World Academy of Science, Engineering and Technology
International Journal of Computer and Information Engineering
Vol:6, No:11, 2012

Dynamic Time Warping In Gait Classification of Motion Capture Data

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***Abstract*—**The method of gait identification based on the nearest neighbor classification technique with motion similarity assessment by the dynamic time warping is proposed. The model based kinematic motion data, represented by the joints rotations coded by Euler angles and unit quaternions is used. The different pose distance functions in Euler angles and quaternion spaces are considered. To evaluate individual features of the subsequent joints movements during gait cycle, joint selection is carried out. To examine proposed approach database containing 353 gaits of 25 humans collected in motion capture laboratory is used. The obtained results are promising. The classifications, which takes into consideration all joints has accuracy over 91%. Only analysis of movements of hip joints allows to correctly identify gaits with almost 80% precision.

***Keywords*—**Biometrics, dynamic time warping, gait identification, motion capture, time series classification, quaternion distance functions, attribute ranking.

I. INTRODUCTION

GAIT is coordinated, cyclic combination of movements which results in human locomotion [1]. It contains individual features allowing to recognize persons. In [2] the experiment, confirming the thesis of human ability to identify person on the basis of visual gait inspection, is presented. Selected group of volunteers tried to notice and remember individual gait features of a prepared train set containing gaits of four different actors. After the training phase, the recognition is performed. The visualization is created on the basis of applied skeleton model - only skeleton poses containing defined segments marked by straight lines are displayed. The average accuracy of the identification is almost 60%, which is much better than random guessing, however it also confirms that gait identification is challenging task. Gait biometric techniques do not require the awareness of identified person, which is its great advantage and gives wide spectrum of possible applications.

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The motion data representations can be divided into two main groups: model free and model based, depending upon whether a priori information about the object shape is employed [1]. In model free approaches the motion data is usually represented by time sequences of silhouettes, extracted from video recordings by background subtraction. To reduce the dimensionality of such a representations linear and nonlinear transformation of silhouette spaces are carried out. Examples of applications of linear Principle Component Analysis and Independent Component Analysis and nonlinear manifold learning can be found in [4], [5] and [6].

In model based approaches specified human body model is assumed. Most often used models are associated with kinematical data and they have a form of kinematic chain with tree like structure. The root object is placed on the top of the tree and is described by its position in global coordinate system. Child objects, representing joints, are rotated relative to their parents. For instance in [2] the feature vectors of kinematical data sequences are calculated and supervised machine learning is performed. In [7] the dimensionality of kinematical data is reduced prior to classification..Other kind of model based approaches is shape based models. Segments are described as rectangular and trapezoid-shaped patches or they are volumetric or surface-based in 2D and 3D models respectively [1].

Regardless of data representation, the classification of motion sequences can be divided into three basic categories feature extraction, dynamic time warping and Hidden Markov Models.

In the feature extraction approach we calculate features describing time sequences of body configuration parameters. As the result we get motion descriptors in the form of vector which can be further classified by supervised learning or expert systems. Features can reflect statistical properties of sequence values as for instance mean value or standard deviation, histogram which estimates whole. Distribution not only their parameters or Fourier components [2], [8].The features can be further processed. In [9] the first two lowest Fourier components of the frequency domain are chosen and afterwards PCA reduction is applied. In medical applications features are usually associated with the supported diagnosis. In [10] four type of health problems of elderly are diagnosed on the basis of 13 different features prepared by the medical expert. For instance, one of them represents the quotient between maximal angle of the left knee and maximal angle of the right knee. Other examples of features are asymmetry indexes [11], which are used for instance in Parkinson disease diagnostics [12]. A feature extraction approach based on the wavelet transform for the distinction between normal and pathological gait is presented in [13].

Dynamic Time Warping tries to synchronize two motions by warping their time domains, which makes the motions faster or slower in the following moments. Matching of the synchronized motions estimates similarities between them, which can be a base for nearest neighbor's classification. In [7] the DTW transform is used for the reduced pose spaces by Principal Component Analysis and in [14] DTW is applied to the sequence of binary relation motion features, which indicates defined relationships between body parts.

