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IMPLEMENTATION OF THE DATA UNCERTAINTY MODEL USING APPEARANCE BASED METHODS IN FACE RECOGNITION

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ABSTRACT

The face images should not be the fully accurate to representation and for an observation. To reducing the uncertainty for representation of the face images and it is to improving the accuracy of face recognition, more observation of the same person face images is required in the face recognition. The data of face images are obtained from different pose, facial expression and, hence a single image of the face occurring the high uncertainty for the face representation. In this paper, develop such a model which is to improve the accuracy in the face recognition by reducing the data uncertainty. The model is to reduce the uncertainty of face images representation by synthesizing the virtual training samples. Here, propose system gives the useful training samples which are selected, and are comparable to the test sample from the set of all the original training samples and synthesized virtual training sample. The proposed work will give the classified virtual training samples which are not contained the duplication of the samples in the model. In the real world face recognition system the uncertainty highly occurred because the limited number of available face images of subject and due to this there is high uncertainty is occurred.

KEYWORDS: Computer Vision; Face Recognition; Machine Learning; Uncertainty; Face Image

INTRODUCTION

Face Recognition being the most attractive biometric technique it is still a challenging task. Various factors like lighting, expression, pose cause the uncertainty. The best way to reduce the uncertainty is to gain more training samples. More training samples reflect more possible variations of the face and less uncertainty of the data and hence the face. There are two ways of representing the uncertainty data. In first way the data is represented by probability distribution rather than deterministic values. In second way data is represented by statistical information for mean and variance. With these two ways the uncertain data is represented and to reduce the uncertain data, the data must be process. These are the methods to process the uncertain data, the Uncertain Data Management, Data Mining and Data Clustering [2][6].

In many practical face recognition applications for the security, such as e-passport, law enhancement and ID-card identification, in the system there is only a single sample per person recorded in the systems. The synthesized multiple virtual views of a person under different poses and illuminations from a single face image and exploited extended training samples to classify the face images [3]. Generally, a smaller norm means a stronger sparsity and conventional sparse representation algorithms are indeed viewed as a problem of minimizing the $l1$-norm of the coefficient vector [15][16]. We conducted experiments on the FERET face databases to compare different approaches.

Fig:(1) Image Samples Of FERET Dataset

RELATED WORK

This section describes the various existing schemes which are compared in this paper:

S. C. Yang, D. Xu, B. Y. Zhang, H. J. Zhang, Q. Yang, and S. Lin[1], in the propose of system the graph embedding framework can be used as a general platform for developing new dimensionality reduction algorithms. To accomplish this task, the designing graphs according to specific motivations. Class discrimination in LDA is based upon interclass and intraclass scatters, which is most advantageous only in cases where the data of each class is approximately Gaussian distributed, a property that cannot always be satisfied in real-world applications. More efforts including the popular null subspace algorithm have been dedicated to improving the performance of LDA, the fundamental issues and limitations of LDA are still unsolved in theory.

J. Yang and S. Gunn[2], in propose of system uncertain information associated with data is often ignored in traditional machine learning algorithms. Many approaches attempt to model any uncertainty in the form of additive noise on the target, which can be effective for simple models. For instance, the traditional support vector classification (SVC) can only accommodate isotropic uncertainty information in the input space. Recent advances in machine learning methods have seen significant contribution from kernel-based approaches. These have many advantages, including strong theory and convex optimization formulation. Support vector machines (SVMs) are one approach that have been extended to incorporate uncertain data. The resulting algorithm is formulated as a second order cone programming (SOCP) optimization problem with adaptive constraints driven by the uncertainties.

P. Shivaswamy, C. Bhattacharyya, and A. Smola[3], in propose of system, a novel second order cone programming formulation which can handle uncertainty in observations for designing robust classifiers. The formulations are resulting for designing regression functions which are robust to uncertainties in the regression setting. This problem was partially addressed, where a second order cone programming (SOCP) formulation was derived to design a robust linear classifier when the uncertainty was described by multivariate normal distributions. The Total Support Vector Classification (TSVC) is another approach, starting from a very similar end up premise, with a non-convex problem with corresponding iterative procedure. The projected formulations are then applied to the problem of patterns having missing values both in the case of classification and regression.

