Comparison of Filtering Methods for Extracting Transient Facial Wrinkle Features

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***Abstract*—Facial local features comprise an essential information to identify a personal characteristic such as age, gender, identity and expression. One of the facial local features is a wrinkle. Wrinkle is a small furrow or crease in the skin. Recently, wrinkle detection has become a topic of interest in computer vision, where many researchers developed applications like age estimation, face detection, expression recognition, facial digital beauty and etc. However, most of the research focused on permanent wrinkles instead of transient wrinkles. Transient wrinkle can be seen during the movement of facial muscle such as a facial expression. This paper presents a comparison of filtering method for extracting transient wrinkles features. The filters that have been selected are Gabor wavelet and Kirsch operator. The extracted features are the number of wrinkles, the maximum perimeter of wrinkle, the average perimeter of wrinkle, total perimeter of wrinkle, the maximum area of the wrinkle, and the total area of the wrinkle. A total of 60 sets of data extracted from Cohn-Kanade database, images from internet and self-images. These images contain weak and strong transient wrinkles at forehead region. Features selection and analysis has been done to select which feature extraction method produces better wrinkle features that can be used for the classification of wrinkle detection system. The results show that both Gabor and Kirsch methods are successful to extract transient wrinkle features, where both methods scored 100% accuracy in the classification with SVM. However, Gabor method is slightly better than Kirsch method in term of detecting weak wrinkles. The Kirsch method requires an additional noise filtering method to eliminate noise particles after the convolution of Kirsch's kernel. In conclusion, Gabor method is more applicable to a variety of applications than Kirsch method.**

***Index Terms*—Gabor Wavelet; Feature Extraction; Kirsh Operator; Transient Wrinkles.**

I. INTRODUCTION

The wrinkles are small furrow lines or creases on the skin that normally appears on the face and it caused by an ageing factor or facial expression. Based on W. Xie, L. Shen, and J. Jiang [1], wrinkles can be categorized into permanent and transient wrinkles. The permanent wrinkles normally located on faces of an aged person and the transient wrinkles appear when the facial expression is generated. The transient wrinkles usually appear in the forehead region, corner of the eyes and corner of the mouth. Transient wrinkles also have unusual shape and pattern for every person. In the forehead region, the wrinkles have a linear shape and appear at the center line of the forehead. Meanwhile, the eyes regions have complex wrinkles between the eyebrows and linear shape wrinkles around the corner of the eyes. For mouth region, it consists of nasolabial wrinkle [2] at each side of the cheek and complex wrinkles below the mouth area. However, some people have weak wrinkles or even they do not have any transient wrinkles when they raise their eyebrows or when they smiling.

Permanent wrinkle features are common features that normally used in the face recognition and age estimation application. However, an application based on transient wrinkles is not easy to develop because the transient wrinkle has an inconsistent pattern. There are numerous wrinkles detection methods have been proposed, but not all methods are able to extract the transient wrinkles features from skin image. To overcome this problem, a good feature extraction algorithm needs to be developed to extract these transient wrinkles so that it can be used in the wrinkle detection for any application that involves wrinkles on the face.

Wrinkles extraction and detection have gained increasing attention for related applications. This is because the wrinkle is the most prominent, distinguishable and representative feature. In the past few years, wrinkles had been used in many research and a few different methods had been created to detect wrinkle by researchers. However, every method has its strength and weakness.

In wrinkle detection algorithm, feature extraction is the most important stage in the overall detection process. With the success of feature extraction method, the detection or classification of wrinkles will produce a higher accuracy. Thus, it is a very challenging task to develop feature extraction method for the transient wrinkles. A few methods that have been proposed in extracting the wrinkles are Gabor wavelet [3], digital template Hough transform (DTHT) [4], Hessian line tracking (HLT) [5], hybrid Hessian filter (HHF) [6], Canny edge detector [7] and etc.

Among various feature extraction methods, Gabor wavelet has been recognized as one of the most successful local feature extraction methods for face representation [8]. Gabor wavelet is favored among many researchers because of its outstanding performance in the task of facial expression analysis [9]. Gabor wavelet consists of 40 sets of complex sinusoids modulated by a Gaussian function, the magnitude at five scales and eight orientations [10]. Although Gabor wavelet has 40 sets of filters, not all wavelets are needed to extract feature.

