Gabor Wavelet based Face Recognition System using EWCVT and Bagging AdaBoost Algorithm

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ABSTRACT
Facial recognition system is a computer application for identifying or verifying a person from a digital image automatically. One among this method involves comparison of the facial features from the test image database with trained facial database. Histogram Gabor Phase Pattern (HGPP) is an extended histogram feature which represents original image by combining Local Gabor Phase Patterns (LGPP) and Global Gabor Phase Patterns (GGPP). This method lacks in efficiency and computational complexity because it involves huge volume of data. To reduce the data, edge weighted centroidal voronoi tessellation (EWCVT) is used and to increase the efficiency a classifier called Bagging AdaBoost is used. Bagging-AdaBoost classifier bridges the semantic gap between the low-level feature vectors of the image and the high-level concepts. The proposed system incorporates the EWCVT and bagging technique to improve the accuracy, stability and robustness of the system. The results obtained prove that the proposed system has improved accuracy in recognition, more stability, less computational complexity and processing time.

General Terms
Face Recognition, Pattern Recognition, Security, Algorithms.

Key words
Face recognition, Gabor Wavelets, Local Gabor Phase pattern, Global Gabor Phase Pattern, Adaptive Binning, Spatial Histograms and Tessellations.

1. INTRODUCTION
Face recognition is a pattern recognition task performed specifically on faces [1]. It can be described as classifying a face either "known" or "unknown", after comparing it with the trained set of data base. Computational models of face recognition must address several difficult problems. This difficulty arises due to the fact that faces are to be represented in such a way so that the important contents in the face information can be retrieved so as to distinguish a particular face from all other faces. Since the normal faces have the same features with slight variations, it is essential to develop a highly sensitive and efficient algorithm for face recognition system.

Face Recognition is a process of identifying a person by scanning his or her face and matching it against a library of known faces. The faces are represented as set of features each of which is a vector describing the face. The input image is compared with the set of faces in the database and a match is found based on the similarity of features. The main aim of this system is to develop an efficient face recognition system by improving the efficiency of the existing face recognition systems such as HGPP [2], Adaptive Binning [3] and AdaBoost [4] Techniques. The rest of the paper is divided into sections with the Two explaining the Voronoi Tessellations techniques and in particular the edge weighted centroidal voronoi tessellation, the Third the classifier techniques and bagging AdaBoost concept, the Fourth the system architecture, and the Fifth revealing the results and analysis. Finally, the paper is concluded with future work.

2. VORONOI TESSELLATIONS
Voronoi diagram is a special kind of decomposition of a metric space determined by distances to a specified discrete set of objects in the space, e.g., by a discrete set of points [5]. It is named after Georgy Voronoi, also called a Voronoi tessellation, Voronoi decomposition or a Dirichlet tessellation. In the partitioning of a plane with 'n' points into convex polygons, each polygon contains exactly one generating point and every point in a given polygon is closer to its generating point than to any other points. The cells are called Dirichlet regions, Thiessen polytopes or Voronoi polygons. A Voronoi Tessellation is a partitioning of a region, defined by a set of points called the generators. Each pixel in the image is assigned to the generator to which it is closest. As a consequence of this scheme, the boundary between two adjacent bins is always the perpendicular bisector of the connecting line between the two generators.

In the simplest case, consider a given set of points(S) in the plane, which are the Voronoi sites. Each site has a Voronoi cell, also called a Dirichlet cell, V(s) consisting of all points closer to '*s*' than to any other site. The segments of the Voronoi diagram are all the points in the plane that are equidistant to the two nearest sites. The Voronoi nodes are the points equidistant to three or more sites.

Centroidal Voronoi Tessellations (CVTs) are special Voronoi tessellations whose generators are also the centroid of the associated Voronoi regions, with respect to a given density function. CVT based methodologies have been applied successfully to diverse disciplines which include image processing and analysis, vector quantization and data analysis, meshless computing and computer graphics and vision. Lots of applications of clustering require the cluster boundaries to be smooth, while keeping the total length of the boundaries to be as small as possible. Using basic CVT technique, zigzag cluster boundaries are obtained to classify the data sets. In image segmentation, those zigzag boundaries form mainly due to noises or natural properties of the images. Smoothing the boundaries can help in reducing or even eliminating the noises or unnecessary details.

