Signature Identification with Gray Level Co-ccurrence Matrix and Extreme Learning Machine

Roseri Sinaga[1] ,Tulus[1], Erna Budhiarti[1] and A M H Pardede[2]
{roseri.sinaga@student.usu.ac.id}

[1]Department of computer science, Universitas Sumatera Utara, Medan, Indonesia
[2]STMIK Kaputama, Jl. Veteran No. 4A-9A, Binjai, Sumatera Utara, Indonesia

Abstract. Identification of the signature is a process used to identify the signature of a person. The Identification of the signature can be divided into two parts. Identification signature off-line and the Identification of signatures on-line. Forgery of signatures is still common in data security systems. So, we need an approach to improve the accuracy of signature recognition on Extreme Learning Machine algorithms. This study use a gray level co - occurrence matrix (GLCM) for feature extraction and modification of Extreme Learning Machine (ELM) for recognition. ELM is a new learning method of a neural network or commonly called the Single Hidden Layer Feed forward Neural Networks (SLFNs). From the experiments the identification of the signature using the gray level co-occurrence matrix (GLCM) and signature classification using extreme learning machine with the addition of elementary transformations showed that the accuracy on identification of the signature is 43% using of features contrast, correlation, energy and homogeneity, while using just ELM accuracy is 36%.

Keywords: Signature Identification, Extreme Learning Machine, Gray Level Co-occurrence Matrix.

1 Introduction

Signature, fingerprint, voice, and handwriting are some that have been used to verify the person's identity. Among all, the signatures have a fundamental advantage that it is the most frequently used in identifying a person in everyday operations such as automated banking transactions, electronic funds transfer, document analysis, and control access. However, the forging of signaturesfrequently occurs among other things due to the unfavorable identification system

The signature identification system can be divided into two parts. The off-linesignature identification and on-line signature identification. The off-line signature identification takes an image of the signature as an input that will be used later in the process. While the input to the on-line signature identification is obtained directly from the digitizer that produces the dynamic values, such as coordinate values, long a signature and signature speed. This study uses Gray Level Co-occurrence Matrix for extract features texture and Extreme learning machine as classification. Gray Level Co-occurrence Matrix (GLCM) was first introduced by

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Haralick to extract texture featuresand perform image analysis based on the statistical distribution of pixel intensity [1]. Extreme Learning Machine (ELM) is a new learning method of the neural network. This method was first introduced by Huang. ELM is a feed forward neural network with a single hidden layer or commonly called the Single Hidden Layer Feed forward Neural Networks (SLFNs) ELM learning method created to overcome the weaknesses of the neural network learning, especially in terms of speed [2]

Research classification using ELM has a lot to do. Among the researches, onewas conducted by FitriatiDesti (2016). She compared the performance of CNN Lenet 5 and Extreme Learning Machine on image recognition handwritten numbers, the results showed that CNN Lenet 5 wasexcellentsince it was able to recognize handwriting pattern number with a confidence level of 78.14% for 98.04% of primary data and secondary data, while ELM achieved 30% accuracy rate. However, in this case the ELM was excellentin terms of computing time reaches 0.00078 milliseconds [3]

Based on the research can be concluded that research using Extreme Learning Machine haspoor accuracy in recognizing the image of handwritten numbers. Therefore, in this study the researchers tried to re-examine by modifying the algorithms that are expected to improve the accuracy of the signature image recognition.

2. Previous Research

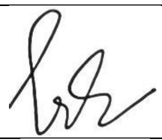
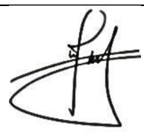
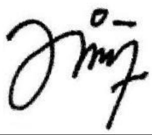
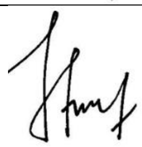
Research using Gray Level Co-occurrence Matrix for extracting texture features of the image has a lot to do, including research by Amalia, I (2014) elaborated on the signature recognition using the Gray Level Co-occurrence Matrix (GLCM) as the algorithm to extract features and Probabilistic Neural Network (PNN) to classify signatures. This study uses dissimilarity, Entropy and homogeneity. The extraction of features it will be input to the classification by using PNN. Each test data consists of 3 feature, measured proximity to three training data feature of the ten classes. These features are able to recognize the signature. Study showed that the average accuracy of PNN in performing signatures recognition was at 71%[4].

