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Performance Evaluation of LDA & RADON in GAIT Recognition

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ABSTRACT
Gait is an emergent biometric aimed essentially to recognize people by the way they walk. Gait's advantages are that it requires no contact like automatic face recognition, and that it is less likely to be obscured than other biometrics. Gait has allied subjects including medical studies, psychology, human body modeling and motion tracking. These lend support to view that gait has clear potential as a biometric. To identify a person using their distinct Gait, the publicly available database is being taken in the video sequence format. By applying PCA analysis the gait points are extracted and trained. To obtain the false positive points LDA and a combined approach of LDA and Radon is used. The performance of the usage of LDA separately and LDA-Radon are being compared and the results are being produced as the graph..

Keywords
Gait Recognition, Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Radon Transform.

1. INTRODUCTION
The ability to identify an individual efficiently and accurately is an important task. Controlled environments such as Banks, Military Installations and even Airports need to be able to quickly detect threats and provide differing levels of access to different user groups. Recent events have brought biometrics a lot of attention as a method of identification.

Gait as a biometric has many advantages which make it an attractive proposition as a method of identification. Gait's main advantage, unobtrusive identification at a distance, makes it a very attractive biometric. The ability to identify a possible threat from a distance, gives the user a time frame in which to react before the suspect becomes a possible threat. Another motivation is that video footage of suspects are readily available, as surveillance cameras are relatively low cost and installed in most buildings or locations requiring a security presence, the video just needs to be checked against that of the suspect. As well as the inherent advantages of gait, the increase in processor power, along with the fall in price of high speed memory and data storage devices have all contributed to the increased availability and applicability of computer vision and video processing techniques. Real time video processing, which is required for gait recognition is a feasible possibility on current home PC technology, making this technology a viable security application.

Approaches in computer vision to the gait recognition problem [1] can be broadly classified as being either model-based or model-free. Both methodologies follow the general framework of feature extraction, feature correspondence and high-level processing. The major difference is with regard to feature correspondence between two consecutive frames.

Model-free methods establish correspondence between successive frames based upon the prediction or estimation of features related to position, velocity, shape, texture, and color [9]. Examples of this approach include the work of Huang *et al.*, whose optical flow to derive a motion image sequence for a walk cycle. Principal Component Analysis (PCA) is then applied [2] to the binarized silhouette to derive what are called Eigen gaits.

A set of video sequences are being selected from the publicly available database. Each database is being trained by separating them into frames and then the silhouettes of the subjects are being separated using the background subtraction algorithm.

After extracting the silhouettes they are stored in the database along with their boundary points in the form of matrices. The Gait of the person is being obtained through the help of the Eigen analysis and then the image is being segmented. Then recognition of those subjects is being done by applying the Linear Discriminant Analysis (LDA) [4] and the Radon Transform Analysis. To test or to get authentication any one of the video sequence is given as the input and it's being checked with the available database set. All the above said procedure is done for the input video sequence also and the gait posture is being obtained.

After obtaining the gait it's being compared with the sequence available in the database. If the trained database contains the same sequence then the video gets authenticated. If a non-trained video sequence is being taken as input it provides negative results.

The total matching of the gait sequences when applying LDA separately is comparatively high to the matching obtained when applying LDA and Radon in a combined form.

2. GAIT FEATURE EXTRACTION
2.1 Principal Component Analysis (PCA)
Principal Component Analysis (PCA), also known as Eigen analysis, is a technique used to reduce the dimensionality of data and examine the relationship between a set of correlated variables. PCA extracts the main variation in the feature vector

and allows an accurate reconstruction of the data to be produced from only a few of the extracted feature values, hence reducing the amount of computation needed.

The aim of using PCA is to be able to represent most of the variation of the original variables using only a few "principle components". This can be seen in the diagram below, after performing PCA; the eigenvectors (which are all orthogonal to each other) represent the new axis, in ascending order of variation in the original data set.