In approaches with Hidden Markov Models (HMMs) the pose sequences are interpreted as states of Markov chains. The training phase has to estimate the Markov Models parameters for all considering motion classes based on the pose sequences. In classification stage, the model with greatest probability of generating classified motion sequence is determined. The crucial challenge is the estimation of pose distributions in the following states. The poses are usually described in the high dimensional continuous spaces, which makes the problem more difficult. To work in fewer dimensions the some kind of pose reduction has to be performed. In [15] the special pose descriptors are proposed called P-style Fourier Descriptor and Feature Examplar Descriptor. In [16] the poses are transforms into low dimensional embedding by manifold learning before modeling their dynamics with HMM

The paper describes obtained results of gait identification by Dynamic Time Warping approach based on the kinematic data captured by a motion capture laboratory. The different pose distance metrics are considered, as for instance ones based on the rotation coded by unit quaternions. What is more a selection on the level of single joints is carried out. It is the main contribution of the presented work, associated with comprehensive evaluation of DTW classification approach to kinematical data of gait and assessment of individuality of subsequent joint movements.

II. Motion Capture

A gait can be captured by a stereovision system of two-dimensional video cameras. Such an acquisition stores motion data in the form of the video clips - sequences of the two-dimensional images. The data has model free representation and does not contain direct information about the actor positions, skeleton model and its kinematic chain.

The most precise measurements of motion data are obtained by the motion capture systems. During the acquisition of a kinematical data man has to put on special suit with attached markers. The positions of the markers are tracked by calibrated cameras. On the basis of gathered data the 3D coordinates of the markers are reconstructed. They are further transformed into the kinematic chain representation with specified skeleton model. The joint rotations can be coded by Euler angles or unit quaternions. The number of values required to describe the pose depends on the assumed skeleton model - the number of joints and theirs degrees of freedom. The motion capture acquisition is very precise, but it suffers also shortcomings. It is time consuming and requires awareness of the identified human. .

Much less precise are markerless motion capture systems, which estimate pose models on the basis of video recordings data. In this approach the proper set of pose parameters which minimizes the difference between the projected body model and the real pose in the image of the analyzed motion frame is determined [1]. The differences is approximated by some kind of likelihood or cost function. The crucial problem is the choice of a proper optimization method. For instance, in [17] the particle swarm optimization algorithm is used.

Summing up, the motion capture is very precise, but its practical deployments to human identification tasks are limited. It is so because of the inconvenience of the acquisition process. The usage of motion capture is suitable in developing phase. It allows us to focus on the proposed method and evaluate it without the influence of the pose estimation errors. However, the system built can be easily extended to work with 2D video data by using proper markerless motion capture technique.

III. Dynamic Time Warping

Dynamic Time Warping synchronizes two motions. It uses a cost matrix which contains the similarities between every pair of poses of compared motions. The synchronization is determined by the monotonic path connecting starting and ending points of the cost matrix with the lowest accumulated cost. The cost of the path found estimates motions dissimilarity. DTW is usually calculated by dynamic programming

The crucial challenge in effective DTW motion comparison is the method of calculating distances between motion frames. The authors of the [20] propose 3D cloud point distance measure. First they build cloud points for compared frames and their temporal context. Further, they find global transition to match both clouds and finally calculate the sum of distances between corresponding points of matched clouds. For the configuration coded by the unit quaternions, the distance can be evaluated as the sum of quaternion distances. In [21] the frame distance is the total weighted sum of quaternion distances because the influence of transformations can differ - the weights depend on the joints. In [14] the DTW transform is applied to the sequence of binary relation motion features, which indicates defined relationships between body parts.

There are many modifications of the DTW approach. For instance, it can be calculated by taking into consideration derivates of the body parameters instead of their values [22] or simultaneously both of them: values and derivates [23]. In case of low capture frequency continuous version of DTW [24] should be used. Another kind of improvement is canonical time warping, which finds the path with minimal cost from possible linear combinations of the body parameters [25]. The synchronization can be performed independently for different body configuration parameters with a multidimensional DTW [26]. To find some short lasting specific movement during the motion the similarity matrix has to be modified by assigning the zero distance value on the borders of the matrix [26].