[5]compared the Extreme Learning Machine and Particle Swarm Optimization Extreme Learning Machine for forecasting total sales of goods in one minimarket in Bali. The results showed PSO method can be applied to the ELM method to optimize the number of hidden nodes. Particle Swarm Optimization Extreme Learning Machine is able to overcome one of the weaknesses of the methods ELM. The number of hidden nodes is determined by trial and error, so it can not be known how many hidden nodes the right to obtain an accurate forecasting results using ELM. Particle Swarm Optimization method to find the optimal number of hidden nodes. The results showed PSO method can be applied to the ELM method to optimize the number of hidden nodes. Mean Square Error (MSE) generated by PSO method is smaller than the ELM methods, ranging from 0.01161 to 0.01121 until ELM PSO method and ranged from 0.01419 to 0.01315 until ELM method. PSO method is able to optimize the number of hidden nodes of ELM method to predict the amount of sales of goods.

3. Data Used

The data used in this study is the signature of a digital image of the acquisition by using Epson L360 scanner which will be used for learning (learning dataset) and set of images for testing (Testing dataset) with image size 200 x 200 px and JPG format. Here is the signaturesdataset shown in table 3.1.

Table 3.1 Signatures dataset

Signatures	
1st Person	
2nd Person	
3rd Person	
4th Person	
5th Person	
6th Person	
7th Person	
8th Person	

9th Person	
10th Person	

4. Gray Level Co-Occurrence Matrix

GLCM is a matrix that is built using second-level histogram statistical texture features. The spatial dependence of gray level is calculated by 14 features of the co-occurrence matrix [6]. GLCM feature selection is based on the analysis of the test results accuracy for picking the best suitable for the identification of the signature. Once the image is converted into gray level images (grayscale), then the next step is feature extraction stage. Feature extraction is done to get the value that can represent the image. In this study, the method used for extraction of image features is the Gray Level Co-Occurrence Matrix (GLCM). Here is a calculation using a statistical features contrast, correlation, energy and homogeneity.[7].

1. Contrast
   contrast feature is used to calculate the different range ofgray degree in an image. The bigger difference in the gray degree of each pair of pixels, the higher the contrast value will be. Contrast is defined as follows in equation (4.1):
   $\text{Contrast} = \sum_x \sum_y (x-y)^2 \, P(x,y)$ ....(4.1)
2. Correlation
   The correlation feature shows the linear dependence of the grayness of the image. Here is the definition of correlation in equation (4.2):
   $$\text{Correlation} = \sum_x \sum_y \quad P(x,y) \left[\frac{(x-u_x)(y-u_y)}{\sqrt{\delta_x^2 \delta_y^2}} \right] \text{...(4.2)}$$
3. Energy
   Energy feature or angular second moment (ASM) states textural uniformity size of an image. Energy on the image will be valuable if the gray intensity is distributed constantly. Following the definition of energy in equation (4.3):
   $\text{Energy} = \sum_x \sum_y p(x,y)^2$................................ (4.3)
4. Homogeneity
   Homogeneity feature will calculate the variations ofgray degree from an image. Homogeneity will gain great value if the pair of elements in the matrix has a small gray level differences. Features homogeneity is defined as follows in equation (4.4):
   $\text{Homogeneity} = \sum_x \sum_y \frac{1}{1+(x-y)^2} \, P(x,y)$ ….... (4.4)

5. Extreme Learning Machine

Extreme Learning Machine (ELM)a new method of neural network.ELM was first introduced by Huang. ELM a feed forward neural network with a single hidden layer or commonly called the Single Hidden Layer Feed forward Neural Networks (SLFNs) ELM learning method created to overcome the weaknesses of neural network learning, especially in terms of speed.

