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INTEGRATING COMPLETE GABOR FILTER TO THE RANDOM FOREST CLASSIFICATION ALGORITHM FOR FACE RECOGNITION

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Abstract

Local feature approach to face recognition such as Local Binary Pattern (LBP) and Gabor has demonstrated to be an excellent facial descriptor. However, due to the large dimension features generated from the Gabor filter, the computation time for feature extraction is lengthy. Likewise, LBP generates lengthy histograms, which ultimately slow down the recognition time. This paper proposes a hybrid face recognition technique called Complete Gabor Filter with Random Forest (CG-RF) in biometrics technologies. CG-RF uses Gabor Magnitude Responses (GMR) and Oriented Gabor Phase Congruency Image (OGPCI) with Random Forest as features classification. For best features, Monte Carlo Uninformative Variable Elimination Partial Least Squares (MC-UVE-PLS) regression is used to select the important features generated from the Gabor filters. The upside of the proposed technique reduces computation time significantly without compromising on the accuracy of face recognition. Further experiments were conducted on Georgia Tech (GT) and Facial Evaluation Recognition Test (FERET) face databases with regards to varied face images such as head positions and orientations, occlusion and light illumination. The outcome of the experiments on both databases demonstrated a short turnaround in computation time and high recognition rates - GT (1735.2 seconds; 94.7%), FERET (8875.6 seconds; 96.7%).

Keywords: Complete gabor filter, Face recognition, Random forest.

1. Introduction

Research on face recognition has been evolving for decades. There are numerous approaches developed with highly desirable outcomes in the face recognition system. However, approaches to face recognition in an environment where varied facial posing, occlusion, orientation, image quality, etc., poses vast challenges to researchers [1, 2]. One of the approaches such as deep learning [3-5] produced remarkable results but with high computational costs.

This paper proposes a face recognition framework that uses Gabor Magnitude Response (GMR), Oriented Gabor Phase Congruency Image (OGPCI) as feature extractor and Random Forest as the feature classifier. Monte Carlo Uninformative Variable Elimination Partial Least Squares (MC-UVE-PLS) regression is used to select the important features, which are generated from the Gabor filters. This paper is the extended work of [6].

The paper is organized as follows. Section 2 provides an overview of approaches and studies conducted in face recognition. Section 3 discusses the hybrid face recognition technique, CG-RF. We have conducted experiments on CG-RF on two different face databases and the results are presented and discussed in Section 4. We conclude the paper in Section 5 by summarizing the capabilities of CG-RF as a face recognition technique.

2. Overview of approaches to face recognition

Feature extraction is one of the most important steps in the process of facial recognition (FR). The process can be divided into two main streams - local feature approach [7] and a global feature approach [8]. Gabor filter [9] and Local Binary Patterns (LBP) [10] are two of the most well-known local feature approach.

Gabor features can overcome local distortions such as face orientation, occlusion. Therefore, it is suitable in unconstrained environments. The parameters used in the filter can control orientation, phase and magnitude. Liu and Wechsler [11] proposed a facial recognition approach called Gabor-Fisher Classifier. The authors used the Enhanced Fisher linear discriminant Model [12] with 40 (5×8) Gabor filters to extract an augmented Gabor feature vector of magnitude. Struc and Pavesic [13] adopted the approach and proposed a complete Gabor-Fisher Classifier, which utilizes both of the magnitude and phase data for face recognition. Chai et al. [14] used the Gabor filter concept and developed the Gabor Ordinal approach. This approach is capable to handle face image with different illuminations, occlusions, and expression. The approach obtained different types of ordinal measures, which developed from Gabor images. Although these approaches produced a good performance, they demonstrated slow convergence and long runtime. Due to these reasons, Yang et al. [15] proposed Monogenic Binary Coding (MBC). This approach extracted the face feature into three components, namely amplitude, orientation and phase. The results achieved reduced time and space complexity.

