SIGNATURE RECOGNITION USING INVARIANT MOMENT METHOD AND RESTRICTED BOLTZMANN MACHINE

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ABSTRACT

Signature recognition research aims to be able to do the application of the Moment Invariant feature extraction method and the classification method that is the Restricted Boltzmann Machine and find out the level of accuracy in signature recognition. Before entering the feature extraction stage, there are Preprocessing processes consisting of Cropping, Resize, RGB Value, Grayscale, Image Binaryisation, and image extraction with invariant moments. Then in the next stage the training and testing process is carried out using the Restricted Boltzmann Machine method. In this study as many as 150 signatures from 10 respondents where each respondent was taken 15 signature data. For training using 120 signatures from which 12 respondents were taken from each respondent, then in the test data tested as many as 30 signatures obtained from each respondent were 3 signatures. Based on the results of tests conducted on training data and test data using the Rule Based method in testing accuracy, the test data obtained by 90%.

Keyword **:** signature, machine learning, moment invariant method, Restricted Boltzmann Machine

1. INTRODUCTION

Signature or in English the signature which also comes from the Latin word siganre which means "sign" or initial is handwritten or inked ink from the hand, sometimes given a certain writing style from someone's name or related sign written on the document as proof of identity and will [1]. Examples of each person's signature are identical but not the same, meaning that a person's signature changes frequently over time. Changes in position, size or signature pressure factor. In fact, these changes are according to time, age, habits and certain mental states [2].

Therefore it is necessary to do automatic signature recognition. Signature recognition can be done using image processing and machine learning methods. The success of signature recognition is influenced by the feature extraction process carried out and the selection of machine learning methods to recognize images.

2. CONTENT OF RESEARCH

2.1 Related work

Based on similar studies previously conducted by Ainun Jariah, et al. Recognition of signature patterns using the moment invariant method and radial nerve base function (RBF) methods can recognize signature patterns with an accuracy of 80%. The moment invariant method is used to extract the signature image into an input vector that represents each signature image [3].

Related research conducted by Susilawati under the title Restricted Boltzmann Machines (RBM) Algorithm for number handwriting recognition, the results obtained in the determination of learning rate parameters, momentum and activation functions in the RBM network greatly affect the performance of RBM. From the results of the study the learning rate of 0.05 with momentum 0.7 has the highest performance, being able to recognize the testing dataset of 93.42% [4].

Based on the problems that have been presented previously, the solution that can be used to overcome this problem is to be able to recognize signatures with the moment invariant method as extraction and Restricted Boltzmann Machines (RBM) as their classification. Then you can see the accuracy results obtained.

2.2 Digital Image

Digital imagery is a two-dimensional image that can be displayed on a computer screen as a set or discrete digital value called pixel / picture elements. In a mathematical review, the image is a continuous function of the intensity of light in the two-dimensional plane [5]. Photos are examples of two-dimensional images that can be easily processed. Each photo in the form of a digital image can be processed using certain software. In this research, image processing is carried out including cropping, RGB value extraction, grayscale, and feature extraction.

2.3 Entering Data

Input data in this study that will be processed by RBM is to take a signature image on paper media, then the scanning process, the results of the scanned signature images are saved in the form of a .jpg file. In this analysis the number taken from 10 correspondents amounted to 150 signatures, each respondent took 15 signatures. The following are examples of signature images that have been collected from correspondents who have a size of 1000x750 pixels like Figure 2.1 below.

Figure 1. Entering Data

The data will be divided into training data and test data with a ratio of 80:20 so that there are 12 data as training data and 3 data as test data.

2.4 Cropping

At the stage of cropping the signature image with a size of 1000x750 pixels then set the width and height of the signature image and then the image will be resized with a size of 200x200 pixels

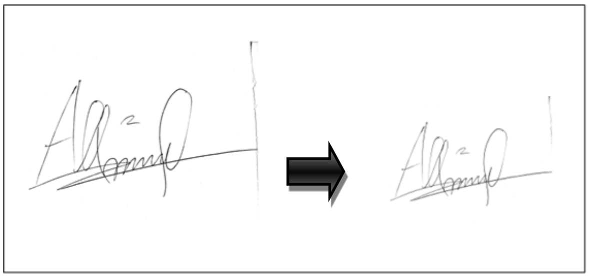


Figure 2 Cropping Image

The picture above has been resized with a size of 200x200pixel.

