What image information is important in silhouette-based gait recognition?

G.V. Veres, L. Gordon, J.N. Carter and M.S. Nixon
School of Electronics and Computer Science
University of Southampton, UK
{gvv,lg2,jnc,msn}@ecs.soton.ac.uk

Abstract

Gait recognition has recently gained significant attention, especially in vision-based automated human identification at a distance in visual surveillance and monitoring applications. Silhouette-based gait recognition is the one of the most popular methods for recognising moving shapes. This paper aims to investigate the important features in silhouette-based gait recognition from point of view of statistical analysis. It is shown that the average silhouette includes a static component of gait (head and body) as the most important image part, while dynamic component of gait (swings of legs and arms) is ignored as the least important information. At the same time ignoring dynamic part of gait can result in loss in recognition rate in some cases, and the importance of better motion estimation is underlined.

1. Introduction

The demand for automated person identification systems is significantly growing in many important applications such as visual surveillance, access control, and smart interfaces, where reliable individual verification is essential. Recently much attention has been devoted to the use of human gait patterns as biometric. Gait recognition aims to discriminate individuals by the way they walk and has the advantage of being non-invasive, hard to conceal, being readily captured without a walker's attention, and is less likely to be obscured than other biometric features [14]. Human gait has always been an active research topic in physical medicine, psychology, biomechanics etc. Medical [13] and psychology [4] studies supported the view that if all gait movements were considered than gait was unique. A more recent study [18] confirmed the possibility of learning gait patterns and recognising people by gait, from video footage.

Approaches to gait recognition can be broadly classified as being model-based and model-free. Model-based methods [3, 11, 9] model the human body structure and extract image features to map them into structural components of models or to derive motion trajectories of body parts. Model-free methods [5, 1, 19, 2] generally characterise the whole motion pattern of the human body by a compact representation regardless of the underlying structure. The majority of current approaches are model-free.

In this paper silhouette-based gait recognition is studied and statistical analysis was performed. Previously statistical analysis was applied to face distinctiveness [15] and to shape analysis for gait recognition [20]. In this paper the purpose of statistical analysis is to answer the question: what image information is the most important in silhouette-based gait recognition? The appearances of subjects are presented as a large number of features, while the number of samples (records for each subject) is small. At the same time, the results of statistical analysis or/and recognition rate are often little changed if a subset of the features is used. As such, the remaining features are redundant and can be discarded. Before discarding features it is good to know what image information is considered to be redundant and what information is the most important in silhouette for gait recognition. It was found that the upper part of the body (a static component of gait) contains the most important information in average silhouette for recognition. Another analysis in this vein suggests that the lowest part of the body (30%) is significant for recognition [16]. However, our analysis is used to investigate the effects of averaging silhouettes, whereas the other analysis concerned matching silhouettes on outdoor data. Further, using outdoor data can lead to imprecise upper torso extraction (which can itself motivate use of averaging to reduce noise), whereas our analysis concerns more basic issues since the gait-silhouettes are extracted from laboratory-derived data.

The remainder of this paper is organised as follows. Section 2 presents statistical tools for extracting image information. Databases are described in Section 3.

Human silhouette representation is given in Section 4. A number of experimental results are presented and described in Section 5. Section 6 concludes this paper.

2. Statistical tools for extracting image information

2.1 One-way ANOVA

The analysis of variance (ANOVA) helps to identify the features which highlight differences between groups (subjects) [6, 7]. Let a database contain records of g subjects (number of groups) and n_l sessions for each subject. Let X_{lj}, where $l = 1, 2, \ldots, g$ and $j = 1, 2, \ldots, n_l$, be a random sample of size n_l from a population with mean μ_l, $l = 1, 2, \ldots, g$. Anova is used to investigate whether the population mean vectors are the same, i.e. the null hypothesis of equality of means could be formulated as $H_0 :\ \mu_1 = \mu_2 = \ldots = \mu_g$, and if not, which implies components differ significantly.

