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The Use of Body Motion Analysis as an Artificial Neural Network Method for Personal Identification

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Abstract.

There is limited evidence to suggest an optimal biometric method in order to achieve an enhanced level of information security as well as recognition accuracy. Recently, novel approaches for the development of practical biometric identification systems have shown that body motion analysis seems to overcome most of the risks and vulnerabilities related to security and privacy and also characterized by simplicity and precision. This study examined the ability of a body motion analysis system to accurately identify individuals throughout specific periods of time. Specifically, thirteen males have performed three trials throughout a single day as well as pre and post an eight-week period. A high speed video camera was used to collect recordings of a full stride (two consecutive steps). Analysis of the video data was performed using a digitizing hardware system. After video analysis, various kinematic variables related to foot motion (total time, stride rate, stride length, flying time, contact time, velocity) were compared in order to measure body motion analysis' recognition efficiency. These kinematic variables are the inputs for a classical artificial neural network (ANN), which is used for the person's recognition. The output is the identity of the person. The ANN's is optimized regarding the values of crucial parameters such as the number of neurons, the time parameter and the initial value of the learning rate, etc. using the evaluation set. The evaluation criterion is the successful percentage of the person's identification. Statistics showed that trials' variations throughout day and the eight-week period for most kinematic variables were small, indicating high data reproducibility. The respective initial ANN results are encouraging and indicate an increased efficiency of body motion analysis on personal identification. In future, more measurement-trials per person during the reference period time and a larger participant sample may allow the results' generalization. It is also suggested that in order to obtain fast and accurate biometric identification even after a relatively long period of time, one may prefer body motion analysis over other biometric methods.

Keywords: Artificial neural network, body motion, person identification

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1 Introduction

Body motion analysis represents the study of the human body movement. In the 1900s, body motion analysis was used as a tool for detecting limb asymmetries via the science of Physiology. In the 1970s it was used as a mean for maximizing performance via the science of Biomechanics [1]. Recently, it was used as a challenging method for personal identification via the science of Biometry [2-4]. Since walking and running are human movements which reflect not only physiological but also complex behavioural characteristics [5] it is quite difficult to analyze and recognize these human patterns and to produce high-level description of actions and interactions [6]. Some of the general analytical methods used for matching time-varying data are the Dynamic time warping [7], the Hidden Markov models [8] the Principle Component Analysis method [9] and the Artificial Neural Network [10]. The aim of this study was to examine the use of the ANN method on body motion analysis in order to assess its accuracy on individual identification.

2 Proposed ANN Method for the Person Identification

The identification of the person is achieved by applying an ANN method through the optimization of the neurons of the back-propagation training algorithm. This method has the following flow chart, shown in Figure 1.

The basic steps of the ANN method are:

Data selection: The input variables were various kinematic variables related to foot motion:

(a) CT - contact time

(b) FT - flying time

(c) LCT - left foot contact time

(d) RCT - right foot contact time

(e) SL - stride length

(f) SR - stride rate

(g) ST - stride time

(h) SV - stride velocity

The output variable is the person identity (1 if the person is the proper one, 0 otherwise).

It is mentioned that a different ANN will be formed for each one of 13 persons, because different ANNs for each output have better performance than one global ANN with all outputs [11].

Data pre-processing: Generally, data are examined for normality, in order to modify or delete the values that are obviously wrong (*noise suppression*). In order to avoid saturation problems [12], the input and the output values are normalized as shown by the following expression:

$$\hat{x} = a + \frac{b-a}{x_{\max} - x_{\min}}\left(x - x_{\min}\right) \qquad (1)$$

where $\hat{x}$ is the normalized value for variable x, $x_{\min}$ and $x_{\max}$ are the lower and the upper values of variable x, a and b are the respective values of the normalized variable.