Another edge detector that has potential in extracting wrinkle features is Kirsch operator. The Kirsch operator is a non-linear edge detector that finds the maximum edge strength in a few predetermined directions. It is named after the computer scientist Russell A. Kirsch [11]. The Kirsch operator has been used in optical character recognition system (OCR), handwritten recognition, object detection and image segmentation. Some researchers had improved the Kirsch operator to make it better on segmenting objects or fused it with other edge detectors to improve its performance.

In this study, one out of forty of the Gabor wavelets is used to extract the transient wrinkles on skin image. Then, it is compared with the Kirsch operator method. The outputs are wrinkle features and then these features are analyzed by using the scatter plot to determine the best features for the classification in the wrinkle detection system. A simulation of classification is done by utilizing a Support Vector Machine algorithm.

II. METHODOLOGY

This section describes the Gabor and Kirsch methods that are used to extract the facial wrinkle features. Both methodologies are divided into 5 primary sections: data collection, image preprocessing, feature extraction, feature selection and classification. At the end of this section, the comparison of both methods will be carried out.

A. Data Collection

To analyze the transient wrinkle from a human face, this study requires many human face images with an expression as a database. A facial database from Cohn-Kanade with around 100 posers are used in this study. Cohn-Kanade Facial Expression Database was released for the purpose of promoting research in automatic facial image analysis and synthesis and for perceptual studies [12]. Each poser image is captured begins with a neutral expression and proceeds with a peak expression. In this study, only 30 posers are chosen and all of them have forehead wrinkles when they express surprise emotion. There are a total of 60 images collected, where 30 images with forehead transient wrinkles and 30 images without wrinkles. These images have 640 x 480 resolutions. Besides from Cohn-Kanade database, 10 facial images from internet sources and 5 self-images are also collected, where these images included facial forehead with wrinkles and facial forehead without wrinkles. These collected images are used to test the algorithm created based on the Cohn-Kanade images. Figure 1 shows the samples of images collected from internet sources, Figure 2 shows the samples of self-images and Figure 3 shows the samples of images from Cohn-Kanade database.

Figure 1: Collected images with forehead wrinkle from online sources.

Figure 2: Collected images with forehead wrinkle from

Figure 3: Collected images with forehead wrinkles from Cohn-Kanade database.

B. Image pre-processing

The collected images are converted into grayscale images. The image color channel is reduced to one channel (grayscale) from three channels (RGB). This is because the time taken for processing one channel image is much faster than the multichannel image, where the output result is almost the same between one channel and multichannel.

Next, the grayscale images are then cropped manually for the region of interest (ROI). The ROI for this study is a facial forehead region. The other region is not used because the extracted features normally appear in the forehead region. Therefore, the processing time also can be reduced because the algorithm does not needs to run for the whole image.

After that, the cropped grayscale image is resized to a new width and height. Every image that is cropped manually has different sizes. Thus, the image is resized to the same size without reducing the quality of the image. The new size image is 160 x 60 resolution and the resized image has 160 pixels width and 60 pixels height. Figure 4 shows the output for the pre-processing tasks.

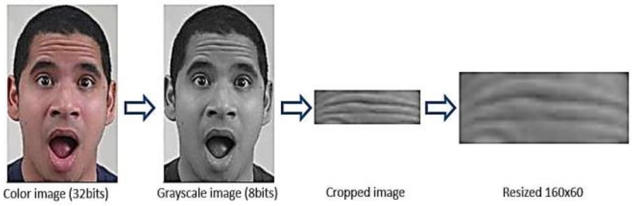

Figure 4: The process of image pre-processing

C. Feature Extraction

After image pre-processing, the images are gone through the feature extraction process. The input image data (pixels) are too large and it is suspected to be redundant, thus it can be reduced into a set of features. In this process, the extracted features are good for classification and maximize the recognition rate with the least amount of unnecessary information. In this study, two different filters are used for feature extraction which are Gabor wavelet and Kirsch operator. The outcome from both filters is compared at the end of this paper. A set of features that obtained from both filters are the number of detected wrinkles, maximum perimeter, average perimeter, total perimeter, maximum area, and total area, which all are the features of wrinkles.