Local Binary Patterns (LPB) uses the value differences between each centre pixel and its neighbouring pixel to create a binary codes table. Concatenating these binary codes into a vector, which used as a facial descriptor, can represent the face image. According to Ahonen et al. [16], LBP is efficient as facial representation. Choi et al. [17, 18] proposed a colour LBP for colour face recognition. The author claimed color LBP (CLBP) processes discriminative information for face recognition. Choi later combined the texture patterns of the images into the CLBP, which led to the Local Color Vector Binary Pattern (LCVBP) approach [19]. Lu et al. [20] modified the LBP approach by encoding the inter-channel colour information of the colour face images. This approach is proven to reduce the redundant information in CLBP and LCVBP. The proposed approach, Ternary-Color LBP (TCLBP) is claimed to achieve higher face recognition performance than CLBP and LCVBP.

By using the parameters from the LBP and the base patterns of the oriented edge magnitude (POEM) [21-23], Nanni et al. [24] present a technique of recognizing faces in unconstrained environments. The authors were applying different preprocessing techniques and parameters from LBP to the accumulated magnitude images. They named the technique as Ensemble of Patterns of Oriented Edge Magnitudes Descriptors (EoPOEM). Later, the same team led by Lumini et al. [25] further improvised this technique by fusing the "learned" and "handicraft" features. Vu and Caplier [22] enhanced the POEM by optimizing the POEM parameters. By using whitening transformation on the Principle Component Analysis (PCA) [26] a more discriminative descriptor is achieved.

In LBP, when the size of the local neighbourhood is increased, the number of binary code increases exponentially. This leads to high memory usage and computation time. Hussain et al. [27] used the concept of Local Quantized Patterns (LQP) to tackle these issues. The authors fused the Gabor filters into the LQP. LQP features are obtained from the raw intensity image. The result achieved good performance of face recognition. Lei et al. [28]explained that, rather than using a handcrafted approach as with LBP, a data-driven approach is used. In his approach, the distance between the face images of the same character in different conditions is minimized and the distance between the face images of a different character is maximized. By doing so, the discriminative ability of face representation is strengthened.

Classification is another important stage in the face recognition process. Random Forest (RF) is one of the popular classification techniques. RF is an ensemble of decision trees and can be used for both classification and regression activities [29]. This technique is able to maintain the accuracy in the absence of complete data and capable to handle large dataset. According to Bosch et al. [30], the computation time of RF in both testing and training stages are shorter than the Support Vector Machine. Pal and Mather [31] further proved that RF computation time is faster than Neural Network.

3. Model Development

Gabor Filter is known as Gabor wavelets has demonstrated to be an effective tool for feature extraction. It allows an efficient space-frequency analysis to code facial feature vector. Researchers often utilize the magnitude of the Gabor filter to form the facial feature vector. This is due to the difficulty to use Gabor phase to extract solid and distinctive features. In the proposed CG-RF technique, Gabor Magnitude Response (GMR) is used to provide the magnitude information.

Kovesi [32] introduced to overcome the above problem encountered in Gabor phase, in which, the technique has been adapted. This technique is called the Phase Congruency Model, which can be applied together with the Gabor Filter to uncover the salient features of the face. It has the advantage of insensitivity towards image illumination variations and contrast.

Random Forest algorithm, which originated from the Learning- based approach is used to classify the images. Built on the ensemble-learning framework, which combines the results of many classifiers to give a final output, Random Forest is used to growing many classification trees.

The proposed approach is divided into two processes; training and testing process. In each process, the CG-RF comprised of four stages that are pre-processing stage, feature extraction stage, feature selection, and classification stage. The stages are depicted on a flow-chart as shown in Fig. 1. With reference to Fig. 1, an individual face image is pre-processed (Section 3.1) before the critical features such as mouth, nose and eyes of the individual are extracted. Two face recognition techniques are used to extract the features-Gabor Magnitude Response (GMR) (Section 3.2.1) and Oriented Gabor Phase Congruency Image (OGPCI) (Section 3.2.2). This is followed by the feature selection stage (Section 3.3). The selected features are classified using Random Forest (Section 3.4) to produce the final image. The matching scores from GMR and OGPCI are used to determine the final matching score for Complete Gabor Filter with Random Forest (CG-RF) (Section 3.5 and Section 4.2).