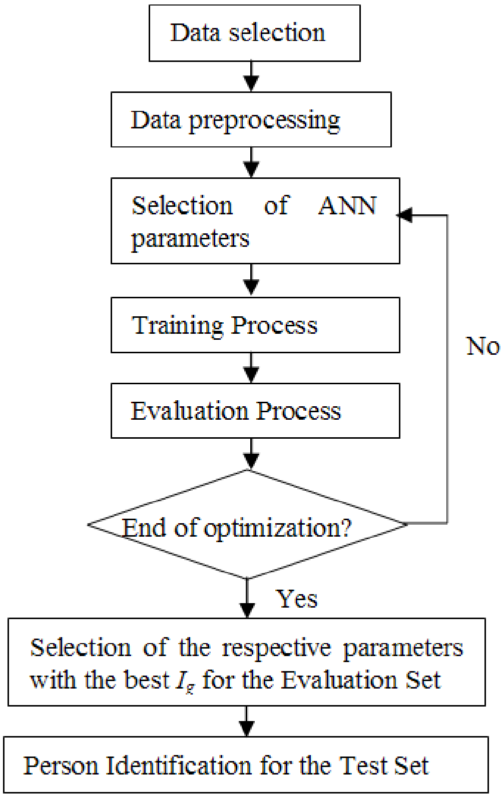

Figure 1. Flowchart of the ANN optimization method

Selection of ANN parameters: The ANN parameters (like the number of neurons etc.) are not already known, but they can be specified empirically through trials. In this paper, the parameter of neurons is examined thoroughly. All artificial neural networks with one hidden layer are formed with different number of neurons from 1 to 20. The one with the best general identification index I_g (see eq. 15) for evaluation set is selected.

Training Process: A multilayer feed-forward neural network is adopted using the stochastic back-propagation algorithm with training rate and momentum term. The neurons in the network can be divided into three layers: input, hidden and output layer (see Fig. 2). According to Kolmogorov's theorem [12], an ANN can solve a problem using one hidden layer, if the latter has the proper number of neurons. In this study one hidden layer is used, but the number of neurons needs to be properly selected. This fact has forced the examination of the various combinations of the critical ANN parameters. It is clarified that the number of neurons at the output layer is equal to the number of output variables, while the input nodes correspond to the input variables. The basic structure of an ANN is presented in Fig. 2, while the latter's basic sub-steps are as follows:

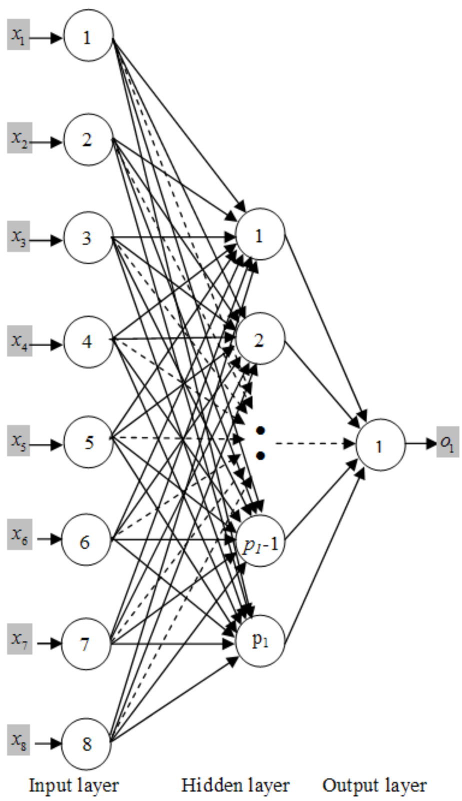

Figure 2. Typical structure of an ANN (8-p_1-1) where there are p_1 neurons in hidden layer and 1 neuron in output layer.

(a) *Initialization*: Connection weights are equal to small random values between [-0.1,0.1] according to uniform distribution.

(b) *Training set's presentation*: During current epoch *ep* all patterns of the training set are presented randomly. For each vector (c) and (d) steps are realized. It is clarified that, in order to converge more rapidly than in the conventional method, both the training rate $\eta(ep)$ and the momentum term $a(ep)$ are changing their values at the beginning of each epoch *ep*:

$$\eta(ep) = \eta(ep-1)\cdot\exp\left(-1/T_\eta\right) \qquad (2)$$

$$a(ep) = a(ep-1)\cdot\exp\left(-1/T_a\right) \qquad (3)$$

where T_η , $\eta_0 = \eta(0)$, T_a , $a_0 = a(0)$ are respectively the time parameters and the initial values of both the training rate and the momentum term.

