize the results obtained in the posture reconstruction of a specific individual to apply them to others characterized by different anthropometric parameters, the input parameters a and b (figure 4) are then normalized. Parameters a and b are divided by the eye height:

$$\bar{a} = \frac{a}{\text{eye height}}; \quad \bar{b} = \frac{b}{\text{eye height}} \tag{4.1}$$

In order to train the *ANN*, in the present study, the spine geometry of three different individuals has been acquired for each of the simulated working environments, which are obtained by combining the parameters, previously defined, in a fully factorial set of experiments. The anthropometric parameters are depicted in figure 8 and the results for each individual are reported in table 1.

That is to say, the 45 working environment configurations (figure 9) are obtained with 5 different values for parameter θ, three values for parameters a and b, and

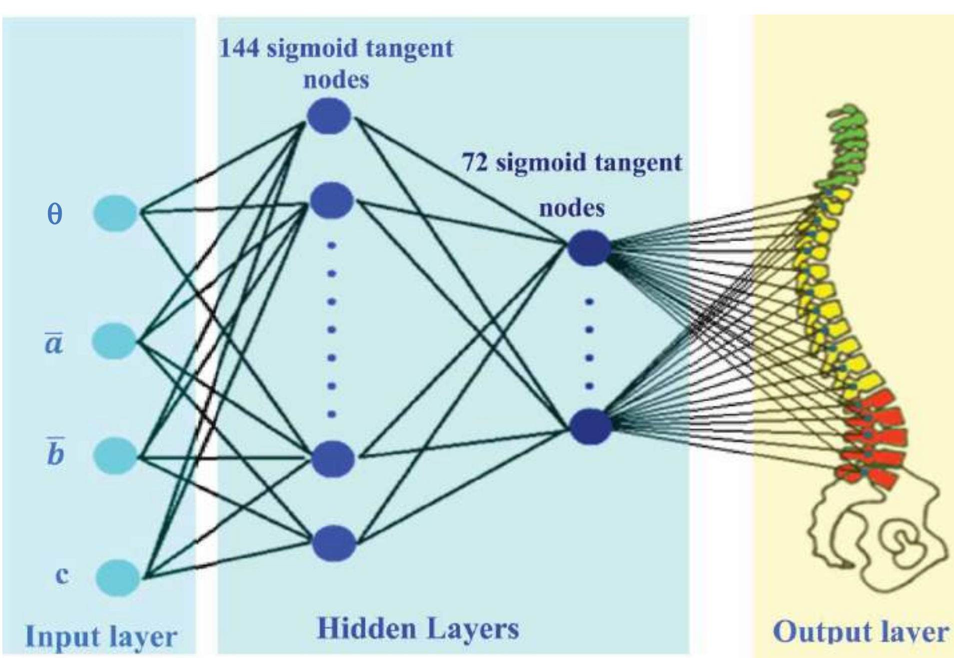

Figure 7. Neural network scheme.

