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# Motion capture as Data Source for Gait-based Human Identification

***Streszczenie.*** *Autorzy prezentują wyniki badań nad identyfikacją osób na podstawie danych chodu uzyskanych za pomocą techniki motion capture. Redukcję wymiarowości przeprowadzono stosując algorytm wieloliniowej analizy składowych głównych (MPCA), który operuje na tensorowej reprezentacji danych. Dla potrzeb identyfikacji osób zastosowano szereg metod klasyfikacji dostępnych w pakiecie WEKA uzyskując największą skuteczność dla perceptronu wielowarstwowego. (**Technika motion capture jako źródło danych dla identyfikacji osób na podstawie chodu**).*

***Abstract****. The authors present results of the research aiming at human identification based on tensor representation of the gait motion capture data. High-dimensional tensor samples were reduced by means of the multilinear principal component analysis (MPCA). For the purpose of classification the following methods from the WEKA software were used: k Nearest Neighbors (kNN), Naive Bayes, Multilayer Perceptron, and Radial Basis Function Network. The maximum value of the correct classification rate (CCR) was achieved for the classifier based on the multilayer perceptron.*

**Słowa kluczowe**: redukcja wymiarowości, algorytm MPCA, ekstrakcja cech, klasyfikacja danych chodu.
**Keywords**: dimensionality reduction, MPCA algorithm, feature extraction, gait data classification.

## Introduction

Gait is defined as coordinated, cyclic combination of movements which results in human locomotion [1]. A unique advantage of gait as a biometric is that it offers potential for recognition at a distance or at low resolution or when other biometrics might not be perceivable [2]. Gait can be captured by two-dimensional video cameras of surveillance systems or by much accurate motion capture (mocap) systems which acquire motion data as a time sequence of poses. Motion capture is defined as “The creation of a 3D representation of a live performance” [3]. The movement of an actor wearing a special suit with attached markers is recorded by NIR cameras. Positions of the markers in consecutive time instants constitute basis for reconstruction of their 3D coordinates.

Direct application of the mocap system for human identification is problematic because of the inconvenience of the acquisition process. On the other hand, its great advantage is high precision of measurements. Thus, the usage of the mocap system in the development stage of the human identification system is reasonable [4].

Motion data lie in high-dimensional space [5], but the components of gait description, discussed in detail in next section, are correlated, what allows dimensionality reduction.

The aforementioned problems formed the general objectives of the research: analysis of effectiveness of human identification based on gait mocap data with reduced dimensionality, and evaluation of the applied classification methods.

A full overview of bibliography describing the methods for solving the discussed problem would be unusually spacious. Generally, gait identification approaches can be divided into two categories: model-free and model-based. The former category can be split into approaches based on a moving shape and those which use integrate shape and motion within the description [2]. In the first example of the model-free approach silhouettes of walking human beings were extracted from individual frames using background subtraction, their morphological skeletons were computed and the modified independent component analysis (MICA) was proposed to project the original gait features from a high-dimensional measurement space to a lower-dimensional eigenspace. Subsequently, the L2 norm was used to measure the similarity between transformed gaits [6]. The principal components analysis (PCA) was also used in a similar way [7]. In [8] the recognition process was based on temporal correlation of silhouettes, whereas a spatio-temporal gait representation, called gait energy image (GEI), was proposed for individual recognition in [9]. The application of the Procrustes shape analysis method and the Procrustes distance measure in gait signature extraction and classification was shown in [10]. Numerous studies present frameworks developed for recognition of walking persons based on the dynamic time warping technique (DTW) [11], [12], as well as on the variants of the hidden Markov model (HMM), inter alia, generic HMM [13], population HMM [14], factorial and parallel HMMs [15].

The model-based approaches use information about the gait, determined either by known structure or by modeling [2]. The Acclaim format (ASF/AMC – Acclaim Skeleton File/Acclaim Motion Capture) is often applied as the skeleton model of the observed walking person. Numerous methods aim to estimate the model directly from two-dimensional images, not requiring actors to wear special equipment for tracking. An example of this markerless approach to motion capture is described in [16] where the particle swarm optimization algorithm (PSO) is used to shift the particles toward more promising configurations of the human model. In [17] 2D motion sequences taken from different viewpoints are approximated by the Fourier expansion. Next, the PCA is used to construct the 3D linear model. Coefficients derived from projecting 2D Fourier representation onto the 3D model form a gait signature. Another set of features used for human identification is extracted from spatial trajectories of selected body points of a walking person (root of the skeleton, head, hands, and feet), named as gait paths [18].