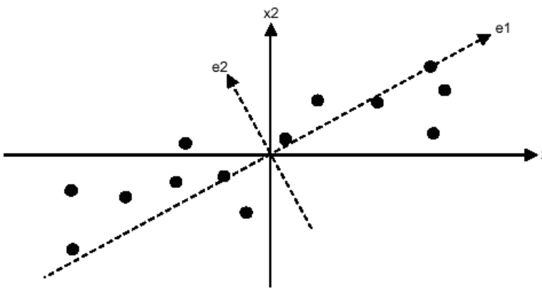

Fig.2.1.PCA in Action

In order to calculate the PC of a given set of feature vectors X = x1,x2, … xn, which are created by placing all of the original data for a given configuration in a single vector, first we find the correlation matrix C. This is a symmetric matrix that helps to reduce the computation when calculating the eigenvalues and eigenvectors.

$$c = 1/N \sum_{k=1}^{N} (x_k - x_n)(x_k - x_n)^t \quad (2.1)$$

The mean value of the vector is given by

$$x_n = \frac{1}{N} \sum_{k=1}^{N} x_k \quad (2.2)$$

The mean is subtracted from all of the vectors in order to produce a set of normalized difference vectors. The correlation matrix can then be represented by a set of special vectors, which satisfy the following equation:

$$Ce_k = \lambda_k e_k \quad (2.3)$$

These vectors are called eigenvectors, each eigenvector, ek, has an associated eigenvalue λk. The largest eigenvalues of the correlation matrix represent the largest inherent variation in the original data set and tell us most about the original data. The eigenvectors can be rearranged back into the form they were derived from at the end process if required (as in face recognition).

The most popular way to derive the eigenvalues and vectors is to use Singular Value Decomposition (SVD), although may other techniques are also possible. The technique for computing these values has been outlined in Numerical Recipes and will not be discussed any further here. It should be noted that if all of the variables are uncorrelated to begin with then the PCA will not be of much use and return nearly as many non-zero eigenvalues as we had variables in the original data.

Given that X is the feature matrix, where the matrix dimensions have the following property, m >> n, calculating the square matrix R=XXT, which is used for PCA becomes computationally infeasible as mentioned earlier, Huang used the following technique based on SVD to reduced the amount of computation needed to computed the eigenvalues and eigenvectors of R.

Given:

$$\lambda_i e_i = Re_i \quad (2.4)$$

Normally the square matrix R which is used for calculating PCA is computed by

$$R = XX^T \quad (2.5)$$

Instead an alternative square matrix R can be computed by

$$R = X^T X \quad (2.6)$$

Once the principle components have been calculated, the next step is to decide how many of the PCs should be kept, in order to maintain a correct and accurate representation of the original data. One method is to define a threshold value t, such that the total number of principle components kept should be greater than this value usually 80-90%. The total proportion of the variance of the original variables, accounted by p principle components is given by:

$$v = \frac{\sum_{k=1}^{p} \lambda_k}{\sum_{i=1}^{N} \lambda_i} \quad (2.7)$$

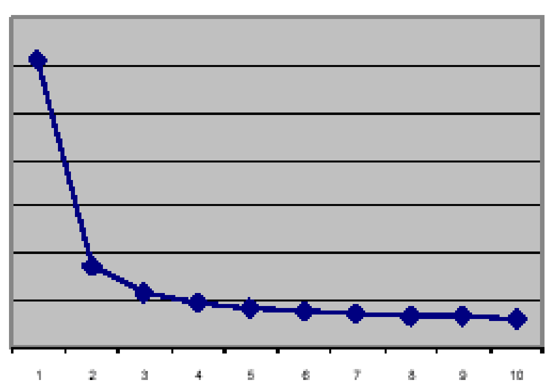

Fig.2.2. Eigen Values of Principal Components

Computing S_b and S_w class variance of the projected eigen points, $y_{i,j}$ represents feature point j of class I (total of c different classes), is done by:

$$S_w = \frac{1}{N_T}\sum_{i=1}^{c}\sum_{y_{i,j}}(y_{i,j} - m_i)\,(y_{i,j} - m_i)^T \quad (2.8)$$

$$S_b = \frac{1}{N_T}\sum_{i=1}^{c} N_i\,(m_i - m_y)\,(m_k - m_y)^T \quad (2.9)$$