1) Gabor Wavelet Method

Gabor Wavelet is a complex sinusoid modulated by Gaussian function. Gabor Wavelets are created by using Gabor formula, which it consists of a few parameters ($\lambda, \theta, \psi, \sigma, ks$) to design the desired wavelet. The parameter λ represents the wavelength of the wavelet, θ represents the orientation of the stripes wavelet, ψ represents the phase offset, σ represent the standard deviation of the Gaussian envelope, and ks represents the kernel size. The formula of Gabor wavelet is shown in Equation. 1, 2 and 3.

$$g(x, y;\ \lambda, \theta, \psi, \sigma, ks) = \exp\left(-\frac{x'^2 + ks^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \psi\right) \quad (1)$$

Where,

$$x' = x\cos\theta + y\sin\theta \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta \quad (3)$$

The parameters for Gabor filter use in this study are ks = 21, σ = 4, θ = 90°, λ = 60 and ψ = 92. The θ value is set to 90°, which the stripe orientation of the wavelet is same as the forehead wrinkles. Kernel size and σ control the size of the wavelets based on image region being analyzed. Lastly, ψ do not have much effect, compare to θ, λ, and kernel size. It controls the position of the wavelet's stripe. Figure 5 shows the created Gabor kernel by the parameters used in this study. The output image from Gabor wavelet is a type of magnitude image as shown in Figure 6.

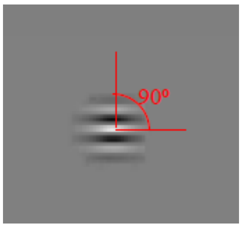

Figure 5: The Gabor kernel created from the parameters

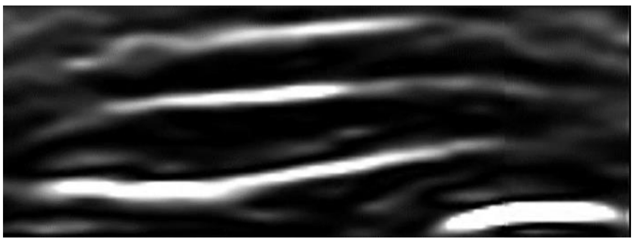

Figure 6: The output magnitude image from Gabor wavelet.

The output image from the Gabor wavelet is processed with edge detector operator, Canny [13]. The output image is converted to Canny image with the threshold range of 120-255 grayscale intensity. The Canny image is a binary image with black and white colors and it is required to extract the wrinkle lines. Then, the *findContours()* function from OpenCV library is applied to detect edges or wrinkles in the image. The input image for *findContours()* function needs to be a binary image. In this function, the binary image is used to increase the accuracy of generated contour compared to the non-binary image. The output contours are listed in Freeman chain code and stored as vector points. In this technique, the contour approximation method is specified using *CV_CHAIN_APPROX_SIMPLE* which it compresses horizontal, vertical, and diagonal segments and leaves only their endpoints [14]. For this method, the mode for this function is *CV_RETR_EXTERNAL* which it retrieves only the extreme outer contours. Lastly, the detected wrinkles are drawn on the grayscale pre-processed images using OpenCV library function, *drawContours()*. The image contains extracted contours is shown in Figure 7.

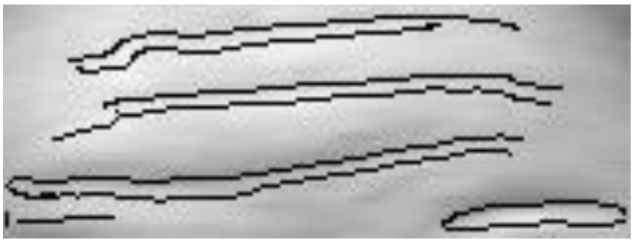

Figure 7: The extracted contours by using Gabor method drawn on grayscale pre-processed images.