Y. Yang, J. K. Song, Z. Huang, Z. G. Ma, N. Sebe, and A. Hauptmann[4], in propose the Multimedia data are typically represented by multiple features, a new algorithm that is Multi-feature Learning via Hierarchical Regression for multi-media semantics understanding, where two issues are considered. Firstly, labeling large amount of training data is as a labor intensive it is meaningful to effectively influence unlabeled data to make possible multimedia semantics understanding. Secondly, the multimedia data can be represented by many features; it is valuable to develop an algorithm which combines verification obtained from different features to conclude reliable multimedia semantic concept classifiers.

George Kollios, Michalis Potamias, and Evimaria Terzi[5], in the propose of this paper, a principled approach to probabilistic graph clustering is motivated by the possible world semantics of probabilistic databases and probabilistic graphs. Typically, such network data are associated with uncertainty. This uncertainty is either due to the data collection process or to machine-learning methods employed at preprocessing. Uncertainty may be also added to data for privacy-preserving reasons. Here model such uncertain networks as probabilistic graphs. Every edge in a probabilistic graph is associated with a probability of existence.

PROPOSED SYSTEM

Here some of the proposed approaches to reduce the data uncertainty.

- *First approach* - Limited test sample of the subject means limited information what we can synthesize these limited samples to acquire more possible variations of the face.
- *Second approach* - Samples obtained in BTTS have both positive and negative effects. So propose to use the samples from the BTTS which are close to the test samples to represent and classify the test samples.
- *Third Approach* - Instead of using Conventional Sparse Representation based algorithm which is time consuming go for the l2-norm -based representation algorithm.

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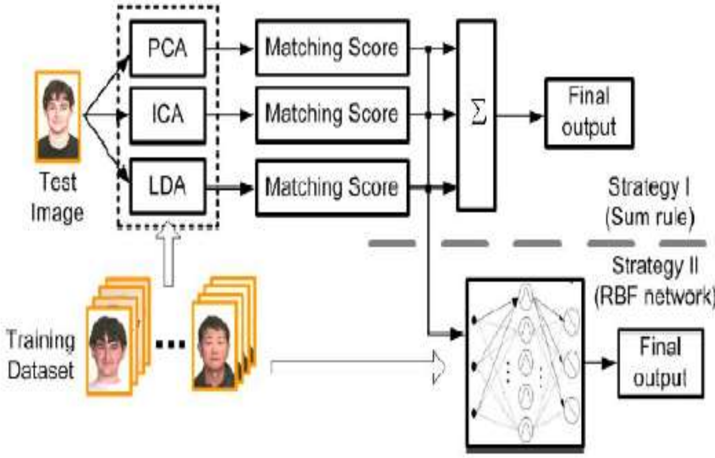

Fig:(3) Structure Of The System

The computationally efficient l_2-norm-based representation algorithm is used for classification, so the proposed approach is very easy to implement and has a much lower computational complexity than the conventional sparse representation method [15][16][17]. Moreover, in our approach the virtual training samples will not greatly deviate from the true training samples from the same subject.

For the improving the accuracy of the propose system LDA (linear Descriminant analysis). In this algorithm solve pose change or misalignment and it requires a test sample to be sparsely represented by a weighted sum of all the training samples. The classification is done by evaluating the demonstration ability on the test sample of each class and by assigning the test sample to the class that has maximum representation ability. Sparse gives that the coefficients of some training samples are equal to zero and the extent of sparsity of the representation coefficients can be measured by the $l1$-norm of the coefficient vector.

IMPLEMENTATION

- ***Synthesized samples***

In our approach, as the mean of two original training samples is taken as a virtual training sample, it seems that the synthesized virtual sample and the original training sample have proper difference.

Fig:(4) Face Sample Of A Subject With Different Expresions

The first step of the proposed approach works as follows: Suppose that X_i is composed of l training samples, and let $X_i = [x^1, \ldots, x^l]$. Every two samples of these l samples are exploited to synthesize one virtual training sample and thus $C_l = (l(l-1))/2$ virtual training samples are generated for this ith class. If x_i and x_i are two original training samples from X_i, then the corresponding virtual training sample will be

$$x_v^j = (x_i^t + x_i^s)/2 \qquad (1)$$

where $j = 1, \ldots, C^2$. The C^2 virtual training samples of the ith class are $x_v, \ldots, x^{C^2}$, respectively. We take i as the label of the original training samples of the *ith* class and the corresponding synthesized virtual training samples. All the original training samples and synthesized virtual training samples of all the subjects are combined to form a blend training sample set (BTSS) [10][11].