The F-test rejects H_0 at level α if

$$F = \frac{SSA/(g-1)}{SSW/(\sum\limits_{l=1}^{g} n_l - g)} > F_{g-1, \sum n_l - g}(\alpha),$$

where $F_{g-1,\sum n_l - g}(\alpha)$ is the upper (100α)th percentile of the F-distribution with $g - 1$ and $\sum n_l - g$ degrees of freedom; $SSA = \sum\limits_{l=1}^{g} n_l(\bar{x}_l - \bar{x})^2$ is the sum of squares among groups, where $\bar{x}_l$ and $\bar{x}$ are estimates of group and overall sample means recpectively; $SSW = \sum\limits_{l=1}^{g} \sum\limits_{j=1}^{n_l} (x_{lj} - \bar{x}_l)^2$ is the total within-group sum of squares, where x_{lj} is an observation of the feature from subject l, session j.

2.2 Principal component analysis

Principal component analysis (PCA) is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables. Given a set of n observations on p observed variables, the pupose of principal component analysis is to determine r new variables, where r is small relative to p. The r new variables, called principal components, must together account for most of the variation in the p original variables. Principal component analysis operates by replacing the original data matrix $\mathbf{X}$ by an estimate composed of the product of two matrices. In matrix notation the approximation $\hat{\mathbf{X}}$ of the matrix $\mathbf{X}$ is given by $\hat{\mathbf{X}} = \mathbf{Z}\mathbf{V}'$, where $\mathbf{Z}$ is the $(n \times r)$ matrix of observations on the first r principal components, and $\mathbf{V}(p \times r)$ is the matrix whose columns are the first r eigenvectors of $\mathbf{X}'\mathbf{X}$. The matrix $\mathbf{Z}'\mathbf{Z} = \Lambda$, where Λ is the diagonal matrix of r eigenvalues λ_k, $k = 1, 2, \ldots, r$. The sum of squares and cross products matrix for the principal components is therefore a diagonal matrix with diagonal elements λ_k, that decline in magnitude. The eigenvalues λ_k are given by $\sum\limits_{i=1}^{n} z_{ik}^2 = \lambda_k$, $k = 1, 2, \ldots, r$. The sum of squares for each principal component is therefore given by the corresponding eigenvalue.

The quantity to be minimised is given by

$$tr(\mathbf{X} - \hat{\mathbf{X}})'(\mathbf{X} - \hat{\mathbf{X}}) = tr\mathbf{X}'\mathbf{X} - \sum_{k=1}^{r} \lambda_k$$

and hence if $r = p$, then this expression has the value zero.

Each of the eigenvectors generates a portion of the total variation (or sum of squares) in $\mathbf{X}$ as measured by $tr(\mathbf{X}'\mathbf{X})$. The contribution to $\sum\limits_{k=1}^{p} \lambda_k$ provided by $\mathbf{z}_l = \mathbf{Z}\mathbf{v}_l'$ is $\mathbf{z}_l'\mathbf{z}_l = \lambda_l$. The proportion of the total variance measured by $tr(\mathbf{X}'\mathbf{X})$, accounted for by the component $\mathbf{z}_l$ is given by $\lambda_l / \sum\limits_{k=1}^{p} \lambda_k$. The number of components actually used for the approximation of $\mathbf{X}$ can be guided by the measure $\sum\limits_{k=1}^{l} \lambda_k / \sum\limits_{k=1}^{p} \lambda_k$, where $l \leq p$.

The principal components depend solely on the covariance or correlation matrix of the data. Much has been written regarding the relative merits of using either the correlation matrix or the covariance matrix in PCA. Throughout the paper covariance matrices will be used due to some specifics of the data which are explained in Section 5. The mathematical principals behind PCA can be found in [6] or any other text book on statistical data analysis.

In multivariate analysis when a large number of variables available the results are often little changed if a subset of the variables is used. The remaining variables are, in a sense, redundant and can be discarded. PCA maybe used to decide how many variables to discard. In the next subsection the algorithm used for discarding variables in PCA is present.

