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An investigation of an Artificial Neural Network method for personal identification using kinematic parameters from specific body parts

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Abstract

In the present study kinematic data elicited via a body motion analysis system were used in order to accurately identify individuals throughout specific periods of time. Fifteen males participated in a series of running trials interspersed with an eight-week training period. Body motion analysis comprised data from video recordings during running. After video analysis, various kinematic parameters related to motion of specific body parts (trunk, hip, knee, calf) were compared in order to measure body motion analysis' recognition efficiency. These kinematic parameters were used as inputs for a classical artificial neural network, in order to recognize each individual, whilst, the output represented the identity of the individual. The artificial neural network is optimized regarding the values of crucial parameters such as the number of neurons, the time parameter and the

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initial value of the learning rate, etc. using the evaluation set. Three identification indices were selected. The general identification index *(Ig)* which expressed the % of the correct positive and correct negative identifications to the total population. The false negative index *(If-neg)* which expressed the % of the incorrect identifications of a non-authentic individual and the false positive index *(If-pos)* which expressed the % of the incorrect identifications of an authentic individual. The statistics showed that even with the use of 16 additional kinematic parameters the efficiency of the identification process was not improved. Further analysis showed that separately some kinematic parameters provided either higher *If-neg* or *If-pos* values whilst others presented low values in both identification indices. It seems that the need for satisfying the biometric criterion of social acceptability resulted in the use of parameters derived from specific body parts which diminished the video analysis efficiency and consequently person identification ability of body motion analysis.

Keywords: Artificial neural network; body motion; kinematic parameters; person identification

1 Introduction

Recent studies have shown that each individual is characterized by a unique walking pattern which can be used as a method to reveal his/her identity [1-4].

There are many methods used in gait analysis identification such as extracted periodical features of leg motion by Fourier analysis [5,6], extracted parameters of shape and stride [7], extracted static shape parameters and gait period with an articulated body model [8] extracted joint angles with an articulated body model [9]. In a study [10] where kinematic parameters from human subjects and not models where used. Preliminary results [10] using Artificial Neural Networks (ANN) were encouraging and indicated an increased efficiency of body motion analysis on personal identification. However, one of the limitations of that study [10] was the low statistical power due to the small sample group and the limited number of tested parameters. It was also noted that human subjects did not feel comfortable to be monitored which supported the notion that the any human identification system needed to be ‘‘acceptable’’ meaning that individuals must be able to accept the use of that characteristic (body motion) in their daily lives. Based on this line of thinking, specific body segment(s) were monitored in the present study in order to ensure subject’s privacy. Additionally, these body segments represented numerous kinematic parameters in order to confirm previous data and to increase the efficacy of the ANN model. Therefore, the aim of the present study was to assess ability of a body motion analysis system to accurately identify individuals without ‘‘invading’’ their personal life but also providing a higher statistical power via a greater number of more kinematic parameters.

2 Proposed Ann Method For The Person Identification

The methodology used was identical to the one described in a previous study [10] with the only exception that the present study used 16 instead of 8 parameters for data analysis. These variables comprised time (ms) as well as angles (degree) of various body parts during landing, mid stand phase and take off of the foot. Analytically the variables used were:

(1) Ascending phase (concentric), (2) Descending phase (eccentric), (3) Knee (landing), (4) Knee (mid stand phase), (5) Knee (takeoff), (6) Calf (landing), (7) Calf (mid stand phase), (8) Calf (takeoff), (9) Hip (landing), (10) Hip (mid stand phase), (11) Hip (takeoff), (12) Trunk (landing), (13) Trunk (mid stand phase), (14) Trunk (takeoff), (15) Centre of gravity (landing), (16) Centre of gravity (takeoff).

3 Case Study

3.1 General

The data set consisted of 15 males with 6 trials per person (three trials throughout a single day as well as pre and post an 8-week period). Their age, body mass and body height (mean ±SD) were 24.1 ± 2.2 years, 76.3 ± 9.1 kg, and 1.78 ± 0.07 m respectively. Informed consent was obtained from each participant before data collection. The training set consisted of the first 3 trials per person of the pre 8-week period and the test set (which is used for generalization results check) consisted of the 3 trials per person of the post 8-week period. The evaluation set was the same with the training set because lack of trials. Experimental procedures and instrumentation were identical to those used previously [10]. Data analysis was conducted according to the procedures described by Dempster [11], Challis [12] and Wood [13].