2.5 Extraction of the RGB Value

As it is known that each colored image has a different RGB color index value. The difference in the percentage of the RGB index makes an image red, green, blue. The higher the color index, the brighter the image will be. And vice versa, the smaller the color index value, the darker the image will be. In this RGB stage, then the signature image is written in the form of an RGB (Red Green Blue) color matrix in order to be able to show the values generated from each process. The input image is 200x200 pixels resized, the matrix can be viewed and symbolized by RGB.

2.6 Grayscale

Grayscale is used to simplify the advanced process by simplifying the values in the image matrix to the range of white and gray values. Grayscale process is carried out to change pixel intentions. This process produces images with binary colors, namely black and white [1]. In grayscale the intensity value can be uniformed with a function. The following is the formula for the conversion of color images (RGB) into grayscale intensity values [7].

$$G = wR.Red + wG.Green + wB.Blue \quad (2.6.1)$$

The values of wR, wG, and wB are the weights for Red, Green and Blue color elements according to the definition of weights for the conversion of color images to gray scale where wR = 0.299, wG = 0.587 and wB = 0.114. The obtained grayscale value will replace the RGB value for each image pixel. The results of the matrix calculated from the grayscale equation change the image as can be seen in Figure 3 below.

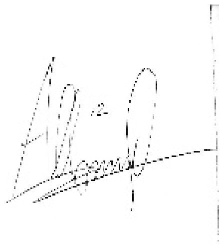


Figure 3 Grayscale Image

2.7 Invariant Moment Image Extraction

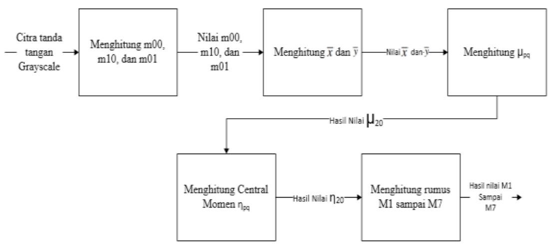


Figure 4 Flow Invariant Moment

Feature extraction is the stage of extracting features / information from objects in the image that you want to be recognized / distinguished from other objects. The extracted traits are then used as input parameters / values to distinguish between objects with each other at the identification / classification stage. This invariant moment is used as an image extraction feature. Moments can provide the characteristics of an object that uniquely represents its shape. The introduction of invariant forms is done by classification in multi dimensional invariant moment space photos. Several techniques have been developed about the decrease in invariant features of object moments for object representation and recognition. This technique is distinguished by the definition of the moment. Such as the type of data being exploited and methods for deriving invariant values from moment images [8].

Invariant Moment there are 7 form descriptor values, which are calculated from the central moment through three degrees that are free of translation, scale and direction of the object [8]. Invariant translation is achieved by calculating the normalized moment with the center of gravity so that the center of the distribution period is at the center moment. The size invariant moment is derived from algebraic invariant but this moment can be shown from the result of simplifying the moment size. From the order values of two and three normalized central moments, 7 invariant moments can be calculated which are also rotation free. Moments are used to form invariant moments that are defined continuously but for practical implementation, moments are calculated discrete.

The first step is to calculate the central moment according to certain p and q parameters. If you see the formula for the first feature:

$$M_1 = (\eta_{20} + \eta_{02}) \qquad (2.4.1)$$

To be able to calculate the formula above first to calculate m00, m01, and m10 using the formula below:

$$m_{pq} = \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=M-1} (x)^p.(y)^q \, f(x.y)$$

In the formula above enter the parameter values m00, m01 and m01 then calculate by entering the values p = 0 and q = 0. After the values m00, m10, m01 are known the next step is to calculate the values of $\bar{x}$ and $\bar{y}$ with the formula below:

$$\bar{x} = \frac{m_{10}}{m_{00}} \; and \; \bar{y} = \frac{m_{01}}{m_{00}}$$

Then after $\bar{x}$ and $\bar{y}$ are obtained, then calculate μ_{pq} in the formula below:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p.(y - \bar{y})^q \, f(x.y)$$

The p and q values used are 2 and 0, after μ_{pq} has been obtained then γ and η_{pq} can be calculated. With the formula below:

γ = [(p + q) / 2] +1

$$\gamma = \left[\frac{p+q}{2}\right] + 1 \qquad \eta_{pq} = \frac{\mu_{pq}}{\mu^{\gamma}{}_{00}}$$

Then do the calculation in the same way but by using p = 0 and q = 2. After knowing how to calculate central moment, the next calculation is to calculate feature moments M1 through M7 by using the following formula:

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta^2{}_{1\,1}$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{03} - 3\eta_{21})^2$$

$$\phi_4 = (\eta_{30} - \eta_{12})^2 - (\eta_{03} + \eta_{21})^2$$

$$\phi_5 = (3\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})x[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 + 4n_{1\,1}(\eta_{30} - \eta_{12})(\eta_{21} + \eta_{03})$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})x\,[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{30})^2]$$

By doing the same thing for the entire signature image. The feature extraction results will be used as input data in the next algorithm, the Restricted Boltzmann Machine algorithm.

