POSSIBILITY FUZZY C-MEANS CLUSTERING FOR EXPRESSION INVARIANT FACE RECOGNITION

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ABSTRACT

Face being the most natural method of identification for humans is one of the most significant biometric modalities and various methods to achieve efficient face recognition have been proposed. However the changes in face owing to different expressions, pose, makeup, illumination, age bring about marked variations in the facial image. These changes will inevitably occur and they can be controlled only till a certain degree beyond which they are bound to happen and will affect the face thereby adversely impacting the performance of any face recognition system. This paper proposes a strategy to improve the classification methodology in face recognition by using Possibility Fuzzy C-Means Clustering (PFCM). This clustering technique was used for face recognition due to its properties like outlier insensitivity which make it a suitable candidate for use in designing such robust applications.PFCM is a hybridization of Possibilistic C-Means (PCM) and Fuzzy C-Means (FCM) clustering algorithms. PFCM is a robust clustering technique and is especially significant for its noise insensitivity. It has also resolved the coincident clusters problem which is faced by other clustering techniques. Therefore the technique can also be used to increase the overall robustness of a face recognition system and thereby increase its invariance and make it a reliably usable biometric modality.

Keywords

FCM, PCM, PFCM, EIGEN FACE, FISHER FACE

1. INTRODUCTION

Although face recognition comes naturally to all of us, but building a computerised system which is nearly as efficient as human brain is yet a task unaccomplished though very much achievable. There have been various face recognition methods proposed in the past but nearly all suffer from the practical aspect of changes in the face, which to a certain extent are unavoidable. Most of the exiting face recognition systems demand precise alignment and correspondence between the testing and the training data sets. This restriction makes the system unusable in practice. The changes in the face image due to variations in pose, illumination, expressions etc. make such strict face recognition systems futile in real world applications. The results are even more deplorable if the variations are collectively present. However there is no escape to such variations in real world and there is a need to design strong reliable face recognition methods.

Various approaches have been proposed for developing an efficient face recognition system. One of the most significant achievements in the area of face recognition was the Eigen Face methodology, proposed by M.A.Turk&A.P.Pentland [1] [2]. It utilizes Principal Component Analysis to extract the features from the facial images [3]. Extending the Eigen face [1] [2] approach further, Hallinan [4] proposed that showed that five Eigen faces were sufficient to represent the face images under a wide range of variations. Changing expressions create a lot of

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variations in the face which makes it very hard to recognize the faces accurately. Extensive work has been done in this area [5] [6]. Pentland, Moghaddam and Starner [7] proposed a view based modular Eigen space approach for Face Recognition. Zhang et al [8] proposed an approach to find features using Active Appearance Model (AAM). Vretos et al [9] also used Appearance based approach and SVM classifier with a reasonably high classification accuracy. P. Ekman and E. e. Rosenberg proposed the facial action coding system (FACS) [10] which captured the variations of face features under facial expressions from a single image frame. Unsupervised techniques have also been extensively studied for their application in the area of face recognition. Mu-Chun Su and Chien-Hsing Chou suggested a modified Version of the K-Means Algorithm for face recognition [11]. Face recognition using Fuzzy c-Means clustering and sub-NNs was developed by Lu J, Yuan X and Yahagi T [12]. Clustering has also found its use in dynamic and 3D face recognition applications too [13] [14]. Extensive research in the field is in progress [17] so as to achieve a high performance face recognition system that can practically usable in real time dynamic environment.

This paper presents a new approach to perform the classification of faces using Possibilistic Fuzzy C-Means (PFCM) clustering [15]. This clustering technique was put to test for face recognition due to some of its properties like noise and outlier insensitivity which make it a suitable candidate for designing such robust applications. PFCM is a hybridization of Possibilistic C-Means (PCM) and Fuzzy C-Means (FCM) clustering algorithms. It is able to overcome various problems of PCM, FCM and Fuzzy Possibilistic C-Means (FPCM) clustering algorithms. PFCM is especially significant as it solved the noise sensitivity defect of FCM. It also has resolved the coincident clusters problem of PCM and also eliminated the row sum constraints of FPCM. Therefore it is evident that the technique is useful for designing robust face recognition systems. It can be applied in collaboration with theexisting face recognition algorithms such that facial biometric systems become increasingly invariant to different kinds of variations due to changes in pose, gait, expressions, illumination etc. The paper explores the performance of the said methodology with respect to the changes in facial expressions which are known to severely impact the efficiency of face recognition systems.

