Human Identification Based on Gait Motion Capture Data

Henryk Josiński, Adam Świtoński, Karol Jędrasiak, and Daniel Kostrzewa

***Abstract*—The authors present results of the research aiming at human identification based on gait motion capture data. Second-order tensor objects were chosen as the appropriate representation of 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 library were used: k Nearest Neighbors (kNN), Naive Bayes, Multilayer Perceptron, and Radial Basis Function Network. The maximum value of the correct classification rate (CCR) equal to 95.71% was achieved for the classifier based on the multilayer perceptron.**

***Index Terms*—gait motion capture data, tensor objects, dimensionality reduction, multilinear principal component analysis (MPCA), data classification**

I. 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.

Direct application of the mocap system for human identification is problematic because of the inconvenience of the capturing 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 [3].

Motion data lie in high-dimensional space [4], but the components of gait description, discussed in detail in section II, 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.

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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 [5]. The principal components analysis (PCA) was also used in a similar way [6]. In [7] 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 [8]. The application of the *Procrustes* shape analysis method and the *Procrustes* distance measure in gait signature extraction and classification was shown in [9]. Numerous studies present frameworks developed for recognition of walking persons based on the dynamic time warping technique (DTW) [10], [11], as well as on the variants of the hidden Markov model (HMM), inter alia, generic HMM [12], population HMM [13], factorial and parallel HMMs [14].

The model-based approaches use information about the gait, determined either by known structure or by modeling [2]. The ASF/AMC format is often applied as the skeleton model of the observed walking person. Numerous methods aim to estimate the model directly from two-dimensional images. In [15] the particle swarm optimization algorithm (PSO) is used to shift the particles toward more promising configurations of the human model. In [16] 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* [17].

It is stated in [18] 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

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structure or the actual physical phenomenon [19]. The dimensionality reduction problem can be solved, inter alia, by encoding an image object as a general tensor of second or higher order [20]. 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 [21], whereas a framework for tensor object feature extraction is presented in [18]. One of the extensions of the MPCA – an unsupervised dimensionality reduction algorithm for tensorial data, named as *uncorrelated MPCA* (UMPCA) – is proposed in [22] and [23].

Tensor objects as a form of representation of gait sequences are discussed in section II, whereas section III contains a brief description of the MPCA algorithm. Section IV deals with procedure of the experimental research along with its results. The conclusions are formulated in section V.

II. GAIT DATA REPRESENTATION

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 [18].

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 [3].

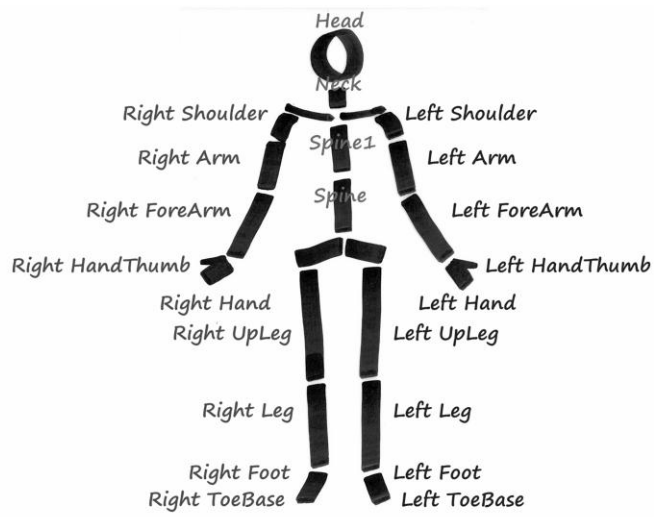

Fig. 1. Components of the skeleton model

The authors propose second-order representation of the gait motion capture data, 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, what 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.

Gait sequences were recorded in the Human Motion Laboratory (HML) [24] of the Polish-Japanese Institute of Information Technology, equipped with the Vicon motion capture system (Fig. 2).