It is stated in [19] that many classifiers perform poorly in high-dimensional spaces given a small number of training samples. Thus, feature extraction or dimensionality reduction is an attempt to transform a high-dimensional data into a low-dimensional equivalent representation while retaining most of the information regarding the underlying structure or the actual physical phenomenon [20]. The dimensionality reduction problem can be solved, inter alia, by encoding an image object as a general tensor of second or higher order [21]. The solution proposed in the aforementioned study includes the criterion for dimensionality reduction called discriminant tensor criterion (DTC) and the algorithm called discriminant analysis with tensor representation (DATER).

Multilinear projection of tensor objects for the purpose of dimensionality reduction is the basis of the multilinear principal component analysis (MPCA). A survey with in-depth analysis and discussions is included in [22], whereas a framework for tensor object feature extraction is presented in [19]. One of the extensions of the MPCA – an unsupervised dimensionality reduction algorithm for tensorial data, named as uncorrelated MPCA (UMPCA) – is proposed in [23] and [24].

**Tensor Representation of the Gait Mocap Data**

Tensor object is a multidimensional object, the elements of which are to be addressed by indices. The number of indices determines the order of the tensor object, whereas each index defines one of the tensor modes. Gait silhouette sequences are naturally represented as third-order tensors with column, row, and time modes [19].

Description of each of the consecutive poses forming a gait sequence depends on the assumed skeleton model. For a typical model containing 22 segments and a global skeleton rotation (Fig. 1), description of a single pose comprises values of 69 Euler angles. Three additional values are required for specification of a global translation.

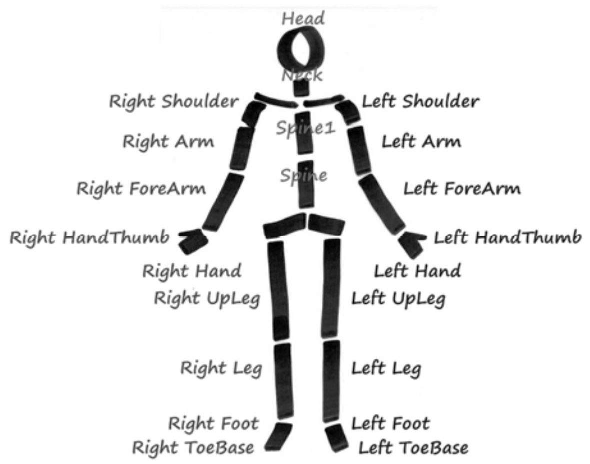


Fig. 1. Components of the skeleton model

The authors propose 2 variants of tensorial representation of gait mocap sequences – based on second-order and third-order tensors.

The second-order representation of the gait mocap data is composed of "time mode" and "pose mode". A single tensor object includes a single gait sequence built of 100 consecutive frames (poses) according to the requirement of the MPCA which accepts tensor samples of the same dimensions. The global translation values were removed from the input data, which guarantees that the identification process is based solely on the body parts movement, not on the gait route. Additionally, values of the angles remaining constant for all consecutive poses were also eliminated as redundant. Consequently, description of a single pose includes values of 51 Euler angles. Hence, total number of features characterizing a single gait sequence comes to 5100.

The third-order tensor representation is based on modes indexed, respectively, by numbers of components of Euler angles ("angle mode"), numbers of skeleton components ("pose mode"), and numbers of sequence frames ("time mode"). Gait sequences as distinct from the data represented as second-order tensors, were elongated to 128 frames. In addition, all Euler angles were taken into account increasing the total number of features characterizing a single gait sequence to 8832.

**The Multilinear PCA Algorithm**

Multilinear projection of tensor objects for the purpose of dimensionality reduction was based on the algorithm presented in [19]. According to the authors of the MPCA algorithm: "Operating directly on the original tensorial data, the proposed MPCA is a multilinear algorithm performing dimensionality reduction in all tensor modes seeking those bases in each mode that allow projected tensors to capture most of the variation present in the original tensors" [19]. Its application leads to feature extraction by determining a multilinear projection – the mapping from a high-dimensional tensor space to a low-dimensional tensor space. As a result of the multilinear projection of the $N$-order input tensor object $N$ projection matrices are constructed. A single point of a tensor object represents a single feature. Thus, number of features $I$ in the $N$-order input tensor object is defined as

(1) $$I = \prod_{n=1}^{N} I_n$$

whereas after dimensionality reduction it is described by the formula

(2) $$P = \prod_{n=1}^{N} P_n$$

where $P_n \le I_n$, $n$ = 1..$N$ $n \in [1;N]$. Symbols $I_n$, $P_n$ denote the $n$-mode dimension of the tensor, respectively, before and after reduction.

