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Human identification based on a kinematical data of a gait

Abstract. *The paper is devoted to the gait identification challenges. It evaluates human abilities to recognize gait on the basis of skeleton animations. Further, it proposes the method of gait identification based on the kinematical data .The feature extraction approach and supervised learning are applied. To explore the most individual joints movements, aggregated feature rankings are calculated. To examine the proposed method, the database containing 353 gaits of 25 different actors is collected in the motion capture laboratory. We have obtained 99.7% of classification accuracy.*

Streszczenie. *W artykule zaprezentowano eksperyment oceniający zdolności człowieka do rozpoznawania chodu oraz zaproponowano metodę identyfikacji chodu na podstawie danych kinematycznych. Bazuje ona na podejściu z ekstrakcją cech i uczeniem nadzorowanym. W celu oceny ruchu poszczególnych stawów pod kątem osobniczych cech różnicujących wyznaczono zagregowane rankingi atrybutów. Do weryfikacji zaproponowanej metody, zgromadzono bazę 353 przejść wykonywanych przez 25 różnych aktorów. Uzyskano ponad 99% skuteczność klasyfikacji. (**Identyfikacja osobnicza na podstawie kinematycznych danych chodu**).*

Keywords: motion capture, biometrics, gait identification, supervised learning, feature extraction, feature selection
Słowa kluczowe: pomiar ruchu, biometria, identyfikacja chodu, uczenie nadzorowane, ekstrakcja cech, selekcja cech

Introduction

Human identification has many applications. For instance, it is used in crime, civil and consumer identification, authorization and access control, work time registration, monitoring and supervision of public places, border control. There are numerous individual features which allow an efficient identification. One of them is a gait during a normal walk. It does not require the awareness of the identified human, which gives a large number of possible deployments.

The most precise measurements of motion data are obtained by the motion capture systems. The example of high tech, multimodal motion capture laboratory is the human motion laboratory in Polish-Japanese Institute of Information Technology [1]. It is equipped with the subsystem dedicated to kinematic data acquisition. During the acquisition a man has to put on special suit with attached markers. The positions of the markers in the following moments are tracked by eight calibrated infrared cameras. On the basis of gathered data the 3D coordinates of the markers are reconstructed. Their sequences represent kinematical characteristic of the captured motion. However, such a representation has essential disadvantages. It is strongly related to the motion location and it does not directly reflect the states of the following joints. For instance, the position of the marker located on a foot depends on the global human location and rotations in the preceding joints - hip and knee. This is the reason for transforming such data into the kinematic chain representation,. in which the root object is placed on the top of the tree and is described by its position in the global coordinate system. Child objects corresponding to bones are connected to their parents and contain information of rotation relative to the parents 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. Such a process of transformation requires calibration phase, in which the markers are clustered to form the groups corresponding to separate bone segments with known lengths. It can be properly done on the basis of motion containing movements of each joint. Thus, before a gait acquisition a man has to perform a special set of exercises, which makes the skeleton estimation more accurate. The motion capture acquisition is very precise, but it suffers also shortcomings. It is time consuming and requires awareness of the identified human. .

There are also possibilities of motion acquisition on the basis of the traditional 2D video recordings by the systems called markerless motion capture. 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 [2]. 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 [3] the particle swarm optimization algorithm is used. The devices with deep buffer estimation give other opportunities. In this case, transformation of the captured data to cloud point representation is much more precise, what should result in a better pose estimation.

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. The system built can be easily extended to work with 2D video data by using proper markerless motion capture.

Gait identification performed by a human

It is believed that a human is able to identify an actor on the basis of the visual gait analysis. We think that we recognize the gait of our friends. However, it is difficult for us to settle the most important individual factors, which are decisive for the discrimination. It could be appearance, body proportions, clothing, gait or all the above mentioned at one time. Probably this factors differ and depend on the identified human.