2.8 Restricted Boltzmann Machine

The Restricted Boltzmann Machine is a stochastic neural network (a neural network which means it has neuron units in the form of binary activations that depend on interconnected neurons, whereas stochastic means activation that has a probabilistic element) which consists of two binary units ie the visible layer is a state state which will be observed and hidden layer are feature detectors and unit bias [9]. Furthermore, each visible unit is connected to all hidden units which are represented by an array of weights, so that each hidden unit is also connected to all visible units and bias units are connected to all visble units and all hidden units. To facilitate the learning process, the network is limited so that no visible units are connected to other visible units and hidden units are connected to other hidden units.

In training RBM, data samples are used as input for RBM through visible neurons, and then the sample network goes back and forth between visible and hidden neurons. The aim of the training is to study the connection of weights to the visible or hidden and the biased activation of neurons so that the RBM learns to reconstruct input data during the phase in which the visible neuron samples from hidden neurons. Each sampling process basically consists of multiplying matrices between a set of training samples and a weight matrix, followed by the function of neuron activation, the truncated exponential distribution (TED) function. Sampling between hidden and visible layers is followed by parameter modifications (controlled by the learning rate) and repeated for each group of data in the training set, and for as many states as needed to achieve convergence.

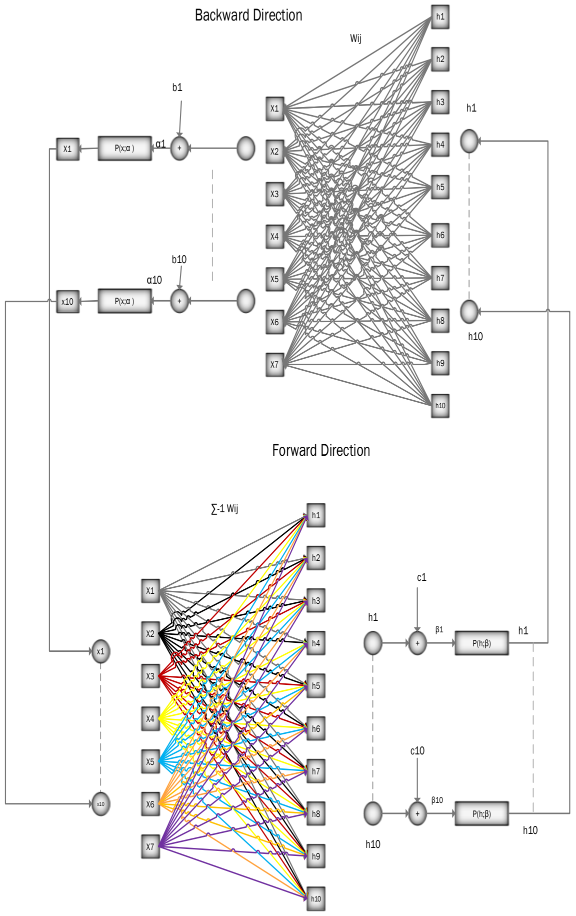


Figure 5. Restricted Boltzmann Machine Flow

The configuration of visible units (x) and hidden units (h) has energy[9]. Ditunjukkan pada persamaan berikut:

$$E(x, h;\ \Lambda) = -x'b - c'h - x'Wh \qquad (2.8.1)$$

Where Λ is the parameter set of RBM {b, c, W}, b is bias for visible, then c is bias for hidden, and W is the weight between visible unit and hidden unit.