In ELM inputrandomly parameters such as weight, hiddenand bias, so that the ELM has a fast learning speed and is capable of producing good generalization performance. Extreme learning machine is a learning algorithm that utilizes hidden architecture of Single-Layer Feed forward Networks (SLFNs). The essence of this method is to learn without iteration. So the learning process of this method is rapid (extreme).

5.1 Neural Networks with Elementary Transformations Extreme Learning Machine

Here are the steps to be taken to the learning process ELM with the addition Elementary Transformations .

Step 1: Initialize all weights and biases with small random numbers [-0.5, 0.5]

Step 2: Each unit of input xi (i = 1,2, ...n) receives the signal and forwards the signal to all units in the hidden layer.

Step 3: Counting each hidden layer unit Zj (j=1,2, ..., m) by summing the weighted input signals:

$$\sum_{i=1}^{N} \boldsymbol{\beta_i}\, \mathbf{g_i}(\mathbf{x_j}) = \sum_{i=1}^{N} \boldsymbol{\beta_i}\ \mathbf{(wi.xj+bi)} = \mathbf{0j} \ldots\ldots\ldots(5.1)$$

The next count output of hidden layer with sigmoid activation function:

$$\mathbf{g(x)} = \frac{\mathbf{1}}{\mathbf{1+e^{-net}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.2)$$

After getting the output of the hidden layer, it will proceed next step.

Step 4 : Establish order mxn matrix H, where m = lots of input units and n= many hidden units

$$H = \begin{pmatrix} g(b_{01} + x_1 * w_{11} & \cdots & g(b_{05} + x_1 * w_{14} \\ \vdots & \ddots & \vdots \\ g(b_{01} + x_4 * w_{41} & \cdots & g(b_{05} + x_4 * w_{44} \end{pmatrix} \ldots(5.3)$$

After getting matrix H with size m x n, Next is calculating the matrix H using Elementary Transformations . The operations performed on Elementary transformations is as follows:

i. Redeeming i th row by row to j, written and columns $B_{ij}K_{ij}$,
ii. Multiplying a row or column with numbers k (scalar) where k> 0.
iii. Adding on every element on the line to -i with scalar that is not equal to zero.

Next calculate$\mathbf{H}^{\dagger}$ which is a pseudo inverse matrix of the matrix H to be used in searching the weights between the hidden layer and output layer, as the following equation:

$$\mathbf{H}^{\dagger} = \mathbf{(H^T H)^{-1} H^T} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5.4)$$

Step 5 : Looking for a weight to the output layer (β) with the following equation: $\boldsymbol{\beta} = \mathbf{H}^{\dagger}\mathbf{t}$

Step 6: Calculating the value of output by using the equation:

$$y_{net} = \sum_{i=1}^{2} \beta ig(w_i . x + b_i) \ldots\ldots\ldots\ldots\ldots\ldots(5.5)$$

5.2 Calculation Extreme Learning Machine

Here is calculation of artificial neural network extreme learning machine, which requires input of objects in the image and label each image will represent the input matrix x and the target matrix$t$, For example, the training process will be conducted for the introduction of two types of objects. Extreme Learning Machine architecture that is used consists of 4 nodes in the input layer, 2 nodes in the hidden layer, and 2nodes in the output layer.

Input	**Target**
X_1=0.47;X_2= 0.67 ;X_3= 0.84 ;X_4= 0.95	t_1= [1,-1]
X_1=0.33;X_2= 0.76 ;X_3= 0.83 ;X_4= 0.95	t_2= [1,-1]
X_1=0.77;X_2= 0.68 ;X_3= 0.87 ;X_4= 0.95	t_3= [-1,1]
X_1=0.77 ;X_2=0.70 ;X_3= 0.85 ;X_4= 0.95	t_4= [-1,1]

Table 5.1 Value of inputs and Targets.

