American Journal of Engineering Research (AJER)
e-ISSN : 2320-0847 p-ISSN : 2320-0936
Volume-03, Issue-03, pp-219-224
www.ajer.org

Research Paper Open Access

Face Feature Extraction for Recognition Using Radon Transform

Justice Kwame Appati[1], Gabriel Obed Fosu[1], Gideon Kwadzo Gogovi[1]
[1]*Department of Mathematics, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana*

Abstract : - Face recognition for some time now has been a challenging exercise especially when it comes to recognizing faces with different pose. This perhaps is due to the use of inappropriate descriptors during the feature extraction stage. In this paper, a thorough examination of the Radon Transform as a face signature descriptor was investigated on one of the standard database. The global features were rather considered by constructing a Gray Level Co-occurrences Matrices (GLCMs). Correlation, Energy, Homogeneity and Contrast are computed from each image to form the feature vector for recognition. We showed that, the transformed face signatures are robust and invariant to the different pose. With the statistical features extracted, face training classes are optimally broken up through the use of Support Vector Machine (SVM) whiles recognition rate for test face images are computed based on the L1 norm.

Keywords: *- Radon Transform; SVM; Correlation; Face Recognition*

I. INTRODUCTION

In recent years, extensive research has been conducted on Face Recognition Systems. However, irrespective of all excellent work achieved, there still exist some problems unhandled fully especially when it comes to databases containing individuals presenting their faces with different poses.

In 1997, Etemad and Chellappa [1], in their Linear Discriminant Analysis (LDA) algorithm, made an objective evaluation of the significance of features extracted for identifying a unique face from a database. This LDA of faces provides a small set of features that carries the most relevant information for classification purposes. These features were obtained through eigenvector analysis of scatter matrices with the objective of maximizing between-class variations and minimizing within-class variations. The algorithm uses a projection based feature extraction procedure and an automatic classification scheme for face recognition. A slightly different method, called the evolutionary pursuit method for face recognition was described by Liu and Wechsler [2]. Their method processes images in a lower dimensional whitened PCA subspace. Directed but random rotations of the basis vectors in this subspace are searched by Genetic Algorithm, where evolution is driven by a fitness function defined in terms of performance accuracy and class separation. From thence, many face representation approaches have been introduced including subspace based holistic features and local appearance features [3]. Typical holistic features include the well-known principal component analysis (PCA) [4-5] and independent component analysis (ICA) [6].

In 2003, Zhao et al [7] made a great progress on database images with small variation in facial pose and lighting. In their study, Principal Component Analysis (PCA) was use as their face descriptor. Following their work, Moon and Jonathon [8] implemented a generic modular Principal Component Analysis (PCA) algorithm where numerous design decisions were stated. Experiment was made by using different approach to the illumination normalization in order to study its effects on performance. Moreover, variation in the number of eigenvectors to represent a face image as well as similarity measure in the face classification proceeds.

This study investigates the problem of feature extraction in face recognition to achieve high performance in the face recognition system. Face Recognition method based on Radon Transform which provides directional information in face image as a feature extraction descriptor and SVM as a classifier was achieved by testing it on Face94 Database.

II. PRELIMINARY DEFINITIONS

Some definitions of the features extracted from a face image *P(i,j)* for performance analysis and the proposed RTFR model using SVM are discussed.

2.1 Energy

It is the sum of squared elements in the GLCMs. The range for GLCMs is given by [0, 1]. Energy is 1 for constant image [9].

$$Energy = \sum_{i=1}^{N}\sum_{j=1}^{N}(P(i,j))^2 \qquad (1)$$

2.2 Contrast

It is the measure of the intensity contrast between a pixel and its neighbour over the whole face image. The range for GLCMs is given by [0, (size (GLCMs, 1) - 1)^2]. Contrast is zero for constant image [9].