That is why, we decide to verify the thesis and prepare an experiment. We collect gaits of four different actors and select group of volunteers who recognize gaits. At the first stage, the volunteers try to notice and remember individual gait features on the basis of a prepared train set. After the training phase, the recognition is performed. The test set consists of eight gaits, exactly two samples of every actor which are different than the ones of train set. The gaits visualizations in training and testing phases are repeated depending on the necessity of the volunteers. The visualization is done on the basis of the applied skeleton model - only skeleton poses containing defined segments marked by straight lines were displayed.

Mean value	Median	Std. deviation
58.25%	68.75%	28.73%

Table 1. Identification accuracy obtained by human

The obtained results presented in Table 1 are surprising. In spite of a small size of the test set the identification accuracy is only 60%. The result is much better than in case of random guessing, which is only 25%, but it is still very poor. To evaluate the influence of individual abilities on the results, median and standard deviation values are calculated in the set containing average accuracies of the following volunteers. There is a strong dependency on the individual skills of the recognizer. Noticeably higher value of the median is caused by one of the volunteers who missclassified all gaits. The best accuracy is 75% and is obtained by two volunteers.

Actor	TP	TN	FP	FN	Accur.	Spec.	Sens.
1	11	45	3	5	87,5%	93,7%	68,7%
2	9	39	9	7	75,0%	81,2%	56,2%
3	7	42	6	9	76,5%	87,5%	43,7%
4	9	44	4	7	82,8%	91,6%	56,2%
AVG	9	42.5	5.5	7	80,4%	88.5%	56.2%

Table 2. Results of authorization tasks based on the gait recognition performed by human.

To examine gait discrimination of the following actors separately - maybe some of them are very easy to recognize but others are difficult, we split the task into four two class problems, similar as in authorization challenges. We calculate true positives (TP), true negatives (TN), false positives (FP), false negatives, specificity and sensitivity [4]. The results are presented in Table 2. There are no huge differences between the actors, the standard deviation is only 5%. Greater specificity values are mainly the result of more negative samples in the test set.

The experiment carried out confirms individual gait features. However, the identification task is very difficult to perform by a human. It requires a long training time, high concentration, good memory and individual abilities of the recognizer. Different joints are activated during typical gait. Thus, to explore individual features a simultaneous observation of the joints movements is necessary We expect that a computer supported identification should be more precise..

Related work

The model based approaches of gait identification can be grouped 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 obtain 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 the whole distribution not only their parameters or Fourier components. [5]. The features can be further processed. In [6] 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 [7] four types of health problems of elderly people are diagnosed on the basis of 13 different features prepared by a medical expert. For instance, one of them represents the quotient between the maximal angle of the left knee and the maximal angle of the right knee. Other examples of features are asymmetry indexes [8]. They are very often used in Parkinson disease diagnostics [9]. In [10] the gait with turning is analyzed for the PD diagnosis. A feature extraction approach based on the wavelet transform for the distinction between normal and pathological gait is presented in [8].

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 the similarities between them. DTW determines monotonic path connecting starting and ending points of the compared motions with the lowest cost in their similarity matrix. It is computed by dynamic programming. In [11] the DTW transform is used for the reduced pose spaces by Principal Component Analysis. In [12] the DTW transform 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 the states of Markov chains. The training phase has to estimate the Markov Models parameters for all considered 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 [13] the special pose descriptors are proposed called P-style Fourier Descriptor and Feature Examplar Descriptor. In [14] the poses are transforms into low dimensional embedding by manifold learning before modeling their dynamics with HMM.

Collected database

We use PJWSTK laboratory with Vicon motion capture system [1] 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.

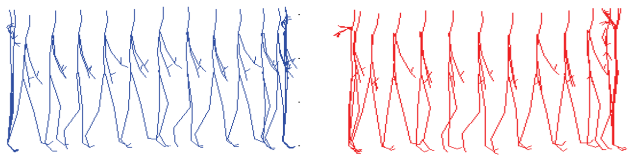


Fig. 1 Examples of collected gaits

We define two motion types: slow gait and fast gait, without strict rules for the actors. Slow and fast gait have been 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.

To detect the main cycle of a gait, including two adjacent steps which are representative for the whole gait [sprawdz acisv], it is sufficient to track distances between two feet and analyze the extremes. The longest distance takes place when a current step is finishing and the next is starting. Details of the method applied can be found in [5].