2) Kirsch Operator

The second method proposes in this paper is a Kirsch operator method. Kirsch Operator is a compass kernel that finds the maximum linear edge strength in eight directions such as north (N), northwest (NW), west (W), southwest (SW), south (S), southeast (SE), east (E), and northeast (NE). Every direction is rotated in 45° increments [15]. The selected direction in this method is south (S) direction, which the direction is same as the direction of lighting setup (from top to bottom). With this direction, the output image obtained maximum edge strength in south direction. The Kirsch kernel mask is shown in Equation 4.

$$S = \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ +5 & +5 & +5 \end{bmatrix} \quad (4)$$

Next, the produced output image is processed with the morphological opening algorithm for noise reduction. The noise is a small particle or a small dot exists after applying the Kirsch operator. The morphological opening is a process of erosion of A by B, followed by dilation of the result by B as shown in Equation 5 [16].

$$A \cdot B = (A \ominus) \oplus B \quad (5)$$

First, the erosion process reduces the size of all objects in the image with structuring element in size of 1. All noises or objects that have a small number of pixels are eliminated and only left a thin line of the edges. After that, the dilation process restores the size of the edges line with same structuring element in size of 1. In this case, the noises are not restored because the noise is already erased during erosion process. Figure 8 shows the image before and after of the process of opening morphology.

Finally, the output image goes through the same process as Gabor method's output image, which is first used *findContours()* function to detect edges or wrinkles in the image. Then, apply Canny operator with the threshold range between 120 and 255. The detected wrinkle is drawn on the grayscale pre-processed images as shown in Figure 9.

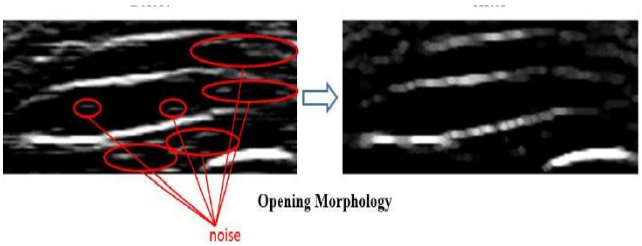

Figure 8: The process of opening morphology to reduce noise

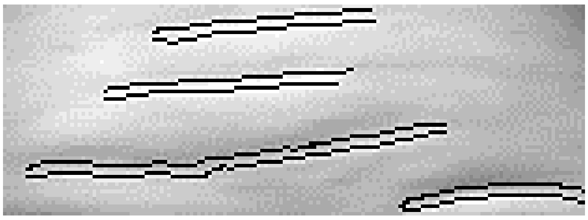

Figure 9: The extracted contours by using Kirsch method drawn on grayscale pre-processed images

D. Feature Selection and Analysis

Feature selection is a process of selecting a subset of relevant features to construct a classification model. The analysis covers the features selection and comparison of the features that generated from Gabor wavelet and Kirsch operator. This analysis is important in finding better features for the classification in the real system.

The extracted features or dataset from Gabor wavelet and Kirsch operator is analyzed in this section. There is a total of five features extracted from wrinkles images, which are the number of detected wrinkles, the maximum perimeter of wrinkle, an average parameter of wrinkle, total perimeter of wrinkle, the maximum area of the wrinkle, and the total area of the wrinkle. The analysis includes the feature selection from both datasets and analysis of both methods to verify which method is better. The feature selection is constructed with scatter plot using a software tool, Weka.

In this study, the extracted features are examined through the visualize panel in Weka. This panel allows to visualize the current feature dataset in one and two dimensions. This step is used to visualize the prediction and to proof that the features are suitable to be used as selected features. Based on the plotted scatter plot, the features from the same class have similar feature values, and features that have different class have different values. Otherwise, it is a "weak features" to be used for classification. The five features of wrinkle from each Gabor and Kirsch method will be determined to be selected as wrinkle feature representative or not. After that, the comparison is made based on the selected features.

E. Classification

At this stage, a classification is done to test the features and to validate the performance of the proposed algorithms, which are Gabor and Kirsch feature extraction methods. A Microsoft Azure Machine Learning Studio tool is used to simulate the classification of skin images. The Support Vector Machine is used as classification algorithm. A total of 45 sets of data extracted from Cohn-Kanade database are used to train the model, while 15 sets (where the images are taken from internet sources and self-images) of the data used to test.