The visible unit is initialized and updated using the following equation, where to find the value of x where the value of h (hidden) is set with probability:

$$p(x|h;\Lambda) = \prod_{i=1}^{N} C\,(\alpha_i) e^{\alpha_i x_i} = C\,(\alpha) e^{\alpha' x} \quad (2.8.2)$$

Where α is obtained from the formula below:

$$\alpha = b + Wh \qquad (2.8.3)$$

Then C (α) is a TED-TED function

$$C\,(\alpha) = \left(\frac{\alpha}{e^{\alpha}-1}\right) \qquad (2.8.4)$$

The hidden unit is initialized and derparui using the following equation, where to find h with the value x, it is set with the following probabilities:

$$p(h|x;\Lambda) = \prod_{j=1}^{M} C\,(\beta_j) e^{\beta_i h_i} = C\,(\beta) e^{\beta' h} \quad (2.8.5)$$

Where β is obtained from the formula below:

$$\beta = c + W'x \qquad (2.8.6)$$

2.8.1 Steps RBM

At the classification stage, there are several parameters that need attention:

a. Determine the number of visible nodes used in the RBM system, in this case the number of visible nodes is 7 nodes because it follows the amount of feature data generated from the moment invariant algorithm.
b. Determine the number of hidden nodes used in the RBM system, in this case the number of hidden nodes is 10 nodes because 10 values are needed to get the best value from various experiments that I conducted.
c. Determine the learning ratio used during the training phase, in this case the value of the learning ratio is 0.01. The lower the value, the training process will require more time, but the higher the value, the training process will not be able to find a value that is expected to be better
d. Determine the number of iterations used during the training phase, Assuming in this case the number of iterations is 70.
e. Steps for using the Restricted Boltzmann Machine algorithm:
   1. Go through the process of finding the best weight and bias values with a small random value
   2. Set learning rate (ε) and maximum epoch
   3. Perform the steps below during (Epoch <Maximum Epoch)
   4. Perform the steps below for (dataset <maximum)
   5. Positive phase (taking data and samples from hidden units)
      a. Calculate the activation energy, probability and state of the hidden unit using equation 2.8.2
      b. Calculate positive associative
         *Pos_Asso = (data) ^ T * P (h)*
         Positive associations are obtained from multiplying the matrix of sample data that is transmitted from visible neurons with the probabilities resulting from step 5a.
   6. Negative Phase (reconstruct visible units and sample data from hidden units)
      a. Calculate the activation energy and the probability of the visible unit using equation 2.8.5
      b. Perform step 5.a to update hidden units
      c. Calculate negative associative

$$Neg\_Asso = (data)^T * P(h) \qquad (2.8.8)$$

Associative negatives are obtained from the data matrix (the probability of the visible unit obtained from step 6.a) which is collapsed with the probability of the hidden unit resulting from step 6.b

d. Parameter Update

a. Update bobot

$$W_{i\,j} = W_{i\,j} + \Delta W_{jk} \qquad (2.8.9)$$

$$\Delta W_{ij} = \varepsilon \left(Pos_{Asso} - Neg_{Asso}\right)$$

Where ε is the learning rate.

e. Calculate Error

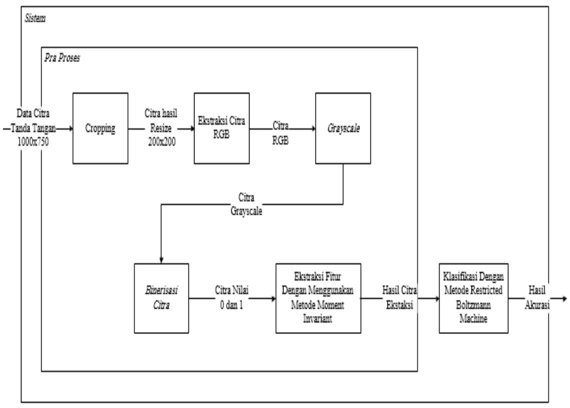
Error = $\frac{1}{2}\sum_{i=1}^{p}(Oi - ti)^2$ (2.8.10)

The error is calculated by reducing the Oi to the sample data and is not a visible probability resulting from the negative phase in step 6.c

2.9 Rule Based

Rule based method is a method of one of the decision support systems which has a knowledge base. The application of rule based is done by testing the rules one by one in a certain order. To test rule based each rule will evaluate whether the condition is true or false. If the condition of the data being tested is correct, then proceed to the next rule being tested. Conversely, if the data condition is wrong then the rule is not saved and the next rule is tested. This process will be repeated until the entire rule base is tested under various conditions.

2.9 Gambaran Umum Sistem



Gambar 6 Alur Umum Sistem

In the diagram above, the initial process is to enter the signature image data into the system. The next step through the image processing stage includes cropping, RGB values, grayscale, and feature extraction with invariant moments. The results of image processing will get 7 values from each image obtained from its feature extraction, then reprocessed at the classification stage with the RBM method both training and testing. This is the case with rule based but not through the training stage. The results of the testing phase are in the form of an accurate classification of signature recognition.