The first applications of DTW are associated with speech recognition tasks [30], [18], [19]. Examples of gait classification with DTW usage for model free data representations are presented in [28] and [29]. In [7] DTW is based on the reduced kinematical data.

IV. Collected Database

We use PJWSTK laboratory with Vicon motion capture system (http://hml.pjwstk.edu.pl) to acquire human gaits. The collected database contains 353 gaits coming from 25 different males at the age of 20 to 35. We specify the gait route, a straight, 5 meters long line. The acquiring process starts and ends with T-letter pose type because of the requirement of the Vicon calibration. Examples of collected gaits are presented in Fig. 1.

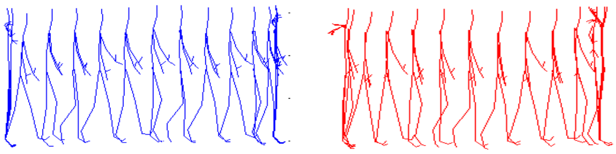

Fig. 1 Examples of collected gaits

We define two motion types: slow gait and fast gait, without strict rules for the actors. Slow and fast gait are interpreted individually. The motions are stored in the Acclaim format with 22 defined segments and 72 dimensional pose space. The applied skeleton model is presented in Fig. 2. There are 66 Euler angles associated with rotations of defined segments, additional three representing global rotation and three dimensional vector of skeleton translation in a pose description.

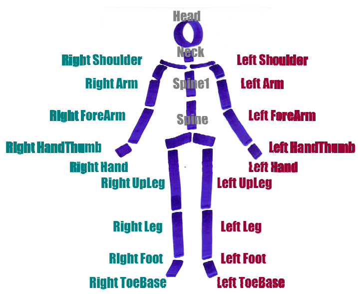

Fig. 2 Skeleton model

The detection of the main cycle of a gait, including two adjacent steps which are representative for the whole gait, is carried out. It is sufficient to track distances between two feet and analyze the extremes, as shown in Fig. 3. The longest distance takes place when a current step is finishing and the next is starting.

The motion data contains a translation value which depends on the gait location. It is possible that some humans start and end gait in specific locations, some walk in the middle of the specified route of the motion capture laboratory and others near its left or right sides. Such a data is related to the capturing place. Thus to perform classification which takes into consideration only the joints movements, which is much more reliable, the global translation values are removed from the pose description

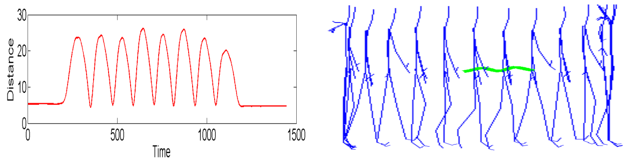

Fig. 3 Main cycle detection

Detailed analysis of individual features of gait paths can be found in [6].

V. Classification Results

The crucial challenge of DTW similarity estimation is the proper determination of distance between pose frames. It has an impact on the cost matrix calculations. The pose is represented only by rotations of the subsequent joints, thus the total pose distance d_{total} of the poses P_1 and P_2 can be defined as cumulated distance between corresponding joints:

$$d_{total}(P_1, P_2) = \sum_{j \in joints} d(P_1(j), P_2(j)) \tag{1}$$

In case where rotations are coded by Euler angles α, β, χ, classical Euclidean and Manhattan distance metrics can be applied.

$$d_{euclidean}(j_1, j_2) = \sqrt{\sum_{a=\alpha,\beta,\chi} (j_1(a) - j_2(a))^2} \tag{2}$$

$$d_{manhattan}(j_1, j_2) = \sum_{a=\alpha,\beta,\chi} |j_1(a) - j_2(a)| \tag{3}$$

However much more flexible representation of rotations give unit quaternions. They are well suited for interpolations and does not suffer gimbal lock problem. Thus comparison of rotation should be more effective. There are many different distance functions defined in quaternion space.

