Selection of individual gait features extracted by MPCA applied to video recordings data

Adam Switonski[1,2], Agnieszka Michalczuk[1], Henryk Josinski[1,2], Andrzej Polanski[1,2], and Konrad Wojciechowski[1,2]

[1] Polish-Japanese Institute of Information Technology, Aleja Legionow 2, 41-902 Bytom, Poland,
aswitonski@pjwstk.edu.pl, hjosinski@pjwstk.edu.pl,
apolanski@pjwstk.edu.pl, kwojciechowski@pjwstk.edu.pl,
WWW home page: http://www.pjwstk.edu.pl

[2] Silesian Univercity of Technology , ul. Akademicka 16, 44-100 Gliwice, Poland
adam.switonski@polsl.pl, henryk.josinski@polsl.pl,
andrzej.polanski@posl.pl, konrad.wojciechowski@polsl.pl,
WWW home page: http://www.iinf.polsl.pl

Abstract. The scope of this article is selection of individual gait features of video recordings data. The gait sequences are considered to be the 3rd-order tensors and their features are extracted by Multilinear Principal Component Analysis. Obtained gait descriptors are reduced by the supervised selection with greedy hill climbing and genetics search methods. To evaluate the explored individual feature sets, classification is carried out and CFS correlation based measure is utilized. The experimental phase is based on the CASIA Gait Database 'dataset A'. The obtained results are promising. Feature selection gives much more compact gait descriptors and causes significant improvement of human identification.

1 Introduction

Gait is defined as coordinated cyclic combination of movements which results in human locomotion [5]. There are strong individual gait features which allows for efficient identification. Such a biometric technique does not require awareness of identified human, which is a great advantage in comparing to other methods. Most simple and most often used gait acquisition is carried out by traditional video cameras. The gait is usually represented by a sequence of binary silhouettes determined by background subtraction.

The classification of a motion data can be performed on the basis of extracted feature sets of the time sequences. For instance in [8] the first two lowest Fourier components are chosen and in [20] four types of features are proposed for gait paths classification: statistical, histogram, Fourier transform and timeline. The features can be calculated by using dimensionality reduction techniques. The classical approaches of dimensionality reduction of motion data do the work at the level of the pose descriptors. In [19] on the basis of distances between the selected body parts, the feature vectors of binary silhouettes are extracted and the first two principal components are chosen. In [10] linear PCA and in [15] nonlinear manifold learning is applied prior to the classification with HMM. In [21] and [19] DTW follows by the reduction of pose descriptors by PCA of feature vectors calculated for video and motion capture data, respectively. In [18] a modified ICA is used for skeletons of binary silhouettes. Other examples can be found in [12], [8] and [11].

Recently the multilinear reduction methods for tensor objects have gained more attention. They allow to reduce multi-dimensional objects indexed by multiple indices. The motion sequences are addressed by the frame number and spatial coordinates, which means that the entire sequences can be reduced, not only the pose descriptors. In [16] the MPCA method is used for the detected cycles of binary silhouettes and the classification is performed by selected distance functions. The MPCA reduction is also extended by LDA method. The application of MPCA to the classification of motion capture data by supervised learning can be found in [22]. In [14] mutlilinear ICA and in [17] uncorrelated MPCA are applied to face recognitions.

It is very challenging task to propose small number of features without loss of individual data. Thus, feature vectors are usually defined in high dimensional spaces, which makes the classification more difficult and less reliable. However, it is still possible to discover a feature subset sufficient for precise motion data classification by a proper search method. That is main contribution of presented research. We apply supervised feature selection for extracted features of video sequences. The effectiveness of selection is evaluated by obtained compression rate and accuracy of a classification.

On the basis of our previous work [6] we decided to extract features of video recordings data by MPCA technique and classify them by supervised machine learning. To reduce the dimensionality of feature space and discover most informative ones the selection is carried out, prior to classification phase. Similar as in [6] CASIA gait database is used to examine proposed identification method.

