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Recognition of Faces – An Optimized Algorithmic Chain

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Abstract

Face recognition has been one of the popular and important parts in Human Computer Interaction (HCI) systems that find tremendous applications, some of which are very critical like access control, surveillance, etc. There are numerous techniques available to process face images and hence, choosing an optimal algorithmic chain is not a straight forward job. The scenario gets much more interesting while implementing face recognition in applications connected to cloud via Internet of Things (IoT) platform. This paper reviews some of the effective face recognition algorithms and proposes an optimized algorithmic chain offering optimal classification accuracy and lower execution time; thereby making it appropriate for IoT related applications targeting human-centric systems. Also, achieving optimum efficiency by selecting appropriate number of features for a given combination of algorithms and the behaviour of algorithms due to partitioning of the images in case of Local Binary Pattern (LBP) is discussed. Results indicate enhanced classification rates with algorithmic fusion by creating chains or process flow of methods. Accuracy of up to 96% was obtained for one of the chains that were designed. Also, it is evident from the results that this chain outperforms some of the well-known state-of-the-art methods.

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Keywords: Face Recognition; HCI; IoT; LBP; Neural Networks (NN).

1. Introduction

HCI systems are finding tremendous application these days with systems like Brain-Computer Interfaces (BCI)[1,24], natural language processing[2], semantic analysis, activity monitoring[3], recommender systems, computer vision, person identification[4], etc. Computer vision is one of the highly researched domains and face recognition is one crucial non-intrusive aspect of it. The main use-case that has driven intense efforts on face recognition research is security oriented applications. Face recognition can greatly foster human-machine interactions if they are embedded with the IoT systems. If face recognition is made available on IoT platform in real time, it can then be utilized for various applications like access control, building and home automation, surveillance cameras, employee safety, location and tracking, connected appliances, etc., as depicted in Fig. 1. The availability of Internet-based services, high-bandwidth connectivity and ubiquitous computing, renders anytime and everywhere access of information, interaction and communication. The IoT assumes that objects have digital functionality and can be tracked and identified automatically; which is possible for face recognition with the advent of many robust algorithms developed

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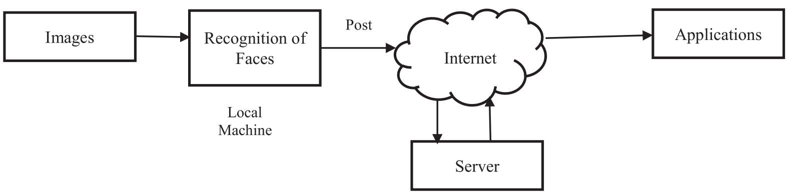

Fig. 1. Face Recognition and Modeling Through IOT.

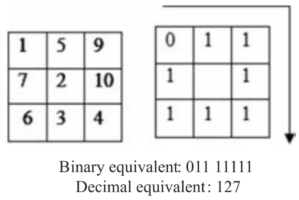

Fig. 2. Example of LBP Texture Descriptor.

in the past few decades. However, the main constraint coming in the way of deploying face recognition in IoT based applications is accuracy, computational cost and time complexity. The aim of this paper is to review the most commonly used robust algorithms in face recognition and find the optimal fusion or chain that bestows better performance. Though the algorithms used are naive, their performance is found to be increased with the proper formation of chains.

