

FUSION AFFINE MOMENT INVARIANTS AND WAVELET PACKET FEATURES SELECTION FOR FACE VERIFICATION

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ABSTRACT

Face recognition under changing lighting conditions is a challenging problem in computer vision. The effect of pose and illumination on face images result in a low accuracy rate in the face verification system. In this paper, we proposed a new framework for solving the above problem and increase the recognition rate of the system. This framework performed on a two dimensional (2D) grayscale face dataset based on the combination scheme that consists of the Voronoi diagram (VD), wavelet packet transform (WPT), affine moment invariants (AMIs) and radial basis function (RBF). The preprocessing technique consists of square morphological, Gaussian low-pass filter, median filter, and histogram equalization, which is applied to solving the problem of pose and illumination on facial images. The face crop is obtained with an arbitrarily window template that is designed by using the distance of eyes, nose, and mouth. All face images reduced the information by transformation with the WPT. The AMIs were applied to select the unique features that are used to classify and verify on the RBF neural network. This work was used on the bed face dataset for experimental use, which yielded good recognition rates and was easily implemented when compared with another technique. The result showed the efficiency of the wavelet coefficient and affine moment invariant features that can be used to verify an image lacking illumination.

Keywords: *Face Recognition; Voronoi Diagram; Wavelet Packet Transform; Affine Moment Invariants; Feature Selection*

1. INTRODUCTION

Face recognition is interesting to research because it is an application area that computer vision research is being used in both military and commercial products. Much effort has been spent on this problem. The study related in this field is currently activities. Such as, finding for a fundamental theory describing how the light and objects interact to produce images from the last published in [1]. However, there is still a lot of work to be done and it's a level pattern recognition problem in which humans are very expert. Automate face image recognition of human is the possible powerful application of computer vision. Both methods and algorithm have been conducted for accurate verification from face image. The goal of these applications needs to use for access control, electronic commerce and man-machine applications [2].

Over the last decade, face recognition approaches can be categorized into two general groups, holistic and feature-based approach. Holistic approaches, the face images are performed in 2D holistic patterns, which determined much more frequently than feature-based approaches.

In feature-based approaches, the relationships of shapes and geometrical are used to analyze the individual facial features, which consist of eyes, mouth and nose. However, feature-based approaches are more robust against than holistic approaches in rotation, scale and illumination variations. In contrast, the success of these approaches depends on the technique of facial feature detection [3].

The aim of face recognition is to identify or verify one or more persons from still images or video images of a scene using a stored database of faces. Many techniques have been focused on how to improve the accuracy of face recognition that is

motivated by the increased number of real-world applications. However, before the face recognition can function on the image, the system should determine the acquisition of an image such as camera image or video image that refer to an automated or semi-automated process of matching facial image. The pipeline of face recognition has emerged that consist of four stages: detection, alignment, representation, and classification [4-6].

A main difficult task in face recognition is the condition of illumination, distortion and cameras that are significantly larger than the image variations. Because of its effect to the change in facial identity or to achieve good recognition results. Face recognition in various lighting conditions is a still difficult problem when the acquisition face images are taken from high dynamic range scenes. It is due to anywhere on the surveillance system that cannot control the illumination and effect to the recognition rate [7]. Thus, the face image variation is still the core challenge of uncontrolled face recognition results. There are difficult for machine to discriminate and cast in the numerable image at any given 2D face image that depends on its position, distance, orientation, lighting and background. Especially, both variations of illumination and pose are influencing to feature descriptor in the case of difference of face image and the same person. At the same time, the uncontrolled face recognition looks like research problems that are paradigmatic and everlasting for pattern recognition [8, 9].

Cheddad et.al [10] suggested a method for segmentation of human face from still image using VD. They presented, face location and extraction step that generates clusters of intensity values using the vertices of the external boundary of Delaunay triangulation (DT). Their results are robust, precise and independent of translation, rotation and scaling. However, the presence of background intensities similar to the face intensities in the image may cause problem for segmentation decisions. DT of facial feature for a face has different size in different area that can be classifying the size of the DT by using VD. Furthermore, it can be separate the different facial image into a number of regions that represent the skeleton of the skin [11]. In addition, Dobrina and Dominique [12] proposed Discrete Delaunay method based on Voronoi graph and DT for extraction boundary from voxel object. Their result shows that method allows a polygonal boundary representation which is guaranteed to be a 2-manifold and is successfully transformed in a triangular quality mesh.