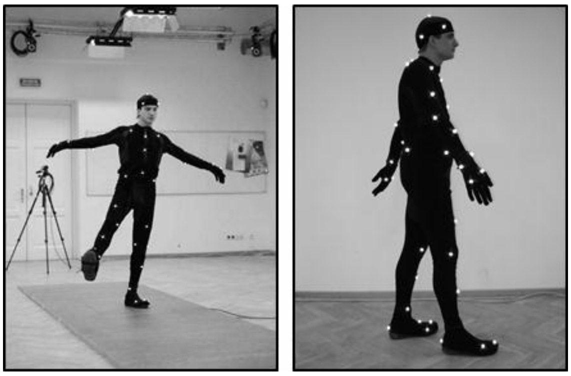

Fig. 2. Mocap sessions in the Human Motion Laboratory

III. THE MULTILINEAR PCA ALGORITHM

Multilinear projection of tensor objects for the purpose of dimensionality reduction was based on the algorithm and its MATLAB implementation presented in [18]. 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" [18]. 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. 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 $I = \prod_{n=1}^{N} I_n$, whereas after dimensionality reduction it is described by the formula $P = \prod_{n=1}^{N} P_n$, where $P_n \leq I_n$, $n \in [1, N]$. Symbols I_n, P_n denote the n-mode dimension of the tensor, respectively, before and after reduction.

As mentioned before, the tensor representation of the gait motion capture data proposed in this paper is composed of "time mode" (consecutive frames) and "pose mode" (significant Euler angles). Hence, as a result of the projection 2 *projection matrices* are constructed.

Computations were performed according to the MPCA algorithm in the following phases:

--Preprocessing – because all tensor samples are required to be of the same dimensions, an input set of 353 second-order tensor samples was normalized and, subsequently, centered by subtracting the mean value.

--Initialization (for each of 2 modes) – eigenvalues and eigenvectors were calculated. Subsequently, eigenvalues were arranged in descending order and cumulative sum of their relative contributions was computed and compared to

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the percentage Q of variation which should be kept in each mode. The first case, when the cumulative sum achieved or exceeded the user-defined value of Q, determined P_n (n = 1, 2) eigenvectors which formed the projection matrix.

--Local optimization of the projection matrices – both projection matrices were computed one by one with the other one fixed.

--Projection of the centered input samples using the projection matrices – 353 *feature tensors* constituting the low-dimensional second-order representation of the input samples with Q % variation captured were obtained.

IV. EXPERIMENTAL RESEARCH

Using the Vicon system 353 gait sequences for 25 men aged 20-35 years were recorded and stored in a database. 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.

The mocap data were transformed into the second-order tensor representation. After the dimensionality reduction by means of the MPCA feature tensors were subject to the classification process.

The first purpose of the numerical experiments was to determine the dependency between the percentage Q of variation kept in each mode and the total number of features P resulting from the dimensionality reduction. The Q values were taken from the range of [80, 100] using a step value of 1 till Q = 99. The range [99, 100] was explored more deeply – a step value was set to 0.01. The obtained dependency between P and Q is presented for clarity in the logarithmic scale in Fig. 3.

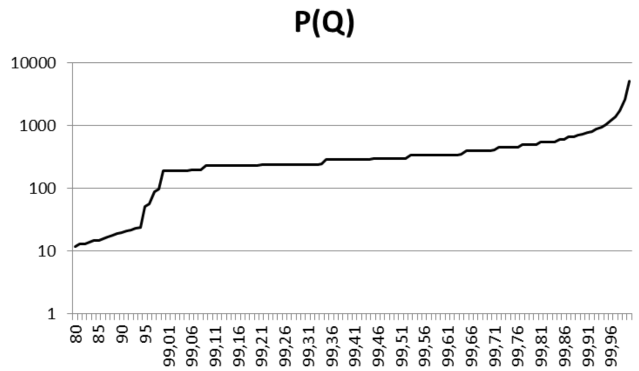

Fig. 3. Dependency between P and Q in the logarithmic scale

The gait motion capture data reduced by means of the MPCA were used in the first phase of the classification process by the following algorithms from the WEKA software [25]: 10 variants of the kNN (k = 1..10) and the Naive Bayes. The effectiveness of both methods expressed by means of the correct classification rate (CCR) was shown in Table I along with the most appropriate values of Q and P.