2.3 Discarding variables in Principal component analysis

Although PCA allows for a reduction of dimensionality, in many applications it is desirable also to reduce the number of variables which are to be considered or measured in the future. Identification of redundant variables, and the selection of subsets of variables, is a long-standing area of interest in multivariate analysis. Many methods are possible for deciding which variables to reject, but, in practice experience and intuition often play part in the selection. However, only a few systematic studies seem to have been made in the context of principal component analysis. Several rejection algorithms were examined and compared by testing them on sets of both artificial data and real data by Jolliffe [8]. A number of methods was discussed for selecting a subset of variables which preserve most of variation of the original variables. McCabe [12] worked with the concept of a “principal variable”, which is a variable containing (in some sense) as much sample information as possible, and showed how the selection of a subset of such principal variables can be made on the basis of various optimality criteria. Krzanowski [10] suggested a new selection method based on Procrustes Analysis. All of these methods have their advantages and drawbacks. In the paper the following algorithm suggested by Jolliffe [8] was used due to its simplicity.

Here a principal component analysis is performed on all original p variables, and the eigenvalues are inspected. The first r components are considered successively, starting with the first. One variable is then associated with each of these r components, namely that variable which has the largest coefficient in the component (eigenvector) under consideration and which has not already been associated with a previously considered component, i.e.

$$i \in \Omega_r \text{ if } \; z_{ij} = \max_{i=1,\dots,p} \mathbf{z}_j \quad \& \quad i \cap \Omega_r = \emptyset,$$

where $j = 1, \dots, r$, Ω_r is the set of indexes of the variables chosen and z_{ij} is jth principal component value for ith variable.

These r variables are retained and the remaining $p - r$ rejected. The number of variables retained, r, is determined by the choice of λ_0, critical eigenvalue. Alternatively, r may be set equal to the number of components needed to account for some portion of the total variation.

3. Databases Description

Three databases were analysed in the paper. The sessions filmed inside were used for analysis. The first database, called the large database (LDB), consists of 115 subjects performing a normal walk. The processed data are derived by averaging a sequence of silhouettes in one gait period, between the heel strike of one foot until the next heel-strike of the same foot. The database arrangements are described elsewhere [17]. LDB can help to determine which image information remains unchanged for a subject in normal conditions and which changes significantly from subject to subject. The small database (SDB) consists of the sample of 10 subjects from the LDB. Each subject was filmed wearing a variety of footwear, clothes and carrying various bags. They were also filmed walking at different speeds. Each subject’s data was captured during a one continuous filming session. The SDB is intended to investigate the robustness of biometric techniques to imagery of the same subject in various common conditions (carrying items, wearing different clothing or footwear). The temporal database (TDB) also consists of 10 subjects from the LDB in normal conditions, but each subject was re-filmed on different dates. The TDB can help to investigate the consequences of time on recognition. It worth noticing that sequence of filming data in time was LDB, TDB and SDB with approximately 6 months difference between LDB and SDB.

4. Methods

In order to derive a signature for a gait sequence each image in a full gait cycle is first pre-processed. To produce binary subject silhouettes from the video the following steps are performed. First, the video is calibrated to correct for radial distortion errors. Second, chromakey analysis is done to mark some known background pixels to assist with extracting the subject. The data was recorded in a laboratory with a fixed green background cloth and the track, on which the subject walks, was painted the same shade of green. The chromakeyed frames from video are then cropped with fixed values adjusted to the gait lab parameters to exclude laboratory equipment. The final silhouette is obtained by connected component analysis and morphological operators. The output is then a series of binary images with the subject in white on a black background. The signature is calculated over a complete gait cycle, period detection is used to determine the beginning and the end of a gait period. This achieved by analysis of the variation of leg width. Finally, normalisation to achieve a common centre of mass was performed.

There are two approaches for obtaining a final signature for a given sequence. First, use a sum of all silhouettes presenting a full gait cycle and obtain an average appearance for each recorded sequence, i.e. if $\mathbf{P}(0)_{x,y}$ is the image at the origin of the time and the next image is $\mathbf{P}(1)_{x,y}$, then average silhouette is $\mathbf{A}(t)_{x,y} = \sum_{i=0}^{t} \mathbf{P}(i)_{x,y}$, where t is a final time moment of the sequence. Second, use a differencing operation on silhouettes describing a full gait cycle to obtain a differential silhouette, an estimate of motion, for each recorded sequence, i.e. the differential appearance is $\mathbf{D}(t)_{x,y} = \mathbf{P}(t)_{x,y} - \mathbf{P}(t-1)_{x,y} - \ldots - \mathbf{P}(0)_{x,y}$. Statistical analysis will be performed both on average and differential silhouettes from LDB, TDB and SDB to find out which image information is the most important. Moreover, since all three databases were recorded at different times and only experiment of 10 subjects walking normally in their own shoes will be analysed, the main question will be answered: what are the most important features remaining through the time when a subject walks normally from variation/recognition point of view?