Wong et.al [13] presented dual optimal multiband features for face recognition, which is invariant to illumination and facial expression variation. The used wavelet packet transform decomposes that image into frequency sub-bands and the multiband feature fusion technique are incorporated to select optimal multiband feature sets. Their results showed that their proposed system achieved high recognition rate under different illumination and facial expression variation. Jadhav and Holambe [14] describe a face recognition system based on a combination of Radon and wavelet transform, which is invariant to illumination and facial expression variations. The DC component of the low-frequency sub-band was removed when testing the algorithm performance in illumination variation. They showed that their proposed system achieved high recognition accuracy in the variation of facial expression and illumination separately. However, the system performance may degrade when it is tested against the combination of variations due to the removal of the DC component.

Feris et.al [15] and Ma et.al [16] used AdaBoost method to train for both face and eye detector with Haar features that is obtained from detection location inside the face region. In addition, Celik et.al [17] proposed a method for facial feature extraction using the directional multi-resolution decomposition offered by the complex wavelet transform. They used the dual-tree implementation of complex wavelet transform using two parallel discrete wavelet transform with different low-pass and high-pass filters in different scales. The linear combination of subbands generated by two parallel DWT is used to generate subbands with complex coefficients. The resulting performance gets better if the diversity in the illumination conditions is less. Moreover, Nanni and Luminia [18] presented a multi-expert approach for wavelet-based face detection based on the multi-resolution analysis of the face. The images are decomposed into frequency sub-bands with different level decomposition using different wavelets. They investigated the speed up the detection and reduce the false positives without discarding real face images. However, their work only performed an upright frontal face image.

A Radial Basis Function (RBF) is the real-valued function whose value depends only on the distance from the origin. RBF networks are claimed to be more accurate than those based on Back-Propagation (BP), and they provide a guaranteed, globally optimal solution via simple, linear

optimization. One advantage of radial basis networks over back propagation is that, if the input signal is non-stationary, the localized nature of the hidden layer response makes the networks less susceptible to the learning rate and tolerance for errors [19].

Recently, RBF neural networks have been found to be very attractive for many engineering problems. They exhibit some advantages including global optimal approximation and classification capabilities, and the rapid convergence of the learning procedures. Despite of these advantages of RBF neural networks, these networks are not free from limitations. In particular, discriminant functions generated by RBF neural networks have the relatively simple geometry which is implied by the limited geometric variability of the underlying receptive fields (RBF) located in the hidden layer of the RBF networks. Those fields are then aggregated in a linear fashion by the neuron located in the output layer [20-22].

In this paper, we propose a new framework for enhanced performance of face recognition system based on VD segmentation, wavelet packet transformation, affine moment invariants and RBF. The aims of this work are: (1) to solve the problem about pose and illumination of face image, (2) to fusion feature extraction to process step by using WPT and AMIs. (3) to combine four processing methods: VD, WPT and RBF neural network.

2. SYSTEM OVERVIEW

The system is based on several modules on a sequential architecture, as shown in Figure 1. We used 2D frontal face image from BioID standard datasets which included several illuminations and expression. Then follow by:

- Preliminary step: pre-processing image using square morphological, Gaussian low-pass filter, median filter, and histogram equalization.
- Face detection steps: using VD and DT detect face image by generating from the points. Then, detect the eyes on the original face image.
- Crop faces: to design rectangle template (like a window) to crop the face.
- WPT: used wavelet decomposition based on wavelet packet transforms level 1 and 2. The typical of mother wavelet is the Daubechies wavelet (*db4*) and determines the Shannon threshold. The output is sub-image or subband image. Wavelet

coefficients are obtained from sub image or sub- window.

- AMIs Extraction: it used for extract feature vectors on a subband face image from previous step.
- Classification and Verification step: The feature vectors are like the mean values and the variance values that can be fed into the input layer of RBF neural network. Further, to designed the hidden layer for adaptive the optimal results that are the comparison between the target and the output network. Both training and testing data are processed same step.