The main advantage of face recognition over other conventional biometric modalities is the passive identification that it provides, as the individual need not come in direct contact with the biometric device[24]. Despite its advantages, there are certain factors that decrease its proliferation. The major ones are changes in facial expressions[5], illumination, pose[6], occlusions, ageing and eye blinks[7]. Another major aspect that causes intricacy to face recognition is the alignment of face. Such artifacts greatly hamper the working of face recognition systems. To have a proper comparison between the face images, the alignment has to be done precisely. This needs the precise facial feature localization which is a very complex task to ascertain. Many algorithms have been designed that primarily aims at handling a single or a mixture of 2 factors that create variations in facial appearance. A wide range of potential applications stimulated extensive research efforts on face recognition. Thus there is an assortment of algorithms available to address the wide spectrum of challenges faced in face recognition. But selecting the least combination of effective algorithms is a must to handle time and space complexity related issues. The main contribution of this paper lies in proposing an optimal algorithmic chain via comparative analysis amongst various existing algorithmic approaches. Results are indicative of the possibility of getting good classification accuracy with SVM classifier if processing steps are selected properly. The paper can be organized as follows. Section 2 deals with a detailed mathematical review of the algorithms used. Section 3 elaborates the implementation schema. The results of the overall implementation are given in Section 4 and the paper concludes in Section 5.

2. Related Work

2.1 Local binary pattern

This method is popularly deployed for texture descriptor operation[8]. The hypothesis inherent in this technique is that the face images are composed of numerous fine micro patterns. We selected this approach to overcome the illumination related artifacts. The operator takes into account, the neighbouring pixels (p_i) of a 3×3 matrix for all the pixels of the image. The central pixel value (p_c) is set to be a threshold and all the pixel values are compared against this. A value of one is allocated if the pixel value is higher than the threshold; else 0. The numbers obtained after running the entire process are considered in a clockwise manner and a binary number is produced from it, which is later converted to its decimal counterpart. Mathematically, the process is well explained as,

$$LBP = \sum_{i=0}^{7} 2^i b(p_i - p_c) \tag{1a}$$

$$B(p_i - p_c) = \begin{cases} 1, & \text{if } p_i - p_c > 0 \\ 0, & \text{if } p_i - p_c \leq 0 \end{cases} \quad \text{where } i = 0, 2, \ldots, 7 \tag{1b}$$

The method can better be explained as in Fig. 2.

2.2 Principal component analysis

This method is well-known for its effective feature extraction ability[9]. This is used in this study for final feature vector dimension reduction, thereby representing the data in a more compact and discriminative manner. Consider a matrix M whose eigenvector is a vector u, which when multiplied with M, yields an integer multiple λ, of that vector. This integer value λ represents the eigenvalue of the eigenvector, u. Mathematically it can be put together as,

$$M \times u = \lambda \times u \tag{2}$$

here λ is the eigenvalue of the eigenvector u of the matrix M. Primarily, the face images that organize the training set (Γ_i) are processed. The average matrix Ψ is given by,

$$\Psi = \frac{1}{M} \sum_{n-1}^{M} \Gamma_n \tag{3}$$

This matrix Ψ, is subtracted from the set of original faces (Γ_i),

$$\phi_i = \Gamma_i - \Psi \tag{4}$$

Then the covariance matrix, C is computed as follows,

$$C = \frac{1}{M} \sum_{n-1}^{M} \phi_n \, \phi_n^T \tag{5}$$

Then the eigenvectors, u_i along with the eigenvalues λ_i are calculated. It also involves the normalization of the eigenvectors in order to make them unit vectors. Since the dimension of C is $N^2 \times N^2$, the calculation of eigenvectors gets more cumbersome when the image dimensionality increases. In order to decrease the intricacy, the solving of eigenvectors, can be done as:

$$(A^T A)u_i = \lambda_i u_i \tag{6}$$

$$A(A^T A)u_i = A(\lambda_i u_i) \tag{7}$$

$$AA^T(Au_i) = \lambda_i(Au_i) \tag{8}$$

Compute Au_i to assess the eigenvector of the larger AA^T matrix. The storage of eigenvectors is then carried out in the order of decreasing eigenvalues as:

$$U_i = Au_i = [\phi_1, \phi_2, \ldots, \phi_n] \begin{bmatrix} u_1^i \\ \vdots \\ u_n^i \end{bmatrix} \sum_{k=1}^{n} u_k^i \phi_k \tag{9}$$

$$W_i = \frac{U_k^T \; (\Gamma_i - \mu_i)}{\lambda_i} \tag{10}$$

The data points returned after LBP process is huge to parse and hence PCA is used as a dimensionality reduction technique. It effectively selects only the principal component which eases the procedure involved in the calculation. These principal components are then fed to the classifier (Support Vector Machines in this case).

