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Development of Signature Image Processing Using Shape and Texture Patterns

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Abstract

A signature is a sign in written form, a person's identity for whether a document is correct or not, commonly known as a Biometric system. The Biometric system is the most basic, crucial and considered a superb process for a signature in detecting a person's identification and security. Signature forgery is a fraud that often occurs, causing bigger and longer expenses. For reasons like these, a signature detection system must be able to quickly and accurately recognize genuine and dummy signatures. The purpose of this study was to present the original and dummy signature pattern recognition by grouping the original signature data. In this study, Image Segmentation was used to divide the image into several parts, the K-Means Clustering algorithm to group several parts according to the properties of each object, and Feature Extraction of Texture Patterns and Shape Patterns with Gray Level Co-Occurrence Matrix (GLCM) to obtain feature values such as Entropy, Energy, Homogeneity, Correlation, and Contrast which has resulted in a study to detect genuine and counterfeit signatures. Preliminary results show that the percentage of identification of the signature biometric system developed using Feature Extraction with signature shapes on texture patterns got an average similarity rate of: 92.74%, and signature shapes on shape patterns attained an average similarity rate of: 79.20%. Therefore, the texture extraction pattern can detect the degree of similarity between the original signature and the dummy signature with a higher percentage value compared to the shape extraction pattern. The proposed method can produce better accuracy.

Keywords: Texture Patterns, K-Means Clustering, Signature, shape extraction, texture extraction

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1. Introduction

Measurement and calculation of body parts related to human characteristics (biometrics) which consists of images of fingerprints, palm prints, faces, retinas are the parts used in identification, where the most common measurements are signatures[1],[2],[3] which can be used as a security system [4],[5]. Based on the use of a biometric system, a signature is a very important part of use such as in the field of electronic commerce, electronic document management and others [6],[7] which are grouped into two types, namely offline signatures and online signatures [8].

According to (P. Singh, P. Verma, and N. Singh) in the automatic signature process comparing the Convolution Neural Networks and Support Vector Machine algorithms using the features of GLCM, the SVM model can distinguish between original and fake signatures and can speed up results. and minimize others being able to forge signatures. In 2019 (Y. Inan and B. Sekeroglu) researched minimizing signature fraud using the Backpropagation Neural Network (BPNN) method, by collecting 27 people's signatures and the accuracy of the system tested reached 86% [4]. In 2021 (Y. Zhou, J. Zheng, H. Hu, and Y. Wang) in research on verifying signatures using Support Vector Machine (SVM) and DynamicTime Warping (DTW), the results show that

using training examples that do not the same in conducting research on existing data sets, the false acceptance rate and false rejection rate obtained are better than the results of offline or online verification [9],[10].

In 2021 (C. Lokare, R. Patil, S. Rane, D. Kathirasen, and Y. Mistry) in verifying signatures using gaussian filtering techniques, feature extraction techniques Gray Level Co-Occurrence Matrix, principle component analysis, and kernel principal component analysis associated with various machine learning algorithms. Comparing the accuracy of datasets on various machine learning algorithms. After the training dataset the lowest accuracy achieved is 56.66% for the Naive Bayes algorithm. The highest accuracy achieved was 82% for K-Nearest Neighbor (KNN) and 81.66% for Random Forest using principle components and kernel principal components from the dataset [11]. According to (H. Mu'jizah and D. C. R. Novitasari) SVM-form feature extraction using the Linear Kernel shows the best performance with an accuracy of 98.44%, a sensitivity of 100%, and a specificity of 97.50% [12].

Manual verification of a signature will remain a challenging problem with counterfeiting, where counterfeiters have access to the user's signature and the practice of imitating it [13],[14], There are three types of forgery namely random forgery, simple forgery and

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steep forgery, forgery of the accuracy of the signature according to (N.Varish) proposed a better verification network that adopts user-independent signature verification resulting in the highest FRR discrimination rate of 10.5%, FAR of 2.06%, and ACC of 96.33% for a mixture of two languages [15].