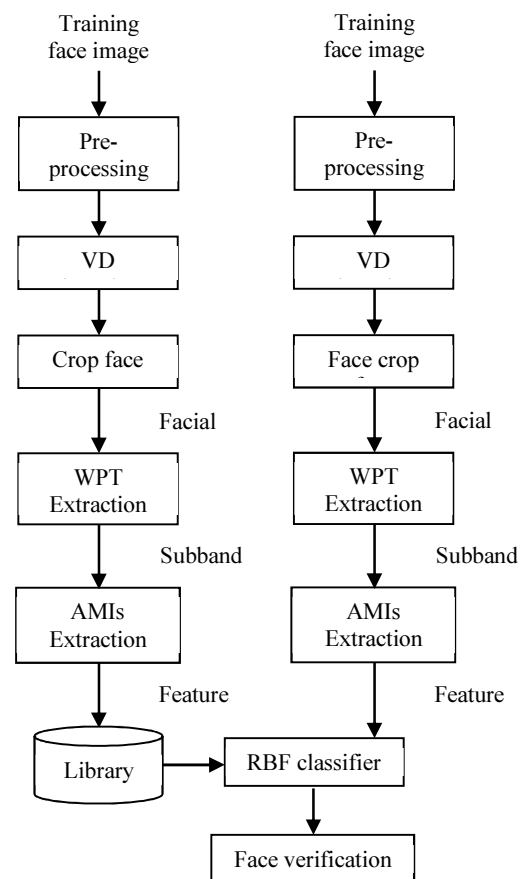


Figure 1: System Overview

3. FACE DETECTION BASED ON VD/DT

3.1 Voronoi Diagram Contents

VD or Voronoi tessellation is a well-known technique in computational geometry, which generates, clusters of intensity values using

information from the vertices of the external boundary of DT. It is employed in many fields, but researchers primarily focus on its use in skeletonization and for generating Euclidean distances; this work exploits the triangulations (i.e., Delaunay) generated by the VD for use in this field that the authors obtained from previous work in our laboratory [10]. VD has been revived many times in the fields of mathematical and computer science. A comprehensive review of the various variations of VD and more than hundred applications of them are proposed by Okabe et.al [23]. Furthermore, Blum and Nagel [24] proposed algorithm for computational analysis of the skeleton and how to construct the VD/DT on the boundary of shape image.

VD of a set of "sites" (points) is a collection of regions that divide the plane. Each region corresponds to one of the sites, and all the points in one region are closer to the corresponding site than to any other site. Given a set of 2D points, the Voronoi region for a point P_i is defined as the set of all the points that are closer to P_i than to any other points. The intersections of the Voronoi regions for the set of points construct the Voronoi Diagram. It has any geometric elements such as Voronoi edges and Voronoi vertices. A Voronoi edge is a boundary line segment limiting its associated Voronoi region. A point on the Voronoi edge is associated with two input points such that each point on a Voronoi edge is equidistant from these two points. A Voronoi vertex is an intersection of Voronoi edges and is associated with three or more input points such that each Voronoi vertex is equidistant from these input points as shown in Figure 2 [25].

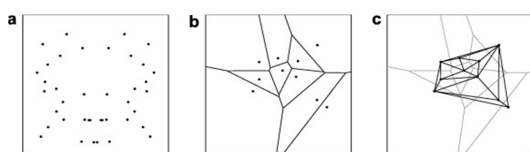


Figure 2: a) set of point, b) VD and c) DT

Let a set $S = \{p_1, p_2, \dots, p_n\}$ of n distinct points in the plane. The Voronoi cell $V(p_i)$ of a point $p_i \in S$ is defined as (1).

$$V(p_i) := \{q \in R^2 : d(p_i, q) \leq d(p_j, q), i \neq j\} \quad (1)$$

Here, $d(p; q)$ denotes the ordinary Euclidean distance between p and q as (2).