5. Results

First all three databases will be analysed separately using ANOVA and PCA to find out which image information (features) is absolutely redundant, which features have a relatively high variation between the subjects, and how the original feature set can be reduced without a big loss in the variance explained and recognition rate. All three databases have redundant features and they are not necessarily all the same. However, if it is desirable to compare LDB, TDB and SDB either together or in pairs, the datasets have to be reduced to the same number of features. Therefore, shared important features between three databases were determined and how the reduction to these features in three databases will affect recognition rate was investigated. Recognition rate was calculated using Euclidean distance and the 1-nearest neighbour rule. No use was made of a more sophisticated classifier, since it is beyond the scope of the paper and the important factor was only the relative reduction/increase in recognition rate at this stage. It is worth noticing that to be able to display all results in an easily understandable way, the initial feature sets were extracted from 64×64 image including zeros when there are no silhouettes. However, to simplify the statistical analysis, the following mask of each database was constructed: features which contain only zero through all considered database were removed and their locations in the original set were marked recorded for later display purpose. However, there are feature vectors which still contain zeros for some subjects. Therefore PCA was run on the covariance matrix rather than the correlation matrix.

In all investigations, features are considered to have the same mean if $F \leq 1.25$ and PCA was run with threshold $\lambda_0 > 0.7$. The features are considered to be significantly different according to Anova, if their F-statistics greater than 50 for the average silhouette and greater than 20 for the differential silhouette. When analysis was performed on each database separately, the database was divided into probe and gallery for calculation recognition rate. Results of analysis of each database are summarized in a figure. A silhouette (average or differential) is presented in the top left corner of the corresponding figure. Top right corner of the figure represents significantly different features according to Anova, the results of PCA are shown in bottom left corner of the figure. How recognition rate changes with adding at first the most important features are presented in the bottom right corner of the figure. In the last case the solid line describes dependency of significant features versus the recognition rate, while the dashed line corresponds to the recognition rate when all features are considered.

5.1 Results on average silhouettes

Fig. 1 shows the results of analysis on the average LDB. According to Anova , significantly variant fea-

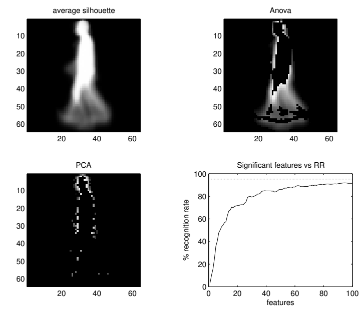

Figure 1. Statistical analysis of average LDB

tures describe contours of the head, body and legs. According to PCA the feature set can be reduced from 4096 features to 237 features with 100% variance explained or to even 100 features with 97.95% of variance explained (the left bottom corner of the Fig. 1). The majority of the most important features are concentrated within contours of the head and body. According to PCA the legs do not play an important part in recognition in an average silhouette. Combining results from Anova and PCA, it could be concluded that features describing inner parts of body, head and legs can be considered as redundant features in average silhouette-based gait recognition. (Though legs have a quite high variance among the subjects, they do not contribute much to the recognition process.) To confirm this, the recognition rate was calculated both for all 4096 features and for a reduced set of 100 features. The recognition rate for all features was 100%, while the recognition rate for 100 features was 95.2%. Although 5% was lost in recognition rate in the case of 100 features, significant dimensionality reduction can be achieved which is very important when only limited number of records for each subject is available and further statistical analysis is necessary.