III. Results and Discussions

There are two methods used for feature extraction, Gabor wavelet and Kirsch operator. In this study, Gabor and Kirsch methods have its own advantages and disadvantages. In terms of algorithm complexity, Gabor algorithm is more complex compared to Kirsch algorithm. However, Kirsch operator requires a noise reduction process to eliminate small particles that appear in the image.

In terms of extracting wrinkle contour of both methods, the qualitative analysis is divided into two different types of image, weak wrinkle image and strong wrinkle image as shown in Figure 10. For weak wrinkle image, the output from the Gabor method is more distinctive compared to Kirsch method. The wrinkle edges in the Gabor image are deep and the wrinkle lines are not broken. The Kirsch operator cannot extract light details or shallow wrinkle. The wrinkle lines appear on Kirsch image is discontinuous. However, in the analysis of strong wrinkle, Kirsch method gives a better result compared to Gabor method. Both methods able to detect the wrinkle contour, but Gabor wavelet produced thick or strong edges that affects to unnecessary small pixels near the wrinkles. This is because Gabor filter will extract the deep of furrow and the topmost surface of the skin. In the Gabor method, the result shows many unnecessary contours appear on the skin. Meanwhile, in Kirsch method, the result shows the wrinkle contours appear as expected and almost similar to the wrinkles on the real skin.

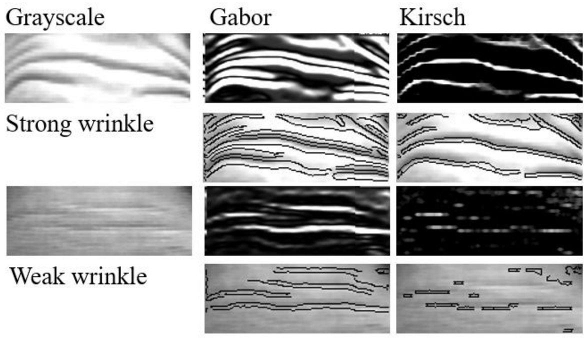

Figure 10: Examples of output for extracting wrinkle on forehead with strong wrinkle and weaker wrinkle

Figure 11 illustrates the measurement of the detected contour and it has produced six features that are used for the features analysis. These six features that are extracted from the output image are a number of detected wrinkles, the maximum perimeter of wrinkles, the average perimeter of wrinkles, total perimeter of wrinkles, the maximum area of the wrinkles, and the total area of the wrinkles.

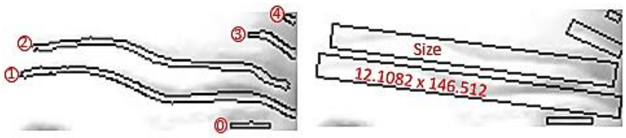

Figure 11: Measurement of detecting contour.

The six features values are aimed at the classification between an image that has wrinkles and images that do not have wrinkles. These feature values can be used for further classification of wrinkles strength in future improvement. However, in this paper only presents a selection of wrinkle features so these features can represent a better wrinkle characteristics and it will give a better classification result. In this study, images without wrinkle also included in the analysis. Refer to Figure 12, for the images that do not have wrinkles, the feature's value is not zero for all datasets. This is because some small object contours are detected and measured. These small objects are edges that cannot be eliminated and it can be categorized as noise. In fact, these small edges that appeared in the skin image are a permanent wrinkle on the forehead.

Feature selection is based on the scatter plot of features values. By using Weka tools, the wrinkle features are visualized by 2-dimensional (2D) scatter plot. Each scatter plot has two features data. In this paper, 15 scatter plot is presented for each method, Gabor wavelet and Kirsch operator. A total of 30 scatter plots is analyzed for the differences of the features between two different classes as illustrated in Figure 13.