The rest of this paper is organized as follows: Section 2 discusses the conceptual details of Possibilistic Fuzzy C-Means (PFCM) [15]. Application of PFCM in face recognition is discussed in detail in the Section 3. Experimental results have beenelaborated in Section 4 and Section 5 discusses the conclusion and the future scope of the proposed technique.

2. Overview of Methodology

Clustering is useful in partitioning of the unlabelled data into various clusters. One of the most popular clustering techniques is Fuzzy C-Means (FCM) [18] algorithm where in a data point is allocated membership values to various clusters based on its relative distance tothe data point prototypesin those clusters representing the cluster centres in the model.However in case a data point is equidistant from two prototypes, then its membership in each one of the clusters will be the same irrespective of the absolute value of its distance from thetwo centroids as well as from the other data points in the data. This leads to a major problem in handling the noise points or the outliers. The issue is that the noise points may belocated far away but if they are equidistant fromthe central structure of the two clusters, they may come to have anequal membership allocated in both. Ideally such noise points or outliers should be given very low / zero membership in eitherof the clusters.

The objective function for FCM is given by:

$$\min\left\{J_m(U,V;X) = \sum_{k=1}^{n}\sum_{i=1}^{c}(u_{ik})^m \|x_k - v_i\|_A^2\right\} \tag{1}$$

where,

U is the partition matrix,
V is a vector of cluster centres,
X is a set of all data points,
x represents a data point,
n is the number of data points,
c is the number of cluster centers which are described by s coordinates,
$\|x\|_A = \sqrt{x^t Ax}$ is any inner product norm,
$u_{ik}$is taken as the membership of x_k in the i^{th} partitioning fuzzy subset (cluster) of X.

D_{ikA} represents the distance between i^{th} cluster and k^{th} data given by:

$$D_{ikA} = \|x_k - V_i\|_A > 0, \text{ for all I and k.} \tag{2}$$

The membership value is expressed as:

$$u_{ik} = \left(\sum_{j=1}^{c}\left(\frac{D_{ikA}}{D_{jkA}}\right)^{2/(m-1)}\right)^{-1}$$
$$1 \le i \le c;\ 1 \le k \le n \tag{3}$$

$$V_i = \sum u_{ik}^m x_k \Big/ \sum u_{ik}^m \tag{4}$$

A new clustering algorithm, Possibilistic C-Means (PCM) was proposed by Krishnapuram and Keller [19] to counter the aforementioned issue of noise and outliers. They relaxed the constraint on the membership,$\sum_{i=1}^{c} u_{ik} = 1$ for all k,suchthat the sum satisfies a looser constraintwhich is interpreted as the typicality of the data point relativeto a particular cluster rather than its membership in the cluster. Theyrepresented each row of the partition matrix as a possibility distribution over cluster.Therefore PCM algorithm indeed helps in identifying outliers and noise points. However this makes PCM is very sensitive to initializations which may sometimes cause it to generate coincident clusters. Also the typicality can bevery sensitive to the values of the various additional parameters neededby the PCM model.

The objective function for PCM is given by:

$$min\left\{P_m(T,V;X,\gamma) = \sum_{k=1}^{n}\sum_{i=1}^{c}(t_{ik})^m \|x_k - v_i\|_A^2 + \sum_{i=1}^{c}\gamma_i\sum_{k=1}^{n}(1-t_{ik})^m\right\} \tag{5}$$

where,

T is the typicality matrix,
V is a vector of cluster centres,
X is a set of all data points,
x represents a data point,
n is the number of data points,
c is the number of cluster centers which are described by s coordinates,
$\|x\|_A = \sqrt{x^t A x}$ is any inner product norm,
t_{ik} is taken as the typicality of x_k in the i^{th} partitioning fuzzy subset (cluster) of X,
$\gamma > 0$ is a user defined constant

The typicality matrix $T = [t_{ik}]_{cxn}$ has independent rows and columns. Therefore minimization of the objective function can be done by minimizing its ij^{th} term with respect to *T*.

$$t_{ik} = \left(1 + \left(\frac{D_{ikA}^2}{\gamma_i}\right)^{1/(m-1)}\right)^{-1} \tag{6}$$

$$V_i = {\sum t_{ik}^m x_k} \Big/ {\sum t_{ik}^m} \tag{7}$$

The value of D_{ikA} can even be zero here unlike FCM making PCM overcome the problem of singularity that FCM suffers from. Therefore with appropriate values of γ and V_0, PCM can significantly resolve the issue of outliers and noise points.