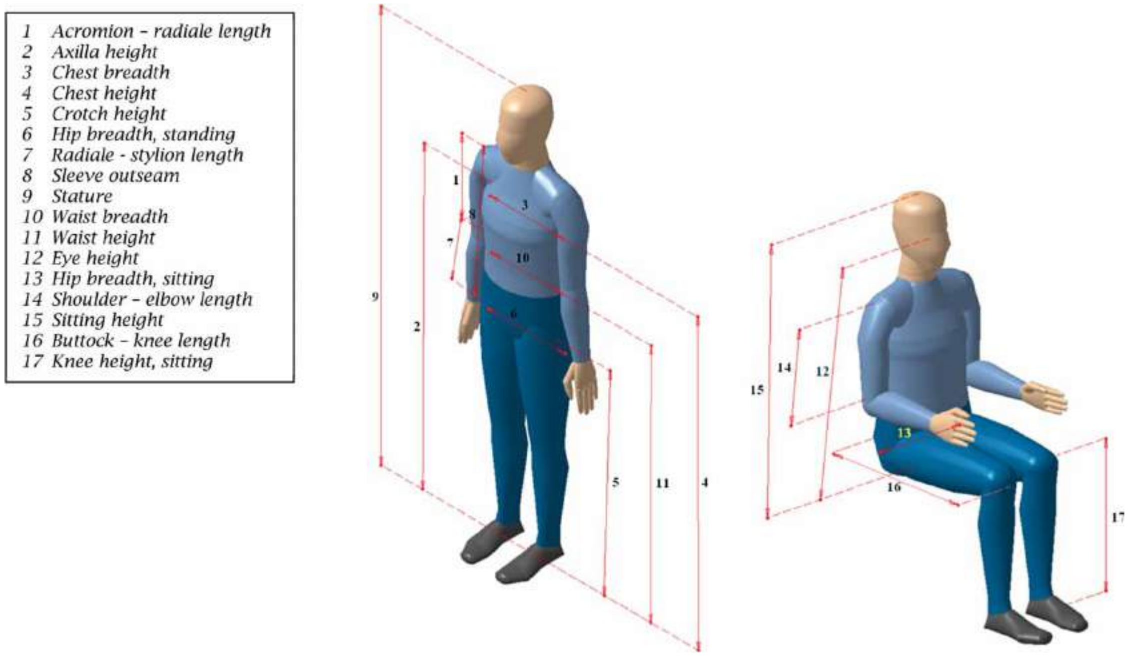

Figure 8. Anthropometric parameters used to characterize an individual.

Table 1. Anthropometric data that characterize the individuals analyzed.

Anthropometric parameters	*Individual No.1 [mm]*	*Individual No.2 [mm]*	*Individual No.3 [mm]*
Acromion – radial length	340	320	330
Axilla height	1390	1290	1440
Chest breadth	320	380	400
Chest height	1350	1270	1360
Crotch height	830	800	870
Hip breadth, standing	360	360	440
Radial - stylion length	240	270	270
Sleeve outseam	620	90	600
Stature	1780	1700	1860
Waist breadth	280	340	360
Waist height	1120	1010	1100
Eye height	760	730	800
Hip breadth, sitting	380	390	430
Shoulder – elbow length	380	360	370
Sitting height	900	890	920
Buttock – knee length	570	550	590
Knee height, sitting	590	570	610

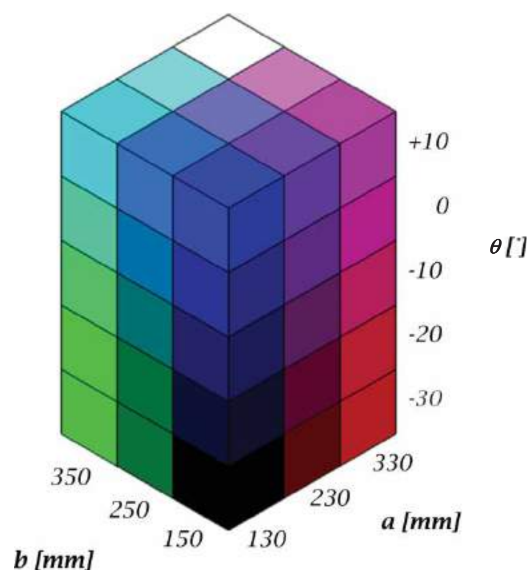

Figure 9. The 45 working environment configurations used in the posture experiments.

assuming a fixed value for parameter c (fixed value for β). In any case, the working environment for the experiment has been defined according to the optimum situation for EN ISO 9241 [7].

Some experiments have been conducted to verify the repeatability of the posture assumed when an individual repeats the sitting process for a given environmental configuration. This preliminary test has confirmed a good repeatability of the sitting posture when the hand position is pinpointed with a marker on the table. Once the repeatability of that posture has been verified, each of the subsequent postures is adopted three times by the same subject, and average values are assumed to be the inclination angles of the motion segments of the spine.

The initial training of the neural network, which has been carried out by using the postural data of subject no.1 (table 1), has required 2200 training cycles. The training process is interrupted, though, for a training mean-square error, for all training data, less than 10^{-5}. Figure 10 shows the output error of the neural network for each of the 17 characteristic angles used to define the