3.2 Algorithm Execution

In this preliminary study 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}).

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 (=0,5 in current case), 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:

$$\hat{s}_i = \begin{cases} 1, & \hat{o}_i \geq \theta \\ 0, & \hat{o}_i < \theta \end{cases} \tag{1}$$

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:

$$I_g = \frac{1}{n} \cdot \sum_{i=1}^{n} \delta\left(s_i - \hat{s}_i\right) \cdot 100\% \tag{2}$$

where n is the population of the respective data set and $\delta(x)$ 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 case of the same I_g index of the evaluation the ANN with the least number of neurons is chosen. 15 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 person under study and 36 of other persons from the pre 8-week period. The test set has 39 members, 3 patterns of the person under study and 36 of other persons from the post 8-week period.

Additionally, other two evaluation indexes are used:

- the identification index $I_{f\text{-}neg}$ of false negative person's identification, which 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:

$$I_{f-neg} = \frac{n_{f-neg}}{n_{pos}} \cdot 100\% = \frac{\sum_{i=1}^{n} \delta\left(\hat{s}_i\right)}{\sum_{i=1}^{n} \delta\left(s_i - 1\right)} \cdot 100\% \tag{3}$$

- the identification index $I_{f\text{-}pos}$ of false positive person's identification, which 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:

$$I_{f-pos} = \frac{n_{f-pos}}{n_{neg}} \cdot 100\% = \frac{\sum_{i=1}^{n} \delta\left(\hat{s}_i - 1\right)}{\sum_{i=1}^{n} \delta\left(s_i\right)} \cdot 100\% \tag{4}$$

Table 1: Results from the execution of proposed ANN method for each person separately

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	97,8	33,3	0,0	95,6	0,0	4,8	1
2	97,8	33,3	0,0	88,9	100,0	4,8	1
3	100,0	0,0	0,0	91,1	66,7	4,8	1
4	100,0	0,0	0,0	93,3	100,0	0,0	1
5	100,0	0,0	0,0	93,3	100,0	0,0	1
6	100,0	0,0	0,0	93,3	100,0	0,0	1
7	100,0	0,0	0,0	93,3	100,0	0,0	1
8	100,0	0,0	0,0	91,1	100,0	2,4	1
9	97,8	33,3	0,0	93,3	100,0	0,0	1
10	97,8	33,3	0,0	93,3	0,0	7,1	1
11	100,0	0,0	0,0	93,3	66,7	2,4	1
12	100,0	0,0	0,0	97,8	33,3	0,0	1
13	100,0	0,0	0,0	91,1	33,3	7,1	1
14	100,0	0,0	0,0	93,3	100,0	0,0	1
15	100,0	0,0	0,0	84,4	100,0	9,5	1
Mean	99,4	8,9	0,0	92,4	73,3	2,9	

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 92,4%, 73,3% and 2,9% 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 and equals to 3. If one false identification exists, the respective percentage is 33,3%.

3.3 Sensitivity Analysis

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 for the validation set and for the test set are summarized in Tables 2 to 5 respectively.

Regarding the validation set it was observed that for the identification index $I_{f\text{-}neg}$ of false negative person's identification there is no uniform performance among different persons. It is obvious that one variable is not sufficient to accurately identify a person. However it seems that the variables (6), (7), (8), (15), (16) provide slightly better results.

Similarly, regarding the test set it was observed that for the identification index $I_{f\text{-}neg}$ of false negative person's identification there is no uniform performance among different persons. It is obvious that one variable is not sufficient to accurately identify a person. However it seems that the variables (1), (5), (6), (7), (9), (12), (14), (15) provide slightly better results.