(c) *Forward pass calculations*: The *n*-th training pattern is defined as { $\vec{x}_{in}(n), \vec{t}(n)$ }, where $\vec{x}_{in}(n)$ is the input vector -consisted of the normalized values of the input variables- with dimension q_{in} and $\vec{t}(n)$ the respective desired normalized output vector with dimension q_{out}. The activation signal of the *k*- neuron of the ℓ - layer is:

$$u_k^{(\ell)}(n) = \sum_{v=0}^{p_{\ell-1}} w_{kv}^{(\ell)}(n)\, y_v^{(\ell-1)}(n) \qquad (4)$$

where $w_{kv}^{(\ell)}(n)$ is the weight between the ℓ - layer's *k*- neuron and the $(\ell-1)$ - layer's *v*- neuron, $p_{\ell-1}$ is the total number of neurons for the $(\ell-1)$ - layer and $y_v^{(\ell-1)}(n)$ is the output of the *v*-respective neuron (see Fig. 3). For $v = 0$, the threshold value is defined as $\theta_k = w_{k0}$, while $y_0^{(\ell-1)} = -1$. The activation function $f(x)$ can be linear $h_1 \cdot x + h_2$, hyperbolic tangent $\tanh(h_1 \cdot x + h_2)$, or hyperbolic sigmoid $\sinh(h_1 \cdot x + h_2)$ for each layer (the parameters h_1 and h_2 should be defined just like the other ANN parameters).

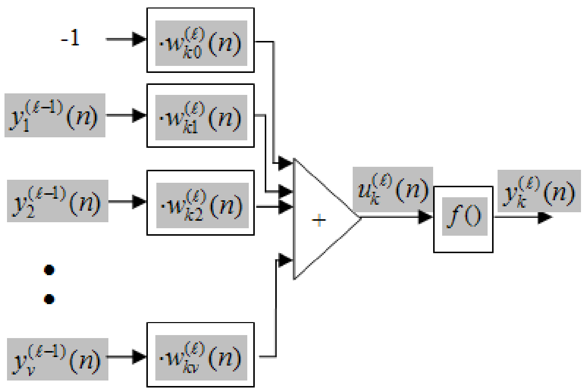

Figure 3. Enlargement of the ℓ-layer's k-neuron during the presentation of the n-th training pattern.

The neuron's output is:

$$y_k^{(\ell)}(n) = f(u_k^{(\ell)}(n)) \quad (5)$$

In the input layer one demands:

$$y_v^{(0)}(n) = x_v(n)\,,\ \forall v \quad (6)$$

where $x_v(n)$ is the *v*-th element of input vector $\vec{x}_{in}(n)$.

In the output layer $L^{/}$ one determines:

$$y_k^{(L^{/})}(n) = o_k(n)\,,\ \forall k \quad (7)$$

where $o_k(n)$ is the *k*-th element of the output vector $\vec{o}(n)$, estimated by the ANN. The error of the output *k*-neuron is:

$$e_k(n) = t_k(n) - o_k(n) \quad (8)$$

where $t_k(n)$ is the *k*-th element of the desired normalized output vector $\vec{t}(n)$.

(d) *Reverse pass calculations*: The weight is calculated by the delta-rule:

$$w_{kv}^{(\ell)}(n+1) = \begin{cases} w_{kv}^{(\ell)}(n) + \\ \eta(ep)\cdot\delta_k^{(\ell)}(n)\cdot y_v^{(\ell-1)}(n) + \\ \alpha(ep)\cdot[w_{kv}^{(\ell)}(n) - w_{kv}^{(\ell-1)}(n-1)] \end{cases} \quad (9)$$

where $\delta_k^{(\ell)}(n)$ is the local descent of the *k*-neuron determined for the output layer and for the hidden one respectively as:

$$\delta_k^{(L)}(n) = e_k^{(L)}(n) \cdot f'\left(u_k^{(L)}(n)\right) \qquad (10)$$

$$\delta_k^{(\ell)}(n) = f'\left(u_k^{(\ell)}(n)\right) \cdot \sum_i \delta_i^{(\ell+1)}(n) w_{ik}^{(\ell+1)}(n) \qquad (11)$$

(e) *Stopping criteria*: The steps (b) to (d) are repeated continuously until the weights to be stabilized or the respective error function not to be improved or the maximum number of epochs to be exceeded.

Analytically the weights criterion is defined with the following expression:

$$\left| w_{kv}^{(\ell)}(ep) - w_{kv}^{(\ell)}(ep-1) \right| < \ell imit_1, \forall k, v, \ell \qquad (12)$$

where $\ell imit_1$ has a proper value and *ep* is the current epoch of training algorithm.