2.3 Support vector machines

A supervised learning based classification can be achieved using SVM to scrutinize and classify the patterns of interest in the given data sets[10]. From all the existing classification methods, we used a SVM-based technique due to its higheraccuracy[11] and due to its high generalization abilities. It is basically a binary classifier that can also be applied in multi class classification problems. It constructs a boundary in order to classify the data into meaningful classes. The boundary is a straight line for 2D, plane for 3D and for higher dimensions, it is known as hyperplanes. An assortment of training points $x_i \in R_n, i = 1, 2, \ldots, N$ are taken where every single point x_i fits in either of the two classes with labels $y_i \in \{-1, 1\}$. Assuming linearly separable data, the aim is to isolate the two classes by a hyperplane in such a manner that the distance to the support vectors is maximized. This hyperplane is called the optimal separating hyperplane (OSH), given by,

$$f(x) = \sum_{i=1}^{l} \propto_i \; y_i x_i \cdots x + b \tag{11}$$

The sign on the right side of equation (11) determines the classification of a new data point. In case of multi-class classification, we use,

$$d(x) = \frac{\sum_{i=1}^{l} \; \propto_i \; y_i x_i \cdots x + b}{\left\| \sum_{i=1}^{l} \propto_i \; y_i x_i \right\|} \tag{12}$$

The result of x is largely dependent on the sign of d. The distance from the hyperplane to x is given by $|d|$. The larger the value of $|d|$, the better is the classification.

2.4 Feed forward back propagation neural network

Feed Forward Back Propagation Neural Network (FFBPNN) is basically a supervised learning approach like that of SVM. Random variables are used to initiate the learning process and the net total input is given by,

$$n_j = \sum_{i=0}^{N} x_i \; w_{ij} \tag{13}$$

where w = weight vector and x = input vector. FFBPNN deploys a sigmoid function as its activation function given by,

$$f(n_j) = \frac{1}{1 + e^{-n_j}} \tag{14}$$

where $f(n_j)$ denotes the hidden layer's activation function.

The net total output is given by

$$n_k = w_k f(n_j) \tag{15}$$

The output at hidden layer and output layer can be given by (16) and (17), respectively,

$$O_j = f(n_j) \tag{16}$$

$$O_k = f(n_k) \tag{17}$$

The input pattern gets transmitted through the whole of the network till the final output is produced. A generalized delta rule is used to determine the overall error:

$$\delta_j = f'(n_j) \sum_{k=1}^{k} \delta_k \; w_{kj} \tag{18}$$

where δ_j denotes error for hidden layers.

$$\delta_k = (t_k - o_k) f'(n_k) \tag{19}$$

δ_k denotes error for output layer.

Now every unit alters its input connection weights in order to lessen the error. Then the process gets repeated for the next pattern of interest. A learning rule η for a weight change for a unit in hidden layer is given by,