$$Contrast = \sum_{i=1}^{N}\sum_{j=1}^{N}(|i-j|)^2 P(i,j) \qquad (2)$$

2.3 Homogeneity

It is a value that measures the closeness of the distribution of elements in the GLCMs to the diagonal. The range for GLCMs is [0, 1]. Homogeneity is 1 for diagonal GLCMs. [9]

$$Homogeneity = \sum_{i=1}^{N}\sum_{j=1}^{N}\frac{P(i,j)}{(1+(i-j))} \qquad (3)$$

2.4 Correlation

It is a measure of how correlated a pixel is to its neighbour over the whole image. The range for GLCMs is given by [-1, 1]. Correlation is 1 or -1 for a perfectly positively or negatively correlated image. Correlation is NaN (not a number) for a constant image. [9]

$$Correlation = \sum_{i=1}^{N}\sum_{j=1}^{M}\frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\delta_i\delta_j} \qquad (4)$$

whereμ is the mean and δ is the variance.

III. MODEL

3.1Radon Transform

Radon transform computed at different angles along with the estimated facial pixel motion gives a spatio-temporal representation of the expression, are efficiently tackled. The motion vector at position *(x, y)* can be expressed as:

$$\hat{v}_k(x,y) = a_k(x,y)e^{j\phi_k(x,y)} \qquad (5)$$

The discrete Radon transform of the motion vector magnitude, at angle θ is then given by:

$$R(\theta) = \sum_{u=-\infty}^{\infty} a_k(x,y)\big|_{x=t\cos\theta-u\sin\theta,\, y=t\sin\theta+u\cos\theta} \qquad (6)$$

As it can be seen from this equation, using Radon transform we estimate the spatial distribution of the energy of perturbation. An attempt to compute the direction of the facial parts motion, although useful, requires extremely accurate optical flow estimation as well as global facial feature tracking.

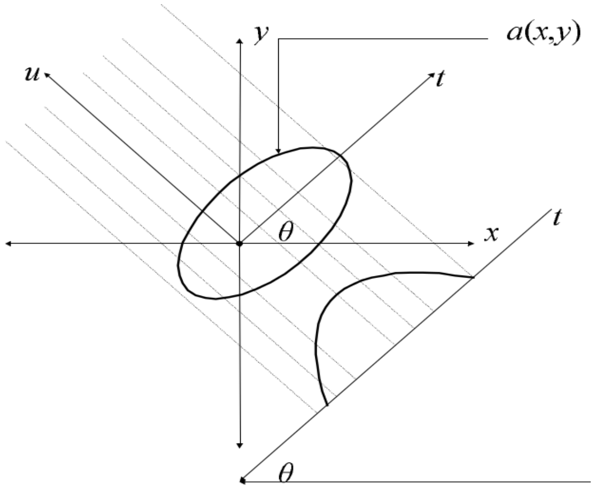

Fig. 1. Concept of the Radon Transform

The projections on the Radon Transform on angles give the face signatures and are used to characterize the expressions.

3.2 Support Vector Machine Classification (SVM)

SVM is class of maximum margin classifier for pattern recognition between two classes. It works by finding the decision surface that has maximum distance to the closest points in the training set which are termed support vectors. Assume training set of points $x_i \in R^n$ belongs to one of the two classes identified by the label $y_i \in \{-1, 1\}$ and also assuming that the data is linearly separable, then the goal of maximum classification is to separate the two classes by a hyperplane such that the distance to the support vectors is maximized. This hyperplane is referred to as the optimal separating hyperplane and has the form:

$$f(x) = \sum_{i=1}^{\ell} \alpha_i y_i x_i \bullet x + b \tag{7}$$

The coefficients α_i and the b in *Eqn (7)* are the solutions of a quadratic programming problem. Classification of new data point x is performed by computing the sign of the right side of *Eqn (7)*. In the following we will use

$$d(x) = \frac{\sum_{i=1}^{\ell} \alpha_i y_i x_i \bullet x + b}{\left\| \sum_{i=1}^{\ell} \alpha_i y_i x_i \right\|} \tag{8}$$

to perform multi-class classification. The sign of d is the classification result for x and $|d|$ is the distance from x to the hyper-plane. The further away the point is from the decision surface, the more reliable the classification result.