The error function is the root mean square error $RMSE_{tr}$ for the training set (where the respective population equals to m_1) according to:

$$RMSE_{tr} = \sqrt{\frac{1}{m_1 \cdot q_{out}} \sum_{m=1}^{m_1} \sum_{k=1}^{q_{out}} e_k^2(m)} \qquad (13)$$

and the respective criterion is:

$$\left| RMSE_{tr}(ep) - RMSE_{tr}(ep-1) \right| < \ell imit_2 \qquad (14)$$

where $\ell imit_2$ is the respective limitation value. Practically, it is an early stopping criterion.

The maximum number of epochs' criterion is:

$$ep \geq \max\_epochs \qquad (15)$$

If one of the above criteria comes true, the main core of back propagation algorithm stops. Otherwise the number of epochs is increased by one, the whole process returns to step (b) and the training rate and the momentum term are re-calculated by eq. (2) and (3). The criterions' purposes are: (i) to avoid the over-fitting problem and (ii) to enable the convergence of the algorithm.

Evaluation Process: After the convergence of the training algorithm, the identification of the person is realized as follows: if the estimation value $\hat{o}_{1i}$ of the *i*-th vector is larger than the threshold value θ, the final estimation will be the positive estimation of the person and the respective estimated value of identification $\hat{s}_i$ will be 1, otherwise it will be 0. This means that:

$$\hat{s}_i = \begin{cases} 1, & \hat{o}_i \geq \theta \\ 0, & \hat{o}_i < \theta \end{cases} \qquad (16)$$

The general identification index I_g between the desired s_i and the estimated values $\hat{s}_i$ of the under study person identification is calculated as follows:

$$I_g = \frac{1}{n} \cdot \sum_{i=1}^{n} \delta\left(s_i - \hat{s}_i\right) \cdot 100\% \qquad (17)$$

where n is the population of the respective data set and δ(x) is the Dirac function. This index expresses the percentage of the correct positive and correct negative identifications to the total population of patterns n. In this case ANN does not identify the under study person ($\hat{s}_i$=0) in case this person has not appeared (s_i=0), or ANN identifies the under study person ($\hat{s}_i$=1) in case this person has appeared (s_i=1).

Additionally, the identification index $I_{f\text{-}neg}$ of false negative person's identification expresses the percentage of the false negative identifications $n_{f\text{-}neg}$ to the total population of correct positive identifications n_{pos}. In this case ANN does not identify the under study person ($\hat{s}_i$=0), while in fact this person has appeared (s_i=1). It is calculated as follows:

$$I_{f-neg} = \frac{n_{f-neg}}{n_{pos}} \cdot 100\% = \frac{\sum_{i=1}^{n} \delta\left(\hat{s}_i\right)}{\sum_{i=1}^{n} \delta\left(s_i - 1\right)} \cdot 100\% \quad (18)$$

Similarly, the identification index $I_{f\text{-}pos}$ of false positive person's identification expresses the percentage of the false positive identifications $n_{f\text{-}pos}$ to the total population of correct negative identifications n_{neg}. In this case ANN identifies the under study person ($\hat{s}_i$=1), while in fact another person has appeared (s_i=0). It is calculated as follows:

$$I_{f-pos} = \frac{n_{f-pos}}{n_{neg}} \cdot 100\% = \frac{\sum_{i=1}^{n} \delta\left(\hat{s}_i - 1\right)}{\sum_{i=1}^{n} \delta\left(s_i\right)} \cdot 100\% \quad (19)$$

End of Optimization Loop: In this section the end of the optimization loop is checked. If all possible combinations of the under study ANN parameters are examined, then the next step will follow, otherwise a new selection of the ANN parameters will take place and the training process will be continued.

Selection of the ANN parameters with the best I_g *index for the Evaluation Set*: From all examined combinations the one with the biggest I_g index for the evaluation set is chosen as the best one with the respective ANN parameters and the finally estimated weights.

Person Identification for the Test Set: The parameters and weights of the previous step constitute the final proposed Artificial Neural Network, which can be used for the person identification for the unknown test set. The quantitative analysis is based on the three indexes (general identification index I_g, $I_{f\text{-}neg}$ of false negative person's identification, $I_{f\text{-}pos}$ of false positive person's identification).