2 Gait data representation

Portions of the research in this paper use the CASIA Gait Database collected by the Institute of Automation, Chinese Academy of Sciences[3]. The database contains raw video recordings as well as extracted binary silhouettes by background subtraction (see Fig. 1). CASIA dataset A is chosen. It contains 240 sequences of gaits coming from 20 subjects, recorded from three different camera perspectives: i.e. parallel, 45 degrees and 90 degrees to the image planes. Subjects walk forward in two opposite directions. To improve the reduction and obtain directly comparable MPCA components, which simplifies classification, gaits are unified. We select only the parallel view and reflected horizontally gaits of opposite direction. To make classification independent from gait location and

[3] CASIA Gait Database, http://www.sinobiometrics.com

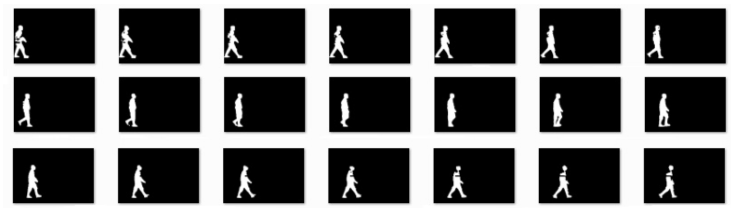

Fig. 1. Gait sequence from the CASIA database - actor "ljg".

to remove useless data, a bounding box of every video frame is determined. It has fixed 100x180 resolution, adjusted to the tallest subject, and is centered to silhouette geometric centroid.

Gait sequences are considered to be the 3rd-order tensors with modes determined by spatial coordinates and time domain. The MPCA requires the same mode dimensionality of all tensors which is satisfied for spatial coordinates, but because of a different number of frames of video recordings the time domain mode has to be normalized. We applied linear scaling with a number of frames determined by an average video size.

3 Gait identification performed by human

To prove the thesis of human ability to identify persons on the basis of visual gait analysis, the experiment was carried out.The disjoint training and test sets, containing gaits of four different persons were selected from CASIA dataset A. We asked the group of ten volunteers to recognize gaits. At the first stage, the volunteers tried to notice and remember individual gait features on the basis of a prepared training set. After the training phase, the recognition was performed. The test set consisted of four gaits, exactly one sample of every actor which are different than the ones of the training 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 determined binary silhouettes as shown in Fig. 2.

Fig. 2. Training set visualization.

Detailed results are presented in Tab. 1. The total average precision in the meaning of percentage of correctly identified gaits is 45%. It is noticeably better than random guessing which has only 25% in case of four actors. Most of the volunteers properly classified two gaits and missclassified other two ones, beside volunteers V7 and V8 which have worse precision with only single correctly identified gait. The standard deviation calculated for subsequent volunteers is 11% and for subsequent gaits is 26%.

Table 1. Identification performed by human, experiment 1

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	**AVG**
FYC	1	0	1	1	1	0	1	1	1	1	**80%**
HY	0	1	1	1	0	0	0	0	0	0	**30%**
lLJG	0	0	0	0	0	1	0	0	1	0	**20%**
LQF	1	1	0	0	1	1	0	0	0	1	**50%**
AVG	**50%**	**50%**	**50%**	**50%**	**50%**	**50%**	**25%**	**25%**	**50%**	**50%**	**45%**

To examine gait discrimination of the following actors separately - maybe some of them are very easy to recognize but others are difficult, we determine confusion matrix and 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, precision, specificity and sensitivity [13]. The results are presented in Tab. 2 and Tab. 3. In most cases the actor FYC is properly identified, it has noticeably the greatest precision, sensitivity and sensibility. His distinctiveness is probably caused by his long hairs, which are easy for human to recognize. The missclassification of remaining actors HY, LJG and LQF is very similar, they are confused quit randomly. Greater specificity values are mainly the result of more negative samples in the test set.

