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IDENTIFICATION OF SIGNATURE USING ZONING METHODS AND SUPPORT VECTOR MACHINE

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Abstract:-
Identification of signatures is the process of identifying and defining a person's signature. Identification of signatures including biometics that use natural human behavior. Identification of signatures can be used in security areas such as money withdrawal permits, check validation, credit card transactions and more. During this signature identification is done manually. Difficulty in this way, if the signature to be identified is large, the examiner will experience fatigue. To simplify it needs to be developed to create a computerized signature identification system. In this research, the development of this signature identification is done using the method of zoning and Support Vector Machine (SVM) classification. Based on the tests that have been done, normal test data test resulted in recognition accuracy of 95.31%. In testing the test data with disturbance obtained accuracy of 20.31%. While the testing of artificial signatures generated an accuracy of 70%. In addition to the registered signature image pattern, there are also signature images that are not registered in the database. The accuracy obtained in this test is 100%.

Keywords:- *signature identification, zoning method, SVM*

1. INTRODUCTION

Identification of signature patterns is included in the type of biometrics that uses the characteristics of human behavior. In general, to identify signatures is done manually by matching the signature at the time of the transaction with the previous signature that is valid using the eye. The manual method has a weakness if the number of signature patterns that must be matched is many at a time, the examiner will be tired so that the matching results are not maximal because the writing of a person's signature will change over time. Changes make someone's signature have a form that is not identical. An identical signature is a signature that has the same and congruent pattern, this is about the position, size and pressure when the signature is done. Changes in a person's signature are influenced by time, age, habits and mental state of a person [1]. Therefore, a method is needed that can simplify the process of signature identification by utilizing digital image processing technology.

Regarding signature identification, many signature biometric studies use various methods. Like using the method of characterizing Image Centroid Zone (ICZ) and Zone Centroid and Zone (ZCZ) [4], combining zoning and diagonal based methods [5], for introduction using artificial neural network methods [7], Principal Component Analysis (PCA) [10].

In this study, the analysis and simulation of the signature identification system using the zoning characterization method to obtain characteristic values from the signature image will be discussed. Then the characteristic values will be classified using the SVM method.

2.METHOD

The system is a software to recognize signatures consisting of training and testing stages.Fig.1 shows that during the training stage it consisted of several processes, namely pre-processing, characterization using the zoning method, and the SVM training process. From the SVM training process, the process will obtained a database that will be used in the classification process.

At the stage of image testing, will through a preprocessing and characterization process. The value of the features obtained will be compared to the database.

2.1 Zoning Identification Method

Characterization or feature extraction is a process where each signal sample will be converted into data vectors. The method that will be used in the process of characterization in signature identification is the zoning method. Zoning has several advantages compared to other methods, including simple characterization methods, low complexity and fast calculation in extracting the characteristics of a character.

Calculating the zoning method can be divided into 3 processes:

[1].Count the number of black pixels for each zone. For example, from Fig.2, the value of black pixels for each zone is shown in Table 1.

[2].Determine zones that have the highest number of pixels. From Table 1 the maximum pixel value is obtained Z highest= 100.

[3].Calculates the feature values of each zone.

Feature values

$$Z_n = Z_n / Z_{highest} \qquad 1 \le n \le 54 \tag{1}$$

Using (1), the value of the feature in Table 2 is obtained.