Edge Weighted Centroidal Voronoi Tessellation (EWCVT) is an algorithm intended for minimize the total energy i.e. sum of classic CVT energy and the weighted length of cluster boundaries [6]. In particular, this new model can appropriately combine the image intensity information together with the length of cluster boundaries, and also can handle very sophisticated data sets.

3. CLASSIFIERS

An AdaBoost classifier is a set of weak classifiers. The classification is done by increasing the weights of the incorrectly classified sets [7]. A Final strong classifier is gained by the sum of weights of weak classifiers. The test image is checked with these function weights and if the resultant value is true for more than 50%, the image is classified as corresponding to the person's face and declared recognized. AdaBoost is a practical version of the classifier and a boosting approach. Boosting is similar in overall structure that keeps track of the performance of the learning algorithm, thus forcing it to concentrate on its efforts on instances that have not been correctly learned. Instead of choosing the 't' training instances by randomly using a uniform distribution, one chooses the training instances in such a manner so as to favour the instances that have not been accurately learned. After several cycles, the prediction is performed by taking a weighted vote of the predictions of each classifier, with the weights being proportional to each classifier's accuracy on its training set.

AdaBoost is a meta-algorithm. It can be used in conjunction with many other learning algorithms to improve their performance. AdaBoost is adaptive in the sense that subsequent classifiers built are tweaked in favour of those instances misclassified by previous classifiers. The advantages of classifier technique are i) it is fast, simple, and easy to program, ii) it has no parameters to tune (except for the number of rounds) and iii) it requires no prior knowledge about the weak learner. So, it can be flexibly combined with any method for finding weak hypotheses. But, some of the demerits of this classifier technique are to be overcome. They are as follows i) performance of boosting on a particular problem is dependent on the data and the weak learner, ii) boosting can perform only poorly when insufficient data are given and iii) boosting is susceptible to noise. To overcome these problems, bagging concept is used. Bootstrap aggregating (bagging) and boosting techniques are useful for improving the performance [8]. Boosting can also be useful in connection with many other models, e.g. for additive models with high-dimensional predictors.

Bagging is a method of the first category. If there is a training set of size '*t*', then it is possible to draw '*t*' random instances from it with replacement (i.e. using a uniform distribution). And, these '*t*' instances can be learned, and this process can be repeated several times. Since the draw is with replacement, usually the instances drawn will contain some duplicates and some omissions as compared with the original training set. Each cycle through this process results in one classifier. After the construction of several classifiers, all the classifiers perform the final prediction. Bootstrap aggregating (bagging) is a machine learning ensemble meta-algorithm to improve machine learning of classification and regression models in terms of stability and classification accuracy. It also reduces variance and helps in avoiding over fitting. Although it is usually applied to decision tree models, it can be used with any type of model. Bagging is a special case of the model averaging approach.

4. EXPERIMENTS

4.1 System using EWCVT

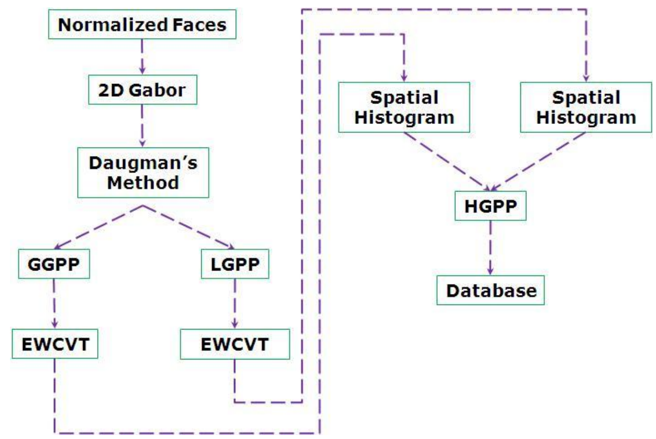

Fig 1: System using EWCVT method

The Figure 1 shows the system which uses EWCVT. The edge related energy calculated is the sum of the number of edge points within a predefined neighbourhood of every pixel. In this method, an edge-weighted centroidal voronoi tessellation (EWCVT) model is developed for image segmentation. EWCVT model can overcome some of the deficiencies contained in the basic CVT model. In particular, the new model can appropriately combine the image intensity information together with the length of cluster boundaries, and also can handle very sophisticated situations.