In multi-class classification, there are two basic strategies for solving q-class problems with the SVM:

In one-vs-all approach, q SVM is trained and each of the SVM separates a single class from all remaining classes.In the pairwise approach, $q(q - 1)/2$ machines are trained and each SVM separates a pair of classes. However, regarding the training effort, the one-vs-all approach is preferable since only q SVM has to be trained compared to $q(q - 1)/2$ SVM.

3.3 Feature Vectors

The Radon transform is used to extract the image intensity along the radial line oriented at a specific angle. Out of this face signature, the Gray-Level Co-occurrence Matrix is computed from which the following statistical features are extracted; Correlation, Contrast, Energy and Homogeneity which are concatenated in row to form the unique feature vector for a particular face image.

3.4 Matching

The final feature vector of the test face image is determined and compared with the trained feature vector. The Euclidean Distance is then computed between trained face database and the test face data. The image matched index which recorded the list Euclidean Distance is selected with the assumption that, it is the correct index for the test image. This is then verified with the original index of the test image. If the indices are the same then a match is recorded otherwise miss-match.

$$\|X - A\|_2 = \sqrt{\sum_{i=1}^{n} (x_i - a_i)^2} \qquad (9)$$

where:
X is the feature vector of the trained image.
A is the feature vector of the test image
$n$is the number of elements in the feature vector
$x_i$is the element of the trained feature vector
$a_i$is the element of the test feature vector

IV. ANALYSIS AND DISCUSSION

Facial images used for this study were taken from Faces94 database which is composed of 152 individuals with 20 been female, 112 male and 20 male staff kept in separate directories. These separate directories were merged into one to achieve the different lighting effect. The subjects were sited at approximately the same distance from the camera and were asked to speak while a sequence of twenty images was taken and this was to introduce moderate and natural facial expression variation. Each facial image was taken at a resolution of 180 × 200 pixels in the portrait format on a plain green background and index 1 to 20 prefixed with a counter. In all, a total of 3040 images were created which make up the database for the study.

Fig. 2. Sample of face image from Database

Table 1. Algorithm for the RTFR

1. Read face image from the database.
2. Convert image from color space to gray scale.
3. Compute the intensity map of each face image in the database by applying the Radon Transform on it.
4. For each intensity image map computed, calculate the Gray-Level Co-occurrence Matrix
5. The global statistical feature, that is: Correlation, Energy, Contract and Homogeneity are established from the Gray-Level Co-occurrence Matrix.
6. A concatenation of these four features forms the final feature vector per face image.
7. Dataset containing feature vector is now divided in to training and test set for performance analysis
8. SVM is applied to compute the recognition rate