Table 2. Confusion matrix, experiment 1

	FYC	HY	LJG	LQF
FYC	8	1	1	0
HY	1	3	5	1
LJG	1	3	2	4
LQF	0	3	2	5

Table 3. Two class problems, experiment 1

	TP	TN	FP	FN	Precision	Sensitivity	Sensibility
FYC	8	28	2	2	90%	93%	80%
HY	3	23	7	7	65%	77%	30%
LJG	2	22	8	8	60%	73%	20%
LQF	5	25	5	5	75%	83%	50%

The obtained average identification precision is definitely better in comparing to random guessing, however it seems that selected gaits are very discriminative and should allow for more accurate identification. That is a reason we repeated experiment with simultaneous presentation of the training and test sets. It means, that volunteers observed and analyzed all gaits in the same moment and their task was only to match samples of the training and test sets. In such a case, the identification is independent on human abilities to memorize noticed individual gait features and relies only the observed gait similarities.

Table 4. Identification performed by human, experiment 2

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	**AVG**
FYC	1	1	1	1	1	1	1	1	1	1	**100%**
HY	1	1	1	1	1	1	1	1	1	1	**100%**
LJG	1	0	1	1	1	1	1	1	1	1	**90%**
LQF	1	0	1	1	1	1	1	1	1	1	**90%**
AVG	**100%**	**50%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**95%**

The results of identification with simultaneous presentation of the training and test sets are presented in Tab. 4, Tab. 5 and Tab. 6. This time they are very close to the ideal case of 100% of classification accuracy, only single volunteer V2 mistook actors LJG and LQF. As we supposed humans are easily able to recognize persons on the basis of their gait inspection, but more challenging task is to keep in mind discovered individual gait features. Probably longer teaching phase would improve the results of the experiment 1. The number of persons to identify by human is obviously limited, because of restriction of simultaneous presentation and observation. On the basis of the experiment performed we can state the thesis that gait allows to high precision human identification.

Table 5. Confusion matrix, experiment 2

	FYC	HY	LJG	LQF
FYC	10	0	0	0
HY	0	9	1	0
LJG	0	1	9	0
LQF	0	0	0	10

4 Multilinear principal component analysis

Multilinear principal component analysis, proposed in [16] is the multilinear extension of classical PCA method. The input and output data are considered to be tensor objects and contrary to PCA dimensionality reduction operates directly on tensors rather than its vectorized form.

Table 6. Two class problems, experiment 2

	TP	TN	FP	FN	Precision	Sensitivity	Sensibility
FYC	10	30	0	0	100%	100%	100%
HY	9	29	1	1	95%	97%	90%
LJG	9	29	1	1	95%	97%	90%
LQF	10	30	0	0	100%	100%	100%

A tensor is a multidimensional object, whose elements are addressed by indices. The number of indices determines the order of the tensor, where each index defines one of the tensor modes [16]. In MPCA an elementary matrix algebra is extended by two operations: tensor unfolding and the product of a tensor and matrix. The unfolding transforms a tensor into a matrix according to a specified mode. The tensor is decomposed into column vectors, taken from the perspective of a specified mode, see Fig. 3. The tensor X multiplication by the matrix U according to mode n $\tilde{\mathcal{X}}_m \times_n \mathbf{U}$ is obtained by the product of the unfolded tensor and the matrix U. To go back to a tensor space, an inverse unfolding operation is applied. In other words, the mode n of the tensor X is projected into the matrix U.

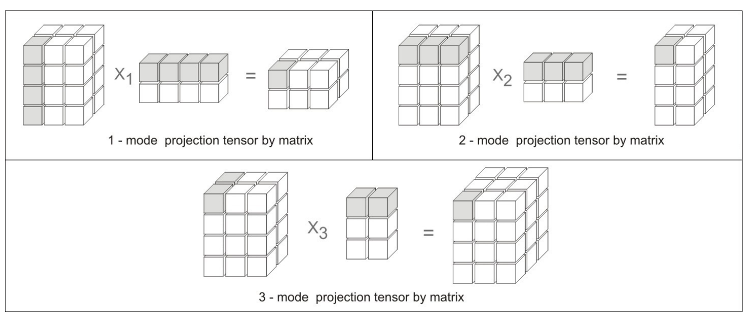

Fig. 3. 1,2 and 3-mode tensor matrix product.