Fig. 2 shows the results of analysis on the average TDB. Anova shows that significantly variant features describe contours of head and body, legs and arm in

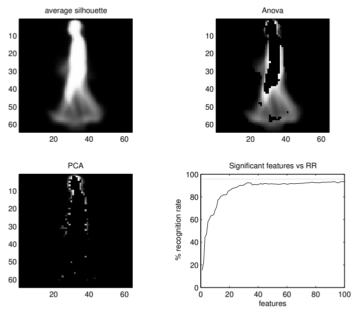

Figure 2. Statistical analysis of average TDB

this case. According to PCA the feature set can be reduced from 4096 features to 1006 features with 100% of variance explained or to 100 features with 95.81% of variance explained. Again the majority of the most important features are concentrated within contours of the head and body. As in the previous case, features describing inner parts of the body, head and legs can be considered as redundant features. The recognition rate was calculated both for all 4096 features and for a reduced set of 100 features. The recognition rate for all features was 95.78%, while the recognition rate for 100 features was 93.48%. In this case only 2.4% was lost in the recognition rate due to significant dimensionality reduction.

Fig. 3 shows analysis on the average SDB. Anova

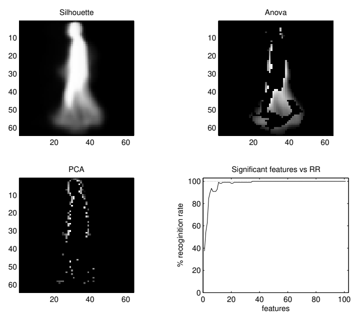

Figure 3. Statistical analysis of average SDB

shows that significantly variant features describe contours of head and body and legs in this case. According to PCA the feature set can be reduced from 4096 features to 218 features with 100% of variance explained or to 100 features with 98.13% of variance explained. Again the majority of the most important features are concentrated within contours of the head and body. However, there is a good number of important features in the area of the legs as well. The recognition rate for all features was 100% and the recognition rate for 100 features was 100% as well. In this case recognition rate was the same even after reduction dimensionality to 100 features.

After analysing three databases separately we can conclude that for all databases the most important features describe contours of head and body (the static components of gait) while using an average silhouette for recognition purposes. The question now arises whether there are any features which are important for all three databases. Two sets of important features were considered. First, the features which explain 100% of variance in each data set, i.e. 237, 1006 and 216 features from LDB,TDB and SDB respectively. These contain 65 features shared among three datasets as important features. Fig. 4 shows the location of the shared 65 features on silhouette at the top left picture. The shared features cover the contours of head, body and some legs. To find out the role played in recognition of these 65 features, LDB was considered as a gallery and SDB was considered as a probe and recognition rates were calculated both for all, 4096 features, and for shared 65 features. The bottom left picture in Fig. 4 shows how the recognition rate changes with adding additional features. Here the solid line describes dependency of significant features versus recognition rate (60.73% for 65 features), while the dashed line corresponds to the recognition rate when all features are considered (62.1%). It is interesting to notice that in

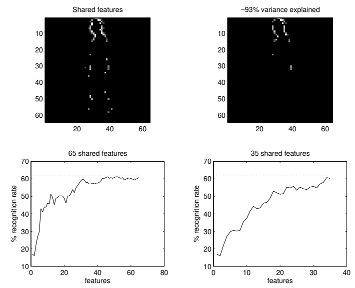

Figure 4. Important shared features for three databases and recognition rates

this case only 2.2% of recognition rate was lost. Further reduction was then tried. From each datasets 100 features obtained by PCA earlier were compared and 35 shared features were selected. It was found that 35 features explain approximately 93% of variance in each databases. These features were projected on silhouette and presented in Fig. 4, top right picture. In this case the most important shared features are contours of head and upper body. The recognition rate versus the shared features are presented in bottom right picture of Fig. 4. In this case the recognition rate for 35 features was 60.27% in comparison to 62.1% for all 4096 features. It leads to the conclusion, that although legs have a high variance among subjects, but they contribute very little or not at all to recognition of subject in average silhouette-based gait recognition. Accordingly, the static component of gait (head and body) appear to be the most important features in average silhouette.

To investigate an inclusion of dynamics components of gait in silhouette-based gait recognition, similar analysis was performed on differentiate silhouettes from LDB, TDB and SDB.