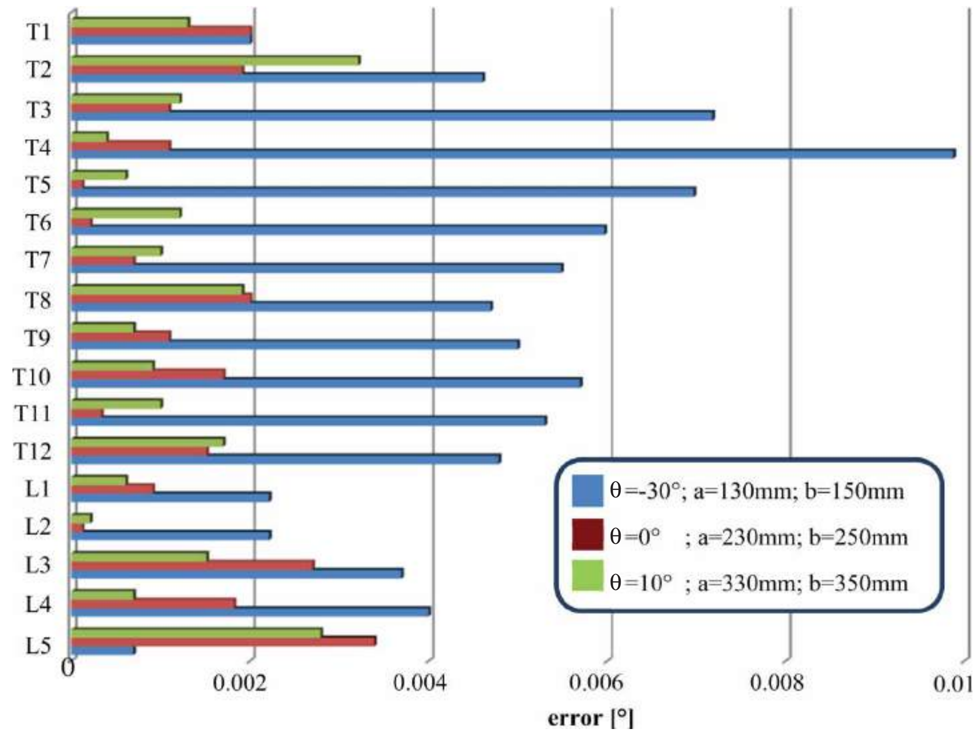

Figure 10. Neural network output angular error for each of the 17 characteristic links used to define the spine geometry, for three environment configurations of the same working place.

spine geometry, and for three environmental configurations. The maximum error does not exceed 2.4% of the inclination angle dimension.

Once the input parameters (θ, a, b, c) are provided to the system, the virtual environment is set up and the manikin, defined by its anthropometric parameters, adopts the corresponding posture. The proposed method automatically configures the virtual manikin to assume the postural attitude of the specific individual that has been previously analysed.

The postures predicted by using the proposed method are compared with the postures generated by the Safework inverse kinematic approach. The inverse kinematic approach is supported by five types of postures (stand, sit, reach, span, kneel) and the specific configuration can be defined by constraining the manikin in the virtual environment at up to 20 points. However, Safework developers do not supply any detailed information about the 7 criteria necessary to define postures (DASSAULT SYSTEMS [4]). Very little, if not anything, is known about

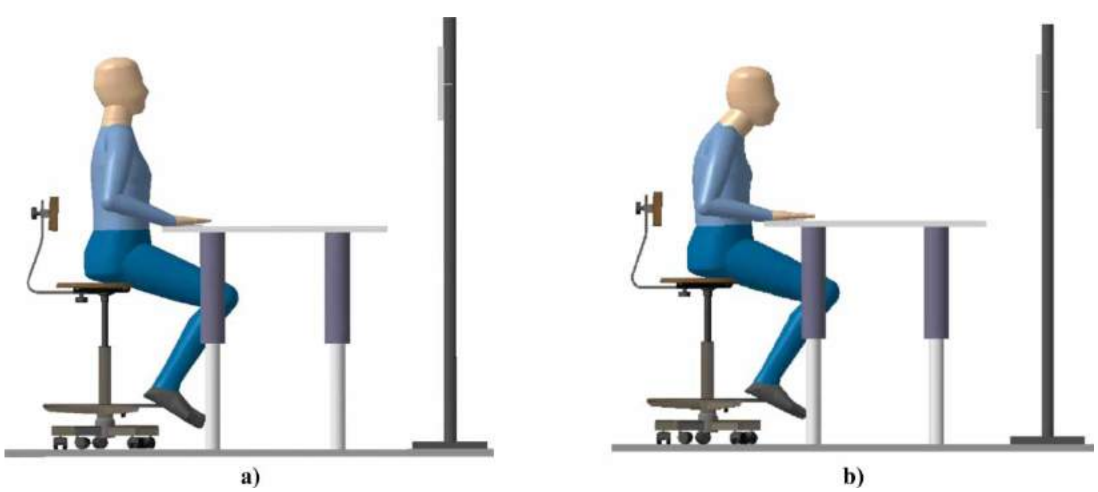

Figure 11. Comparison of the postures predicted with Safework (a) and with the proposed method (b) for a given working environment: $\theta = 0°$, a = 230 mm e b = 250 mm.