$$\Delta \; w_{ij} = \eta \; \delta_j \; x_i \tag{20}$$

3. Implementation

The combinations of algorithms as mentioned in Table 1 were implemented. These chains were tested on 2D and 3D face images. 2D face images were selected from the AR face database (detailed in Section 3.1. Different case studies were studied such as when the face images were taken whole and then partitioning the face images equally into 2, 4, 6, 8, 10 and 12 parts. The partitioning strategy is invariant to monotonic grayscale changes, and is beneficial while handling large expression variations in the face images. LBP was applied on these components. This results into a huge dataset which is then subjected to dimensionality reduction by using PCA. See Fig. 3 for the overall implementation flow and Table 1 for detailed explanation. In total, we define three chains- 1) 2D LBP + PCA + SVM *(Path 1, 3)* 2) 3D LBP + PCA + SVM *(Path 2, 4)* and 3) 3D LBP + PCA + FFBPNN *(Path 2, 5)*. We used balanced training, i.e. the first 50% of the samples are used for training the classifier and the rest of the 50% face images were used for the testing purpose. The accuracy determining parameters includes Receiver Operator Characteristics (ROC) curves, execution time, sensitivity and accuracy. The modeling of 2D face images to 3D was rendered through Vizago face modeler[12] which involves manual segmentation and localization of facial landmarks like lips, eyes, etc. Here the gender needs to be specified and manually click on 12 points – 2 on ears, 2 on the corners of the mouth, 3 on the contour of the face-chin and sides, 2 on eyes and 3 on the nose.

3.1 Details of the face database used

The face images used for this study were from the AR face database. It was created in 1988 in the Computer Vision Center (CVC) at the U.A.B. by Aleix Martinez and Robert Benavente. This is the first face database to include occlusions. The database provides provisions for variation in eye glasses, illumination, frontal poses, scarves, expressions, etc.[13]

Table 1. Details of Various Algorithmic Chains Designed.

Motivation	Algorithm Chain	Approach Used
Choice of dimensionality of the images used:- 2D images were taken and were either used as 2D itself, or were converted to its 3D counterpart using Vizago modeler[12]	*Path 1*: $1 \rightarrow 2 \rightarrow 4 \rightarrow 6 \rightarrow 9 \rightarrow 10 \rightarrow 13 \rightarrow 16 \rightarrow 17 \rightarrow$ 18, 19, 20, 21, 22	i) Pre-processed with LBP ii) Image partitioning into n parts ($n = 1, 2, 3, 4, 6, 8, 10$ and 12) iii) Dimensionality reduction via PCA iv) Classified with SVM v) Balanced training
	Path 2: $1 \rightarrow 3 \rightarrow 5 \rightarrow 7, 8 \rightarrow 9 \rightarrow 11, 12 \rightarrow 14, 15 \rightarrow 16 \rightarrow 17 \rightarrow$ 18, 19, 20, 21, 22	i) Preprocessed with LBP ii) Image partitioning into n parts ($n = 1, 2, 3, 4, 6, 8, 10$ and 12) iii) Dimensionality reduction via PCA iv) Classified with SVM and FFBPNN v) Balanced training
Choice of classification algorithm used:- SVM and FFBPNN were tested separately for efficiency	*Path 3*: $1 \rightarrow 2 \rightarrow 4 \rightarrow 6 \rightarrow 9 \rightarrow 10 \rightarrow 13 \rightarrow 16 \rightarrow 17 \rightarrow$ 18, 19, 20, 21, 22 And *Path 4*: $1 \rightarrow 3 \rightarrow 5 \rightarrow 7 \rightarrow 9 \rightarrow 11 \rightarrow 14 \rightarrow 16 \rightarrow 17 \rightarrow$ 18, 19, 20, 21, 22	i) Using SVM
	Path 5: $1 \rightarrow 3 \rightarrow 5 \rightarrow 8 \rightarrow 9 \rightarrow 12 \rightarrow 15 \rightarrow 16 \rightarrow 17 \rightarrow$ 18, 19, 20, 21, 22	ii) Using FFBPNN
Effect of partitioning of images:- To assess the effectiveness in recognition achieved via partitioning of images into parts	Preferred path with partitioning into various parts	i) Selected preferred path from Path 1 through Path 20
		ii) Selected same path but without partitioning of images