However due to lack of constraints placed on the typicality matrix, PCM itself may face the issue of coincident cluster generation. To deal with the same Possibility Fuzzy C-Means algorithm was proposed [15].

PFCM which is a hybrid of FCM and PCM uses the membership and typicality aspects from both of the clustering models and optimizes the following objective function:

$$min \left\{ J_{m,\eta}(U,T,V;X) = \sum_{k=1}^{n} \sum_{i=1}^{c} \left(a u_{ik}^m + b t_{ik}^\eta\right) \times \|x_k - v_i\|_A^2 + \sum_{i=1}^{c} \gamma_i \sum_{k=1}^{n} (1 - t_{ik})^\eta \right\} \tag{8}$$

where,

U is the partition matrix,
T is the typicality matrix,
V is a vector of cluster centres,
X is a set of all data points,
x represents a data point,
n is the number of data points,
c is the number of cluster centers which are described by s coordinates,
$\|x\|_A = \sqrt{x^t A x}$ is any inner product norm,
$\gamma > 0$ is a user defined constant
u_{ik} is taken as the membership of x_k in the i^{th} partitioning fuzzy subset (cluster) of X,
t_{ik} is taken as the typicality of x_k in the i^{th} partitioning fuzzy subset (cluster) of X.

It is subject to the constraints $\sum_{i=1}^{c} u_{ik} = 1$ for all k and $u_{ik} \geq 0$ and $t_{ik} \geq 1$, a>0, b>0, m>1, η>1,

The constants a and b define the relative importance of fuzzy membership and typicality values in the objective function. By suitable combination of these parameters we can make PFCM behave more like FCM or PCM if and when required.

For PFCM, D_{ikA}which represents the distance between i[th] cluster and k[th] data is given by:

$$D_{ikA} = \left[\sum_{j=1}^{s}(x_{kj} - v_{ij})^2\right]^{1/2} \tag{9}$$

Using the above equation we can have the following expressions for the membership and typicality values.

$$u_{ik} = \left(\sum_{j=1}^{c}\left(\frac{D_{ikA}}{D_{jkA}}\right)^{2/(m-1)}\right)^{-1}$$
$$1 \leq i \leq c;\ 1 \leq k \leq \mathrm{n} \tag{10}$$

$$t_{ik} = \frac{1}{1+\left(\frac{b}{\gamma_i}D_{ikA}^2\right)^{1/(\eta-1)}}$$
$$1 \leq i \leq c;\ 1 \leq k \leq \mathrm{n} \tag{11}$$

To reduce the effect of outliers on centroids, we must use a higher value for b as compared to a and also control the choice of η as per the values of m.

$$v_i = \frac{\sum_{k=1}^{n}(au_{ik}^{m}+bt_{ik}^{\eta})x^k}{\sum_{k=1}^{n}(au_{ik}^{m}+bt_{ik}^{\eta})}$$
$$1 \leq i \leq c \tag{12}$$

Therefore by relaxing the constraint (row sum = 1) on the typicality values but retaining the column constraint on the membership values we can achieve the best of both the FCM and PCM algorithmsand achieve significant robustness against the presence of noisy data or outliers. This methodology can be applied for the classification of the facial images in a face recognition system which is known to be very sensitive and prone to outliers, noisy data and even minute variations.

PFCM can be used for clustering after feature extraction from the data set. In this paper the clustering technique was applied over the data received from Eigen Face [1][2] and Fisher Face [20] methods to evaluate its performance for face recognition. Clustering was done over a set of Eigen faces and Fisher faces to classify the face images of different individuals with varying expressions.