Fig:(5) Synthesized Samples Of Original Training Samples

To reduce random uncertainty is to use these limited training samples to synthesize virtual training samples, which are able to reflect more possible variations of the face. Limited training samples of each subject mean that they provide insufficient observations of the face. That is, these limited training samples of each subject cannot comprehensively reflect different variations of the face.

- ***Generating synthesized and normalized sample***

To obtain the reasonable virtual training sample, if the synthesized virtual training sample is too similar with the original training sample, it cannot well play a role of a training sample. However, if the difference between the synthesized virtual training sample and the original training sample is too great, which may result in the case that the synthesized virtual training sample is more similar with the training sample from another class, which of course brings side effect to the subsequent classification. Therefore, a good virtual training sample should have a proper difference with the corresponding original training sample [11][20].

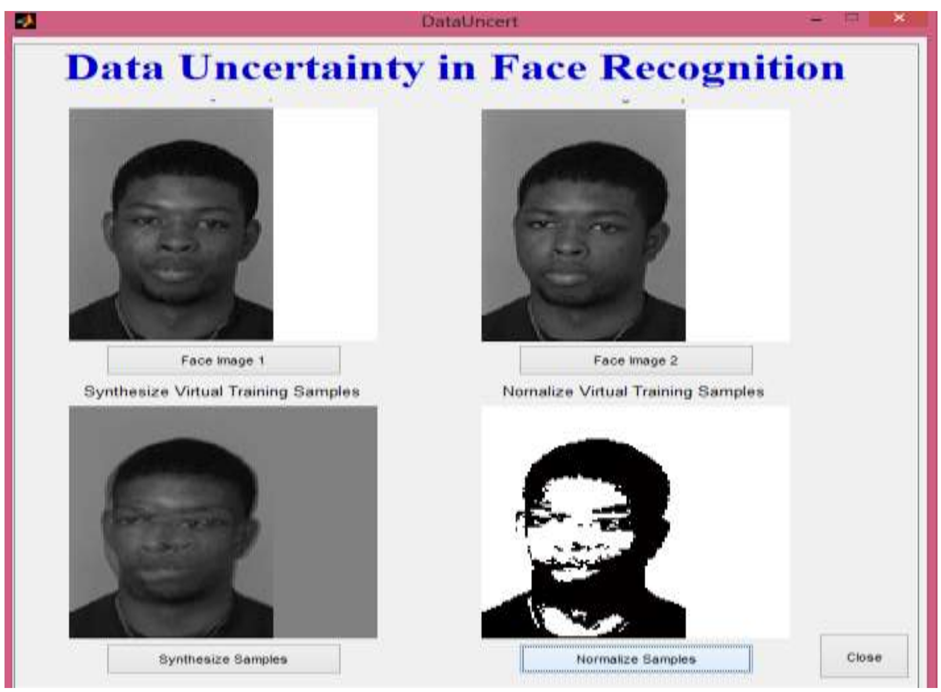

Fig:(6) Synthesized And Normalized Sample

- ***BTSS Algorithm***

The BTSS (Blend training sample set) Algorithm is used to generate training samples. In system, propose to select the training samples that are similar to the test sample from BTSS as useful training samples and use them to represent and classify the test sample. Suppose that in BTSS there are training samples from classes for training sample in BTSS. The samples obtained in BTSS have different representation abilities in representing the test sample. Here referred to these training samples that have negative effects in representing the test sample as improper training samples. Therefore, in practice, just need to select these training samples that have positive effects in representing the test sample. Previous studies have shown that the training samples that are close to the test sample are very helpful for correct classification of the test sample.

The second step of the proposed approach works as follows: Suppose that in BTSS there are f training samples from c classes and $xj(j = 1, \ldots, f ; f > n)$ stands for the jth training sample in BTSS. Once a test sample $y \in Rm$ comes, we calculate the distance between y and xj by using

$$dist_j = \| y - x^j \|_2 . \qquad (2)$$

Equation(2) can be somewhat viewed as a measurement of the similarity between xj and y. A small $distj$ means that xj is similar to test sample y.