Grouping an image in deciding a problem, at this time is very important for researchers in solving a problem. There are a number of limitations in the data acquisition phase. The first is signature length [16]. If the data analysis signature is too long it may be difficult for the recognition system to identify unique data points [17].

One good method in the extraction process is the Gray level co-occurrence matrix (GLCM). GLCM is composed by a two-dimensional histogram using gray level for pixel pairs and separated by spatial relationships and textured volumetric data classification [18],[19] extracted for texture information of an image [20]. The features obtained are extracted into different classifiers [21]. The purpose of this study is to produce a method that can identify and classify the suitability of a signature using shape and texture patterns.

In this research, verification of original and fake signatures was developed, using texture pattern extraction with statistical methods, namely GLCM and shapes with metrix and eccentricity parameters. The aim of this study was also to detect the degree of similarity of signatures using the K-Means Clustering algorithm. Signatures were obtained as many as 50 samples by direct signature and scanned to get a signature image using an Epson L3210 printer. Image saved in Jpg format

2. Research Method

The methodology used in this study discusses how to detect between signatures which is done manually. The aim of this study is to first carry out segmentation and the next step is to extract texture [22] and shape by applying the gray level co-occurrence matrix (GLCM) method to find metric values, centrality, contrast, correlation, energy and homogeneity [23] to obtain the value of pattern form and texture. A flow chart illustrating the method for developing signature image processing using the proposed shape and texture patterns can be presented in Figure 1.

2.1 Image Acquisition

Signature images are obtained from the results of a collection of signatures carried out manually / offline as many as 50 samples and will be compared with fake signatures (copy results) to make it easier to take pictures, scan the data using the Epson L3201 printer and produce an image as shown in Table.1

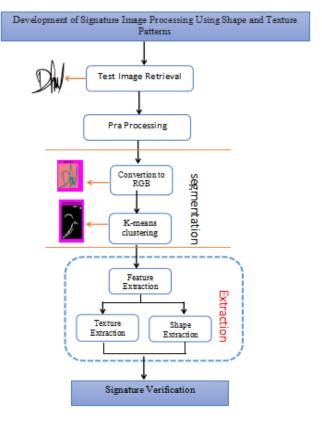


Figure .1. Flowchart of the Proposed Method

Table 1. Example Of Signature



2.2 Segmentation

This process is carried out by segmenting grayscale images with the k-means clustering method. The K-Means algorithm is used to partition the two cluster regions. The K-Means Clustering method utilizes the intensity/gray level of the image, this image intensity is the basis for image clustering. Different intensities will be grouped into different clusters. The clusters formed will be represented by a certain color so that each cluster can be visualized. Segmentation results can be presented in Figure 2.

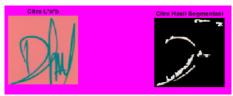


Figure.2. Segmentation Result

2.3 Extraction Characteristic

The method for analyzing feature extraction/texture uses the GLCM method. Gray Level Co-occurrence is a matrix that shows the frequency of the existence of a pair of two pixels at a certain intensity in an image. Gray Level Co-occurrence Matrices (GLCM) use texture calculations of the second order. Texture measurement in the first order uses statistical calculations based on the original image pixel value alone, such as variance and does not pay attention to the pixel adjacency relationship. on fig. 3 there are four angles of 0, 45, 90, 135 degrees [24] each for metric, eccentricity, energy, correlation, contrast and homogeneity features [25] can be presented in Figure 3.

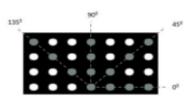


Fig. 3. Example of the GLCM Direction for an Angle $0^{\circ},45^{\circ},90^{\circ}$, 135°

The Gray Level Co-occurrence Matrix (GLCM) method is one of the second order extraction of texture statistical features. The second order extraction shows the statistical relationship between the 2 pixels. To get GLCM features, you can use contrast, correlation, energy, homogeneity, and entropy. The GLCM equation is presented as follows:

1. Contrast can be calculated with the following question:

$$\sum_{k} k^{2} \left[\sum_{s} \sum_{r} B(s, r) \right] \tag{1}$$

2. Correlation can be calculated with the following question:

$$\sum_{s,r} \frac{(s-\mu s)(r-\mu r)B(s,r)}{\sigma s \sigma r}$$
 (2)

3. Energy can be calculated with the following question:

$$\sum_{s,r} B(s,r)^2 \tag{3}$$

4. Homogeneity can be calculated with the following question:

$$\sum_{s,r} \underline{B(s,r)}_{1+|s-r|} \tag{4}$$

5. Entropy can be calculated with the following question

$$\sum_{s,r} B((s,r) \log B(s,r) \tag{5}$$

2.4 Shape Extraction

Shape features provide an effective alternative for describing an object and for reducing the amount of information stored [26]. Shape is one of the characteristics that can be extracted from an object to distinguish that object from other objects. In extracting shape features, using values from metrics and eccentricity [27].

3. Result and Discussion

The result of this study is to obtain an accuracy value for the level of similarity using feature extraction. This test was carried out on the Matlab tool by taking a sample of 50 signature images using feature extraction based on texture using GLCM and shape extraction. The steps used are prepossessing, segmentation, and feature extraction.

3.1 Preprocessing and Segmentation

Furthermore, the segmentation stage is carried out by separating the foreground from the background using the k-means clustering method. The clustering process is carried out by converting the image color space which was originally RGB to L*a*b. Furthermore, the a and b components of the L*a*b image are used as input values in the K-Means algorithm. Fig.2 shows the results of prepossessing and segmentation.

3.2 Texture and Shape Extraction

Feature extraction is used to determine the degree of similarity of signatures at the classification stage. In this study feature extraction uses shape patterns and texture patterns which will later be used as a comparison at the image testing stage. The Texture Pattern uses contrast, correlation, energy, homogeneity and form patterns using the values of metric and eccentricity. The results of image processing on texture patterns and shapes are presented in Table II, Table III, Table IV and Table V.

Table II. Test Results In Original Signature Texture Pattern.

			Texture	Pattern		
No	Original Signature	Cont rast	Correl ation	Ener gy	Hom ogen ety	Total
1.	Deni	3.26	0.83	0.44	0.89	5.43
2.	Febri	2.56	0.87	0.47	0.92	4.81
3.	Firdaus	1.15	0.71	0.87	0.97	3.69

4.	Arlis	0.79	0.72	0.89	0.97	3.38
5.	Hadi	2.27	0.82	0.64	0.93	4.66
6.	Hezi	1.54	0.75	0.77	0.94	4.01
7.	Husna	2.51	0.72	0.64	0.90	4.77
8.	Ikhlas	2.51	0.89	0.46	0.94	4.80
9.	Masri	1.97	0.79	0.66	0.92	4.34
10.	Nadya	2.05	0.78	0.70	0.93	4.47
		Total				44.36

Table III.	Test Results	In Fake	Signature	Texture	Patterns
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			Texture I	Pattern		
No	Fake	Contr	Correla	Ener	Hom	Total
140	Signature	ast	tion	gy	ogen	Total
					ety	
1.	Deri	3.08	0.76	0.57	0.90	5.31
2.	Febri	1.63	0.82	0.71	0.93	4.09
3.	Nur	0.79	0.78	0.89	0.98	3.45
4.	Arlis	0.35	0.73	0.96	0.99	3.02
5.	Hadi	2.11	0.78	0.70	0.94	4.53
6.	Hezi	1.26	0.78	0.83	0.96	3.83
7.	Husna	1.88	0.76	0.75	0.94	4.33
8.	Ikhlas	2.15	0.88	0.56	0.95	4.55
9.	Masri	1.58	0.77	0.77	0.94	4.05
10.	Nadya	1.57	0.69	0.82	0.95	4.03
		Tot	al			4.12

Table IV. Test Results In The Original Signature Form Pattern

NO	Original	Text	ure Pattern	Total
NO	Signature	Metric	Eccentricity	Totai
1	Deri	0.36	0.86	1.22
2	Febri	0.34	0.72	1.06
3	Firdaus	0.36	0.94	1.30
4	Arlis	0.34	0.99	1.33
5	Hadi	0.27	0.96	1.23
6	Hezi	0.43	0.98	1.40
7	Husna	0.39	0.87	1.26
8	Ikhlas	0.63	0.97	1.59
9	Masri	0.13	0.94	1.07
10	Nadya	0.54	0.97	1.51
	T	'otal		12.98

Table V. Test Results In Patterns Of Typical Signature Shapes.