The MPCA algorithm consists of the following steps:

1. Preprocessing - the normalization of input tenor samples to zero mean value.
2. Learning phase of MPCA - a loop with specified number of iterations,
   - Initialization - for each mode k:
     - set matrix: $\mathbf{\Phi}^{(k)*} = \sum_{m=1}^{M} \tilde{\mathbf{X}}_{m(k)} \mathbf{X}^T_{m(k)}$, where $\mathbf{\Phi}^{(k)*}$ denotes the desired matrix and $\mathbf{X}_{m(k)}$ is the m^{th} input tensor sample in the k-mode vector subspace, determined by unfolding operation.
     - Eigen-decomposition of the matrix $\mathbf{\Phi}^{(k)*}$,
     - Selection of P_k most significant eigenvectors which form a projection matrix $\mathbf{U^{(k)}}$. Eigenvectors are evaluated by corresponding eigenvalues and the number of selected eigenvectors is determined by the

variation cover $Q = \frac{\sum_{i_k=1}^{P_k} \lambda_{i_k}^{(k)*}}{\sum_{i_k=1}^{I_k} \lambda_{i_k}^{(k)*}}$, where I_k specifies the dimensionality of mode k and λ_{i_k} is i-th eigenvalue of matrix $\Phi^{(k)}$.
  - Local optimization - for each mode update tensors: $\tilde{\mathcal{Y}}_m = \tilde{\mathcal{X}}_m \times_1 \mathbf{U}^{(1)} \times_2 \mathbf{U}^{(2)} \times_3 \ldots \times_{(k-1)} \mathbf{U}^{(k-1)} \times_{(k+1)} \mathbf{U}^{(k+1)} \times_{(k+2)} \ldots \times_n \mathbf{U}^{(n)}$
3. Reduction phase of MPCA - calculate the output tensors by their projection on the determined matrices $\mathbf{U^{(k)}}$.

Our implementation of MPCA is based on Jama-1.0.2 library[4], supporting matrix operations and eigen decomposition.

5 Previous work

In [6] we proposed and examined method of gait identification based on the MPCA reduction and supervised learning. The experimental phase was carried out on the basis of dataset A of CASIA Gait Database. We considered two approaches of MPCA reduction called "Single dataset" and "train set and test set". In the first one all gait sequences are involved in learning phase of MPCA - determining the eigenvalues and eigenvectors. In the train set and test set approach, the gait database is divided into the training and test sets - two sequences of each actor are included in the training set and the remaining two in the test set. Similarly to the supervised classifiers, MPCA uses only the training set in the learning phase. In Fig. 4 the relationship between variation cover Q and obtained number of MPCA components is presented. For the maximum considered parameter Q = 0.99, each of gait sequences is reduced approximately twice from the initial size of 900 to about 500 thousands of attributes in both cases. A single attribute is obtained when Q is less than 0.08. The compression rate is very similar for both analyzed train datasets.

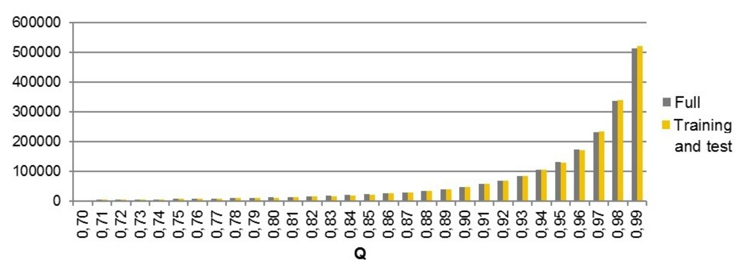

Fig. 4. Dimensionality reduction after applying MPCA algorithm.

The reduced data was classified by two statistical WEKA[5] classifiers. It is a Naive Bayes (NB) and the 1-nearest neighbor (1NN) classifier. The classification

[4] http://math.nist.gov/javanumerics/jama/
[5] http://www.cs.waikato.ac.nz/ml/weka/

was repeated twice for both proposed reduction approaches. In case of the "single dataset", 10-fold cross-validation is used to split data into the training and test parts. The classification accuracy is evaluated by percentage of correctly classified gaits out of the test set.