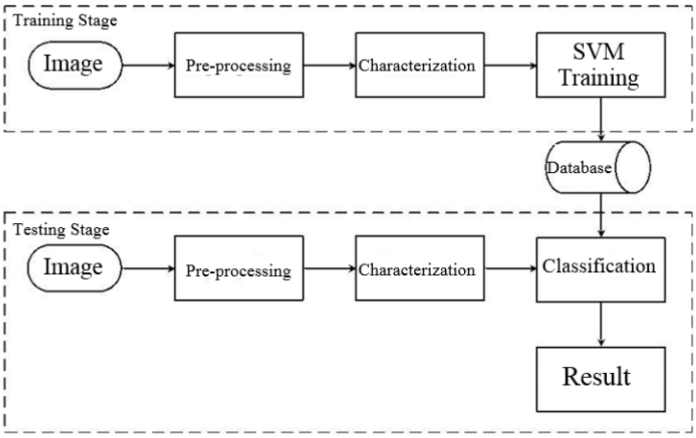

Fig 1. Block diagram of the signature identification system

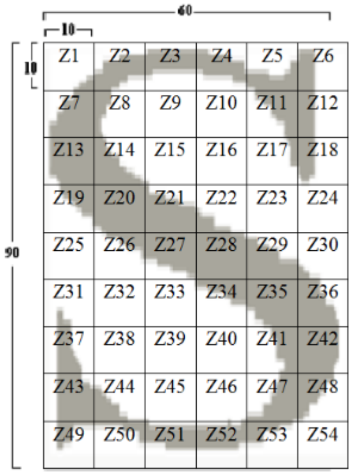

Fig.2. Distribution of zones into 6 columns and 9 rows

TABLE1. NUMBER OF BLACK PIXELS PER ZONE

Z1= 15	Z2= 56	Z3= 41	Z4= 45	Z5= 55	Z6= 30
Z7= 86	Z8= 10	Z9= 0	Z10= 0	Z11= 46	Z12= 30
Z13= 98	Z14= 44	Z15= 0	Z16= 0	Z17= 6	Z18= 29
Z19= 47	Z20= 100	Z21= 65	Z22= 11	Z23= 0	Z24= 0
Z25= 0	Z26= 33	Z27= 88	Z28= 98	Z29= 54	Z30= 3
Z31= 2	Z32= 0	Z33= 3	Z34= 47	Z35= 98	Z36= 57
Z37= 35	Z38= 0	Z39= 0	Z40= 0	Z41= 47	Z42= 89
Z43= 76	Z44= 8	Z45= 0	Z46= 0	Z47= 42	Z48= 56
Z49= 45	Z50= 43	Z51= 38	Z52= 46	Z53= 51	Z54= 5

TABLE 2. FEATURE VALUES FOR EACH ZONE

Z1= 0.15	Z2= 0.56	Z3= 0.41	Z4= 0.45	Z5= 0.55	Z6= 0.3
Z7= 0.86	Z8= 0.1	Z9= 0	Z10= 0	Z11= 0.46	Z12= 0.3
Z13= 0.98	Z14= 0.44	Z15= 0	Z16= 0	Z17= 0.06	Z18= 0.29
Z19= 0.47	Z20= 1	Z21= 0.65	Z22= 0.11	Z23= 0	Z24= 0
Z25= 0	Z26= 0.33	Z27= 0.88	Z28= 0.98	Z29= 0.54	Z30= 0.03
Z31= 0.02	Z32= 0	Z33= 0.03	Z34= 0.47	Z35= 0.98	Z36= 0.57
Z37= 0.35	Z38= 0	Z39= 0	Z40= 0	Z41= 0.47	Z42= 0.89
Z43= 0.76	Z44= 0.08	Z45= 0	Z46= 0	Z47= 0.42	Z48= 0.56
Z49= 0.45	Z50= 0.43	Z51= 0.38	Z52= 0.46	Z53= 0.51	Z54= 0.05

2.2 Support Vector Machine (SVM)

SVM is a learning system that uses hypothetical space from a linear function in a high-feature dimension space developed by Boser, Vapnik, and was first presented in 1992 at the Annual Workshop on Computational Learning Theory. SVM aims to find the best hyperplane that separates two classes in input space. The best separator hyperplane between the two classes can be measured by measuring the hyperplane margin that obtained from measuring the maximum margin between non-linear input spaces and the characteristic space using the kernel rules.