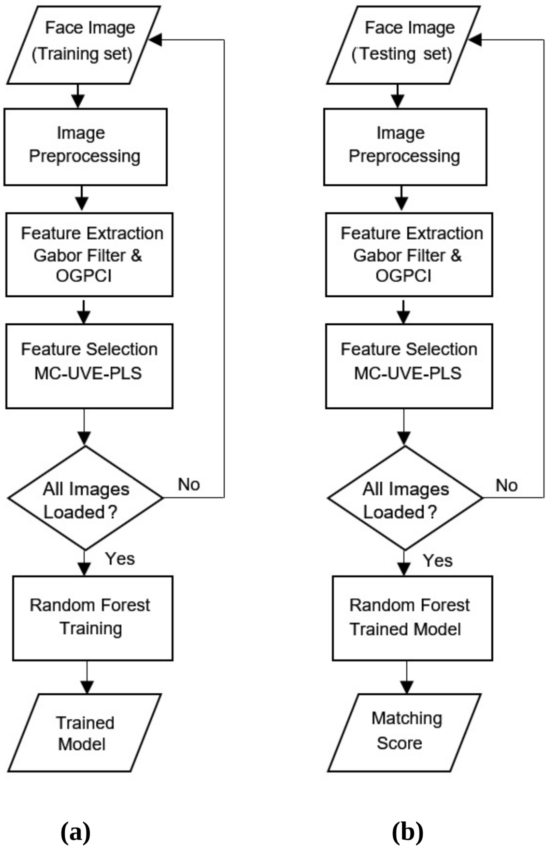

Fig. 1. Flowchart of CG-RF (a) Training, (b) Testing.

Pre-processing

Pre-processing is a process of optimizing image quality. The Red Green Blue (RGB) colour image is converted to grayscale image followed by dimension reduction. For example, images from the Georgia Tech database are cropped to 64×64 pixels. The grayscale image will then undergo illumination normalization to be illumination invariant. This will reduce the redundant features, which are not required in the feature extraction stage.

Features extraction

Gabor Magnitude Response (GMR) and Oriented Gabor Phase Congruency Image (OGPCI) [13, 33] are used in the feature extraction process.

3.2.1. Gabor magnitude response (GMR)

Gabor transform is one of the most used for feature extraction. In this study the Gabor wavelet, $\psi_{u,v}$ is given by Eq. (1) [9].

$$\psi_{u,v}(x,y) = \frac{{f_u}^2}{\pi\kappa\eta} e^{-\left(\left(\frac{{f_u}^2}{\kappa^2}\right)x'^2 + \left(\frac{{f_u}^2}{\eta^2}\right)y'^2\right)} e^{j2\pi f_u x'} \tag{1}$$

where

$$x' = x\cos\theta_v + y\sin\theta_v \tag{2}$$

$$y' = -x\sin\theta_v + y\cos\theta_v \tag{3}$$

$$f_u = \text{Gaussian center frequency} = \frac{f_{max}}{2^{\left(\frac{u}{2}\right)}} \tag{4}$$

$$\theta_v = \text{Gaussian orientation} = \frac{v\pi}{8} \tag{5}$$

The κ and η are the ratio between centre frequency and size of Gaussian envelop and f_{max} is the maximum frequency of the filter. Here, the parameters κ and η are defined as $\sqrt{2}$ and f_{max}defined as 0.2. The filter bank with five scales and eight orientations, $v \in \{0,1,2,3,4,5,6,7\}$ and $u \in \{0,1,2,3,4\}$ is constructed. These will be used in feature extraction operation. The input face image is grayscale, which having the pixels size of$p \times q$. The filtering operation is defined as follow:

$$F_{u,v}(x,y) = B(x,y) * \psi_{u,v}(x,y) \tag{6}$$

where $B(x,y)$ is a grayscale face image, $\psi_{u,v}(x,y)$ with centre frequency, f_u, and orientation,θ_v.