The distance can be reflected by the shortest path on the unit hypersphere S^3 in four dimensional space, connecting q_1 and q_2

$$d_{angle}(q_1, q_2) = \frac{2}{\pi} \cdot \arccos(\langle q_1, q_2 \rangle) \tag{4}$$

where $\langle q_1, q_2 \rangle$ denotes scalar product in R^4 and gives cosinus of the angle between q_1 and q_2.

If we do not calculate arccosinus of the scalar product, the function is nonlinear and it is formed by cosines of the angle between q_1 and q_2

$$d_{cosinus}(q_1, q_2) = 1 - \langle q_1, q_2 \rangle \tag{5}$$

Other approach of quaternions comparison is based on the distance in tangent space, into which quaternions are transformed by logarithm operator

$$d_{\tan gent}(q_1, q_2) = \left\| \log(q_1) - \log q_2 \right\| \quad (6)$$

where $\log(q_1) = [0, \alpha \cdot \vec{n}]$, α is rotation angle and $\vec{n}$ is unit length vector corresponding to rotation axis.

The last, simple distance function concatenates rotations q_1 and inverse rotation to q_2 represented by conjugate quaternion $\overline{q_2}$ and takes real part of the of resulted quaternion which corresponds the rotation angle.

$$d_{tsimple}(q_1, q_2) = re(q_1 \cdot \overline{q_2}) \quad (7)$$

In Fig. 4 the example cost matrices and determined DTW paths are shown of the gaits coming from single and different actors. For the Euler angles representation Euclidean distance metric is applied and in case of quaternion representation distance function called angle is used. The matrices are prepared on the basis of accumulated distance of all corresponding joints and on the basis of LeftUpLeg joint rotation differences. In case when gaits belong to different actors, DTW path is usually more irregular and matrix scale contains greater values. For the LeftUpLeg joint there are wide very similar regions in a cost matrix, which correspond to the standing phase of a left leg in a gait cycle. In this moment gait is performed by the right leg. The quaternions distances seem to be a bit more reliable; however the final assessment would be given by classification accuracies.