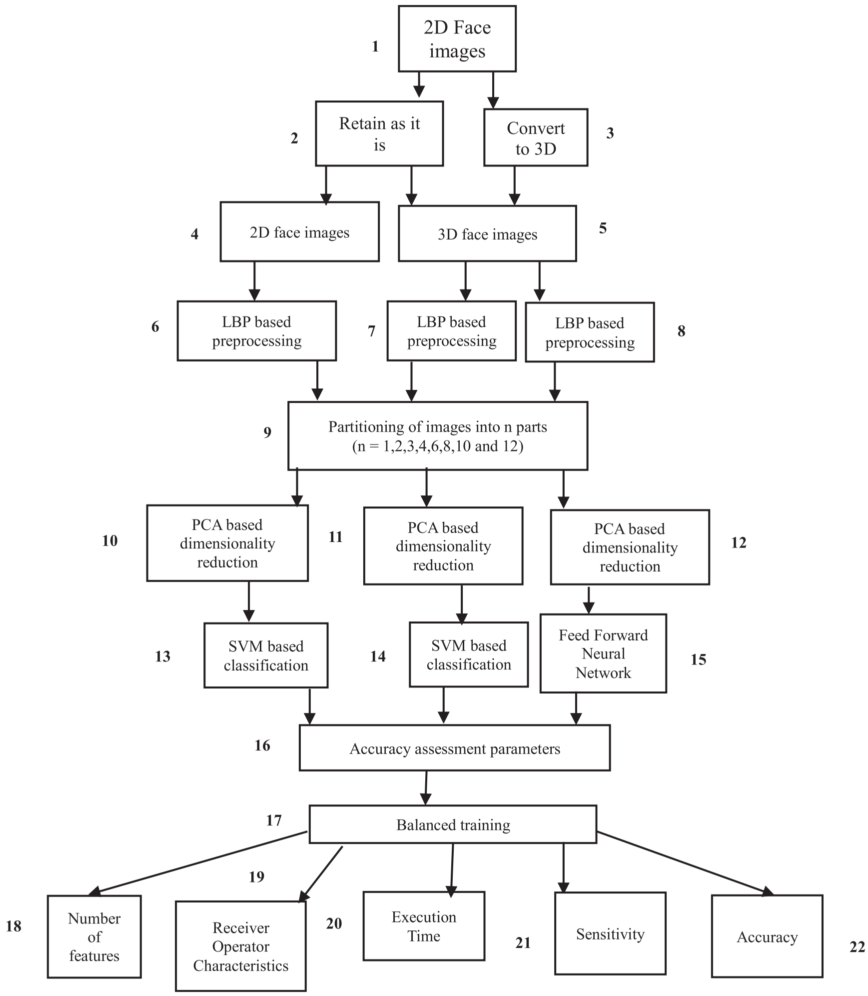

Fig. 3. Overall Methodology for Face Recognition.

3.2 Comparison of algorithms

Algorithms were compared based on: i) Accuracy of classification, ii) sensitivity, and iii) execution time required to complete the processing.

The accuracy is defined as the probability of correctly identifying the face image and is given by

$$\text{Accuracy} = \frac{TP + TN}{(TP + FN + TN + FP)} \tag{21}$$

where True positive (TP) – correctly identified, False positive (FP) – incorrectly identified, True negative (TN) – correctly rejected, False negative (FN) – incorrectly rejected.

Sensitivity relates to the test's ability to identify an image correctly; i.e. sensitivity is the probability of having a positive test and is given by

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \tag{22}$$

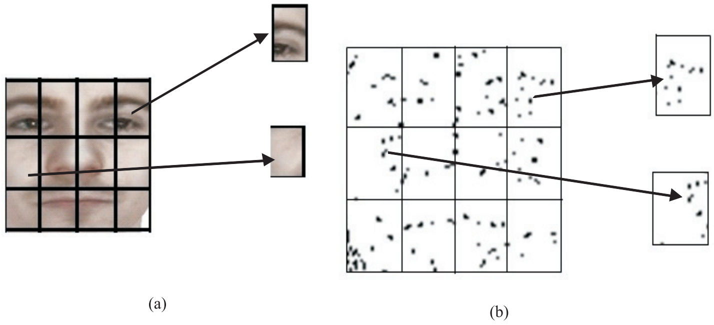

Fig. 4. Illustration of the Variations in the Amount of Information Possessed by Various Regions of Face. (a) Face Image Showing the Sparsely Contained Information (pixel intensity variations) in the Cheek Regions when Compared to the Regions Around the Eyes; (b) The Same Image Undergoing LBP Operation, Focusses more on the Information thereby Reducing Further Processing.