In Fig.3 the two classes are separated by a pair of parallel boundary lines. The first limiting line limits the first class (box),while the second delimiter limits the second class (circle), so the pattern that includes class 1 (negative sample) affects the inequality:

$$x_i.w + b \leq -1 \quad (2)$$

While the patterns included in class 2 (positive samples) can be formulated using inequality:

$$x_i.w + b \geq +1 \quad (3)$$

w: weight
x: class label
b: bias

It is assumed that both class -1 and +1 can be completely separated by the hyperplane. The best separator hyperplane between the two classes can be found by measuring the margin of the hyperplane and looking for the maximum point. Margin is the distance between the hyperplane and the closest pattern of each class. The margin value (distance) between the hyperplane based on the distance formula to the center can be defined:

$$\frac{1 - b - (-1 - b)}{w} = \frac{2}{|w|} \quad (4)$$

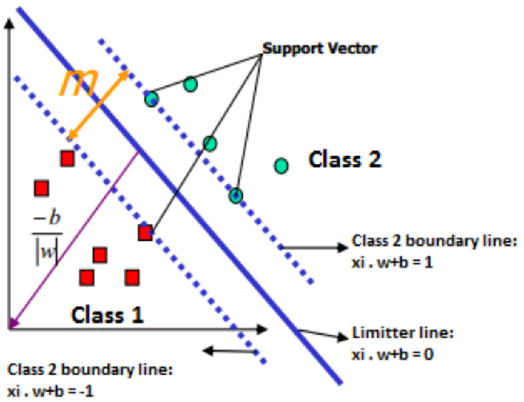

Fig.3. Linearly Separable Data Ilustration

By multiplying b and w with a constant, it will produce a margin value multiplied by the same constant. SVM uses the concept of margin which is defined as the closest distance between the decision boundary and any training data, by maximizing the margin value, a certain decision boundary will be obtained. The biggest margin is obtained by maximizing the value of the distance between the hyperplane and its closest point, which is $\frac{1}{|w|}$. So the search for the best hyperplane with the largest margin value can be formulated into a problem of optimization of constraints, which is finding the minimum point of (4) by paying attention to the constraints of(5).

$$\min \frac{1}{2} |w|^2 \quad (5)$$

$$y_i(x_i.w + b) - 1 \geq 0 \quad (6)$$

$$f(x_d) = \sum_{i=1}^{ns} \alpha_i y_i x_i x_d + b \quad (7)$$

xi: support vector
xd: data to be classified
ns: number of support vectors

Besides use to solve linear problems, SVM is designed to solve non-linear problems by mapping the problem into a higher dimensional feature space and then applying a linear classification in that space.

3. RESULT AND ANALYSIS

Tests were carried out on 16 individuals, each of individual consisted of 12 training images and 4 test images. Tests are carried out to determine the success of the program in recognizing the signature as the correct individual on the identification of signatures. After the image file to be trained as well as the image that to be tested is selected, the image will through a preprocessing process such as Fig.4.

The test image is an RGB image, to facilitate the next process, the image will be converted into a grayscale image. The next process is to convert the image into a binary image. Binary imagery consists of two bits, namely 1 and 0. The next

process is the bounding box, this process will determine the series of pixels that become the boundary between the object and background. Then the image will be truncated and left only the part that is considered the signature object. Then the image will be equalized to 150x90 pixels.
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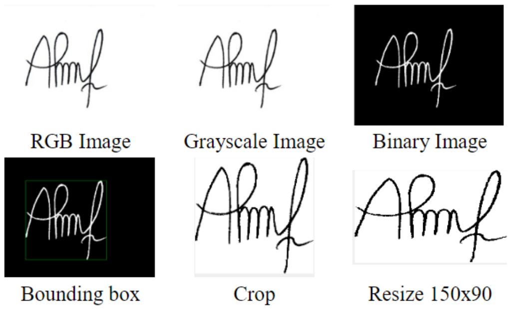

Fig.4.The process of pre-processing a signature image

The tests that carried out were divided into five experiments, namely:
1. Testing with normal test data is a test that aims to find the accuracy of the recognition of 64 untrained image data. Fig. 5 shows the testing graph.
2. Testing test data with disturbane. This test aims to test whether the method used is resistant to disturbance and shown in Fig. 6. The disturbance used is a salt & pepper disturbance with a density of 0.05.
3. Image testing of imitated signature is a test using an imitation of the signature pattern contained in the database. Number of imitated respondent's signature pattern in the database are5 images each of them, so this experimenttests80 signature images in total.
A total of 24 signature images were recognized correctly, and the accuracy obtained was 30%.
4. The test uses a signature pattern image that is not found in the database. In this test, all images are recognized as names in the database. This test uses 20 data images. And all data is identified incorrectly and its accuracy is 0%.