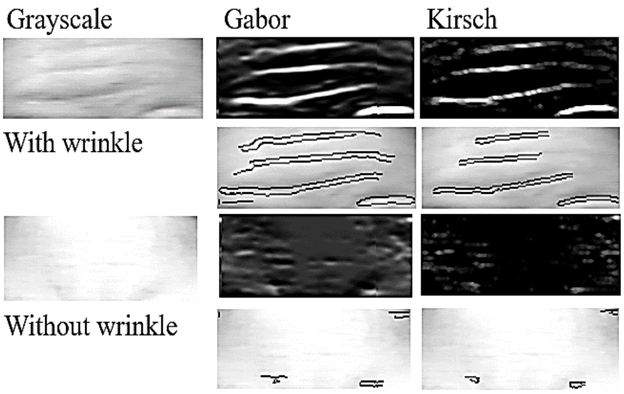

Figure 12: Examples of the output image for extracting wrinkle on the forehead with wrinkle and without wrinkle.

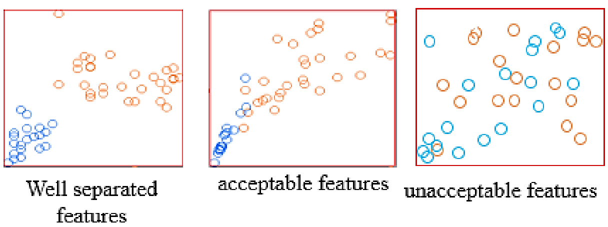

Figure 13: Examples of distribution feature on scatter plot.

For the Gabor method, all features are "good features". Features with the same class are grouped well and features from the group of two classes can be separated as shown in Figure 14. For the Kirsch method, as shown in Figure 15, some scatter plots have a small amount of the features from two classes are overlapped. Only one scatter plot presents feature distribution that is not overlapped, which is an average perimeter versus the number of wrinkle line plot. Although most results show overlapped features, its number is very little. Overall features still scattered in each group and it shows that these features also can be used for the classification in the future process.

In classification with SVM algorithm, both datasets from Gabor and Kirsch feature extraction methods scored 100% accuracy. 10 images which are not from the Cohn-Kanade database are used to test the trained model and it scored 100% accuracy. It shows that both feature extraction algorithms can be used to extract the wrinkle features from the skin image.

In the comparison of Gabor and Kirsch methods, there are not much different in features datasets, but the Gabor method performed a slightly better than a Kirsch method in class separation. Both methods have pros and cons in this study. The advantages Gabor method are, this method does not require noise filtering as Kirsch method and it is available to extract weak wrinkles. However, to set Gabor wavelet parameters that are suitable for the wrinkle is quite tedious compared to Kirsch operator that only have 3 x 3 matrix kernel and its value is fixed. The disadvantage of Kirsch method is, it cannot extract a weak wrinkle, where some edges are missing and discontinuous. Meanwhile, this method requires noise filtering after applying the Kirsch filter. From the feature selection result, it shows that wrinkle features produced by Gabor method give better data separation compared to Kirsch method.