The detailed classification results for the "single dataset" approach are shown in Fig. 5. The mean classification accuracy for all considered Q values of 1NN classifier is 42.94% and the best result is 73.75% obtained by Q = 0.19 and Q = 0.20. There is a noticeable downward trend for the increasing Q parameter. More MPCA components undoubtedly contain more individual data, but also more noise.

The situation is quite different for Naive Bayes, which has a higher average score: 53.32% Beside the cases of strongly reduced gaits, ranging to Q = 0.48 with 358 MPCA components, it is much more precise. There is a very clear extreme for Q = 0.78 and 9064 attributes, in which the best classification accuracy of 86.25% is obtained. More MPCA components not only do not improve classification, but very strongly decrease it, to the worst performance of 16.25% for Q = 0.99.

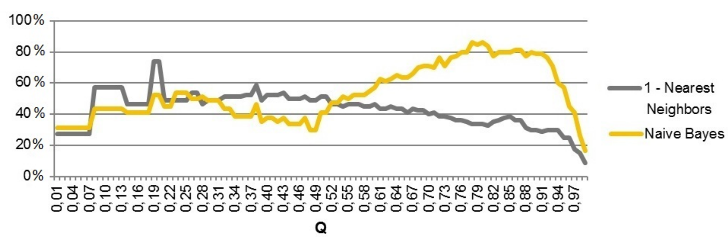

Fig. 5. 1NN and NB classification results for the single dataset approach.

When the training set of MPCA and the supervised classification contain only half the data in case of "train set and test set" approach, the results are much worse as shown in Fig. 6. The performance does not exceed 30% and 43% of classification accuracy for Naive Bayes and 1NN classifiers, respectively. It is much better than random guessing, which gives only 5%, but still very poor. It is probably caused by the weak representativeness of input and reduced spaces because of the small size of the training set. Only two gait instances of each class are insufficient for effective probability estimation of high dimensional continuous spaces, necessary in statistical classification. To improve the classification we applied supervised discretization of reduced feature spaces, which should make statistical estimation easier. Because calculating distances in discrete spaces seems to be much less accurate than in the continuous ones, which is a crucial step of 1NN, we repeated the tests only for Naive Bayes classifier. In discretization we applied MDL method proposed by Fayyad and Irani [7]. The results shown in Fig. 7 are even better than we expected. Regardless of the poor representativeness of the training set, the maximum accuracy is 92.50% for Q=0.67 and 0.85, which means only three misclassified gaits. We can locate

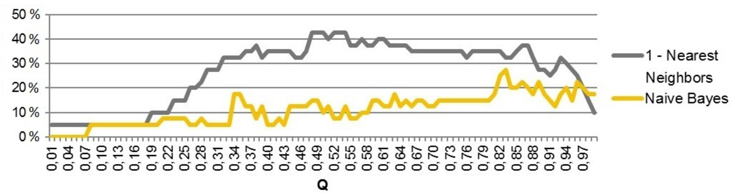

Fig. 6. 1NN and NB classification results for the train set and test set approach.

extreme once again. However the influence of noise in high dimensional spaces is weaker, for Q=0.99 accuracy is still greater than 60%.

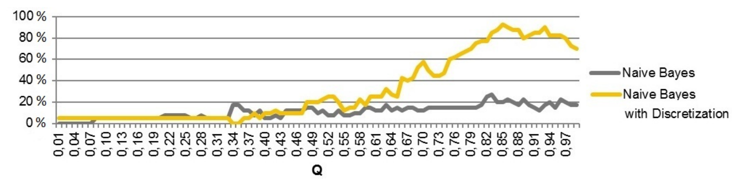

Fig. 7. Naive Bayes classification results for continuous and discretized spaces for train set and test set approach.