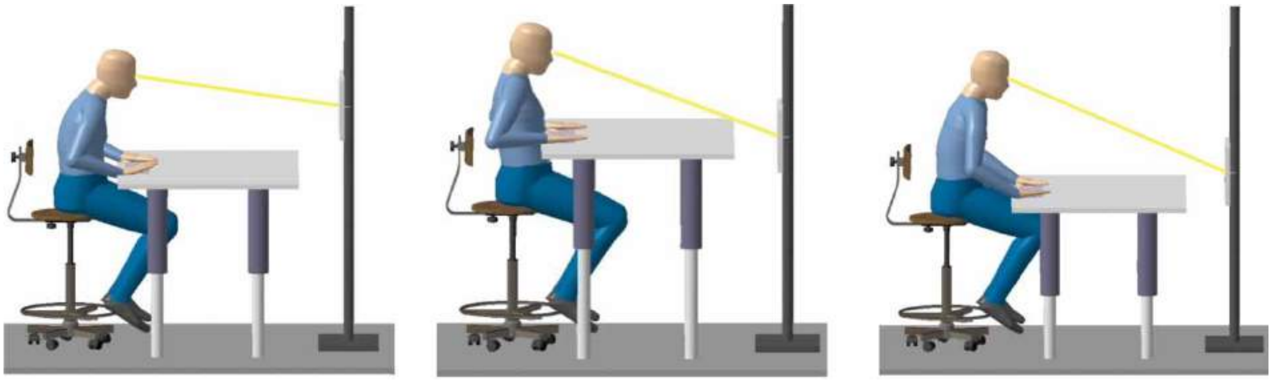

Figure 12. Examples of predicted postures for three different environment configurations.

those criteria of use. Figure 11a illustrates an example of a Safework manikin posture in a pre-defined working environment where the view direction and the position of the pelvis, feet and hands are constrained in the virtual environment. Figure 11b, on the other hand, shows the posture of the manikin for the same environment but this time simulated by the proposed method. The postures predicted with the proposed method appear to be more natural, since it faithfully reproduces the postural attitude of the individual. The postures adopted for the different configurations of the working environment are shown in figure 12. All these postures are assumed with environment parameters which fall outside the training range.

5. Conclusion

The use of Artificial Neural Network to predict posture is not new in absolute, but new is the use of this technique to simulate posture using information concerning the spine configuration. With the proposed method it is possible to predict the spine posture of a virtual human model that interacts with a virtual working environment. The model can implement the postural attitude of a reference individual in order to predict postures in specific settings where a particular activity is carried on. The *EDHM* here proposed overcomes the weakness of the typical methods used in commercial DHM to predict postures, performing a prediction of a more natural posture. The method is devoted to the reproduction of the posture of the upper trunk of VDT operators; this is a part whose posture is particularly difficult and complex to simulate. For these reasons, what has been verified in this work proves that it can used in posture prediction for the whole body and in other working activities.

The tests of the implemented method show high accuracy in posture reproduction for a single individual. Some problems have been encountered, though, when the method used to predict posture is extended to other individuals for whom the neural network has not been trained. In fact, the postural attitude is not merely a function of the anthropometric parameters and can, rather, vary a great deal from one individual to another. Future works should be addressed to define apposite parameters suited to classify and describe classes of postural attitude, such as koilorachic and kurtorachic attitudes.

This approach can be extended, in the future, to implement data related to new critical human activities in which women and men could take non correct postures for long time due to new habits. It could be the case in young people which use intensively tablets and mobiles.

The method could be improved by considering the rotation of the vertebrae around the sagittal and coronal axes. In this way, it would be possible to simulate and predict those postures assumed, consciously or forcedly, by workers in a typical factory workplace which are highly asymmetric.

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