$F_{u,v}(x,y)$ is made up of real and imaginary parts:

$$R_{u,v}(x,y) = Re\left[F_{u,v}(x,y)\right] \tag{7}$$

$$I_{u,v}(x,y) = Im\left[F_{u,v}(x,y)\right] \tag{8}$$

Refer to Eqs. (7) and (8), the magnitude information of the filtering output can be determined as follows:

$$J_{u,v}(x,y) = \sqrt{{R_{u,v}}^2(x,y) + {I_{u,v}}^2(x,y)} \tag{9}$$

The image features generated are large, as 40 Gabor Filters are applied on a single image, resulting in increases of dimension size by 40 times. After the filtering process, an image of 64×64 pixels will become 163840 (64×64×40) dimensional size, which consumes significant computational power. To resolve this, down sampling using rectangular grid method is implemented. In this technique, only the pixels within the rectangular grid are retained, while the remaining pixels are removed, similar to the resizing concept. In the Gabor Filter technique, the down-sampling factor is set to 128.

3.2.2. Oriented gabor phase image (OGPCI)

For the second part of the feature, this study used the Gabor Phase Congruency Image (OGPCI), which is given as follows [13]:

$$OGPCI_v(x,y) = \frac{\sum_{u=0}^{p-1} A_{u,v}(x,y)\Delta\Phi_{u,v}(x,y)}{\sum_{u=0}^{p-1}(A_{u,v}(x,y)+\epsilon)} \tag{10}$$

where $A_{u,v}(x,y)$ is the magnitude response of Gabor filter, ϵ is set to 0.0001 to prevent equation divided by zero. $\Delta\Phi_{u,v}(x,y)$ is defined as follow:

$$\Delta\Phi_{u,v}(x,y) = cos(\,\phi_{u,v}(x,y) - \overline{\phi_v}(x,y)) - \left|sin(\,\phi_{u,v}(x,y) - \overline{\phi_v}(x,y))\right| \tag{11}$$

where $\overline{\phi_v}(x,y)$ is the mean phase angle at v -th orientation and $\phi_{u,v}(x,y)$ is the phase angle of Gabor Filter defined as follow:

$$\phi_{u,v}(x,y) = tan^{-1}\left(\frac{I_{u,v}(x,y)}{R_{u,v}(x,y)}\right) \tag{12}$$

The phase congruency is calculated by summing of p filter scale for each orientation, v. For example, by selecting an input image size of 64×64 pixels, using a filter bank of 8 orientations × 5 scales, the total features generated are 32768 (64×64 ×8) dimensional size. This number is considered too large for computation, so a down-sampling process is required to reduce the dimensional size. In Gabor magnitude filter, a down-sampled image with a factor of 128 could generate 1000 features. The dimensional size for OGPCI is 5 times lesser than Gabor magnitude. Thus, the feature size generated for OGPCI is only 200.

Feature selection

In the proposed system, before sending the features to the classifier, the system will undergo feature selection using Monte Carlo Uninformative Variable Elimination Partial Least Square (MC-UVE-PLS) regression to remove the less important features. Feature selection is needed to select only important or dominant features. After performing feature selection, only informative features will remain for classifier training. The combination of Monte Carlo (MC) method and Uninformative Variable Elimination (UVE) method is used to select features generated by Gabor filters. Each feature's set reliability is evaluated based on its stability. Usually, the UVE employs the leave-one-out procedure, however, the Monte Carlo method is used instead of the leave-one-out procedure [34, 35].

The samples are divided randomly into a training set, evaluation set and prediction set. The Monte Carlo randomly choose a number of subsamples from the training set (at 75%) to build the Partial Least Square (PLS) model and this process repeats 1000 times. The PLS regression coefficients and the stability of each feature set are computed.

$$\gamma = \alpha X + \kappa \tag{13}$$

where γ is the prediction, X is the information of the feature sets, α is the regression coefficients, and κ is the offset.

The regression coefficients, α_i define the contribution of that particular feature to the prediction model. The reliability of a feature is evaluated using its stability level, $\mathcal{s}_i$:

$$\mathcal{s}_i = \frac{mean(\alpha_i)}{standard\ deviation(\alpha_i)} \tag{14}$$

where i = 1,2, …, number of features.