5.2 Results on differential silhouettes

Fig. 5 shows the results of analysis on the differential version of the LDB. Anova shows that significantly

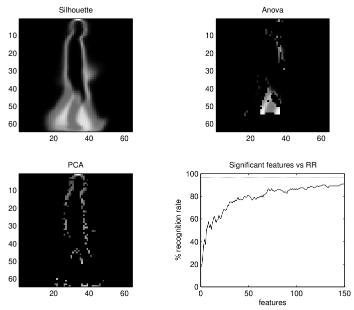

Figure 5. Statistical analysis of differential LDB

variant features describe some parts of body, legs and head. According to PCA the feature set can be reduced from 4096 features to 236 features with 100% of variance explained or to 150 features with 94.65% of variance explained. The majority of the most important features are concentrated within contours of the head and body as well as at some parts of the legs. The legs are less distinguished than the head and body in this picture. The recognition rate for all features was 96.67% and for 150 features was 90.83%. Although $\sim 6\%$ was lost in recognition rate in the case of 150 features, but the significant dimensionality reduction can be achieved.

Statistical analysis on the TDB and SDB produces similar results to above. The TDB can be reduced from 4096 features to 1001 features with 100% of variance explained or to even 150 features with 86.67% of variance explained. The recognition rate for all features was 92.82% and for 150 features was 92.03% with only 0.86% lost in recognition rate. The SDB can be reduced from 4096 features to 217 features with 100% of variance explained or to even 150 features with 96.54% of variance explained. The recognition rate for all features was 99.1% and 98.11% for 150 features with only the small reduction in recognition rate.

In case of differential silhouettes the legs are playing a bigger role than in the case of average silhouettes. Two sets of important features, which are the same in all three databases, were considered. First, the features which explain 100% of variance in each data set, i.e. 236, 1001 and 217 features from LDB, TDB and SDB. These features contain 115 shared among three datasets important features. Fig. 6 shows the location of shared 115 features on silhouette at the left top picture. The shared features cover the contours of head, body, some legs and some features of arm. To find out which role in recognition these 115 features play, LDB was considered as a gallery and SDB was considered as a probe and recognition rates were calculated both for all, 4096 features, and for shared 115 features. Bottom left picture in Fig. 6 shows how recognition rate changes with adding additional features. Again here the solid line describes dependency of significant features versus recognition rate (46.33% for 115 features), while the dashed line corresponds to recognition rate when all features are considered (56.42%). In this case 17.88%

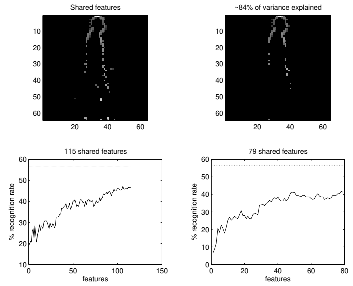

Figure 6. Important shared features for three databases and recognition rates

of recognition rate was lost. The further reduction was tried. From each dataset 150 features obtained by PCA earlier were compared and 79 shared features were selected. It was found out that 79 features explain approximately 84% of variance in each databases. These features were projected on silhouette and presented in Fig. 6, top right picture. In this case the most important shared features are contours of the head and body. The recognition rate versus the shared features is presented in bottom right picture of Fig. 6. In this case recognition rate for 79 features was 41.28% in comparison to 56.42% for all 4096 features, i.e. lost of 26.83%. Practically it means that it is not enough for a differential silhouette to include only static component of gait, in spite of the fact that static components of gait account for 84% of explained variance. Legs play the important role in a differential silhouetes, however a practically negligible amount of features desribing legs is shared through time, i.e. through all three databases. This then suggest that the motion estimation is crude and should be improved in future analysis.

6. Conclusions

The paper is devoted to answering the question: what image information is important in silhouette-based gait recognition. Three databases were considered, both separately and together. Two types of silhouettes were investigated, i.e. average silhouettes and differential silhouettes. The statistical significance is explained by principal components and analysis of variance. For averaged silhouettes the static components around the head and upper body were sufficient for recognition and there was little contribution from the dynamic parts, the legs and arm. For differential silhouettes , including the legs improved the recognition rate. The statistical analysis suggests that estimates of motion should be improved for deeper study. Intuitively appearence-based gait recognition is achieved by the disposition of body shape and how it moves. However, we showed that in all approaches that average silhouette information, the body shape is the most important cue.