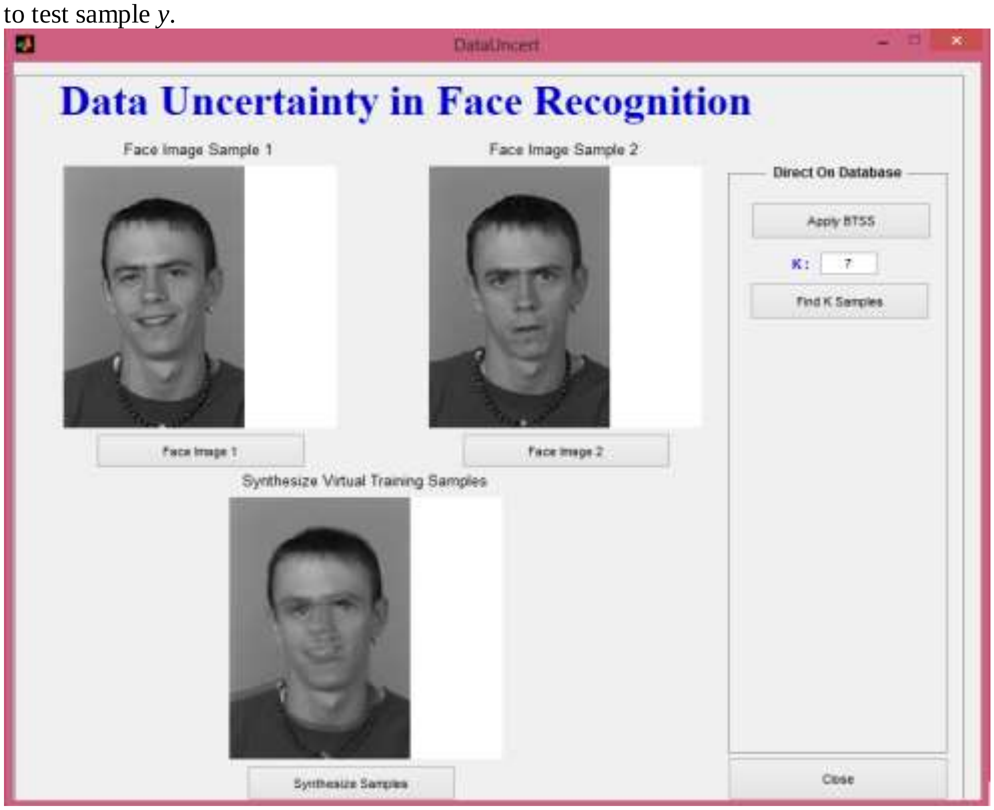

Fig:(7) Applying BTSS Algorithm On Test Samples

- ***Virtual Traininig Samples***

We should select the most useful training samples as many as the original training samples from BTSS. In other words, Theorem 1 gives the largest possible number of the useful training samples for our approach. Furthermore, as among the original and virtual training samples the samples that are very far from the test sample usually have side effect on the classification of the test sample, to select and exploit fewer useful training samples to represent and classify the test sample can obtain a good recognition accuracy. To demonstrates that it is not necessary to use all training samples in BTSS to represent and classify the test sample from the viewpoint of numerical computation. The main reason is that the matrix corresponding to the BTSS has the same rank as the original training sample [12][14].

The third step of the proposed approach represents the test sample as a linear combination of the selected K useful training samples and requires that the $l2$-norm of the vector of the representation coefficients should be minimized. Thus, the objective function is as follows:

$$\min_{\widehat{\beta}} \| y - \tilde{X}\widehat{\beta} \|_2^2 + \lambda \| \widehat{\beta} \|_2^2 \qquad (3)$$