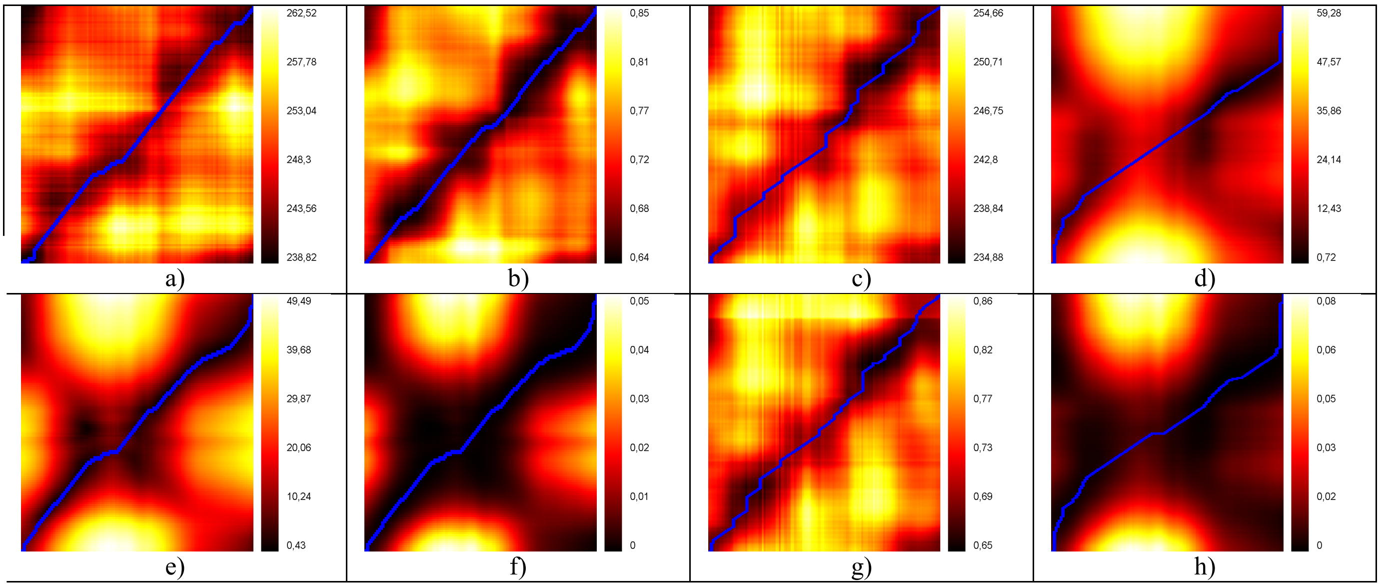

Fig. 4 Cost matrices and DTW paths of compared motions Euler angles – a), b), c), d) ; Quaternions – e), f), g). h) ; All joints – a), c), e), g) ; LeftUpLeg joint – b), d), f), h) ; Both gaits of the single actor – a), b), e), f) ; Gaits coming from different actors – c), d), g), h)

The obtained human identification results are presented in Table I. It contains percent of correctly classified motions. The nearest neighbor classifier with motion similarity measure corresponding to the cost of determined path by Dynamic Time Warping Transform is used. Different pose distance functions with rotation coded by Euler angles and unit quaternions are considered. In the basic approach the pose containing rotations data of all joints is prepared. However to evaluate individuality of the subsequent joints movements, the classification is repeated in case where the pose is described only by the rotation data of the selected joint. The results of classification based on single joints form a joint ranking, as presented in Table II.

Our Dynamic Time Warping implementation is based on the dynamic programming technique [30]. The database was split into two equal parts – train and test sets, prior to classification.

The total best identification accuracy is 91%. It is obtained by complete pose description with rotations coded by unit quaternions, cosinus and tangnent space distance functions. According to expectations, in most cases more effective comparison of joints rotation requires unit quaternions. It is only the single joint – RightFoot for which Euler angles give bit more efficient classification, however unit quaternions are only 2% worse in this case. The average scores of every distance function of unit quaternions space are very similar.

Individual features of the joint movements are strongly related to their activity during gait. Subsequent steps are preformed mostly by hip, knee and ankle joints, however the greatest range of motion have hip joints. It explains why LeftUpLeg and RighUpLeg are ranked on the top and have over 75% of classification accuracy. Ankle and knee joints have smaller range and they allow to identify humans with 50% efficiency. To improve body balance man waves his arms during gait, it is the reason why LeftArm and RightArm joints have 50%. Individual features of spine and root rotation data are probably caused by the posture disorders of the humans – some of them slouch other walk straight.

From the opposite side, head, toes and hands are mainly static during gait and their slight movements are insufficient for robust classification.

TABLE I
CLASSIFICATION RESULTS

	Euler angles		Unit quaternions			
	Euclidean	Manhattan	Simple	Tangnet	Angle	Cosinus
All joints	82,78%	86,11%	86,11%	91,11%	86,11%	91,11%
Head	26,11%	25,56%	26,11%	25,56%	26,11%	25,56%
LeftArm	46,67%	46,67%	50,56%	46,67%	50,56%	47,78%
LeftFoot	58,89%	61,11%	62,22%	62,22%	62,22%	62,22%
LeftForeArm	24,44%	24,44%	23,33%	24,44%	23,33%	24,44%
LeftHand	32,22%	33,33%	30,56%	30,56%	30,56%	30,56%
LeftLeg	48,33%	48,33%	47,22%	48,33%	47,22%	48,33%
LeftShoulder	36,11%	35,00%	36,11%	34,44%	36,11%	35,00%
LeftToeBase	32,78%	32,78%	33,33%	32,78%	33,33%	32,78%
LeftUpLeg	73,89%	72,22%	75,56%	73,33%	75,56%	73,33%
Neck	26,67%	28,89%	27,22%	26,67%	27,22%	26,11%
RightArm	48,89%	48,33%	49,44%	49,44%	49,44%	50,00%
RightFoot	54,44%	56,11%	54,44%	54,44%	54,44%	54,44%
RightForeArm	27,22%	27,22%	26,11%	27,22%	26,11%	27,22%
RightHand	23,89%	24,44%	26,11%	25,56%	26,11%	25,56%
RightLeg	45,56%	45,56%	47,78%	45,56%	47,78%	45,56%
RightShoulder	34,44%	35,00%	36,67%	34,44%	36,67%	34,44%
RightToeBase	33,33%	33,33%	31,67%	33,33%	31,67%	33,33%
RightUpLeg	52,22%	50,56%	76,11%	73,33%	76,11%	73,33%
Root	52,22%	50,56%	53,89%	53,89%	53,89%	53,89%
Spine	48,89%	48,89%	51,11%	50,00%	51,11%	50,00%
Spine1	47,78%	46,67%	46,67%	47,78%	46,67%	47,78%