Acknowledgment

We gratefully acknowledge partial support by the European Research Office of the US Army under Contract No. N68171-01-C-9002 and by the Defence Technology Centre $8-10$ supported by General Dynamics.

References

[1] A.F. Bobick and A. Johnson. "Gait extraction and description by evidence-gathering", *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 423–430, 2001.

[2] R. Collins, R. Gross and J. Shi. "Silhouette-based human identification from body shape and gait", *Proceedings of the International Conference on Automatic Face and Gesture Recognition*, pp. 366-371, Washington, DC, 2002.

[3] D. Cunado, M.S. Nixon and J.N. Carter. "Automatic Extraction and Description of Human Gait Models for Recognition Purposes", *Computer Vision and Image Understanding*, Vol. 90(1), pp. 1-41, 2003.

[4] J. Cutting, D. Proffitt and L. Kozlowski "A Biomechanical Invariant for Gait Perception", *J. Experim. Psychol. Human Percept. Perform.*, pp. 357-372, 1978.

[5] P.S. Huang, C.J. Harris and M.S. Nixon. "Recognizing humans by gait via parametric canonical space", *Artificial Intelligence in Engineering*, Vol. 13(4), pp. 359-366, 1999.

[6] J.D. Jobson *Applied Multivariate Data Analysis, Volume 1: Regression and Experimental Design*, Springer-Verlag, New York, 1999.

[7] R.A. Johnson, D.W. Wichern *Applied Multivariate Statistical Analysis*, Printice Hall , New York, 2002.

[8] I.T. Jolliffe *Principal Component Analysis*, Springer-Verlag , New York, 1986.

[9] A. Kale, N. Cuntoor and R. Chellappa. "A framework for activity-specific human recognition", *Proceedings of the International Conference on Acoustics, Speech and Signal Processing*, Orlando,Fl, May 2002.

[10] W.J. Krzanowski. "Selection of variables to Preserve Multivariate Data Structure, Using Principal Components", *Applied Statistics*, Vol. 36, pp. 22-33, 1987.

[11] L. Lee and W.E.L. Grimson. "Gait analysis for recognition and classification", *Proceedings of the IEEE Conference on Face and Gesture Recognition*, pp. 155-161, 2002.

[12] G.P. McCabe. "Principal Variables", *Technometrics*, Vol. 26, pp. 137-144, 1984.

[13] M. Murray. "Gait as a total pattern of movement", *Amer. J. Phys. Med.*, Vol. 46(1), pp. 290-332, 1967.

[14] M.S. Nixon, J.N. Carter, D. Cunado, P.S. Huang and S.V. Stevenage "Automatic gait recognition", in *BIOMETRICS Personal Identification in Networked Society*, A.K. Jain, Ed. Norwell, MA:Kluwer,1999.

[15] A.J. O'Toole and S. Edelman "Face distinctiveness in recognition across viewpoint: An analysis of the statistical structure of face spaces", *Proceedings of the International Workshop on Automatic Face and Gesture Recognition.*, Los Aalamitos, CA : IEEE Computer Society Press, pp. 10-15, 1996.

[16] P.J. Phillips, S. Sarkar, I. Robledo, P. Grother and K. Bowyer "Baseline results for the challenge problem of human ID using gait analysis", *Proceedings of the 5th IEEE International Conference on Automatic Face and Gesture Recognition*, Washington, D.C., USA, 2002

[17] J. D. Shutler, M. G. Grant, M. S. Nixon, and J. N. Carter "On a Large Sequence-Based Human Gait Database" *Proc. 4th International Conf. on Recent Advances in Soft Computing*, Nottingham (UK), 2002

[18] S.V. Stevenage, M.S. Nixon and K. Vince. "Visual analysis of gait as a cue to identity", *Appl. Cogn. Psychol.*, Vol. 31, pp. 513-526, 1999.

[19] L. Wang, W.M. Hu and T.N. Tan. "A new attempt to gait-based human identification", *Proceedings of the International Conference on Pattern Recognition*, pp. 115-118, 2002.

[20] L. Wang, T.N. Tan, W. Hu and H. Ning. "Automatic gait recognition based on statistical shape analysis", *IEEE transactions on image processing*, Vol. 12(9), pp. 1120-1131, 2003.