The PCA can be done by the eigenvalue decomposition. Assuming that in case of the $N$-order input tensor object eigenvalues for the particular modes are described as follows:

(3) $$\lambda_{i_n}^{(n)}, i_n \in [1;I_n], n \in [1;N]$$

the ratio $Q$ expresses the remained portion of the total scatter in the $n$-mode after the truncation of the $n$-mode eigenvectors beyond the $P_n$th [19]:

(4) $$Q = \frac{\sum_{i_n=1}^{P_n} \lambda_{i_n}^{(n)}}{\sum_{i_n=1}^{I_n} \lambda_{i_n}^{(n)}}$$

According to the MPCA algorithm computations for both considered variants of tensorial representation of gait mocap sequences were performed in 4 phases described below.

Preprocessing – because all tensor samples are required to be of the same dimensions, an input set of tensor samples was normalized and, subsequently, centered by subtracting the mean value.

Initialization – eigenvalues and eigenvectors were calculated for each mode separately. Subsequently, eigenvalues were arranged in descending order and cumulative sum of their relative contributions was computed and compared to the percentage $Q$ of variation which should be kept in each mode. The first case, when the cumulative sum achieved or exceeded the user-specified value of $Q$, determined $P_n$ eigenvectors which formed the projection matrix for the $n$-mode.

Local optimization of the projection matrices – improved versions of all projection matrices were computed one by one with all the others fixed.

Projection of the centered input samples using the projection matrices – feature tensors constituting the low-dimensional representation of the input samples with $Q$ % variation captured were obtained.

**Experimental Research**

Gait sequences were recorded in the Human Motion Laboratory (HML) of the Polish-Japanese Institute of Information Technology by means of the Vicon Motion Kinematics Acquisition and Analysis System equipped with 10 NIR cameras with the acquisition speed of 100 to 2000 frames per second at full frame resolution of 4 megapixels and 8-bit grayscale (http://hml.pjwstk.edu.pl).

The gait route was specified as a 5 meters long straight line. The acquiring process started and ended with a T-letter pose because of requirements of the Vicon calibration process. Two types of motion were distinguished: a slow gait and a fast one. As a result of the acquisition procedure 353 sequences for 25 men aged 20-35 years were stored in a gait database.

For the purpose of human identification the mocap data were transformed into the tensor representation. After the dimensionality reduction by means of the MPCA feature tensors were subject to the classification process.

Analysis of the MPCA results confirmed the expected type of dependency between the percentage $Q$ of variation kept in each tensor mode and the total number of features $P$ resulting from the dimensionality reduction (Fig. 2). The $Q$ values were taken from the range of [99; 100] using a step value of 0,01.

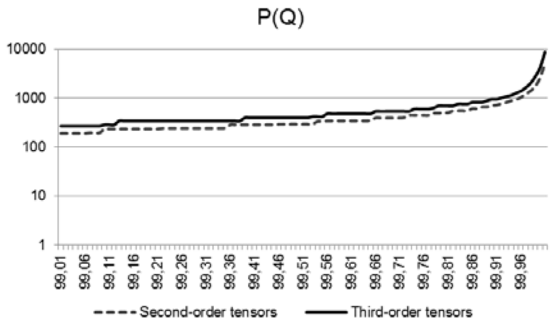


Fig. 2. Dependency between $P$ and $Q$ in the logarithmic scale

In the first phase of the classification process the second-order feature tensors reduced by means of the MPCA were processed by the following methods from the WEKA software [25]: 10 variants of the kNN ($k$ = 1..10) and the Naive Bayes. The best effectiveness 93,03% expressed by means of the correct classification rate (CCR) was obtained for the 3NN classifier using $P$ = 287 features. As a consequence of this result, two other WEKA methods – Multilayer Perceptron and Radial Basis Function Network – were used solely for classification of the feature tensors previously reduced to 287 features. The maximum value of the CCR equal to 95,71% was achieved for the classifier based on the multilayer perceptron after 1600 epochs, whereas the best result of the Radial Basis Function Network was only 90,35%.

In the next research phase, which was focused on the third-order feature tensors, the authors, inspired by the above-mentioned results, used the following methods for the purpose of classification: 5 variants of the kNN ($k$ = 1..5), the Naive Bayes with discretized attributes and the Multilayer Perceptron. The best effectiveness (CCR = 100%) was obtained anew for the classifier based on the multilayer perceptron.

The effectiveness of all methods was shown in Table 1 along with the most appropriate values of $Q$ and $P$.