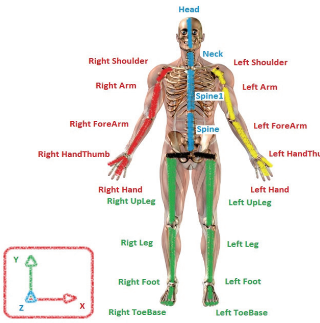
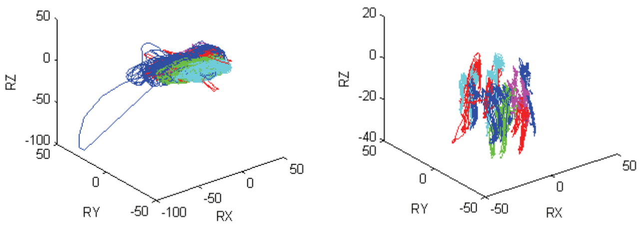


Fig. 2 Skeleton model

In Fig. 4 the motion trajectories representing Euler angles of RightUpLegi and RightShoulder joints are shown. The charts contain 15 motions of five different actors. Trajectories of given actor are labeled by unique color. There are visible gait loops corresponding to the adjacent steps, which have more regular shapes for the RightUpLeg joint. It is difficult to state discrimination rules only on the basis of visual analysis of motion trajectories.



a) b)

Fig. 4 Motion trajectories of five different actors representing Euler angle of rotations sequences in the following joints a) RightUpLeg, b) RightShoulder (see Fig. 2).

Proposed method

For motion classification we chose feature extraction approach. We decide to prepare four different sets of features: i) Statistical, ii) Histogram based, iii) Fourier transform based, iv) TimeLine.

In the statistical set there are included mean values and variances of each pose attribute. In the histogram based one, we build separate histogram for each attribute with different number of bins: five, ten, twenty, fifty and one hundred. It means that there are five different histogram representations of every gait.

For the Fourier feature set we transform the motion into frequency domain and take into consideration one to twenty components with the lowest frequencies. The feature set includes the module and phase of the complex number. We expected that Fourier transform would be more powerful for the gait representation with the main cycle detection. Only in that case, the same Fourier components store similar information and are directly comparable. What is more, because of different gait speeds, we decide to build additional representation by applying linear scaling of the time domain to the equal number of frames. That satisfies even more the direct comparability of the same Fourier components.

We call the last feature set timeline. The feature set stores information of attribute values as time sequence. The moments in which attribute values are taken into the set are determined by the division of the motion to the given number of intervals. For the same reason as described in the previous approach, the timeline feature sets are expected to be most informative for the motions with the main cycle detection. We have prepared timeline motion representation with sequence of five, ten, twenty, fifty and one hundred different time moments.

As the result of the feature extraction we obtain motion descriptors in the vector form. To classify gaits the supervised learning is applied. We chose two statistical classifiers: Naive Bayes with normal distribution and distribution estimated by kernel based method and k Nearest Neighbors classifier with number analyzed nearest neighbors ranging from 1 to 10. To split motions into train and test part we use cross validation method.

There is a great number of features in the proposed feature extraction approaches. For instance, there are almost 3000 features in the Fourier sets. Some of the surly contain a noise which decreases the classification efficiency.

That is why we manually define feature selections. For the statistical datasets we select means and variances and for Fourier datasets we limit the number of Fourier components and select modules and phases of the complex numbers. To explore better feature sets and to find the most discriminative joint movements we apply feature rankings. Two entropy based rankers: InfoGain and GainRatio and ranker which uses ChiSquare statistical test are chosen [4].

Results and conclusions

In Fig. 5 the aggregated classification accuracies are presented for all the examined approaches of feature calculations, separately determined for the whole gait and gait reduced to the main cycle. In aggregation we chose the best precision obtained by the examined classifiers with their parameters and for all combinations of manual feature selections performed. The accuracy is evaluated by the percentage of correctly classified gaits.