Usage of 3D head modules was done to assess its impact on the overall recognition process. The main benefit of 3D based approaches is that the 3D head module preserves all the information pertaining to face geometry. In a 3D face module, facial features are represented by local and global curvatures, which can be used as the unique characteristics to identify people. The 3D facial representation is a promising tool which is capable of coping with many of the human face variations. Next the LBP and PCA algorithm with SVM and FFBPNN as the classifier was tested on 3D head modules. Again, different cases are studied, such as when the face is taken whole, and then divided equally into 2, 4, 6, 8, 10 and 12 parts. For all these cases accuracy, ROC and execution time are computed for balanced training.

3.3 Partition analysis

It can be noted that occlusions and expressions on face images can be tackled with partitioning process. A finer partitioning renders more blocks for comparisons but too larger subsets decrease the recognition rates as small blocks around some facial regions like eyes, lips tend to get shifted towards the neighbouring blocks. Hence, in our case, we found that the recognition rates were lesser for partitions below and above 10 partitions on LBP processed images. The reason for partitioning images on LBP operated images rather than the original image itself can better be understood from Fig. 4. Figure 4(a) is indicative of the variations in information contained in different regions of the face regions. It is to be noted that LBP operated images retain much of the information rich regions; unlike the regions of the cheek which have sparse data, since they are almost homogenous. Hence, the hypothesis that is anticipated is identifying a particular number of partitioning that would boost up the performance, which is discussed in the results and discussions section.

4. Results and Discussions

The face recognition algorithm for both 2D and 3D face images using LBP operator and PCA algorithm with SVM as the classifier provided very good results, in terms of recognition rates. Figure 5 shows the accuracy of the developed methodology of using LBP and PCA algorithms with SVM as the classifier for 2D and 3D face images. A significant increase in accuracy is observed for the 3D face recognition system.

The 3D face recognition accuracy was optimum when the developed algorithm of LBP and PCA with SVM as the classifier was used. We further tested the face recognition accuracy using Feed Forward Back Propagation Neural Network (FFBPNN). The developed chain of LBP and PCA was used with feed forward BPNN as the classifier. Figure 6 shows the accuracy analysis of 3D images on LBP and PCA algorithms with SVM as the classifier and LBP and PCA algorithms with FFBPNN as the classifier. The face recognition accuracy achieved in the latter case was lesser than the former. The reduced accuracy was due to the fact that this method is very sensitive to illumination and noise. Therefore images with varying background cannot be used in this method. Comparing the face recognition accuracy of the two 3D methods in Fig. 6, it is noted that the face recognition accuracy in the developed algorithm

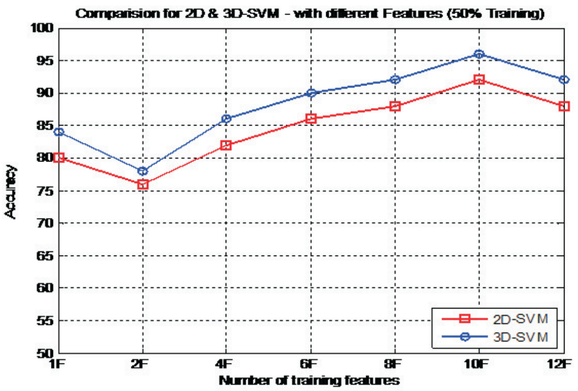

Fig. 5. A Comparison of the Face Recognition Accuracy for 2D LBP, PCA, SVM and 3D LBP, PCA, SVM Face Recognition Methods.