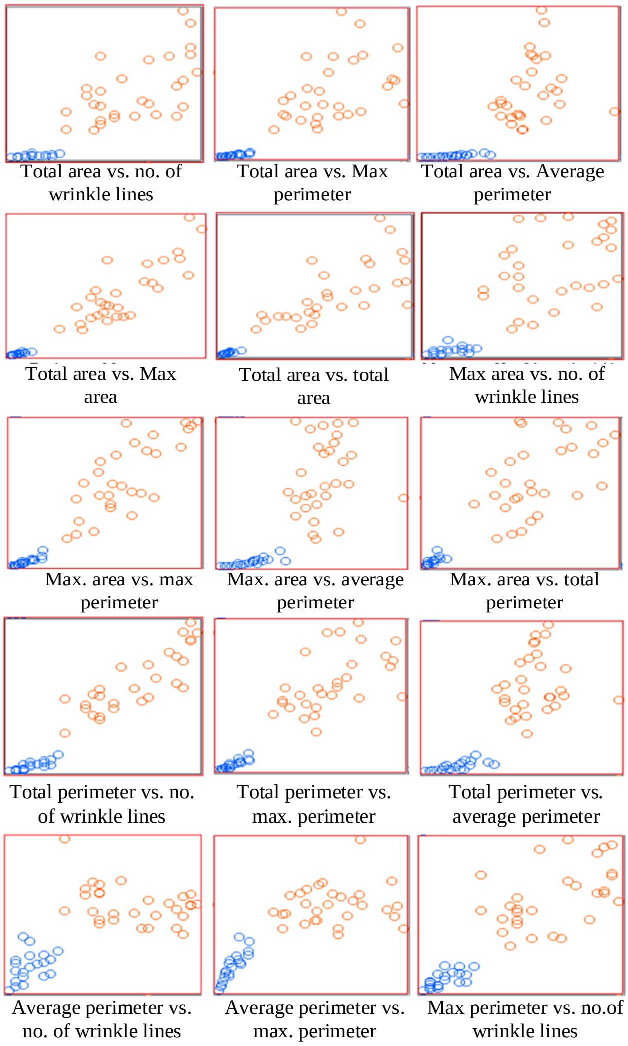

Figure 14: 15 scatter plots of Gabor features. The blue circles are feature data without wrinkle and the orange circles are feature data with wrinkles.

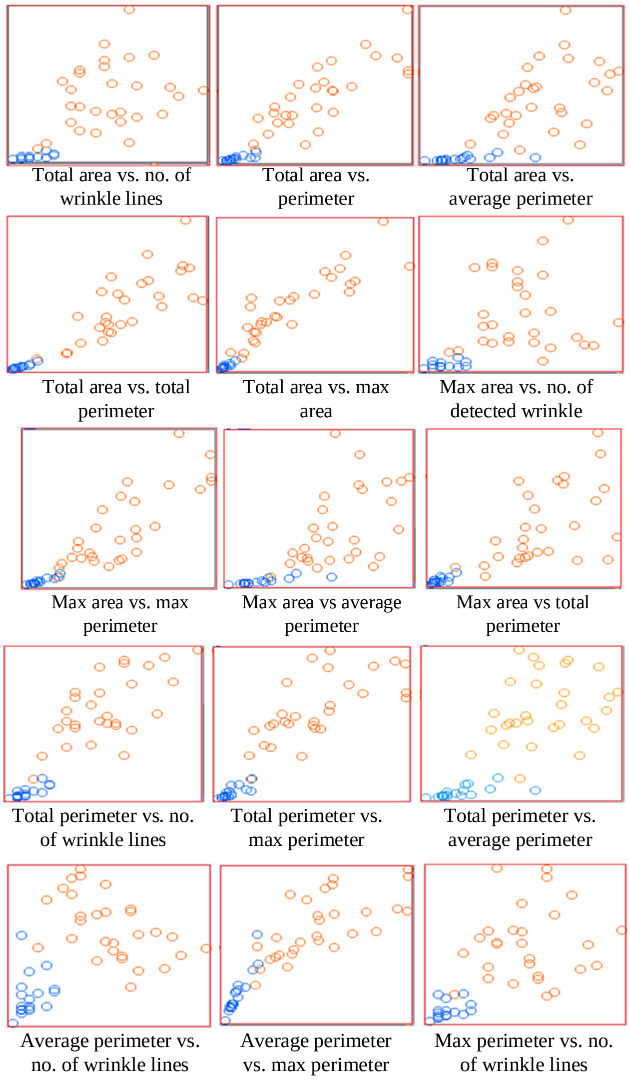

Figure 15: 15 scatter plots of Kirsch features. The blue circles are feature data without wrinkle and orange circles are feature data with wrinkle.

IV. Conclusion

In conclusion, wrinkle features are successfully extracted from the skin image by using Gabor wavelet and Kirsch methods. Gabor wavelet method performed better than Kirsch method. When it can extract weak wrinkles, it does not require any noise filtering algorithm and the extracted wrinkle features data can be grouped into two different classes, which are image with wrinkle and without wrinkle. These features can be used for the wrinkle detection system. In term of simplicity, Kirsch operator is simpler compared to Gabor wavelet. Even though this filter comes with eight different orientations, but it still well performed with only one direction, which is the south direction. Meanwhile, its kernel only has 3x3 matrix with fixed values. Unlike the Gabor wavelet, the parameter setting has to be done carefully, since it has five parameters and a lot of possible direction can be chosen from 0° to 360°.

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