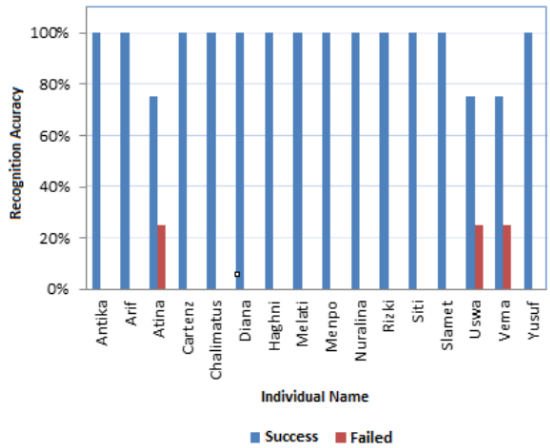

Fig.5. Testing graph of test data

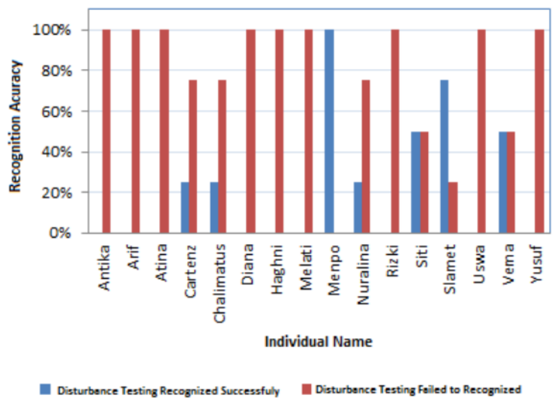

Fig.6.Testing graph of normal test data and disturbance test data

In Fig.7, it can be seen that testing using training images has perfect accuracy that is equal100%. This is because the training images that tested are the same as the trained images. Testing of the test image is a test using images that are not trained from people who are in the database. For testing the test data has a good value of accuracy that is equal to 95.31%. For testing using the image disturbance is a test image that is added salt & pepper disturbance with a density of 0.05. The zoning method is not suitable if the image used is disturbed because the zoning method will look for the average value of black pixels for each zone. Because the disturbance that added is considered a signature part, so the value of resulting feature is different from the database. The recognition accuracy that obtained from testing using disturbance was 21.87%. Imitated image testing is a test using the signature pattern image on the database and has been imitated before. Accuracy of testing using imitated image is influenced by the degree of similarity with the pattern in the database, the accuracy of the test image testing is 30%. Testing using external image is testing using a signature image pattern that is not found in the database. All images are recognized as patterns in the database, this is because the software design made does not use a threshold value so that the approach used by all images will be considered as the owner of the signature in the database. The value of accuracy in testing uses external data is0%.

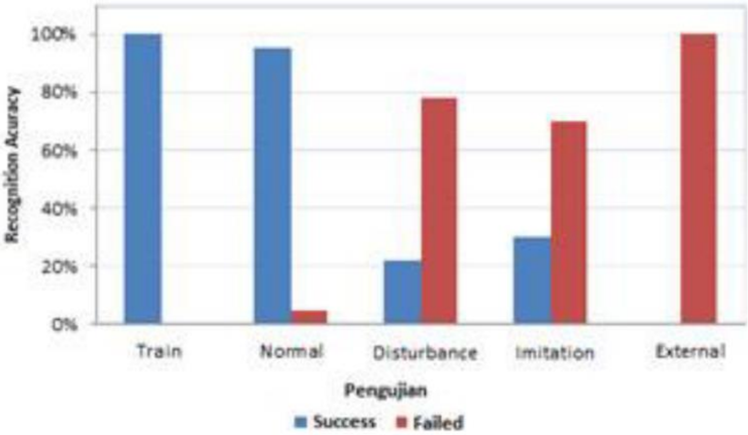

Fig. 7. Accuracy of testing graph.

4. CONCLUSION

Based on the results of the tests carried out, obtained several points that need to be considered including the amount of data that is trained influences the recognition process. Accuracy in normal testing is 95.31%. The zoning method is not suitable for use in images that have disturbance, the accuracy that obtained in this test is 21.87%.

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