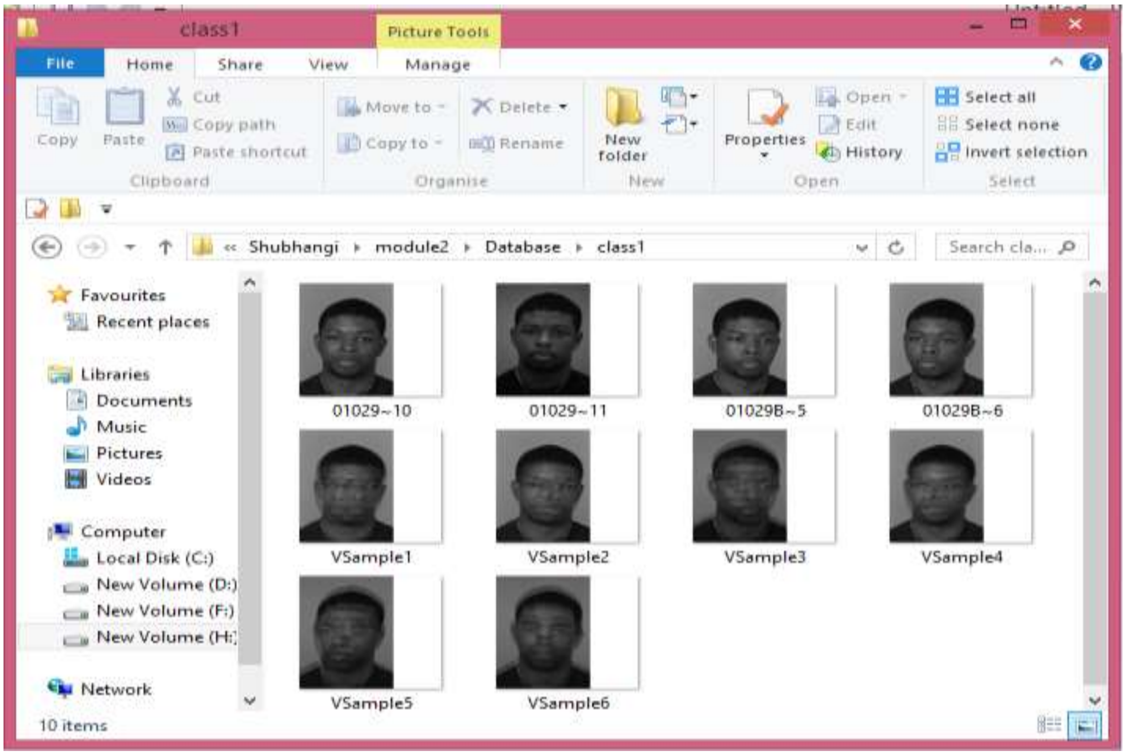

Fig:(8) Generated Vsamples And Original Test Samples

➢ ***Selecting and determinig samples***

We select K useful training samples from BTSS and discard remaining training samples. In other words, the second step of our approach neglects some training samples that are far from the test sample and the third step exploits only K training samples to represent the test sample.

$$\widehat{\beta} = (\tilde{X}^T \tilde{X} + \lambda I)^{-1} \tilde{X}^T y \qquad (4)$$

Here samples are determined from the original training samples and from the generated virtual training samples by K Samples algorithm. It is not necessary to use all training samples to represent and determine the test sample from the viewpoint of numerical computation. The main reason is that the matrix corresponding to the BTSS has the same rank as the original training sample