For the identification index $I_{f\text{-}pos}$ of false positive person's identification the result is no longer 0% (desired value), but again a non-uniform performance exists. Best results are shown by the variables (4), (11) and (16), whilst worst results by the variables (8), (9), (10), (14) and (15). Some variables such as (14) and (15) present good performance in relation to $I_{f\text{-}neg}$ index but bad performance

Table 2: Results for the identification index $I_{f\text{-}neg}$ of false negative person's identification of the validation set from the execution of proposed ANN method for each different variable separately for all persons

		Persons															Mean value
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Variables	1	100%	100%	100%	67%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97,8%
	2	100%	100%	100%	100%	100%	100%	67%	100%	100%	100%	100%	100%	67%	100%	100%	95,6%
	3	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	67%	100%	67%	100%	95,6%
	4	100%	67%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97,8%
	5	67%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	67%	95,6%
	6	100%	100%	100%	33%	100%	100%	100%	100%	100%	100%	67%	100%	100%	100%	100%	93,3%
	7	100%	100%	100%	67%	100%	100%	100%	100%	100%	33%	100%	100%	100%	100%	100%	93,3%
	8	100%	100%	100%	100%	100%	100%	33%	100%	100%	100%	67%	100%	100%	100%	100%	93,3%
	9	67%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97,8%
	10	100%	100%	67%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	97,8%
	11	100%	100%	100%	100%	100%	100%	100%	100%	100%	67%	100%	67%	100%	100%	100%	95,6%
	12	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	67%	100%	100%	100%	100%	97,8%
	13	100%	100%	100%	100%	100%	100%	100%	100%	33%	100%	100%	100%	100%	100%	100%	95,6%
	14	100%	100%	100%	100%	100%	100%	100%	100%	100%	67%	67%	100%	100%	100%	100%	95,6%
	15	100%	100%	100%	100%	100%	100%	100%	100%	100%	67%	100%	33%	100%	100%	100%	93,3%
	16	67%	100%	100%	100%	33%	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%	93,3%
Total set		33%	33%	0%	0%	0%	0%	0%	0%	33%	33%	0%	0%	0%	0%	0%	8,9%

Table 3: Results for the identification index $I_{f\text{-}pos}$ of false positive person's identification of the validation set from the execution of proposed ANN method for each different variable separately for all persons

		Persons															Mean value
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Variables	1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	3	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	4	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	5	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	7	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	10	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	12	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	13	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	14	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	15	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	16	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
Total set		33%	33%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 4: Results for the identification index $I_{f\text{-}neg}$ of false negative person's identification of the test set from the execution of proposed ANN method for each different variable separately for all persons

		Persons															Mean value
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Variables	1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	3	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	4	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	5	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	7	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	10	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	12	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	13	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	14	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	15	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	16	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
Total set		33%	33%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Table 5: Results for the identification index $I_{f\text{-}pos}$ of false positive person's identification of the test set from the execution of proposed ANN method for each different variable separately for all persons

		Persons															Mean value
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
Variables	1	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	2	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	3	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	4	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	5	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	6	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	7	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	8	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	9	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	10	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	11	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	12	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	13	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	14	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	15	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
	16	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0,0%
Total set		33%	33%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%

in relation to $I_{f\text{-}pos}$ index. Conversely, variable (4) presents good performance in relation to $I_{f\text{-}pos}$ index but bad performance in relation to $I_{f\text{-}neg}$ index. Others, such as variable (8) present bad performance in relation to both indices. Finally, no variable has found to favour simultaneously both indices.

Discussion

These preliminary results are quite satisfactory, as they confirm previous experiments where the same methodology was used [10]. In more detail, 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 92,4%, 73,3% and 2,9% respectively. However, these values are lower than the respective values of 98%, 12,8% and 1,1% obtained previously [10]. Specifically, the present dataset failed significantly to indentify an authentic person whilst, successfully rejected a non-authentic one. It seems that the present kinematic variables used provided either higher *If-neg* or *If-pos* values, a disadvantage which must be considered in future studies.

The present study also showed that body segment motion analysis is characterized by limitations such as non-distinguishable motion (due to anatomical structure or/and clothing). Alternatively, the selection of the most efficient variables from the present study combined with other forms of biometrics data [14] and/or cancellable biometrics [15] may provide a more accurate biometric system. That system would then meet the basic criteria of an ideal human identification system which means that it would be unique, precise, simple, cost-effective and socially acceptable.

Conclusion

The need for satisfying social acceptability has led to the use of parameters derived from specific body parts which diminished the efficiency of motion analysis especially on rejecting a non-authentic person. However, the combination of distinguishable body motion parameters (mainly in lower limbs) alongside with other forms of biometric characteristics can improve biometric efficiency.

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