The higher level of stability means that a particular feature is more important. The features are rank based on the stability level from highest to lowest.

Random forest

The features extracted from both GMR and OGPCI techniques undergo a filtering process to remove redundant features and to select critical features. Random Forest is used for evaluating these critical features. Each node in Random Forest is split using randomly selected features instead of best features. Ho [36] proposed the selection of a random subset of features resolved the overfitting data problem. Figure 2 depicts a Random Forest framework. Random Forest is constructed by *T* classification trees, where *T* is the total number of tree. The process of random forest training is explained as follows:

- There will be *N* number of training sample and *M* number of image features.
- At bootstrap process, *t* sets of bootstrap samples of the same size as *N* subjects will be generated where *t* is the number of decision trees. The bootstrap samples are chosen randomly from *N* subjects with replacement.
- Typically, only around two-thirds of distinct samples are chosen from the original samples to form the bootstrap samples. The one-third unchosen samples are known as Out-Of-Bag (OOB) samples.
- *m* features will be selected from the *M* features in each decision tree split to achieve correlation. For classification, $m = \sqrt{M}$ to prevent overfitting of trees.
- As a result, *t* number of decision trees will be grown from the training process without pruning. A trained classifier model consisting of *t* number of the grown decision trees is produced.
- At the testing stage, images will be tested one after another, unlike the training stage where all features from feature extraction are trained in one go. The features will split based on the split criterions at each node. When the features reach the end of the tree, a matching score will be created based on the matching probability of the class.
- This process is repeated for every tree grown and *t* number of matching scores will be produced.
- The matching class is voted based on the average scores of all decision trees.

The quality of the random forests is evaluated by measuring the generalization error. According to Breiman [37], the generalization error (PE) is represented as follow:

$$PE \leq \frac{\bar{\rho}(1-s^2)}{s^2} \tag{15}$$

where $\bar{\rho}$ represents the correlation and s represents the strength. The performance of the random forest depends on the ratio of $\bar{\rho}$ to s^2. A good random forest classifier should have high strength and low correlation. However, increasing the number of trees will at the same time increase the correlation. Therefore, it is important to decide an optimum value for the number of trees to achieve high accuracy and low error rate. Breiman [37] suggested the optimum number of 500 trees and the number larger than 500 should not contribute to any increase in performance. The Out-Of-Bag (OOB) will be used to determine the optimum number of trees.

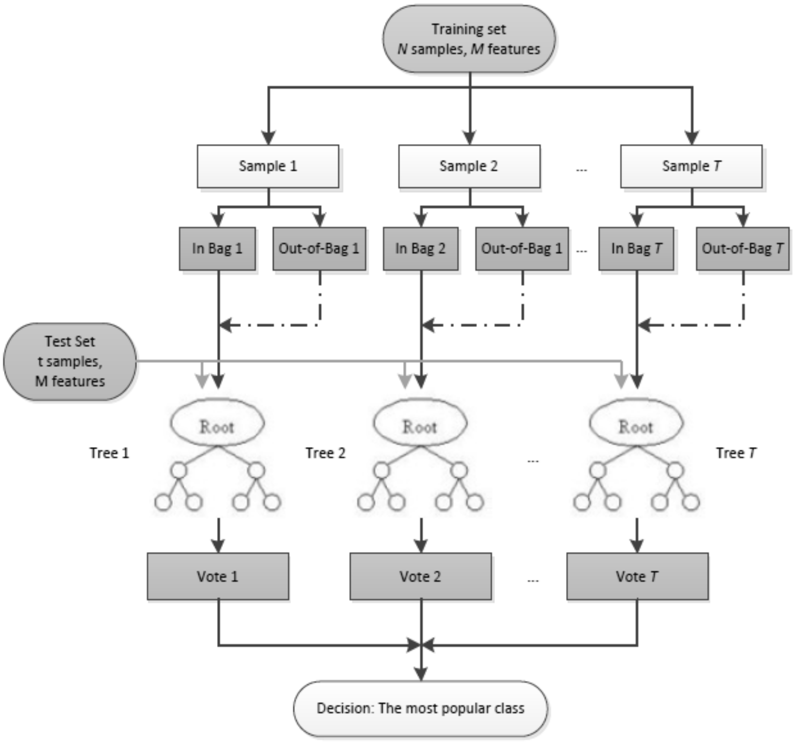

Fig. 2. Random forest framework.