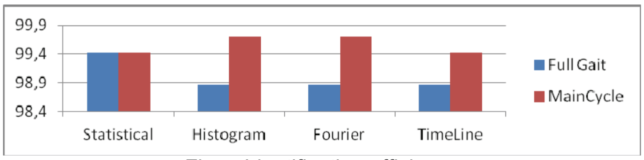


Fig. 5 Identification efficiency

The results are satisfactory. For the Fourier and histogram based motion features and main cycle detection we achieved 99.7% of classification accuracy, which means only a single missclassified gait out of 353 samples. There are no remarkable differences between feature extraction approaches. The statistical features get 99.4% of precision - - two missclassified gaits, for both cases of gait durations Timeline is only bit worse in comparison to Fourier and histogram based approaches.

The main cycle detection slightly improves the classification, but the individual gait features are still available and can be directly extracted from the whole gait.

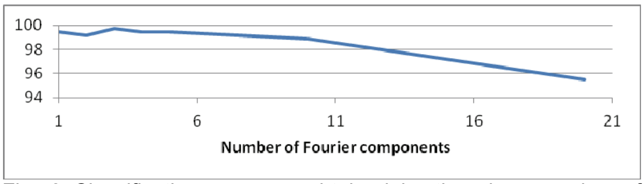


Fig. 6 Classification accuracy obtained by the given number of Fourier components

The analysis presented below is limited to the feature set containing Fourier components of the main cycle of a gait. In Fig. 6 the dependency between the number of considered Fourier components and the obtained classification accuracy is presented. To achieve best result we need three components, but selecting only the first lowest frequency component, similar to the statistical approach, causes only one more missclassfied gait. Higher frequency components contain some noise, which worsens the classification, but even for a twenty component feature set, the results are still acceptable.

All Actors		Actor 1		Actor 2		Actor 3		Actor 4	
LeftFoot	11,99	RightFoot	4,21	LeftUpLeg	4,86	Spine1	1,50	RightUpLeg	5,00
RightFoot	11,38	LeftUpLeg	3,87	root	3,50	RightFoot	0,81	RightFoot	4,68
LeftToeBase	10,29	LeftToeBase	3,64	RightUpLeg	3,03	Spine	0,79	LeftUpLeg	4,27
LeftUpLeg	9,91	RightUpLeg	2,50	LeftLeg	1,49	LeftArm	0,75	root	3,79
RightUpLeg	9,85	LeftFoot	1,85	RightShoulder	1,31	RightHand	0,70	Neck	3,60
Spine	9,19	Head	1,81	Head	1,29	LeftUpLeg	0,65	LeftFoot	2,81
RightToeBase	8,13	Spine	1,62	LeftShoulder	1,25	RightToeBase	0,51	RightToeBase	2,29
Spine1	6,53	Spine1	1,62	Spine	1,14	LeftHand	0,50	RightArm	1,83
root	5,49	RightToeBase	1,56	LeftFoot	1,13	RightArm	0,41	LeftShoulder	1,67
RightShoulder	5,36	LeftHand	1,27	RightFoot	1,06	RightLeg	0,33	Head	1,66

Table.3 Aggregated feature rankings

In Table 3 the aggregated top ten rankings of the following joints determined by InfoGain measure are presented. To aggregate data for the group of features associated with the given joint the sum is calculated. Such a value reflects some kind of approximation of total discrimination of the joint movements.

We determine rankings for the dataset containing all actors - the results correspond to the whole population and for the preprocessed datasets, which discriminate only a single randomly selected actor. The actors' names are substituted with two values, for instance "Peter Nowak" and "not Peter Nowak". The rankings in such a case point joints which are most distinctive for the selected actor. The results are similar for the GainRation and ChiSquare test based rankers.

The gait is mainly performed by legs - it means their movements are informative and that is the reason why they are at the top of the rankings. Root and spine attributes do not seem to have noticeable variations, but they probably achieve high scores. because of poster defects of some of the actors.

The attributes rankings determined on the basis of the datasets with discrimination of single actors are quite different. For instance, Actor 1 is hunching during the walk, which increases the spine and head attributes assessment and Actor 2 waves their hands in not typical way, which promotes shoulder attributes. The attributes evaluations for Actor 3 are much worse than others. It means his discrimination is more difficult.

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