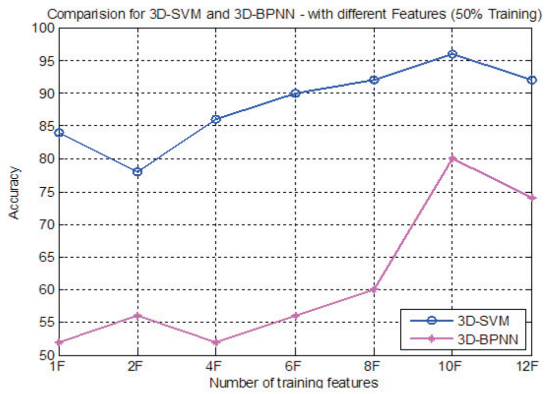

Fig. 6. Comparison Analysis of 3D LBP, PCA and SVM and LBP, PCA and FFBPNN Algorithmic Chain.

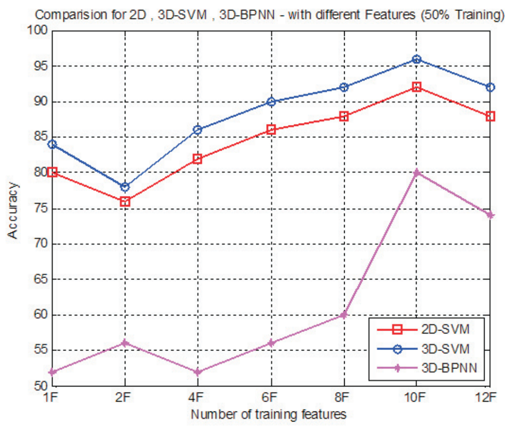

Fig. 7. Comparison of the Face Recognition Accuracy for 2D LBP, PCA, SVM; 3D LBP, PCA, SVM and 3D LBP, PCA, FFBPNN Face Recognition Methods.

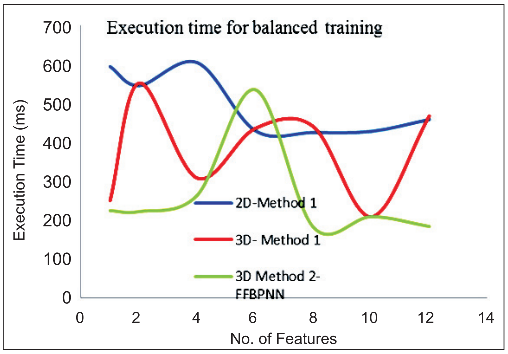

Fig. 8. Execution Time Comparison for the Methods Used.

of 3D images on LBP and PCA algorithm with SVM as the classifier is significantly higher as compared to LBP and PCA algorithm with FFBPNN as the classifier.

Figure 7 shows the overall summary of face recognition accuracy for 2D LBP and PCA algorithm with SVM as the classifier, 3D LBP and PCA algorithm with SVM as the classifier and 3D LBP and PCA algorithm with FFBPNN as the classifier.

Figure 8 shows the execution times of the three methods used. It can be noted that the time taken varies considerably with the number of features selected. In case of 3D face images, the time taken is lesser at 10 features.

Figure 9 shows the Receiver Operator Characteristics (ROC) curves for the three methods discussed in the implementation. It is evident from the figure that SVM outperforms FFBPNN in this regard.

Table 2 gives the summary of the chains used. Chains 1 and 2 were analogous to chains 4 and 5 respectively and hence are omitted. Thus we see Path 4 as the best possible approach in terms of classification accuracy, execution time and sensitivity for 10 number of features or partitions of the image while using SVM as: i) Partitioning of images into 10 partitions is optimum as it gives more information while at the same time reducing redundancy (as in case of 12 partitions), thereby reducing the time complexity, ii) Uses 3D counterpart of the 2D images gives the depth related information, thereby enhancing classification, iii) bypasses FFBPNN.