2.10 Signature Image Processing

In processing the image, several processes are carried out so that the input image can be used at the classification stage using the Restricted Boltzmann Machine (RBM) method. Following is the description of the image processing that is carried out in accordance with the system flow that is made.

1. Cropping

The 1000x750piksel signature image data that has been scanned then needs to be uniformed to a certain size so that the system can consistently read the image. In this study the image in the crop according to size and resized to a predetermined size.

2. RGB Value

In the process of RGB values (red, green, blue), each colored image has a variety of RGB color index values. In this RGB stage, then the signature image is written in the form of an RGB (Red Green Blue) color matrix in order to be able to show the values generated from each process.

3. Grayscale

Grayscale image process, in this process the results of the previous RGB value will be processed to the Grayscale stage which will produce an image with a color range from 0 to 255 which is a gray scale.

4. Image Binaryzation

The next step in image processing is tresholding. This process is carried out on grayscale images. The treshold method used in this study is simple treshold. The end result of this process is a black and white image with a value range of 0 and 1.

5. Feature Extraction (*moment invariant*)

The result of this process is in the form of 7 binary number values in each image which will be used as input data at the classification stage using the Restricted Boltzmann Machine (RBM) method.

2.11 Accuracy Testing

Testing accuracy in this study will be calculated the value of the accuracy or suitability of the signature recognition system results in detecting the respondent's signature. In this test the training parameters used are the same and the resulting accuracy of RBM testing and rule base are as follows.

Table 1 Test Data Accuracy

Name	Highest Output	Detected as	True / False
'ACEP',	0.6774	ACEP	True
'ACEP',	0.6774	ACEP	True
'ACEP',	0.7245	ACEP	True
'ARI',	0.68	ARI	True
'ARI',	0.68	ARI	True
'ARI',	0.7245	ARI	True
'ERVAN',	0.6826	ERVAN	True
'ERVAN',	0.6826	ERVAN	True
'ERVAN',	0.6826	ERVAN	True
'FADLI',	0.7929	FADLI	True

'FADLI',	0.7929	FADLI	True
'FADLI',	0.7082	FADLI	True
'FAJAR',	0.68	FAJAR	True
'FAJAR',	0.68	FAJAR	True
'FAJAR',	0.7245	FADLI	False
'IQRAM',	0.68	IQRAM	True
'IQRAM',	0.68	IQRAM	True
'IQRAM',	0.68	IQRAM	True
'MAARIF',	0.6696	MAARIF	True
'MAARIF',	0.6696	MAARIF	True
'MAARIF',	0.6696	MAARIF	True
'OKI',	0.7881	OKI	True
'OKI',	0.7881	OKI	True
'OKI',	0.7881	OKI	True
'RIZKI',	0.7463	RIZKI	True
'RIZKI',	0.7463	RIZKI	True
'RIZKI',	0.7463	RIZKI	True
'SAEFUL',	0.6455	OKI	False
'SAEFUL',	0.5269	OKI	False
'SAEFUL',	0.4928	SAEFUL	True

3.1 Conclusion

Based on the results of the study there were 150 signature images of 10 respondents, from each respondent having 15 signatures. For training data as many as 120 signatures, from each respondent 12 signatures were taken, then the remainder was used as test data of 30 signature images obtained from each respondent namely 3 signature images. From the tests that have been carried out with the RBM method the signature image produces an accuracy with an average accuracy for all features tested by the RBM which is quite good at 90%. The following is an explanation of the cause of the accuracy value produced by the system, its accuracy is very good, namely the training data and test data taken in the pattern are selected for the same uniformity and determined in size, then in [5] the process of calculating learning ratio or learning rate, then the number of iterations and hidden nodes values right. Therefore the accuracy obtained is very good.

It can be concluded that the accuracy value of the RBM method classification is very good, and can still be improved for use in the signature recognition system, but by developing or adding a feature process in image processing and reproducing the training data in order to classify it better.

3.2 Suggestion

Based on the results of tests that have been carried out, the expected suggestions are as follows.

1. Adding signature image data in training data and test data, to obtain better results in recognizing the signatures of each respondent.
2. Adding features that do not yet exist in this study to complete the signature recognition system to get good results in recognizing signatures.

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