5.2.1 Training

Step 1: Initialize the weights connected to the unit hidden by the random number [-1, 1]

	Z_1	Z_2
x_1	w_{11}= 0.56	w_{12} =-0.99
x_2	w_{21} = - 0.2	w_{22} =0.77
x_3	w_{31}= -0.54	w_{32} = -0.23
x_4	w_{41} = 0.11	w_{42} = 0.12
b_0	b_{01}= 0.55	b_{02}= 0.43

Table 5.2 Weights and Biases

Step 2 : Each unit inputs x_i (i = 1,2, ...n) receives the signal and forwards the signal to all units in the hidden layer.

Step 3 Calculate the output of the unit hidden by the formula:

$z\_net_j = b_{0j} + \sum_{i=1}^{n} x_i w_{ij}$, For n = number of input values and j = 1,2

For j = 1

$$z\_net_1 = b_{01} + \sum_{i=1}^{4} x_i\, w_{i1}$$
$$= 1.05582$$

For j = 2

$$z\_net_2 = b_{02} + \sum_{i=1}^{4} x_i\, w_{i2}$$
$$= 0.4016$$

The results of the above calculation will be enabled using sigmoid activation function.

$$z_j = g\,(z\_net_j) = \frac{1}{1 + e^{-z\_netj}}, j = 1{,}2$$
$$z_1 = \frac{1}{1+e^{-\,1.05582}} = 0.347907$$
$$z_2 = \frac{1}{1+e^{-0.4016}} = 0.669248$$

Step 4 : Establish order nxm matrix H, where n = lots of input units and m = many hidden units

$$H = \begin{pmatrix} g(b_{01} + x_1 * w_{11} & \cdots & g(b_{05} + x_1 * w_{14} \\ \vdots & \ddots & \vdots \\ g(b_{01} + x_4 * w_{41} & \cdots & g(b_{05} + x_4 * w_{44} \end{pmatrix}$$

$$\mathbf{g(b_{01} + \ x_1 * w_{11})} = 0.773353$$
$$\mathbf{g(b_{02} + \ x_1 * w_{12})} = 0.278392$$
$$\mathbf{g(b_{01} + \ x_2 * w_{21})} = 0.779167$$
$$\mathbf{g(b_{02} + \ x_2 * w_{22})} = 0.449826$$
$$\mathbf{g(b_{01} + \ x_3 * w_{31})} = 0.910209$$
$$\mathbf{g(b_{02} + \ x_3 * w_{32})} = 0.062038$$
$$\mathbf{g(b_{01} + \ x_4 * w_{41})} = 0.9321$$
$$\mathbf{g(b_{02} + \ x_4 * w_{42})} = 0.073935$$

Next is to calculate the matrix H using Elementary Transformations . The operations

$$H= \begin{pmatrix} 0.773353 \quad 0.278392 \\ 0.7791670.449826 \\ 0.9102090.062038 \\ 0.9321 \quad 0.073935 \end{pmatrix}$$

Performed transformations redeeming elementary is the i-th row by row to j, written with.B_{ij} Line 3 is replaced with the line 2:

$$H=\begin{pmatrix} 0.773353 & 0.278392 \\ 0.910209 & 0.062038 \\ 0.779167 & 0.449826 \\ 0.9321 & 0.073935 \end{pmatrix}$$

After calculating the inversion of H^TH matrix, the next step is to calculate the MoorePenrose as follows:

$$\mathbf{H}^{\dagger} = (H^TH)^{-1}H^T$$
$$H^T=\begin{pmatrix} 0.773353 & 0.910209 & 0.779167 & 0.9321 \\ 0.278392 & 0.062038 & 0.449826 & 0.0739 \end{pmatrix}$$