$$\sqrt{(x_p - x_q)^2 + (y_p - y_q)^2} \quad (2)$$

The Voronoi diagram $V(S)$ of S is the family of subset of R^2 consists of the Voronoi cells and all of their intersections. The bound of a Voronoi cell consists of Voronoi edges and Voronoi vertices. A point $q \in R^2$ is on the Voronoi edge $(p_i; p_j)$ if (3)

$$d(q, p_i) = d(q, p_j) \text{ and } d(q, p_k) \geq d(q, p_i) \text{ if } k \neq i, j \quad (3)$$

3.2. Face Segmentation and Detection

Image segmentation is a basic processing for many images processing application. On the part of analysis of image for face segmentation, the identification and isolation into regions are essential to distinguish between the object image so-called "foreground" and the part of non-object so-called "background". Before attempting this step, we perform pre-processing step that showed in system overview. It begins with an input face image for enhancing quality of the original image such as the lighting uneven effect, noise, and the impact background on the object. Our procedure used square morphological, Gaussian low-pass filter, median filter (remove noise), and histogram equalization. From this step, we can reduce gray values of face image to 27.87 % that show the benefit or cost for the next process step such as storage and speed. The histogram equalization stage is enhancing the contrast of intensity image that is very important for us to generate convex hull in the next stage. The convex hull of a set of featured points is the smallest convex set containing these points that have the outer boundary supplying the VD. This idea was not conducted on the image but instead of a few selected points less than 255 [10]. It is the represented point sets that can well reflect on the dense point sets and a set of unique dot patterns are obtained. The two global maxima are obtained from the host image histogram which get minima between these two peaks, set all the point below the first peak and all points beyond the second peak to zeros, set all points that are also equal to zeros to be equal the argmax (peak 1, peak 2). This process step will yield a local flip effect image histogram as show in Figure 3-4. The new set points for the part of the convex hull as corresponding with Delaunay Triangulation that are then sorted in ascending order to form ranges for decision for merging and splitting regions refer to (4).

$$Val_{new}(x) = |(Val(x) - \max(Val(x)))| \quad (4)$$

where $Val_{new}(x)$ denotes the highest frequency in the host image histogram.

In location face region stage, the authors introduced the distance transformation to separate the face region from the background that used function operators on Euclidean distance between two points ($\text{DisT} \geq \text{Threshold value}$). Next, we used the rule that is well known strategy for face estimation and segmentation as follows: ellipse fitting, cross correlation, and Euler number. Lastly, face boundary repairing stage is solving a problem about some parts on face unsuccessful. For example, one of the eyes is missing. This problem can be repaired by a convex image that obtained the complete output face image.

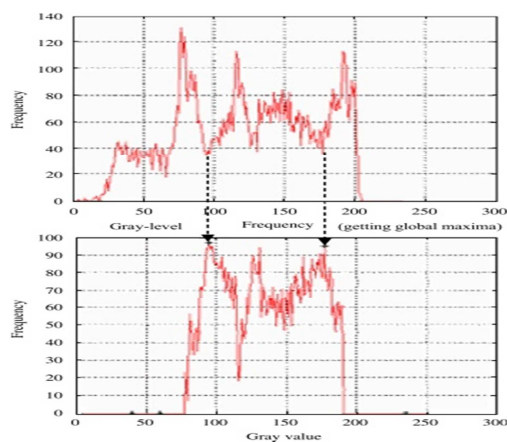


Figure 3: Global maxima and local minima

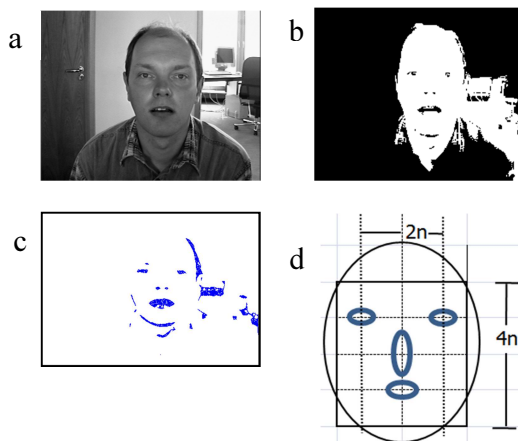


Figure 4: a) Original face, b-c) Face segmentation, and d) Face crop model

4. FACE CROPPING

The face crop model that we developed (shown in Figure 4 -d) for crop each face image in BioID dataset. After detecting the eye center, we evaluated the distance between the two eyes ($2n$) and then multiply by two. The value of between