Table 1. Effectiveness of classification methods

| Classifier | CCR [%] | Q [%] | P | Tensor order |
|---|---|---|---|---|
| 1NN | 92,49 | [99,21; 99,33] | 240 | 2 |
| 2NN | 90,88 | [99,09; 99,20] | 234 | 2 |
| 3NN | 93,03 | [99,35; 99,44] | 287 | 2 |
| 4NN | 92,22 | [99,06; 99,08] | 195 | 2 |
| 5NN | 91,96 | 99,34 | 246 | 2 |
| 6NN | 90,62 | 99,34 | 246 | 2 |
| 7NN | 89,81 | [99,06; 99,08] | 195 | 2 |
| 8NN | 88,74 | [99,06; 99,08] | 195 | 2 |
| 9NN | 87,67 | [99,00; 99,05] | 190 | 2 |
| 10NN | 86,06 | [99,21; 99,33] | 240 | 2 |
| Naive Bayes | 90,35 | 98,00 | 99 | 2 |
| Multilayer Perceptron | 95,71 | [99,35; 99,44] | 287 | 2 |
| Radial Basis Function Network | 90,35 | [99,35; 99,44] | 287 | 2 |
| 1NN | 99,72 | [99,12; 99,37] | 343 | 3 |
| 2NN | 98,58 | [99,12; 99,37] | 343 | 3 |
| 3NN | 98,30 | [99,09; 99,11] | 286 | 3 |
| 4NN | 98,02 | [99,09; 99,11] | 286 | 3 |
| 5NN | 98,58 | [99,00; 99,08] | 271 | 3 |
| Naive Bayes + discretization | 98,02 | [99,52; 99,54] | 421 | 3 |
| Multilayer Perceptron | 100,00 | [99,82; 99,84] | 757 | 3 |

Results of the most effective variants of the kNN, the Naive Bayes (denoted by NB and NBd) and – in case of the third-order tensors – the Multilayer Perceptron (MLP) were depicted in Fig. 3 (second-order tensors) and Fig. 4 (third-order tensors).

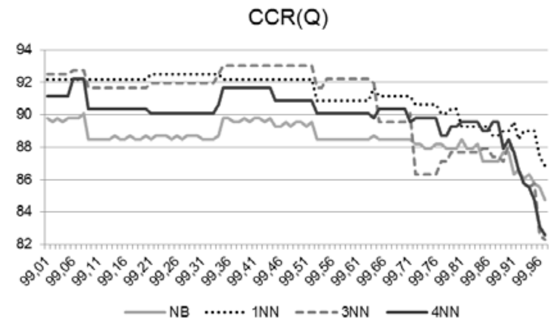


Fig. 3. Dependency between CCR and $Q$ for the most effective kNN variants and the Naive Bayes technique for the case of second-order tensors

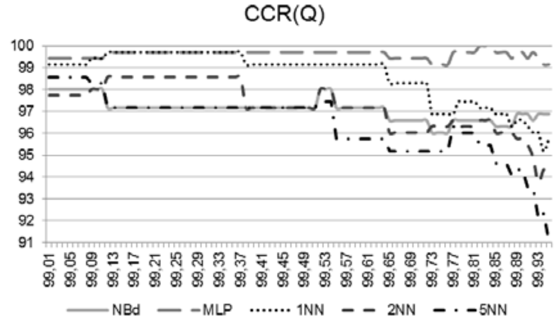


Fig. 4. Dependency between CCR and $Q$ for the most effective kNN variants, the Naive Bayes with discretized attributes and the Multilayer Perceptron for the case of third-order tensors

The third-order tensorial representation turned out to be more effective for gait mocap data classification than the second-order variant.

## Conclusion

In this paper the authors have discussed results of the research aiming at human identification based on gait motion capture data represented as second-order or third-order tensor objects. High-dimensional tensor samples were reduced by means of the MPCA and subsequently classified using kNN, Naive Bayes (optionally with discretized attributes), Multilayer Perceptron, and Radial Basis Function Network. The most effective classifier for gait mocap data was based on the multilayer perceptron. However due to long time of computation it is worthwhile to continue searching for more efficient classification methods.

The sizeable reduction of dimensions of tensorial samples based on mocap data was achieved at the percentage of variation kept in each mode of only a little less than 100. Furthermore, classification based on the reduced number of features turned out to be more effective than at the full variation kept in each mode.

Conclusions drawn from experiments with mocap data will be helpful during the next stage of the research which was started analysing video sequences taken from the CASIA Gait Database (http://www.cbsr.ia.ac.cn/english/Databases.asp) and will be continued using video material from the municipal surveillance system.

Future research will also explore the influence of the feature selection methods on the effectiveness of the gait based identification process. The promising Invasive Weed Optimization (IWO) metaheuristic will be adapted to the searching the feature space for an adequate subset of features. Nonlinear techniques (Isomap, Landmark Isomap, Locally Linear Embedding (LLE)) are planned to be applied for dimensionality reduction as well.

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