Because of such promising results obtained by the classification based on discretized spaces for the "train set and test set" approach, we evaluated the influence of discretization on classification performance for the single dataset approach. As seen in Fig. 8, the results have once again improved noticeably. The maximum precision is 98.75% for a wide range Q values starting from 0.76. It is always the same gait of the same subject, which is wrongly misclassified.

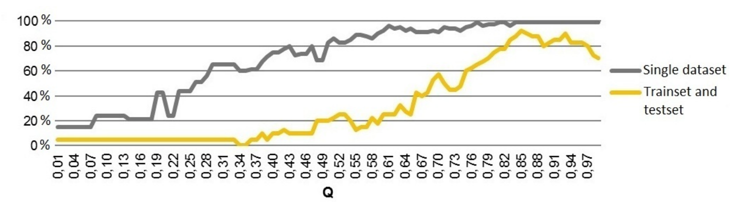

Fig. 8. Naive Bayes classification results for discretized spaces

6 Feature selection

The separate challenge is the automatic feature selection task, the choice of the most remarkable features from the point of view of the given classification problem. The exhaustive search of the all possible combinations of the features subsets is unworkable because of the computation complexity, the problem is NP complete. For the simple case of 50 features there are 1.1259e+015 possible combinations to test. That is the reason why the approximate methods have to be used. There are two main approaches in feature selection: attributes rankings and search strategies based on the evaluation of the whole subsets [13]. In the ranking approach we evaluate each of the attribute separately by the some kind of the quality index and select the highest scored ones. The number of attributes to select could be specified or could be determined based on the scores obtained. The crucial problem is the way attributes are evaluated. The most well known rankers are based on the calculated statistics as for instance GINI index, chi square test, Fisher ratio or depend on the determined entropy as for instance information gain and gain ratio. However the assumption of existence only simple relations between single attributes and class values is very naive. In many cases the worth of the attribute can be noticed only if considered with others. That is a reason why the methods with evaluation of whole feature subsets are gaining more attention. They are more reliable and usually give more compact representation, with greater predictive abilities. In approach with whole subset evaluation there are two crucial issues. It is the search method which specifies how the feature space is explored and the way subset are evaluated. In most cases the greedy hill climbing and genetic algorithms are used as search methods. In the hill climbing exploration [13], we start with empty subset and in the subsequent steps choose that attribute added to the currently determined subset which causes the best subset evaluation score. The loop is iterated till the total evaluation score is improving. In backward direction strategy, we start with complete feature set and in the following steps remove single attributes. The search also can be bidirectional. To minimize the probability of termination in local extreme, we can apply greater number of non-improving nodes to consider before finishing search. In genetic search strategy [1] candidate solutions represented feature subsets are coded by binary strings. The subsequent generations of feature subsets are inherited from previous ones with usage of basic genetic operators as selection, crossover and mutation. The most obvious way of subset evaluation can be performed by the precision of a subsequent classification [4]. Such an evaluator is called wrapper. Its main disadvantages are associated with great computational complexity and its dependency on a classifier and its parameters choices. More simple, consistency evaluator determines the level of consistency in the class values when the training instances are projected onto the subset of attributes [3]. The are also correlation based subset evaluators. Proposed in [2], CFS evaluator estimates the individual predictive ability of each feature along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low intercorrelation are preferred.

7 Experiments and results

We extend the work presented in [6] by supervised feature selection carried out prior to classification. It allows to obtain more compact gait description with lower dimensionality. The assesment of selected subsets of features corresponds to obtained compression rate and classification accuracy.

Supervised selection requires to supply a training set to be able to discover most remarkable attributes. This is a reason why the approach called "train and test set" [6] is utilized. The single training set is used to determine MPCA projection matrix, select most valuable MPCA components and teach classifier.

Greedy hill climbing with forward direction and genetic search methods and wrapper with nearest neighbor classification and CFS subsets evaluators are chosen to perform selection. To classify gait descriptors similar as in [6] statistical nearest neighbor and Naive Bayes classifiers are applied. At the current stage, discretized MPCA spaces, which obtained best accuracy in classification ([6], Fig. 8) are not taken into consideration in feature selection. Both utilized subset evaluation approaches based on nearest neighbor classification scheme and estimation of correlation seems to be more precise if carried out for continuous spaces rather than corresponding them discrete ones.