eyes (n) is used to create the size of square angle (windows), from the center of the eyes to the top border and the bottom border of the window are setted n and $3n$ respectively. Next, set the distance from center of eyes (left eye and right eye) to the border of the window are 20 pixels. There are 200 face images corresponding to 20 persons in the databases, each with a resolution of 384×286 pixels. The face cropped model obtains the result correct location rate 91.4%, each facial image consists of eyes, nose and mouth as shown in Figure 5 (a-b).

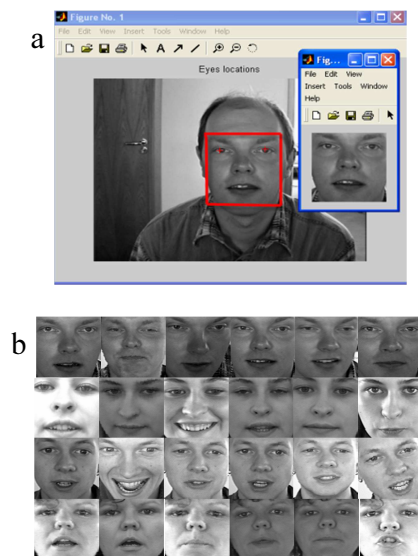


Figure 5: a) Eyes detection, b) Some results of face crop

5. FACE DECOMPOSITION USING WPT

The wavelet transform is focused on the low frequency decomposition that transform may not be suitable for images with large regions of textures. This approach aimed to reduce information of the image. Both the scaling coefficients and wavelet coefficients can be decomposed, which leads to the so-called wavelet packet transform (WPT). Similarly, 2D WPT can be obtained by the tensor product of 1-D WPT [26]. Basically, wavelet packet is a generalization of the standard wavelet tree decomposition of a signal. The wavelet packet tree decomposes the signal by applying a series of successive filters to the lowest frequency subband. The choice of exactly which subbands to decompose depending on the characteristic of the signal [27]. Mallet [28] and Daubechies [29] showed a complete framework built in particular for what concerns the construction of wavelet bases and efficient

algorithms for its computation. This lead to an efficient real-space implementation of the wavelet transform using quadrature mirror filters [30]. In the 2D case, the wavelet transform is performed by applying a separable filter bank to the image that used both low filter and bandpass filter (H and G respectively). The convolution with the low pass filter results in a so-called approximation image and so-called details images with the bandpass filter.

In this paper, we have selected level one and level two of decomposition according to the small size of face image that suggested by [31] as shown in Figure 6. Whereas, we obtained one image of estimation that is a low resolution facial image and 3 facial images of details in level one. In addition, level two obtained one image low resolution facial image and 15 facial images of details as shown in Figure 7 (a-b). Thus, the most of images are described by 20 wavelet coefficient matrices that represent the most information about the texture of the image. Next, we extracted two measures from a low resolution image, the mean value μ_m and the variance σ_m^2 of the area inside face image that will provide information about face texture and skin tone. It is different in [31] work, because our facial images were obtained by cropping image step. In addition, the other 3 and 15 details image will also be extracted by using the means μ_i and the variance σ_i ($i = 2, \dots, 18$). In fact, the mean values μ_i are null, because of the bank filters rule. Therefore, the maximum of feature vectors is 18 components for contents in one image that are described as follows:

$$\nu = \bigcup_{i=0}^{16} \{\mu_i, \sigma_i^2\} \quad (5)$$

Where $\forall i \geq 2, \mu_i = 0$ and the indices $i = 0, 1$ stand, respectively.