3. PROPOSED METHODOLOGY

3.1. Possibility Fuzzy C-Means Clustering on Eigen Faces

PFCM was used for clustering of the data retrieved after computinga set of Eigen Faces from the data source of facial images:

1. Obtain face images I_i (i = 1,2...M) of same size, where M = No. of images in image data set.
2. Transform all the training images $I_{1.....i}$ to a column vector $J_{1....i}$
3. Calculate the Mean face
$$m = \frac{1}{M}\sum_{i=1}^{M}(J_i) \tag{13}$$
4. Normalise the images
$$N_i = J_i - m \tag{14}$$
5. Obtain the Covariance matrix
$$Cov = \frac{1}{M}\sum_{n=1}^{M} N_n N_n^T = AA^T \tag{15}$$
6. Derive the eigenvectors for the matrix A^TA of size m x m.
7. If v is a nonzero vector and λ is a number such that Av = λv, then v is said to be an eigenvector of A with eigenvalue λ.
8. Consider the eigenvectors v_i of A^TA:
$$A^TAv_i = \mu_i v_i \tag{16}$$
9. Pre-multiplying both sides by A such that,
$$AA^T(Av_i) = \mu_i(Av_i) \tag{17}$$
10. The eigenvectors of covariance matrix are
$$u_i = Av_i \tag{18}$$
11. Face space is given by
$$F_i = u^T N_i \tag{19}$$
12. Perform the Possibility Fuzzy C-Means clustering over the set $\sum_{P=1}^{C} N_i^P$, for P = 1 to c, where c is no. of classes (or subjects) and minimise the following objective function as mentioned in equation 8,

$$min\left\{J_{m,\eta}(U,T,V;X) = \sum_{k=1}^{n}\sum_{i=1}^{c}\left(au_{ik}^{m} + bt_{ik}^{\eta}\right) \times \|x_k - v_i\|_A^2 + \sum_{i=1}^{c}\gamma_i\sum_{k=1}^{n}(1-t_{ik})^{\eta}\right\}$$

where,

U is the face class partition matrix,
T is the face typicality matrix,
V is the vector of cluster centers,
X is theinput set ofEigen Faces from$F_i = u^T N_i$,
x represents a data point,
n is the number of data points,
c is the number of cluster centers,

$||x||_A = \sqrt{x^t A x}$ is any inner product norm,
$\gamma > 0$ is a user defined constant
u_{ik} is taken as the membership of x_k in the i^{th} partitioning fuzzy subset (cluster) of X,
t_{ik} is taken as the typicality of x_k in the i^{th} partitioning fuzzy subset (cluster) of X,
$\sum_{i=1}^{c} u_{ik} = 1$ for all k and $u_{ik} \geq 0$ and $t_{ik} \geq 1$, a>0, b>0, m>1, η>1,

13. Find the distance between i^{th} cluster and k^{th} data item, membership matrix and typicality matrix and updated values of cluster means as explained in equation 9,10 and 11.
14. Generate P clusters C_1………….. C_P. Obtain the optimal value of the membership for each face image among all clusters, for P = 1 to c.
15. All the face images are assigned to a particular cluster based on whether they match the membership threshold condition following which theywill be correctly assigned to the particular cluster representing the face of an individual subject.

3.2. Possibility Fuzzy C-Means Clustering on Fisher Faces

PFCM was also evaluated for clustering the data retrieved after computing a set of Fisher Faces from the data source of facial images:

1. X_1, X_2, …,X_c represent the c classes of face in the database. Each face class is represented by vector X_i, i = 1, 2, …, c has k facial images x_j, j=1, 2, …, k.
2. Find the mean image μ_i of each class Xi as:

$$\mu_i = \frac{1}{k}\sum_{j=1}^{k} x_j \tag{20}$$

3. Mean image μ of all the face classes in the database can be calculated as:

$$\mu = \frac{1}{c}\sum_{i=1}^{c} \mu_i \tag{21}$$

4. Calculate the within-class scatter matrix:

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T \tag{22}$$

5. Calculate the between-class scatter matrix:

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu)(\mu_i - \mu)^T \tag{23}$$

6. We find the projection directions as the matrix W that maximizes

$$\hat{Z} = \text{argmax} J(Z) = |Z^T S_B Z| \,/\, |Z^T S_W Z| \tag{24}$$

7. We can observe that it represents a generalized eigenvalue problem where the columns of Z are given by the vectors Z_i such that,
8.

$$S_B Z_i = \lambda_i S_W Z_i \tag{25}$$

9. Find the product of S_W^{-1} and $S_B$and calculate its eigenvectors after reducing the dimension of the feature space.
10. Compose a matrix Z that represents all eigenvectors of $S_W^{-1} * S_B$ by placing each eigenvector Z_i as a column in Z.