3 Case Study

Methods

Thirteen (13) male students participated in this study with mean ±SD age 24.8 ± 2.6 years, body mass 76.7 ± 9.8 kg, and body height 1.77 ± 0.09 m. Informed consent was obtained from each participant before data collection. They performed six running trials with the first three trials per person to consist the training set and the last three trials per person constitute the test set. An eight-week period was interceded between the training and the evaluation set. The evaluation set was the same with the training set because lack of trials.

Procedures

The sprint running test took place on a running track lane (30 m), which was covered with the same synthetic track surface. All tests were performed on the same day using natural light, there was no wind and the ambient temperature was 25^{o} C. After completion of a 20 min warm up, the participants ran three times at full speed.

The time period between the repetitions was sufficient for the participants to fully recover (10 min) [13]. Before the tests, all participants had three weeks of familiarization, training three times per week on the specific surface. The adoption of three trials for each participant in each condition was to establish the magnitude of variability associated with repeated trials.

A high speed video camera (Casio EX-F1; Casio Electronics Co, Ltd., London, UK) was used to collect video recordings of the sagittal plane of a full stride (two consecutive steps) of all three trials in each condition, sampling at 300 Hz. Collection of video performed with the camera placed at the end of each 30 m run and approximately 10 m from the performance plane such that its optical axis was approximately horizontal, forming an angle of 90° with the horizontal plane of running. A metal calibration frame (1 x 1 m) was filmed such that the x-axis was parallel to the runway and the y-axis was perpendicular to the surface of the runway.

Analysis of the data

An automated video analysis system (Ariel Performance Analysis System, Trabuco Canyon, USA) was used for the analysis of the data. A standard 17-point [14], 14-segment model of the human performer based on the data of Dempster [15] was used to represent the human performer and to calculate the position of the centre of mass. Whilst surface markers were used as an aid in the process of digitisation, the digitiser operator identified the points for digitisation based on superficial anatomical landmarks and an understanding of axes of rotation at the joints [16]. Digitised points consisted of the vertex of the head and both right and left joints (glenohumeral, elbow, wrist, 3rd metacarpophalangeal, hip, knee, ankle, 5th metatarsophalangeal). The following segments were defined: head/neck, trunk, right and left upper arm, forearm, hand, thigh, shank and foot. Prior to storing the data on disk, each frame was checked visually after digitisation by means of a stick figure drawn on the screen of the computer in order to detect any digitising errors. This visual analysis checked that the points were digitised in the correct order to represent the appropriate landmarks.

For each trial digitising started three frames before the touchdown of the ipsilateral foot and ended three frames after the touchdown of the contralateral foot. This provided sufficient redundant data for smoothing. Touchdown was defined as the instant at which the participant made contact with the ground and takeoff as the instant at which the participant broke contact with the ground. The appropriate frames defining touchdown and takeoff were identified through visual inspection by the researcher who digitised all the trials. Prior to further processing, the displacement-time data for the digitised joint landmarks were smoothed via a 2^{nd} order quintic spline curve fitting program [17].

The step cycle had as a starting point touchdown of the ipsilateral foot, it continued through the flight phase and terminated at touchdown of the contralateral foot. Three step cycles (one step cycle from each trial) for each participant were digitised. Contact time (CT), flight time (FT), step time (ST), step length (SL), flight distance (FD), step rate (SR) and maximum running velocity (MRV) were calculated according to the methods of Mero and Komi [18]. Contact time was defined as the period of time from the touchdown of the ipsilateral foot to the takeoff of the same foot. Flight time was defined as the period of time from the takeoff of the ipsilateral foot to the touchdown of the contralateral foot. Step time was defined as the period of time of a step. Step length was defined as the horizontal distance covered by the centre of mass along the line of progression during a step. Flight distance was defined as the horizontal distance covered by the centre of mass along the line of progression from the takeoff of the ipsilateral foot to the touchdown of the contralateral foot. Step rate was defined as the number of steps per second. Maximum stride velocity was calculated in terms of the average velocity of a step cycle according to the formula:

$$SV = SL \div (CT + FT).$$

The running velocity was recorded at the end of the $30\ m$ distance so it should be near to maximal running velocity as evidence from the literature has showed that maximal running velocity is achieved at about $30\ m$ [19].