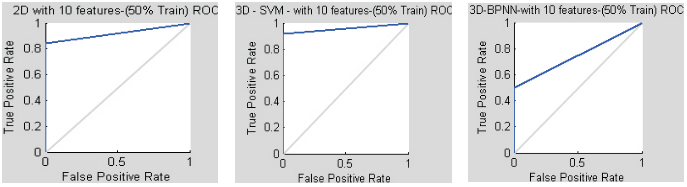

Fig. 9. ROC Analysis for the Methods Used.

Table 2. Comparison of Various Algorithms in Terms of Accuracy Parameters.

	Path 3			Path 4			Path 5		
No. of Features	Accuracy (%)	Sensitivity	Exec. Time (ms)	Accuracy (%)	Sensitivity	Exec. Time (ms)	Accuracy (%)	Sensitivity	Exec. Time (ms)
1	80	0.375	594.375	84	0.404762	249.688	52	0.0384615	224.063
2	76	0.342105	545.313	78	0.358974	551.875	56	0.107143	221.875
4	82	0.390244	604.688	86	0.418605	307.813	52	0.0384615	263.438
6	86	0.418605	429.688	90	0.444444	435.313	56	0.107143	535
8	88	0.431818	425	92	0.456522	440.313	60	0.166667	181.875
10	92	0.456522	427.813	96	0.479167	208.438	80	0.375	208.75
12	88	0.431818	458.438	92	0.456522	467.5	74	0.324324	183.438

Table 3. Comparison of the Proposed Approach with the State-of the-art Methods.

Author	Accuracy	Approach
Jinhui Chen *et al.*[14]	91%	SURF+PSM+SVM
J Li *et al.*[15]	94%	SURF_Ada
TimoAhonen *et al.*[16]	79%	LBP + NN classifier
Linlinshen *et al.*[17]	92%	Gabor features + SVM + OG-SVM
PAN Hong *et al.*[18]	83–91%	DMQI + LBP
Dong-Ju Kim *et al.*[19]	70.7–96.43%	LDP + 2D-PCA + NN classifier
Wu FengXiang[20]	95.2% (with noise)	HCPP + RDW-LBP + Chi-square
Singh *et al.*[21]	80–95.7% (pose variations)	LBP
	95.45% (with noise)	LBP
	55%, 55%	PCA
	54%, 56%	2D PCA
Peng Yang *et al.*[22]	95.2%	Gabor features + Adaboost
Faith Kahraman *et al.*[23]	95%	Active appearance model
Our method	92% (10 blocks)	Path 3
	96 % (10 blocks)	Path 4
	80 % (10 blocks)	Path 5

It can be seen that our results are comparable with some of the state-of-the-art methods including the combination of SVM, PCA, LBP and neural networks with various other approaches or taken in seclusion (see Table 3).

5. Conclusions

In this paper, we proposed an optimal algorithmic chain capable of recognizing faces with increased accuracy. The paper draws sharp inferences on the selection of appropriate feature extraction and classification algorithms for face recognition. Also, the fact that the number of features selected plays a major role in overall accuracy, execution times, etc. is also stressed. From the results it is evident that SVM based classification on LBP operator and PCA based feature extraction yields better accuracy when compared to FFBPNN based classification, keeping the feature extraction paradigms constant. Also, in case of SVM, 3D face images bestow better classification results, owing to the ability of 3D images in retaining the depth related information. However, the modeler used in the study was inefficient since it involves manual identification of the facial landmarks and does not render detailed information on the modeled face image. In spite of this shortcoming, the results show enhanced recognition rates over their 2D counterparts. Usage of better and automated 3D modelers is encouraged to obtain much higher accuracy rates.

The results and the methods this article introduces, can serve as a guideline while selecting algorithms to implement face recognition within the desired design space. This in turn, can foster applications in human-machine interactions to be carried out beyond ubiquitous computing to everyday computing with and within the IoT. The proposed optimum algorithmic chain requires minimum computational resources thereby making it appropriate for face recognition related IoT applications.

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