Complete gabor with random forest (CG-RF)

The matching score for Gabor magnitude and Gabor phase is obtained after the forests are grown. By adding the matching score of Gabor filter, δ_{GF}, and OGPCI, δ_{OGPCI}, a final matching score, δ_{CG} is calculated as follows:

$$\delta_{CG} = (1-\gamma)\delta_{GF} + \gamma\delta_{OGPCI} \tag{16}$$

where γ sets the proportion between Gabor magnitude and phase components and $\gamma \in [0,1]$. It is important to ensure the highest recognition rate is obtained by selecting the right value of γ (discussed in Section 4.2). The Random Forest will predict the class of test image based on the input features set.

Program framework

The proposed CG-RF comprises of two stages, training stage and testing stage. The training stage involves training the framework to classify the face sample from the training database. The critical features of the face region are extracted from the database. The extracted features are used to grow a Random Forest. At the end of the training stage, the forest is built and the performance of the trained forest is evaluated.

In the testing stage, the test sample is classified by applying the trained framework. The test sample (face region) is read by using the same feature extraction method as the trained forest. The extracted features are used to obtain the final output class through the trained Random Forest. The class of the test image is the maximum class output vote of the Random Forest.

4. Experimental Results and Discussion

The proposed hybrid technique is evaluated by piloting face recognition experiments on two popular face databases namely, FERET [38], and Georgia Tech Face [39]. In this section, we performed experiments by assessing the recognition rates of GMR and OGPCI on these two databases. Monte Carlo Uninformative Variable Elimination Partial Least Squares (MC-UVE-PLS) regression is used to select the important features, which are generated from the Gabor filters. The following explains the details of the experiments conducted and the results.

Experiment setup

The experiments are carried out on Intel I5-4430S 2.7 GHz processor with 8 GB memory PC under the Windows 10 operating system. The algorithms are implemented using MATLAB, R2016.

We also carried out a comparison of our experimental results against a few proposed algorithms. These are discussed in Section 4.3.

Complete Gabor filter- GMR and OGPCI

As discussed in Section 3.5, a final recognition rate is achieved by adding the matching score of Gabor magnitude and OGPCI using the right chosen value for the fusion parameter, γ.

In order to determine the best value of γ, several facial recognition experiments on the Georgia Tech and FERET dataset were carried out. 5-fold cross validation (Georgia Tech database) is performed with different values of γ. The average recognition rate is recorded, and it is found that $\gamma = 0.3$ gives the best recognition rate for both databases. The average recognition rate for Georgia Tech database is shown in Table 1.

Table 1. Complete Gabor filter on Georgia tech face using 500 trees.

Fusion parameter, γ	Average recognition rate (%)	
	Full features	Best features (MC-UVE-PLS)
0.0	92.3	91.9
0.1	93.1	92.3
0.2	93.5	93.9
0.3	**95.1**	**94.7**
0.4	94.7	93.9
0.5	91.9	93.9
0.6	90.3	92.3
0.7	89.1	89.5
0.8	86.7	87.9
0.9	80.7	81.5
1.0	77.1	75.9

Data sets and evaluations

The following experiments were performed:

- Sample images from the databases were downsized for Gabor Filter and OGPCI.
- The system is tested on a full feature selection.
- The system undergoes feature selection using MC-UVE-PLS regression to remove the least important features.
- The output features generated from these images were used to grow trees for the random forest. The number of trees to be grown is in the range of 100 to 500 with an interval of 100.
- The recognition rate, which represents the matching score of the output features against the number of trees grown, is measured.
- The computational time for both the full feature and best feature (MC-UVE-PLS) are recorded. This is based on the non-optimized MATLAB code.