$H^TH= \begin{pmatrix} 2.902466 & 0.691168 \\ 0.691168 & 0.289161 \end{pmatrix}$

Next determine the inverse matrix: H^TH

$$(H^TH)^{-1} = \frac{1}{\det H^{+}H}\begin{pmatrix} 0.289161 & -0.69117 \\ -0.69117 & 2.902466 \end{pmatrix}$$

$$= \frac{1}{ad-bc}\begin{pmatrix} 0.289161 & -0.69117 \\ -0.69117 & 2.902466 \end{pmatrix}$$

$$= \frac{1}{0.36156}\begin{pmatrix} 0.289161 & -0.69117 \\ -0.69117 & 2.902466 \end{pmatrix}$$

$$= \begin{pmatrix} 0.799744 & -1.91159 \\ -1.91159 & 8.027466 \end{pmatrix}$$

After calculating the inverse of a matrix then the next is to calculate the matrix MoorePenrose as follows:

$$\mathbf{H}^{\dagger} = (H^TH)^{-1}H^T$$

$$\mathbf{H}^{\dagger} = \begin{pmatrix} 0.086313 & 0.609342 & 0.23675 & 0.60410 \\ 0.75645 & -1.24194 & 2.121516 & -1.18828 \end{pmatrix}$$

Step 5 : Then calculate the matrix that weights between the hidden layer to the output layer to the formula: $\beta = \mathbf{H}^{\dagger}\,\mathbf{t}$

$$\mathbf{H}^{\dagger} = \begin{pmatrix} 0.086313 & 0.609342 & 0.23675 & 0.60410 \\ 0.75645 & -1.24194 & 2.121516 & -1.18828 \end{pmatrix}$$

$$\mathbf{t} = \begin{pmatrix} 1 & -1 \\ 1 & -1 \\ -1 & 1 \\ -1 & 1 \end{pmatrix}$$

$$\beta = \begin{pmatrix} 0.328297 & -0.3283 \\ -1.41872 & 1.418723 \end{pmatrix}$$

after obtaining the weight of the process of training the next step is to perform the testing process.

5.2.2 Testing

Once the training process is done, then the next step will be tested using the weights and biases resulting from the training process. The testing process requires input in the form of images and will give an output in the form of the object image recognition.

Features of images:

$x_1 = 0.33$ $x_2 = 0.76$ $x_3 = 0.83$ $x_4 = 0.95$

Calculating the value of output

$$y_{net} = \sum_{i=1}^{2} \beta i g(w_i . x + b_i)$$

$= \beta_1 g\ (w_1 * x + b_1) + \beta_1 g\ (w_2 * x + b_2)$
$= [0.461507, -0.46151] +$
$[-0.48645, 0.486452]$
$= [0.947959, -0.94796]$

The results obtained are 0.947959 > 1 and -0.94796 < 0 then obtained matrix [1, -1]. Based on table 3.1 the image is identified with the target [1, -1].

6. Results And Discussion

The testing process was conducted to determine the accuracy of Extreme Learning Machine learning on the identification of the signature. In this study show the results of the learning accuracy of extreme learning machine using gray level co - occurrence matrix as feature extraction.

6.1 Testing Using Extreme Learning Machine

This test was conducted to determine the accuracy obtained using extreme learningmachine with features contrast, correlation, energy and homogeneity. Here is a interface feature extraction.