Algorithm Execution

The abovementioned method has been implemented in Visual Fortran 6.0. In this preliminary study [20] the number of neurons varies from 2 to 20, while the remaining parameters are assigned with fixed values ($a_0 = 0.5$, $T_a = 1000$, $\eta_0 = 0.5$,

$T_\eta = 1000$, activation functions in both layers: hyperbolic tangent, h_1=0.5, h_2=0.0, max_epochs=10000, $\ell imit_1$=10^{-4}, $\ell imit_2$=10^{-4}).

The respective threshold is 0.5. In case of the same I_g index of the evaluation the ANN with the least number of neurons is chosen. 13 different ANNs are formed (one per person) and the respective results are summarized in Table 1. For each case the evaluation (=training) set has 39 members, 3 patterns of the under study person and 36 of other persons from pre 8-week period. The test set has 39 members, 3 patterns of the under study person and 36 of other persons from post 8-week period.

Person	Evaluation set (=training set)			Test set			Neurons
	I_g (%)	$I_{f\text{-}neg}$ (%)	$I_{f\text{-}pos}$ (%)	I_g (%)	$I_{f\text{-}neg}$ (%)	$I_{f\text{-}pos}$ (%)	
1	100,0	0,0	0,0	97,4	33,3	0,0	1
2	100,0	0,0	0,0	97,4	33,3	0,0	1
3	100,0	0,0	0,0	100,0	0,0	0,0	1
4	100,0	0,0	0,0	94,9	33,3	2,8	2
5	100,0	0,0	0,0	97,4	0,0	2,8	1
6	94,9	66,7	0,0	97,4	33,3	0,0	1
7	100,0	0,0	0,0	94,9	0,0	5,6	1
8	100,0	0,0	0,0	94,9	33,3	2,8	1
9	100,0	0,0	0,0	100,0	0,0	0,0	1
10	100,0	0,0	0,0	100,0	0,0	0,0	1
11	100,0	0,0	0,0	100,0	0,0	0,0	1
12	100,0	0,0	0,0	100,0	0,0	0,0	1
13	100,0	0,0	0,0	100,0	0,0	0,0	1
Mean	99,6	5,1	0,0	98,0	12,8	1,1	

Table 1. Results from the execution of proposed ANN method for 13 different persons.

Discussion

These preliminary results are quite satisfactory, as the average percentages of the general identification index I_g, the identification index $I_{f\text{-}neg}$ of false negative person's identification and of the identification index $I_{f\text{-}pos}$ of false positive person's identification are 98%, 12.8% and 1.1% respectively. The large values of the identification index $I_{f\text{-}neg}$ of false negative person's identification is due to the small population of positive person's identification test set, which equals to 3. If one false identification exists, the respective percentage is 33.3%.

These general identifications values are similar to those reported by [21] who tested individuals during running indoors.

However, body motion analysis is also related with various disadvantages such as problems with picture quality (luminescence, dirt, objects), use of specialized personnel for data processing and data alterations throughout lifetime (injuries, training). These problems can be overcame with the evolution of biometric technology (i. e. more sophisticated instrumentation) novel bioencryption methods [22], multimodality biometrics data [23], cancellable biometrics [24] as well as with the development of a more efficient neural network with multiple parameters.

The present data are of paramount interest since they derive from a small sample group (only 13 participants) who followed a full athletic training programme between the two sets of data. This training programme improved running ability, in most of these participants, and actually ‘‘forced’’ them to change their kinematic characteristics. However, the ANN system was still able to identify them with a high accuracy. Furthermore, data collection obtained with the participants performing not walking but running on maximum speed which made the identification process more difficult to the ANN system.

One of the limitations of the present study was the inadequacy on recording repeated trials for each participant, leading to the inclusion of few kinematic parameters in the analysis and consequently to the reduction of statistical power. Future studies should utilize a greater sample group performing multiple trials before (training set) and after (test set) using multiple cameras (for three dimensional analysis) in order to produce various performance parameters and maximize ANN efficiency.

4 Conclusion

The respective initial ANN results are encouraging and indicate an increased efficiency of body motion analysis on personal identification. However, there are a number of quality data concerns raised about the use of body motion analysis which can be overcame with the evolution of biometric technology and a more efficient system.

It seems that the present method can be useful in various military applications such as access control in military bases and detection of personnel's health deterioration in time via multiple biometrics (skin texture, gait and ear).

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