No	E-1 Cit	Tex	— Total	
NO	Fake Signature	Metric	Eccentricity	- Totai
1	Deri	0.09	0.87	0.96
2	Febri	0.08	0.67	0.75
3	Nur	0.18	0.99	1.16
4	Arlis	0.04	0.96	1.00
5	Hadi	0.27	0.90	1.17
6	Hezi	0.27	0.99	1.26
7	Husna	0.21	0.97	1.18
8	Ikhlas	0.04	0.76	0.81
9	Masri	0.11	0.72	0.83
10	Nadya	0.12	0.95	1.07
	,	Total		10.19

Feature extraction for texture patterns uses 4 parameters namely Contras, Correlation, Energy, and Homogeneity, the results of the GLCM example are presented in Table II and Table III. in signature detection. For shape patterns using 2 parameters, namely metric and eccentricity, the results of examples of shape patterns are presented in Table IV and Table V for signature detection.

3.3 Classification

From the results of feature extraction, they are grouped into 2 parts, namely texture patterns and shape patterns. In this study, calculations were carried out on each of the existing parameters. Based on Table VI, it can be seen by testing a signature sample of 10 images, it is obtained that the level of similarity between the original and the imitation reaches an average of 92.74%. Table VII shows the level of accuracy of the similarity of original and fake signatures of 79.20%, where the shape pattern is lower in detection compared to the texture pattern in detecting original signatures and fake signatures.

Table Vi. Results Percentage Level Of Similarity In The Texture Pattern Between The Original Signature And Fake Signature

NI.	C:	Val	ue	Percentage
No	Signature	Original	Fake	Similarity(%)
1	Deri	5.43	5.31	97.79
2	Febri	4.81	4.09	85.03
3	Nur	3.69	3.45	93.50
4	Arlis	3.38	3.02	89.35
5	Hadi	4.66	4.53	97.21
6	Hezi	4.01	3.83	95.51
7	Husna	4.77	4.33	90.78
8	Ikhlas	4.80	4.55	94.79
9	Masri	4.34	4.05	93.32
10	Nadya	4.47	4.03	90.16
	Α	verage		92.74

From testing 10 images, the results are shown in Table VI. From the test results it was found that the accuracy value of signature recognition was 92.74% using a texture pattern.

Table VII. Percentage Results

No	α	Value		Percentage
	Signature -	Original	Fake	Similarity (%)
1	Deri	1.22	0.96	78.69
2	Febri	1.06	0.75	70.75
3	Nur	1.3	1.16	89.23
4	Arlis	1.33	1	75.19
5	Hadi	1.23	1.17	95.12
6	Hezi	1.4	1.26	90.00
7	Husna	1.26	1.18	93.65
8	Ikhlas	1.59	0.81	50.94
9	Masri	1.07	0.83	77.57
10	Nadya	1.51	1.07	70.86
	Ave	erage		79.20

From testing 10 images, the results are shown in Table VII. From the test results, it was found that the signature recognition accuracy value was 79.20% using a shape pattern.

4. Conclusion

This research in identifying the accuracy of the types of original signatures and fake signatures by using feature extraction, namely the texture of patterns and shapes, the results obtained: very high accuracy. The percentage of signature shape identification results using texture

patterns with an average similarity level of: 92.74%, the results of this study indicate a very high accuracy. The percentage of signature identification results uses a shape pattern with an average similarity level of: 79.20%. The proposed method obtains better accuracy. Therefore, the texture extraction pattern can identifying he accuracy of the types of original signatures and fake signatures with a higher percentage value compared to the shape extraction pattern.

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