Where

$$m_i = \frac{1}{N}\sum_{y_{i,j}} Y_{i,j} \quad (2.10)$$

$$m_y = \frac{1}{N_T}\sum_{i=1}^{c}\sum_{j=1} Y_{i,j} \quad (2.11)$$

Once S_b and S_w have been calculated the generalized eigenvector problems needs to be solved in order for us to find the new set of canonical axis. This will give use a set of eigenvectors which represent the orthogonal axis in canonical space where classification can take place:

$$S_b\, w_i = \lambda_i S_w\, w_i \quad (2.12)$$

This problem can be solved by initially preparing the Sb and Sw matrix in order to be able to calculate the eigenvalues and eigenvectors. Firstly we perform Singular Value Decomposition on Sw:

$$S_w = VSV^T \quad (2.13)$$

where V is orthogonal (i.e. V = inv (V)), and S is a diagonal matrix, where the diagonal elements represent the singular values. The next step is to calculate a matrix U:

$$U = (VS^{\frac{1}{2}})^T S_b (VS^{\frac{1}{2}})^T \quad (2.14)$$

Next the matrix U is split using Singular Value Decomposition:

$$U = ABA^T \quad (2.15)$$

$$\text{delta} = VS^{1/2}A \quad (2.16)$$

Delta is used to diagonalize the values between and within matrices; this is needed to be able to compute the eigenvectors and eigenvalues. Finally the matrix of Eigen problem is computed, and this is the matrix from which we can derive the eigenvectors and eigenvalues for which will represent the axis of the canonical space. There will be c-1 (c is the number of different classes, i.e. number of different people caught on video), non-zero eigenvectors which can be used for projecting the points into canonical space:

Eigenproblem=delta*B*inv(delta) (2.17)

Image segmentation is used to separate dynamic objects such as people, which are part of the foreground, from the background of the image sequence. It is a very important pre-processing step in many computer vision applications, accurate retrieval of the foreground objects are vital in order to minimize distortion or inaccuracies. These may propagate into other parts of the vision system, which could affect results at later stages in the processing.

One of the most common and simplest methods for performing segmentation is to first carry out image subtraction. The known background image is subtracted from the current picture frame, comparing the intensities of relating pixels, then threshold is performing. A pixel is considered part of the foreground when the current pixel value differs from its mean value by more than a pre defined threshold value.

Segmentation is a complex process and there are several problems inherent with extracting foreground regions, such as occlusion, shadows (cast by the foreground objects as they move) and noise. The process is complicated by the fact that the background may not be static. Also a foreground objects intensity/color at a given point may be very similar to the background and hence the foreground object may be considered part of the background. Several techniques have been developed that include both range and color in order to minimize the distortion of these effects. The effect of these distortion factors can be seen in figure 2.3 below where simple subtraction has taken place:

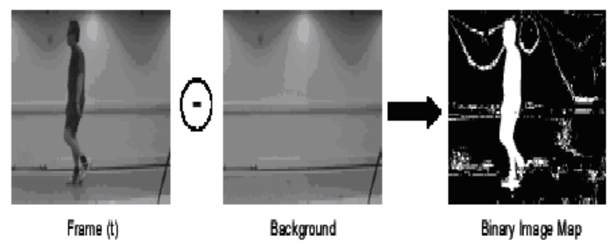

Fig.2.3. Background Subtraction Process

In the above pictures, although the background is static, the flicker of the light, which is undetectable to the human eye causes large changes in intensities, along with the subject's shadow, resulting in poor segmentation, the binary image shows just the subtraction process.

Segmentation can be improved by building a model of the background pixel intensities. The model of the background can be built on a combination of statistical range and color values for each pixel in the scene. If the background is continually changing gradually over a period of time, the model will have to be updated over time to reflect these changes. Various simplification assumptions can be made in controlled environments to enhance the performance of segmentation.

2.2 Linear Discriminant Analysis (LDA)

The purpose of Discriminant Analysis is to classify objects (people, customers, things, etc.) into one of two or more groups based on a set of features that describe the objects (e.g. gender, age, income, weight, preference score, etc.). In general, we can assign an object to one of a number of predetermined groups based on observations made on the object.