4.3.1. Georgia tech database evaluation and discussion

Georgia Tech face database consists of 50 subjects with 15 face images in a cluttered background. The face images are in the average size of 150×50 pixels. In this database, 12 images are selected as the training set. The remaining three images are selected as a test set. 5-fold cross validation is employed in this experiment; therefore, the experiment is repeated five times with different train and test dataset. This is to ensure the accuracy of the recognition rate is achieved. The computational time is recorded based on the average time of the 5-fold cross-validation. The recorded computational time is including the pre-processing, feature selection and random forest matching time.

The results tabulated in Table 2 indicated that when 500 trees were grown on 1000 features, the recognition rates for GMR was 92.3% and 77.1% for OGPCI. Thereafter, the variances in recognition rate were minimal beyond 500 trees for both extraction methods. The number of features in each of the methods also affects the recognition rate. GMR, which consisted of 1000 features, produced a better recognition rate than OCPCI, which has only 200 features. The average training time if 500 trees are used in Gabor magnitude (1000 features) and OCPCI (200 features) is 4514.7 seconds. The results also show that the GMR has a better recognition rate than OGPCI because GMR contains more features that OGPCI.

In the second experiment, Random Forest was rebuilt using the best features. MC-UVE-PLS method is used to rank the features and parts of the least important features are removed. The results of the new classification performance for Gabor filter and OGPCI features are shown in column 5 and column 6 of Table 2. The average training time if 500 trees are used is 1735.156 seconds. The training time is reduced by 61.57% as compared to the first experiment where full features are used. The recorded time is the average time obtained from the 5-fold cross-validation.

The results indicated Random forest computed using the best features have slightly lower performance compared to full features in Georgia Tech database. In Gabor filter, the recognition rate using the best features of MC-UVE-PLS is 91.9%. The recognition rate using full features is 92.3% (500 trees with 1000 features). As with OGPCI, the highest recognition rate is 75.9% computed if the best feature is used, slightly lower than 77.1% (500 trees with 200 features). These showed that full features are computational inefficient compared to the best feature.

Table 2. Recognition rate and computation time according to number of trees used to build the random forest for full features and best features in GMR and OGPCI.

Number of trees	Recognition rate (%)		Computation time (seconds)	Recognition rate (%)		Computation time (seconds)
	GMR-full features[1]	OGPCI-full features[2]		GMR -best features[3]	OGPCI -best features[4]	
100	86.3	69.1	4023.5	89.5	66.5	1145.5
200	92.3	72.7	4053.0	90.2	71.5	1175.8
300	90.3	75.9	4110.4	90.5	73.9	1319.0
400	91.9	75.9	4283.3	90.3	75.5	1491.1
500	**92.3**	**77.1**	4514.7	**91.9**	**75.9**	1735.2

[1] 1000 features
[2] 200 features
[3] 250 features (MC-UVE-PLS)
[4] 50 features (MC-UVE-PLS)

In the third experiment, we investigate the impact of fusion parameters on the recognition rate. The best matching score obtained from the Gabor filter and the OGPCI are added to determine the recognition rate. The results are tabulated in Table 1.

The results showed that the fusion parameter, $\gamma = 0.3$ gave the highest recognition rate (95.1%, 94.7%) for full features and best features respectively. CG-RF exploits the information of Gabor magnitude and phase information by combining the Gabor Filter and OGPCI matching score, resulting in increased recognition rate. This suggested the hybrid of Gabor and OGPCI techniques produced better performance than individual method.

In the last experiment for GT database, the proposed technique is compared with the existing algorithms. The results showed that the proposed CG-RF for both full features and best features outperformed the TCLBP, LCVBP and CLBP. The results are tabulated in Table 3. The recorded recognition rate for CG-RF (full features) is 95.10% and 94.70% for best features.

Table 3. Recognition of the proposed approach and comparison with existing algorithms on GT database.