The EWCVT-based algorithms are essentially classical clustering algorithms as they are often computationally less expensive than the popular and powerful partial differential equation based segmentation methods. The efficiency in computational cost, the ability to handle any number of clusters, the robustness with respect to noises, and the flexibility to control the segmentation accuracy made the researchers to work using EWCVT. The advantages of EWCVT are i) the mathematical model of EWCVT is easy to understand and implement just like the basic CVT model. Further, its performance in segmenting images over the CVT model is much better, i.e., the segmentation results are more accurate and ii) the EWCVT model and its segmentation algorithms can be directly and easily applied to handle multi-cluster situations i.e., dividing an image into any specified number of clusters.

4.1.1. Algorithm of EWCVT

1. Edge Related Energy is calculated.
2. Edge Weighted Clustering Energy is calculated.
3. Rewrite the Edge Weighted Clustering Energy based on the distance from (x, y) to Cluster.
4. Edge Weighted Distance is calculated.
5. Based on the distance and the image, Edge Weighted Voronoi region is found.
6. The result obtained is given to the EWCVT algorithm to obtain the output.

Given an Integer $L=2$, where L is the number of Clusters and choose arbitrarily a partition $\{D^{\sim}_l\}_{l=1 \text{ to } L}$ of the image $U = \{u(I, j)\}(i, j)\ \varepsilon\ D$

1. For each cluster D_l, determine its cluster centroid
2. Take w as the generators, determine the edge –weighted Voronoi clustering D'
3. If the edge weighted Voronoi clustering D' and D are the same, return (w and D) and exit the loop else set $D= D'$ and go to step 1

4.2 System using EWCVT and Bagging Adaboost

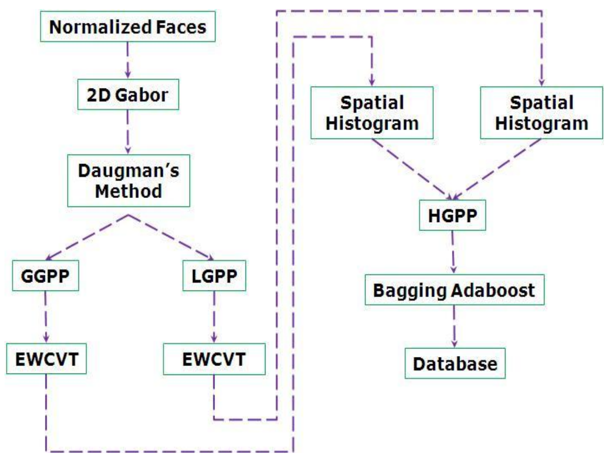

Fig 2: System using EWCVT and Bagging AdaBoost method

The Figure 2 shows the proposed system which applies a classifier technique called Bagging AdaBoost ensemble over EWCVT. Bagging-adaboosting ensemble (BAE) approach is to bridge the semantic gap between the low-level feature vectors of the image and the high-level concepts. This classifier uses both the bagging technique and the AdaBoost technique to improve the accuracy, stability, and robustness of the final results. BAE consists of two processes. They are i) the training process which constructs the classifier ensemble and ii) the testing process which predicts the concepts in the basic concept repository.

Bagging and boosting are among the most popular re sampling ensemble methods that generate and combine a diversity of classifiers using the same learning algorithm for the base-classifiers. Boosting algorithm is considered stronger than bagging on noise free data. However, there are strong empirical indications that bagging is much more robust than boosting in noisy settings.