TABLE II
JOINT RANKING ON THE BASIS OF THE JOINT CLASSIFICATION ACCURACY

Joint	Rank	Best Distance Function(s)
All joints	91,11%	Tangent,Cosine
RightUpLeg	76,11%	Simple,Angle
LeftUpLeg	75,56%	Simple,Angle
LeftFoot	62,22%	Simple,Tangent,Angle,Cosine
RightFoot	56,11%	Manhattan
Root	53,89%	Simple,Tangent,Angle,Cosine
Spine	51,11%	Simple,Angle
LeftArm	50,56%	Simple,Angle
RightArm	50,00%	Cosine
LeftLeg	48,33%	Euclidean,Manhattan,Tangent,Cosine
RightLeg	47,78%	Simple,Angle
Spine1	47,78%	Euclidean,Tangent,Cosine
RightShoulder	36,67%	Simple,Angle
LeftShoulder	36,11%	Euclidean,Simple,Angle
LeftHand	33,33%	Manhattan
LeftToeBase	33,33%	Simple,Angle
RightToeBase	33,33%	Euclidean,Manhattan,Tangent,Cosine
Neck	28,89%	Manhattan
RightForeArm	27,22%	Euclidean,Manhattan,Tangent,Cosine
Head	26,11%	Euclidean,Simple,Angle
RightHand	26,11%	Simple,Angle
LeftForeArm	24,44%	Euclidean,Manhattan,Tangent,Cosine

VI. SUMMARY AND CONCLUSION

The method of gait identification based on the nearest neighbor classification technique was proposed. To compare motions, cost matrix containing pose dissimilarities of compared gaits is calculated. The assessment of whole motion similarity is determined by the path connecting starting and ending points of the cost matrix with lowest cost. The dynamic time warping technique is used.

The method is examined on the basis of kinematic data of a gait, acquired by a motion capture laboratory. The applied skeleton model contains 22 joints with rotations coded by Euler angles and unit quaternions. Different pose distance functions are considered. In case of Euler angles Euclidean and Manhattan metrics are used and in case of quaternions distance functions based on the shortest path on the unit hypersphere S^3, tangent space and result of concatenation of the first rotation and inverse rotation to the second one are examined. To evaluate individual features of the subsequent joints movements during gait, simple joint selection is carried out.

To asses proposed approach database containing 353 gaits of 25 humans is used which is split into two equal parts – train and test sets, prior to classification. Obtained results are promising. Identification, which takes into consideration all joints have accuracy over 91%. Individual features of the joint movements are strongly related to their activity during gait. Hip joints allow to correctly identify gaits with almost 80%

precision, ankle, knee and spine joints with approximately 50% precision.

Quaternions allows to more efficient assessment of rotation similarities, in comparison to Euler angles, and in most cases give better classification results.

It is still possible that there is a combination of joints which would improve the classification. To state such a hypothesis, an exhaustive joint selection which analyzes whole subsets of joints has to be carried out. On the current stage only the simple combinations containing single joints have been analyzed.

The method can be easily extended to work with traditional video recordings data. It requires only to apply proper markerless motion capture technique.

ACKNOWLEDGMENT

This work has been supported by the research project OR00002111: "Application of video surveillance systems to person and behavior identi_cation and threat detection, using biometrics and inference of 3D human model from video."

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