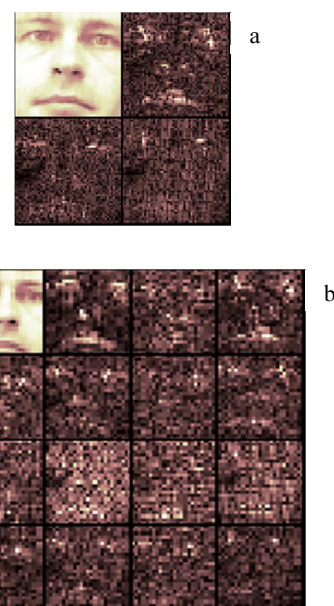


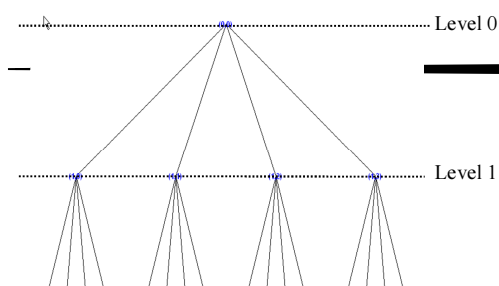
Figure 7: Facial subband (WPT) a) Level 1 and b)

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5. FACE EXTRACTION WITH AFFINE MOMENT INVARIANTS (AMIs)

Moment-based invariants are widely applicable to describe features of moment invariants on 2-D image. Many applications have been used as pattern feature extraction and object recognition [32, 33]. Initially, Hu [34] introduced a set of invariants based on non-linear combinations using regular moments. The significant of central moments are invariant towards rotation, translation and scale [35].

To investigate in this proposed framework, the AMIs were obtained from Flusser and Suk [36] and Petrou and Kadyrov [37] that used the mean of the theory of algebraic invariants. The six simplest of affine invariants that we have used for face recognition are defined below:



$$\begin{aligned}
I_1 &= \frac{1}{\mu_{00}^4} (\mu_{20}\mu_{02} - \mu_{11}^2) \\
I_2 &= \frac{1}{\mu_{00}^{10}} (\mu_{30}^2\mu_{03}^2 - 6\mu_{30}\mu_{21}\mu_{12}\mu_{03} - 4\mu_{30}\mu_{12}^3) \\
I_3 &= \frac{1}{\mu_{00}^7} (\mu_{20}(\mu_{21}\mu_{03} - \mu_{30}^2) \\
&\quad - \mu_{11}(\mu_{30}\mu_{03} - \mu_{21}\mu_{12}) + \mu_{02}(\mu_{30}\mu_{12} - \mu_{21}^2)) \\
I_4 &= \frac{1}{\mu_{00}^{11}} (\mu_{30}^3\mu_{03}^3 - 6\mu_{20}^2\mu_{11}\mu_{12}\mu_{03}) \\
&\quad - \mu_{20}^2\mu_{21}\mu_{12}\mu_{03} + 9\mu_{20}^2\mu_{02}\mu_{12}^2 + 12\mu_{20}\mu_{11}^2\mu_{03}\mu_{21} \\
&\quad + 9\mu_{20}\mu_{11}\mu_{02}\mu_{30}\mu_{03} - 18\mu_{20}\mu_{11}\mu_{02}\mu_{21}\mu_{12} \\
&\quad - 8\mu_{11}^3\mu_{03}\mu_{30} - 6\mu_{20}\mu_{02}^2\mu_{30}\mu_{12} + 9\mu_{20}\mu_{02}^2\mu_{21}^2 \\
&\quad + 12\mu_{11}^2\mu_{02}\mu_{30}\mu_{12} - 6\mu_{11}^2\mu_{02}^2\mu_{30}\mu_{21} + \mu_{02}^3\mu_{30}^2) \\
I_5 &= \frac{1}{\mu_{00}^6} (\mu_{40}\mu_{04} - 4\mu_{31}\mu_{13} + 3\mu_{22}^2) \\
I_6 &= \frac{1}{\mu_{00}^9} (\mu_{40}\mu_{04}\mu_{22} + 2\mu_{31}\mu_{22}\mu_{13} \\
&\quad - \mu_{40}\mu_{13}^2 - \mu_{04}\mu_{31}^2 + \mu_{22}^2) \quad (6)
\end{aligned}$$

where μ_{pq} is defined by

$$\mu_{pq} = \iint_{object} f(x, y) (x - x_t)^p (y - y_t)^q dx dy$$

with $f(x, y)$ being the gray-level image function and (x_t, y_t) the center of mass of the object.