The first purpose is feature selection and the second purpose is classification. In discriminant analysis, the dependent variable (Y) is the group and the independent variables (X) are the object features that might describe the group. The dependent variable is always category (nominal scale) variable while the independent variables can be any measurement scale (i.e. nominal, ordinal, interval or ratio).

If we can assume that the groups are linearly separable, we can use linear discriminant model (LDA). Linearly separable suggests that the groups can be separated by a linear combination of features that describe the objects. If only two features, the separators between objects group will become lines. If the features are three, the separator is a plane and the number of features (i.e. independent variables) is more than 3, the separators become a hyper-plane.

LDA Formula

$$f_i = \mu_i C^{-1} x_k^T - \frac{1}{2}\mu_i C^{-1} \mu_i^T + \ln(p_i) \qquad (2.18)$$

iii) Radon Transformation Analysis

R = radon (I, theta) returns the Radon transform R of the intensity image I for the angle theta degrees.

R = radon (I, theta)

[R, x_p] = radon (...) (2.19)

The Radon transform is the projection of the image intensity along a radial line oriented at a specific angle.

If theta is a scalar, R is a column vector containing the Radon transform for theta degrees. If theta is a vector, R is a matrix in which each column is the Radon transform for one of the angles in theta.

[R, x_p] = radon (...) returns a vector x_p containing the radial coordinates corresponding to each row of R.The radial coordinates returned in x_p are the values along the *x'*-axis, which is oriented at theta degrees counterclockwise from the *x*-axis. The origin of both axes is the center pixel of the image, which is defined as floor ((size (I) +1)/2).

3. EXPERIMENTAL RESULTS

For each gait sequence, gait measurement is used to monitor person's movement. Before the training and projection, we transform the 2-dimensional silhouette image sequence into 1-dimensional distance signal sequence. For the 75 sequence of silhouette in the experiment, we take one sample sequence as testing sample, and train the rest. After training and projecting, the testing sample is classified by its similarity against training samples. The statistical property of performance is reported as iterative matching values.

The recognition ratio obtained by the LDA method is worse than that based on the method of LDA and Radon transform. This paper illustrates the nearest matching of those subjects original gait samples with PCA training and recognition through applying LDA separately and also with a combined approach of LDA and Radon.LDA could raise the veracity of recognition.

Here as result of this experiment the false positives in LDA combined with Radon is most nearer than the false positive of LDA alone. In following graph, the horizontal axis is false alarm rate and vertical axis is the verification rate of those subjects. There is a high deviation between the verification rate of LDA and LDA combined with Radon Transform.

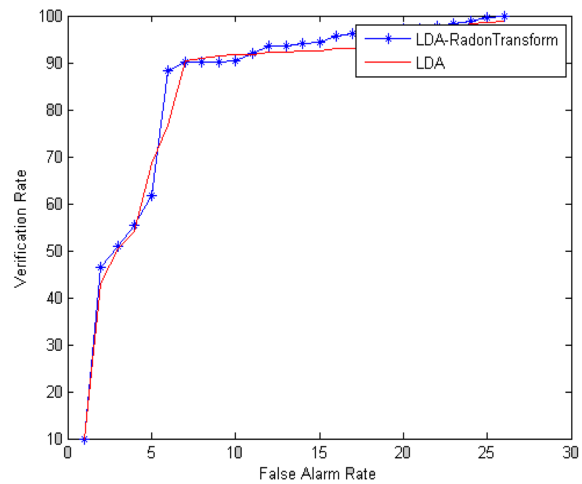

Fig.3.1.Recognition Rate for LDA and LDA with Radon

4. CONCLUSION

This paper implements a system for effective GAIT Recognition using LDA and Radon in a combined form. Results of this work show that the usage of LDA along with Radon to extract the feature provides better results than that of the implementation of LDA alone. This proves that the false alarm rate is low for LDA combined with Radon when compared to the false alarm rate of LDA alone. Hence, the methodology used in this paper achieved satisfied recognition result.

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