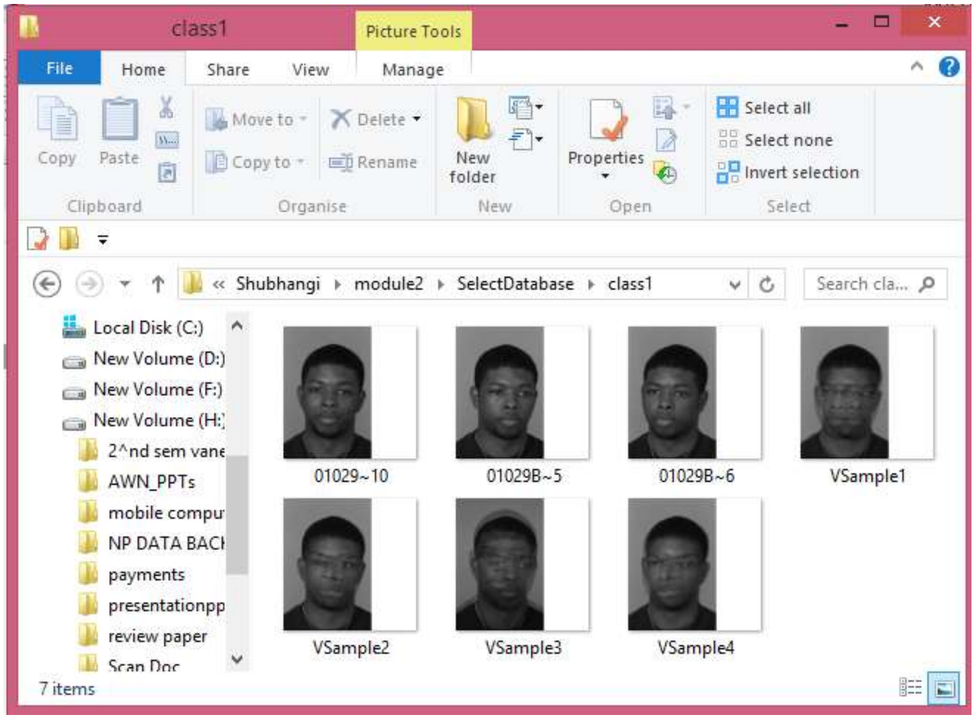

Fig:(9) Selecting Use Full Training Samples

Fig:9 shows the variation of the recognition accuracy with K, the number of the useful training samples. From this figure, we can see that when K becomes small, our proposed approach trends to obtain better performances. This is because when K is small, many improper training samples that have side effect on the classification of the test sample are excluded from our approach.

- ***Classification Of Usefull Training Sample***

The l_2-norm-based representation algorithm has gained reputation as a powerful and attractive algorithm showing excellent results in terms of recognition accuracy and computational efficiency in face recognition [19].

$$g_r = \widehat{\beta}_s \tilde{x}_r^s +, \ldots, +\widehat{\beta}_t \tilde{x}_r^t \qquad (5)$$

A smaller residual Dr means a greater contribution to representing the test sample. Thus, we classify y into the class that produces the smallest residual.