Method	Georgia Tech face database recognition rate (%)
Color LBP [18]	90.9
CLBP [17]	93.4
LCVBP [19]	92.0
TCLBP [20]	94.6
CG-RF (full)*	**95.1**
CG-RF (best)**	**94.7**

*CG-RF (full) is Complete Gabor Filter with Random Forest using full features
**CG-RF (best) is Complete Gabor Filter with Random Forest using the best features of MC-UVE-PLS

2.3.2. FERET database evaluation and discussion

The FERET database is divided into 5 categories. Category 1 is named as *Fa*, consists of 1,196 frontal face images from 1,196 individuals. Category 2 is named as *Fb*, consists of 1,195 face images with a different expression from 1,195 individuals. Category 3 is named as *Fc*, consists of 194 face images with different lightings conditions from 194 individuals.

Category 4 is named as Dup1, consists of 722 face images from 243 individuals taken with an elapsed time within a year with respect to the images in *Fa*. Category 5 is named as Dup2, a subset consists of 234 images from 75 individuals, which the elapsed time of a year later with respect to the images in *Fa*.

In the proposed system, the two eyes of the face images are aligned at the same position and cropped to 128×128 pixels. The 1,196 face images are used as a target image and *Fb*, *Fc*, Dup1, and Dup2 are used as a test image to determine the recognition rate of the proposed technique. The same approaches and parameters are adopted as in Georgia Tech Face database.

For the purpose of presentation, only critical parameters and values are shown in Table 4. Comparison of the state-of-the-art algorithm is included in the table. These results are obtained from the respective cited papers. From the results, the proposed methods CG-RF (full features) and CG-RF (best features) is close to the reported results in E_P [24], GOM [14] and SVM and SML [25].

The recorded average recognition rate for CG-RF (full features) is 96.95% and 96.70% for best features. Table 4 indicate GOM produced slightly higher recognition rate compared to the proposed technique. From the cost-benefit analysis, the proposed technique utilized fewer parameters and produce comparable recognition rate than GOM [14].

As the training images from the category *Fa* in FERET database is larger compared to the Georgia Tech database, the computation time for training is 17916.98 seconds for full features and for best features is 8875.60 seconds. The result indicated the CG-RF (best features) takes less training time compared to full features.

Table 4. Recognition of the proposed approach and comparison with existing algorithms on FERET database.

Methods	Recognition rate (%)					Computation time (seconds)
	Fb	Fc	Dup1	Dup2	Average	
POEM+WPCA [22]	99.6	99.5	88.8	85.0	93.23	-
LQP+WPCA [27]	99.8	94.3	85.5	78.6	89.55	-
MBC-F [15]	99.7	99.5	93.6	91.5	96.07	-
E_P [24]	98.7	100	94.6	93.6	96.70	-
GOM [14]	99.9	100	95.7	93.1	97.17	-
SVM and SML [25]	99.2	100	94.6	94	97	-
Color LBP [18]	-	-	-	-	84.7	
CLBP [17]	-	-	-	-	86.19	-
LCVBP [19]	-	-	-	-	76.67	-
TCLBP [20]	-	-	-	-	86.73	-
CG-RF (full features)*	**98.9**	**100**	**95.5**	**93.7**	**96.95**	**17916.98**
CG-RF (best features)**	**98.7**	**100**	**95.0**	**93.1**	**96.70**	**8875.6**

5. Conclusion

The study proposed a face recognition system called Complete Gabor Filter with Random Forest (CG-RF). The performance of the proposed technique is evaluated on FERET and Georgia Tech (GT) database. The features of the Gabor Magnitude Response (GMR) and Gabor Phase Congruency Image (OGPCI) were discussed. CG-RF exploits the features from magnitude and phase. Monte Carlo Uninformative Variable Elimination Partial Least Square (MC-UVE-PLS) regression method is used to rank the features and part of the least important features are removed. The Random Forest is used as classifier models. It is noted that the training time correlates with the sample size increases as the number of splits is increased in each tree. In our findings, the CG-RF with a selection of full features generates a higher recognition rate than the best features with a variance of 0.4% (GT database) and 0.6% (FERET database). Full features will have greater localization and narrower frequency scope. Therefore, the higher the number of features is selected, the more globally representative in describing a face image. However, in terms of computation time for training and testing stage, best features selection consumes less time than full features. The results from the experiments shown the recognition rate is high and at par with state-of-the-art approaches. Future work may investigate how to merge the proposed technique with a deep learning approach.

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