11. Each face image $x_j \in X_i$ can be projected into this face space as:

$$F_i = Z^T(x_j - \mu) \tag{26}$$

12. Perform the Possibility Fuzzy C-Means clustering over the set $\sum_{P=1}^{C} F_i^P$, for P = 1 to c, where c is no. of classes (or subjects) and minimise the following objective function as mentioned in equation 8,

$$min\left\{J_{m,\eta}(U,T,V;X) = \sum_{k=1}^{n}\sum_{i=1}^{c}\left(au_{ik}^{m} + bt_{ik}^{\eta}\right) \times \|x_k - v_i\|_A^2 + \sum_{i=1}^{c}\gamma_i\sum_{k=1}^{n}(1-t_{ik})^{\eta}\right\}$$

where,

U is the face class partition matrix,
T is the face typicality matrix,
V is the vector of cluster centers,
X is theinput set ofFisher Faces from $F_i = u^T N_i$,
x represents a data point,
n is the number of data points,
c is the number of cluster centers,
$\|x\|_A = \sqrt{x^t A x}$ is any inner product norm,
$\gamma > 0$ is a user defined constant
u_{ik} is taken as the membership of x_k in the i^{th} partitioning fuzzy subset (cluster) of X,
t_{ik} is taken as the typicality of x_k in the i^{th} partitioning fuzzy subset (cluster) of X,
$\sum_{i=1}^{c} u_{ik} = 1$ for all k and $u_{ik} \geq 0$ and $t_{ik} \geq 1$, a>0, b>0, m>1, η>1,

13. Find the distance between i^{th} cluster and k^{th} data item, membership matrix and typicality matrix and updated values of cluster means as explained in equation 9,10 and 11.
14. Generate P clusters C_1………….. C_P. Obtain the optimal value of the membership for each face image among all clusters, for P = 1 to c.
15. All the face images are assigned to a particular cluster based on whether they match the membership threshold condition following which they will be correctly assigned to the particular cluster representing the face of an individual subject.

The resultant clustering classifies the face images of subjects with varying degrees of expressions to their correct individual classes.

4. EXPERIMENTAL RESULTS

Open source data sets were used to evaluate the performance of the technique. JAFFE database [25] contains the face images with varying expressions and emotions. The face images were segmented and pre-processed following which Eigen Face and Fisher Face algorithms were applied.Clustering of the data set thus retrieved was done using Possibility Fuzzy C-Means clustering technique which was found to be very effective in classifying the facial images correctly even in the presence of variations in the images owing the presence of outliers, noise and changes in expressions and emotions. The results were compared to the methods of Eigen Face and Fisher face. When combined with PFCM both these methods performed significantly better and yielded favourable results with more robustness towards variations in expressions. Thus use of PFCM was found to amplify the invariance of the face recognition system and make it sturdier. Therefore it encourages the application of PFCM in combination with various standard and upcoming face recognition methodologies to boost their overall performance even in the presence of variations in the frontal image of the face like the changes in expressions. The technique can be extended further to allow its collaboration with different methodologies that aid in forming strong face recognition algorithms.