$$D_r = \| y - g_r \|^2 . \qquad (6)$$

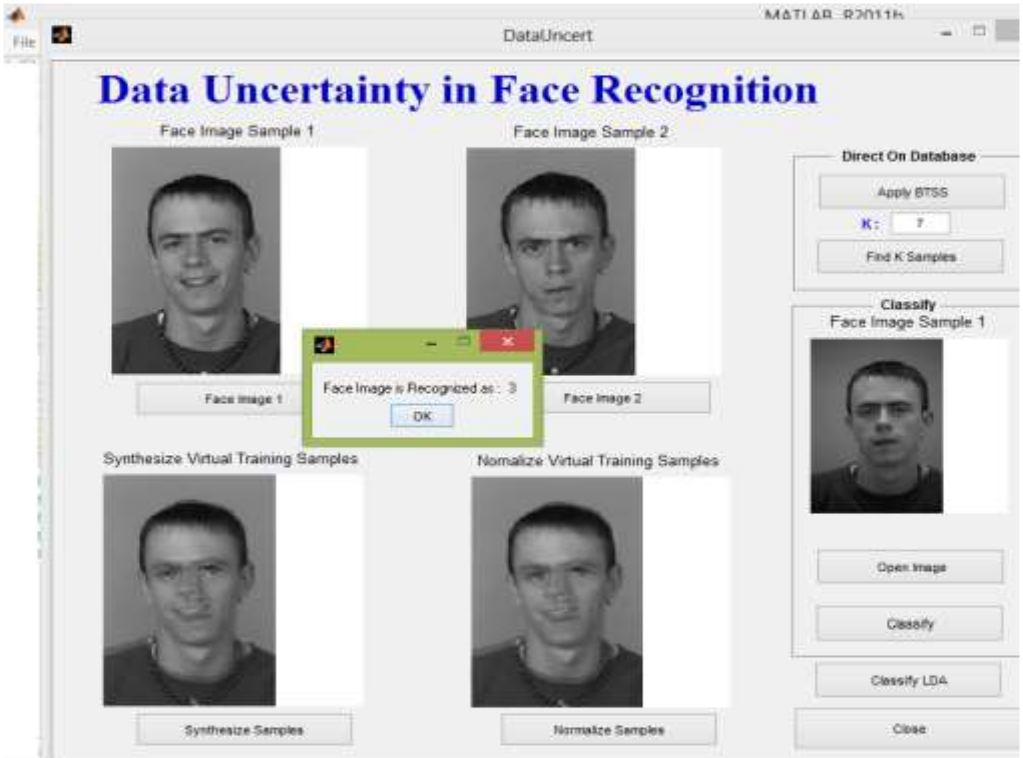

Fig:(10) Classifying The Classes Of Samples

EXPERIMENTAL RESULTS

In this paper, we have done our experimental setup based on the image processing tool to make the classification of images in the data sets on *l2* norm algorithm. The classification of the samples is done on the different classes of the face samples. The LDA algorithm is used for classification, with this the proposed approach is very easy to implement and has a much lower computational complexity than the other discriminat methods. Moreover, in our approach the virtual training samples will not greatly deviate from the true training samples from the same subject which much efficient to reduce the data uncertainty in face recognition.

The graph shows the comparision of *l*2 norn-based technique and our approach where we used the LDA algorithm for the improving the recognition accuracy of the system. The time required to make the classification is reduced with our approach. Here shows the result of this recognition system and reducing the data uncertainty of the system.

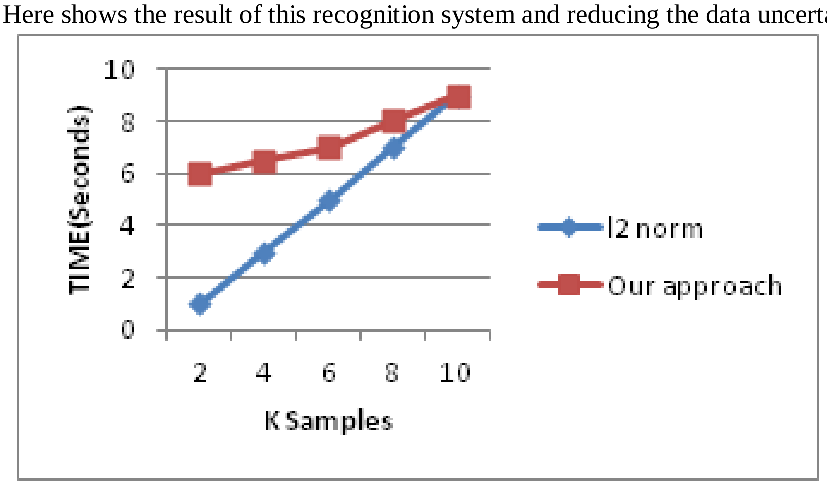

Fig:(11) Graph Of K Samples Vs Time The Comparosion Of Two Methods

The above discussed approach is implemented and tested on 26 classes. On the basis of these effective image samples it can classify the effective samples from the selected samples. Table I shows the result of 26 classes. Out of 26 classes running through the algorithm it has correctly generate 260 images that are the synthesized virtual training samples. From the generated virtual training samples our approach can select 182 select virtual samples. This falsely identified the remaining 26 classes, gives the success rate of 90%approximately.

Here in table I show the two cases. In the first case (Case I), we used the first four images of each subject as training samples. In the second case (Case II), we used the five images as training samples and comparing both cases with the *l*2 norm algorithm and with the LDA algorithm. In the table I show the results of comparison of both cases.

Experi-mental protocol	Case I		Case II	
	Recogn-ition accura-cy	Time (sec)	Recog-nition accura cy	Time (sec)
*l*2 norm	78.33	0.1912	77	0.2014
LDA algo.	90	0.0351	89	0.0312

Table: (I) Recognition Accuracy And Running Time Of System

In our current work, with this success rate we remove highly the data uncertainty in face recognition as compare to the previous work. So it will detect it as a different face image samples. The algorithm is based on simple feature calculation which provides us with the ease of implementation.

CONCLUSION

In this paper, we propose an approach for improving the face recognition accuracy, it by reducing the uncertainty. This algorithm produces recognition accuracy in face recognition and produces the proper data analysis. We first exploited the original training samples to synthesize virtual training samples which reflect possible variations of the face and then proposed a scheme of selecting and exploiting useful training samples to represent and classify a test sample. This scheme is helpful for eliminating the improper training samples which have side effect on classification of the test sample, and thus can improve the recognition accuracy.

FUTURE WORK

We will address the problem of how to automatically select the most appropriate number of useful training samples for the test sample in the future. Because, we noted that the most appropriate number of useful training samples is generally much smaller than the number of the original training samples. Moreover, a theorem gives the upper bound of the number of useful training samples.

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