The dependency between CCR and the number k of neighbors taken into consideration by the kNN classifier was presented in Fig. 4.

TABLE I
EFFECTIVENESS OF CLASSIFICATION BY MEANS OF THE KNN

Classifier	CCR [%]	Q [%]	P
1NN	92.49	[99.21, 99.33]	240
2NN	90.88	[99.09, 99.20]	234
3NN	93.03	[99.35, 99.44]	287
4NN	92.22	[99.06, 99.08]	195
5NN	91.96	99.34	246
6NN	90.62	99.34	246
7NN	89.81	[99.06, 99.08]	195
8NN	88.74	[99.06, 99.08]	195
9NN	87.67	[99.00, 99.05]	190
10NN	86.06	[99.21, 99.33]	240
Naive Bayes	90.35	98.00	99

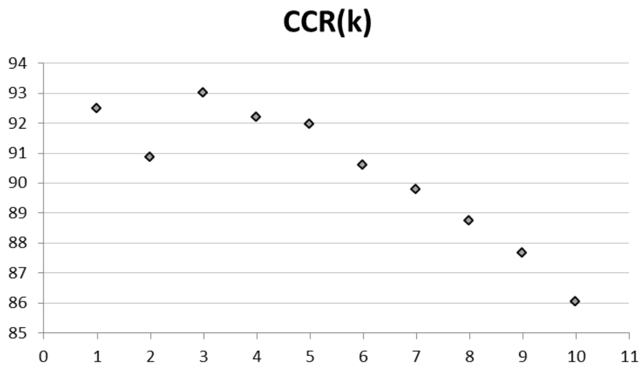

Fig. 4. Correct classification rate for 10 kNN variants

The effectiveness of the 3 best variants of the kNN classifier (k = 1, 3, 4) and of the Naive Bayes technique for the complete tested range of Q values was depicted in Fig. 5.

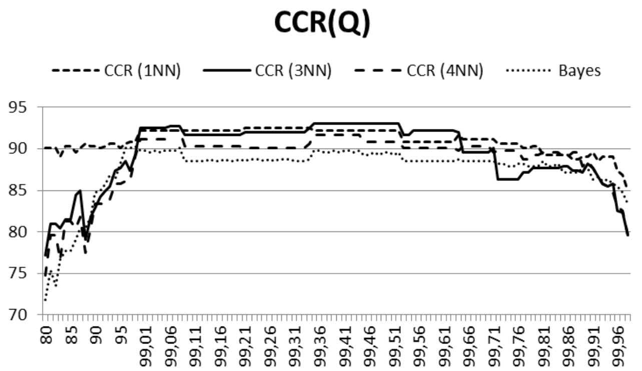

Fig. 5. Dependency between CCR and Q for the most effective kNN variants and the Naive Bayes technique

The best effectiveness (CCR = 93.03%) was obtained for the classifier 3NN using P = 287 features. As a consequence of this result, in the second phase of the classification process this value was assumed to be fixed. Thus, the methods applied in this phase – Multilayer Perceptron and Radial Basis Function Network – were used solely for classification of the feature tensors previously reduced to 287 features. Results of this process were shown in Table II.

TABLE II
EFFECTIVENESS OF CLASSIFICATION BY MEANS OF MULTILAYER PERCEPTRON AND RADIAL BASIS FUNCTION NETWORK

Classifier	CCR [%]	P
Multilayer Perceptron	95.71	287
Radial Basis Function Network	90.35	287

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The maximum value of the CCR equal to 95.71% was achieved for the classifier based on the multilayer perceptron after 1600 epochs.

V. 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 tensor objects. High-dimensional tensor samples were reduced by means of the MPCA and subsequently classified using kNN, Naive Bayes, Multilayer Perceptron, and Radial Basis Function Network.

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.

Future research will explore the influence of the feature selection methods on the effectiveness of the gait based identification process. Nonlinear techniques (Isomap, locally linear embedding (LLE)) are also planned to be applied for dimensionality reduction. Conclusions drawn from experiments with mocap data will be taken into account during the next stage of the research which will be carried out using video sequences.

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