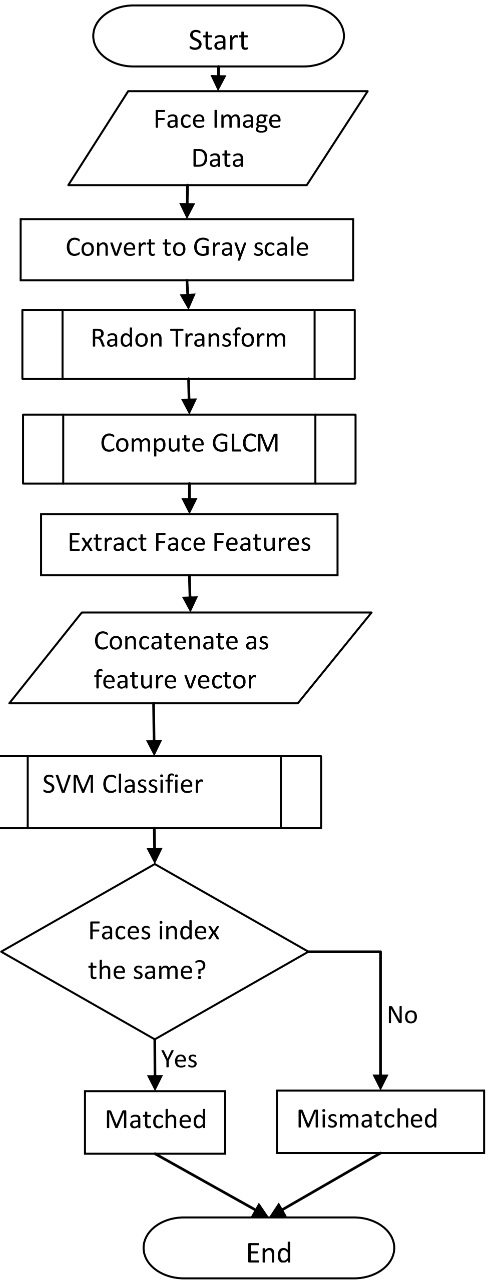

Fig. 3. Block Diagram of RTFR

This proposed algorithm accept face image as input and returns a verified face image from the trained dataset as output. The objective of this design is to extract the least features from a face image which is global and spacio-temporal in nature so as the make face recognition invariant to pose.

The performance of our proposed method (RTFR) was revealed by testing it on the face94 database. Before this performance was carried out, the feature vector containing 12,160 features with four features for each face image was partitioned into two disjoint set that is the trained features and the test features. At the end of the partition, the test data has 2,432 features whiles the trained date has 9,728 features resulting in 608 and 2432 face images for test and train respectively. Each face feature in the test data is matched against all the face features in the train dataset while the Euclidean distance is taken. Out of the many distance taken, the minimum distance is selected along with it image index. At the end of all these processes, the recognition rate was computed which gave 97% accuracy.

V. CONCLUSION

In this paper, we observed that our Radon Transform based feature extraction for face recognition (RTFR) yielded a good recognition rate though only four features were extracted from the face for recognition purpose. This may be due to the fact that the Radon transforms extract features that are highly correlated therefore throwing away the less relevant intensity values. This act as a feature reduction method since only face projections are of interest to us for further reduction and hence makes feature storage easier for computation aside the good performance rate recorded.

REFERENCES

[1] K. Etemad and R. Chellappa, *"Discriminant Analysis for Recognition of Human Face Images",* Proc. First Int. Conf. on Audio and Video Based Biometric Person Authentication, Crans Montana, Switzerland, Lecture Notes In Computer Science; Vol.1206, August 1997, pp.127 - 1422

[2] C. Liu and H. Wechsler, *"Face Recognition usingEvolutionary Pursuit",* Proc. Fifth European Conf. on Computer Vision, ECCV, Freiburg, Germany, Vol II, 02-06 June 1998, pp.596-612.

[3] S. Z. Li and A. K. Jain, *"Handbook of Face Recognition"*,New York,Springer-Verlag, 2005

[4] M. A. Turk and A.P. Pentland, *"Face Recognition usingeigenfaces"*, Proc. IEEE Computer Society Conf. Comput. vs. Pattern Recognition, June 1991 pp. 586-591.

[5] P. Belhumeur. J. Hespanha and D. Kriegman, *"Eigenfacesvs. fisherfaces: recognition using class specific linear projection",* IEEE Trans. On Pattern Analysis and Machine Intelligence, vol. 26, no. 9, Sept. 2004, pp.1222-1228

[6] P. Conor, *"Independent component analysis a new concept",* Signal Processing, vol. 36,1994, pp. 287-314.

[7] W. Zhao, R. Chellappa, P. J. Phillips, *"A. Rosenfeld, FaceRecognition: A Literature Survey"*, ACM Computing Surveys, Vol. 35, No. 4, 2003, pp.399-458.

[8] H. Moon, P Jonathon Phillips, *"Computational andPerformance Aspects of PCA Based Face Recognition Algorithms"*, Perception 30(3), 2001, pp.303 – 321

[9] D. R. Shashi Kumar, K. B. Raja, R. K. Chhotaray, and S.Pattanaik, "DWT Based Fingerprint Recognition using Non Minutiae Features", International Journal of Computer Science Issues, vol 8(2), 2011, pp. 257-265.