In Fig. 9 the obtained compression rates for successive variation covers Q of MPCA and for every combination of considered search method and evaluator are presented. The relation of number of MPCA components and variation cover Q is presented in Fig. 4. Compression rate is calculated to be a ratio of number of selected attributes to number of attributes in an input space. It can be noticed that greedy hill climbing gives much more compact descriptors with lower number of features in comparison to genetic search. For instance in case of variation cover Q=0.50 which gives 504 MPCA components, greedy hill climbing selects 7 and 34 features with wrapper and CFS evaluators respectively and genetic search selects 194 and 78 components. The difference rises with increasing variation cover Q. In case of Q=0.80 and 10773 MPCA components greedy hill climbing selects 10 and 240 features and genetic search selects 1746 and 1903 components. It is so because of the complexity of considered selection problem. The input set is very high dimensional and discriminative properties are scattered across MPCA components. It is extremely difficult to improve the classification accuracy by adding a single attribute, because only specified subsets of features have distinctive abilities. It is a reason why greedy hill climbing with wrapper subset evaluator terminates at first local extreme and it not able to discover efficiently individual gait features.

However much more important assesment of selected MPCA components gives classification accuracy presented in Fig. 10. It shows percentage of correctly classified gaits of a test set in respect to MPCA variation cover Q and applied selection strategy. Globally best precision is 95%, obtained by 449 attributes selected from the input set containing 29400 MPCA components for Q=0.87, which means 0.03% of compression rate, by hill climbing search and CFS evaluator. Genetic search with CFS evaluator is very similar. It has 92.5% of classification precision and it has very similar dependency on a number of fea-

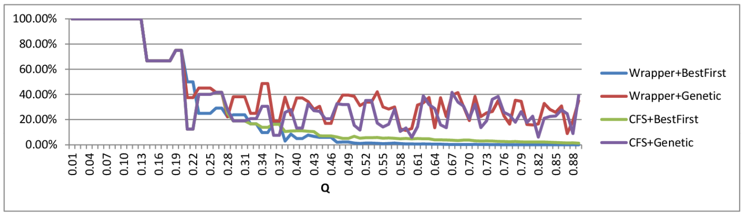

Fig. 9. Compression rates

tures of an input space. Much worse results gives wrapper evaluator, especially if combined with hill climbing search, which is caused by the same reason as explained in compression rates analysis.

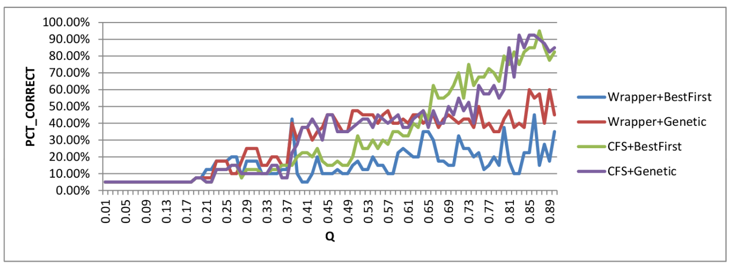

Fig. 10. Selection results

8 Conclusions

The general conclusion are consistent with those presented in [6]. Multliinear principal component analysis is an effective method of feature extraction of a motion data, which allows to identify humans precisely. However individual gait features are scattered across numerous MPCA components. Thus attribute selection simplifies gait description, discovers most discriminative features and allows for more efficient classification.

The identification performed on the basis of reduced MPCA space, as presented in Fig. 10 is improved significantly in comparing to raw MPCA space as presented in Fig. 6. What is more, although strong dimensionality reduction, selected attributes preserve most of individual gait features.

The obtained features subsets strongly depends on utilized subset evaluation strategy. Wrapper evaluation approach which in general is considered to be more precise, in our problem gives significantly worse results. It can be explained by scattering of individual gait features across MPCA components, so correlation based measures as for instance CFS evaluator, are more efficient in the input space exploration.

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