6. FACE CLASSIFICATION USING RBF NEURAL NETWORK

Artificial Neural Network (ANN) is a machine learning algorithm that has been used widely in research problems such as robotics, machine learning, computer vision, and pattern recognition. The ANN classifier has advantages for classification which have both the special properties about incredible generalization and good learning ability [38]. Neural networks-based methods have been widely used in classification for its learning ability and good generalization [39]. In this work, we used tree layer of the ANN with layer ANN with RBF neural networks: input layer, hidden layer, and output layer as shown in Figure 8. The number of output nodes is equal as the number of subjects in the training set. Facial image feature vectors or so, called the mean values and the variance values which are provided by the wavelet packet transform approach. Whereas, we used well

known of the mother wavelet packet, typical “Daubechies wavelet” and assumed the standard threshold typical “Shannon”. Thus, the coefficient image is the feature vector representation. Next, we are normalized within -1 and 1 independently and are fed into input layer neurons. During the training stage, we adjust the weights of RBF neural networks based on the errors traced at each neuron output. Each subject is trained towards getting an output and is not threshold output layer neural, which is described as follows:

$$f(x) = \frac{1}{1 + e^{-x}} \quad (7)$$

7. THE EXPERIMENT OF FACE CLASSIFICATION

After feature extraction, we have resized resolution of 64 x 64 pixels every facial image which obtained 18 coefficients per image. BioID face database contains 20 distinct subjects, and each subject consisted of 10 subsets of the distinct facial image or 200 different facial images, the imaged vary in terms of light, expressions and included gray-scale. In addition, each subset contains three facial features (eye, nose and mouth). The features are 6 vectors per subband facial image. Thus, the most of the vectors are 108 features per facial image and 1080 features per subject (person). Those are the input vectors for classification in RBF neural network. The most of coefficients are computed to the mean and the variance values, then, fed into input the RBF neural network. It contains 20 hidden neurodes, 21600 input and output neurodes. The author used the K-Fold Cross Validation method to evaluate the performance of the dataset and selected 10 face images per subject in three subsets: training, validation, and testing. Each subject was divided into 10 subsets (S_1, S_2, \dots, S_{10}) that consists of 6 subsets for training, 1 subset for testing and 3 subsets for validation. The result of recognition rate and the comparison with different methods of other researchers in the same database as shown in Table 1:

Table 1: Comparison of Face Recognition Rate Between Proposed Method With Other Method Based on BioID Face Database

Method	Recognition Rate
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ILMNN [40]	85.0
SiCoNNet [41]	86.4
Gabor + IPCA + OSELM [42]	86.9
Gabor + SVM [43]	90.0
Wavelet + PCA [44]	91.6
The proposed method	94.6

Table 1, reports the comparison results of recognition rate between the proposed method and other method based on BioID face database. The proposed method is the best performance recognition rate, which achieved 94.6%. This exhibit that the proposed method with the cropped facial consisted of eyes, nose, and mouth is working well for improving the recognition rate in face recognition. The combination between wavelet transform and moment invariants can achieve the highest result on BioID face database. Other methods which are Gabor + IPCA + OSELM, Gabor + SVM, and Wavelet + PCA also achieved good results at the average of 86.9%, 90.0% and 91.6%, respectively. In contrast, ILMNN achieved the lowest performance recognition rate (85.0%).

8. CONCLUSION

In this paper, a new framework of face classification for enhanced face recognition performance is investigated. The new framework was considered as the integration of VD, WPT and RBF neural networks. We used this method to construct the proficiency of a face recognition system with a high recognition rate. For the BioID database, our method can achieve a high average recognition rate of 94.6% with expressions variation, low and poor contrast. In addition, WPT can extract and reduce the information on the low resolution of facial face. Whereas, RBF neural network can classify face image using confident WPT well. The experimental results, when compare with some several works in the same database of face recognition approach has better performance clearly. In the future work, we will continue our work by increasing the numbers of datasets; vary expression variation and other dataset.

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