The results obtained clearly depict an increase in the recognition accuracy in spite of the presence of noise, outliers and variations in expressions in the face images when the PFCM is used with standard methods of Eigen Face and Fisher Face as shown below:

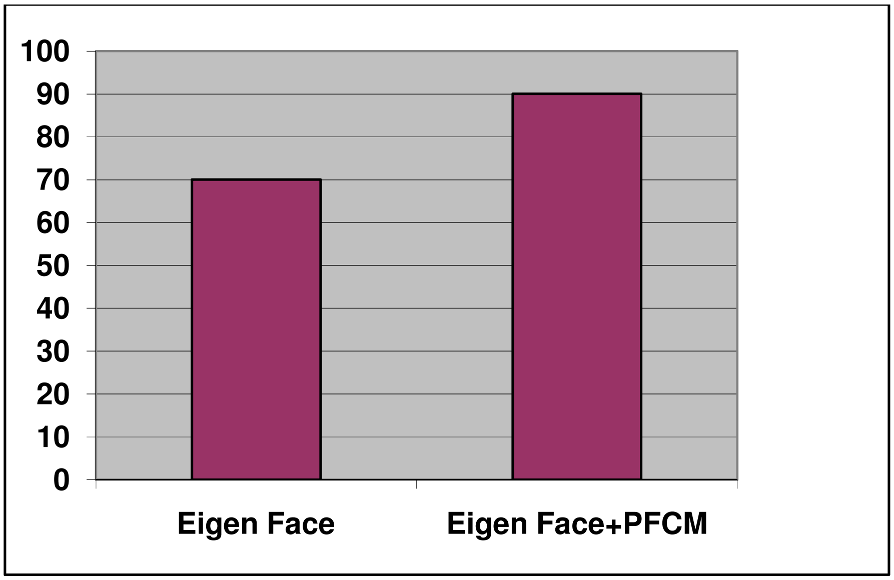

Figure 1.Performance of Eigen Face vs. PFCM+Eigen Face

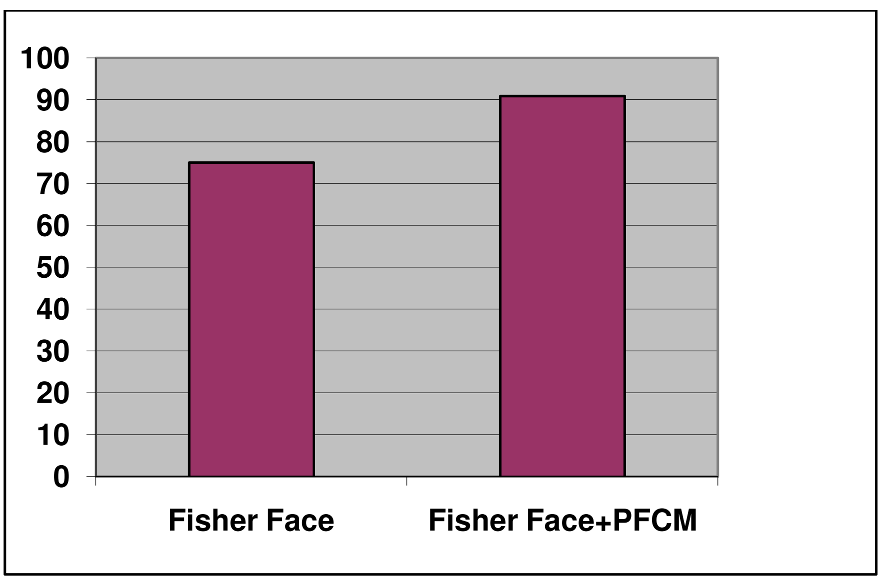

Figure 2.Performance of Fisher Face vs. PFCM+Fisher Face

5. CONCLUSIONS AND FUTURE SCOPE

The properties of outlier and noise insensitivity of Possibility Fuzzy C-Means clustering have contributed to its use in designing a strong face recognition system in this paper. Increase in performance of face recognition by applying PFCM with standard techniques of Eigen Face and Fisher Face leads us towards its application in designing robust face recognition systems. As observed through the experimental analysis, PFCM has made significant amplification in the success rate of the face recognition even in presence of the outliers, noise and changes in expressions.

The clustering technique may be analysed and studiedfurther for if it can also contribute to designing face recognition applications that are invariant to changes in pose, illumination, facial distractions like makeup and hair growth. Facial variations are not limited to changes in expressions. In fact different light conditions and posture changes make extreme variations in the face image which are more difficult to deal with as well. These changes are bound to occur in practical scenarios therefore PFCM needs to be tested and improved if required for catering to nullifying the effect of such changes to the best possible extent. The technique may be used to work in collaboration with various other methodologies for reducing the impact of such changes.

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