4.2.1. Bagging AdaBoost Ensemble Algorithm

1. BAE first generates a set of new training datasets $\{D_1, D_2, ..\ D_B\}$ from the original training dataset D.

1.1 Assume that the original training set D contains 'n' sample pairs $D = \{(x_1, y_1)\dots (x_n, y_n)\}$ (where x_i is the sample, y_i is the label of the sample x_i), the i'-th sample pair $(1 \leq i' \leq n'$, n is the size of the new training dataset, and $n' \leq n$)

1.2 In the new training dataset $D_b (1 \leq b \leq B)$ is selected as follows:

$(x_i' ; y_i') = (x_r; y_r); (x_i' ; y_i')\ \varepsilon\ D_b; (x_r; y_r)\ \ D\ \varepsilon\ (1)$

where γ is a uniform random index over the set $\{1 \dots\dots n\}$, and $(x_i' ; y_i')$ and $(x_r; y_r)$ are sample pairs which belong to the new training dataset D^b and the original training dataset D respectively.

1.3 BAE repeats the above process 'n' times and selects 'n' sample pairs for the new training dataset D^b (where $n'=\rho n$ and ρ is a sub-sampling rate which is pre-specified by the user).

2. In the second step, BAE trains a set of classifiers $\{C_1;C_2; ..;C_B\}$ based on the AdaBoost algorithm.

2.1 Specifically, each of the classifier is trained using one of the training datasets generated through the previous bagging step.

2.2 Given the new training set Db with 'n' sample pairs $(D^b = \{(x_1; y_1)\dots\dots\dots (x_n' ; y_n')\})$(where $y_i'\ \varepsilon\ \{0; 1\}$ for two-class classification problem), the goal of AdaBoost is to find a classification rule 'R' from the training data, so that when given a new input testing sample 'x', we can assign to it a class label $R(x)$.

5. RESULTS AND ANALYSIS

In recent years, the Gabor transformation has been widely used as an effective element in the image processing and pattern recognition tasks. The Gabor wavelet is a sinusoidal plane wave with a particular frequency and orientation, modulated by a Gaussian envelope [9, 10]. It can characterize the spatial frequency structure in the image while preserving information of spatial relations, and hence suitable for extracting the orientation dependent frequency contents of patterns. As a powerful descriptor, Gabor wavelet is also used in many applications such as data compression, Optical Character Recognition, texture analysis, finger print recognition, and so on.

In this system, a normalized faces are given as input to 2D Gabor wavelet and the output is given as input to Daugman's method, where Daugman's method does the job of demodulation of each pixel, in which the resultant image is encoded into two bits [11]. After quantifying the Gabor features using Daugman's method, global Gabor phase patterns are generated to form a byte to represent 256 different orientation modes, in GGPP totally 10 (5 real and 5 imaginary) images are obtained. To encode the local variations in a pixel, local Gabor phase pattern is applied to all Gabor features using local XOR pattern [12, 13]. For five frequency and eight orientations, the phase patterns obtained will be 90 "images" (five real GGPP, five imaginary GGPP, 40 real LGPPs and 40 imaginary LGPPs), with the same size as the original image. The generated patterns are given as input to edge weighted centroidal voronoi tessellation method, where the system tends to find the edge points over the pixels neighbourhood and increases the performance of face recognition.

In using EWCVT method, the system gets segmented portions of image by applying spatial histograms over portions of local patches and extracts class specific features for better object recognition. Local binary pattern (LBP) is used to pre-process portioned images. Local binary pattern is a relatively new and simple texture model with powerful feature in texture classification. Basic LBP operator uses neighbourhood intensities to calculate the region central pixel value. In any sample image, a histogram-based pattern representation is computed by applying variance normalization on gray image to compensate the effect of different lighting conditions. Basic local binary pattern operator transforms the image into LBP image, and finally computes histogram of LBP image as representation. The resultant output is Histogram Global Phase Patterns [HGPP] [8]. For improved accuracy in face recognition, less computational complexity, and less processing time and stability bagging AdaBoost classifier technique is used.

5.1 Datasets

5.1.1. Indian Face Database

This database contains human face images captured in February, 2002 on the campus of Indian Institute of Technology Kanpur. This database contains images of male and female with different poses of individuals. As an example, images corresponding to one individual are shown below.

Fig 3: Indian Face Database

For our experiment, a separate probe sets such as frontal image (fb), illuminated image (fc), aging and subsets of aging called DupI and DupII are created. The size of each image is 256x256 pixels, with 256 grey levels per pixel.

The main idea to go for EWCVT algorithm is to calculate the edge energy so that the edges can be clearly recognized. To reserve the spatial information in the phase patterns obtained after applying the EWCVT algorithm, the GPP and LGP images are spatially divided into the non over-lapping rectangular regions, from which the spatial histograms are extracted. Then, all of these histograms are concatenated into a single extended histogram feature called HGPP. HGPP value of the test image and trained images are compared to obtain the matched images as output. To further increase the efficiency and to reduce the data set, a new classifier ensemble called Bagging AdaBoost technique is adopted. Bagging AdaBoost does the job of training the data set twice and applies AdaBoost to train and reduce the data set. In an AdaBoost, every iteration trains a set of weak classifiers on each dimension of HGPP features. And it is because of this HGGP features are grouped and classified in order to reduce the feature space set. AdaBoost is used to find the CHI difference, which is calculated by subtracting the HGGP features for registered image with the HGPP feature of test image. The difference between the two is used to gain the judgment true or false. The subtraction of HI (HGPP feature for test image) from HP (HGPP feature for registered image) is called CHI difference. This is done for all features of HGPP and if more than half of the values are true then the face is identified as true and found recognized. In Bagging-AdaBoost, the Bagging means training the image twice and AdaBoost is used to find the CHI value between the HGPP value of the test image and the trained dataset. This method trains the image twice in order to increase the recognition rate and efficiency of the system. The Tables 1 and 2 show the results for EWCVT and EWCVT using Bagging AdaBoost respectively. From the Tables we can notice that the accuracy of the system is improved.

Table 1: Result Analysis of EWCVT

Training Time	6.28 minutes	
	Accuracy[%]	**Time Taken**
Frontal [fa]	95	3.20 to 3.50 minutes
Illumination [fc]	99	
Aging	97	
Dup I	98	
DupII	98	

Table 2: Result Analysis for EWCVT and Bagging AdaBoost

Training Time	8.4 minutes	
	Accuracy[%]	**Time Taken**
Frontal [fa]	97	4.30 to 6.15 minutes
Illumination [fc]	99	
Aging	98	
Dup I	98	
DupII	98	

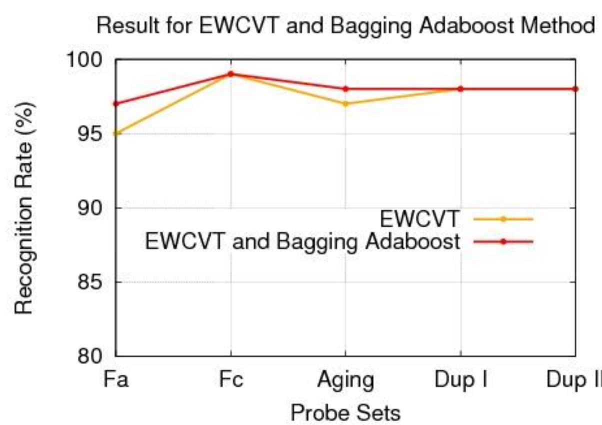

Fig 4: Experimental results for proposed system

Figure 4 shows the recognition rate for EWCVT and Bagging AdaBoost with EWCVT. The probe sets used are frontal images (fa), illuminated (fc), Aging and subsets of Aging called Dup I and Dup II. In the proposed system, when compared with the system which uses EWCVT, there is a linear increase in recognition rate. Especially for aging probe set, EWCVT method produces 97% of efficiency. But when it is combined with bagging AdaBoost, it produces 98% of efficiency.

The result obtained by using EWCVT algorithm is not highly efficient since the accuracy of retrieving the images are to be retrieved from a large database. So, in order to obtain a better recognition system and make the training process efficient a classification method is used. This method, which has a concept of training for two times, yields good results and makes the system more efficient.

6. CONCLUSION

In this paper, a new system for face recognition using two algorithms namely, Edge Weighted Centroidal Voronoi Tessellation and Bagging AdaBoost is proposed and developed. The system is tested with a larger database, and the results tabulated show not only better identification of face and but also better efficiency of the proposed system compared with any other systems. The feature space of this system is reduced drastically when compared with those of the available systems. And this can be noticed in reduced processing time and low complexity with the proposed system. The execution time of this proposed system is also decreased when compared with that of any other available systems. Our future work is to concentrate on more probe sets with rotated poses and backgrounds.

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