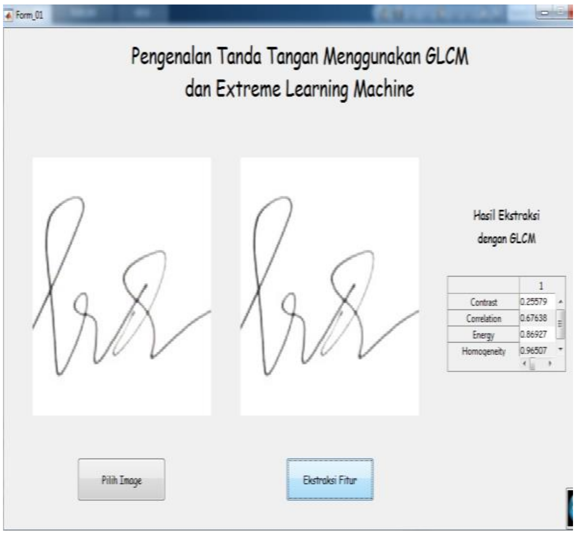


Figure 6.1 Interface feature extraction

After obtaining the value of the data features throughout the entire training data will be trained. After training data, then the next step for testing. The entire test data will be entered into the software testing. Here's signature test software uses extreme learning machine with features contrast, correlation, energy and homogeneity.

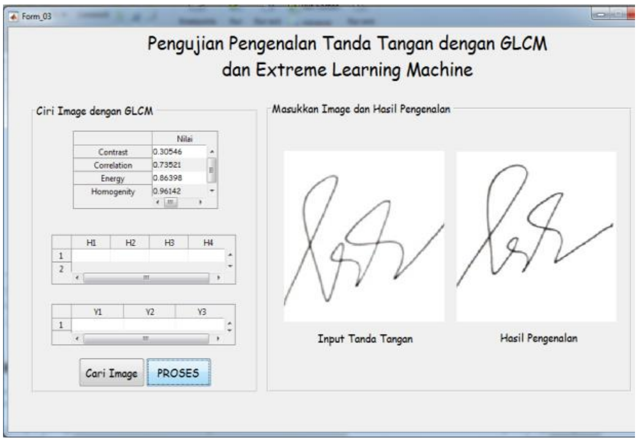


Figure 4.3 Testing signature

Based on experiments the accuracy of gray level co-occurrence matrix and extreme learning machine with the addition of elementary transformations have an accuracy better than just using extreme learning machine. In this test the accuracy of ELM + Elementary transformations is 43% while the test results using extreme learning machine accuracy is 36%. Table 6.1 The Result Of The Signature Identification Using Elm And ELM + Elementary Transformations.

features	Signatures	Result	
		ELM	ELM +TE
Contrast Correlation Energy Homogeneity	**1st Person**	×	×
		✓	×
		✓	✓
	2nd Person	×	✓
		×	×
		×	×
	3rd Person	×	✓
		×	×
		×	✓
	4th Person	✓	✓
		✓	✓
		✓	✓
	5th Person	✓	×
		✓	×
		✓	✓
	6thPerson	×	×
		×	×
		×	✓
	7thPerson	×	×
		×	×

		✓	✓
	8th Person	×	×
		×	×
		×	✓
	9th Person	×	×
		×	×
		×	✓
	10th Person	✓	×
		✓	×
		×	✓
	Recognize	11	13
		11/30	13/30
	Accuracy	36%	43%

7. Conclusion

From experiments to identify the signature image using feature extraction gray level co-occurrence matrix (GLCM) and identification using extreme learning machine with the addition of an elementary transformations obtained a better accuracy rate compared to only use extreme learning machine. Experiment results show that the accuracy is 43%, while using just ELM accuracy is 36%. Accuracy in this study was very small, it is caused by ELM learning that does not use iteration parameters so that the accuracy is only dependent on the hidden nodes, weights and biases.

References

[1] V. Sulochana, "Texture Based Image Retrieval Using Framelet Transform – Gray Level Co-occurrence Matrix (GLCM)," vol. 2, no. 2, pp. 68–73, 2013.

[2] G. Huang, Q. Zhu, and C. Siew, "Extreme learning machine : A new learning scheme of feedforward neural networks Extreme Learning Machine : A New Learning Scheme of Feedforward Neural Networks," no. February, 2014.

[3] D. Fitriati, "Perbandingan kinerja Cnn LeNet 5 dan extreme learning machine pada pengenalan citra tulisan tangan angka Desti Fitriati," vol. 2, no. 1, 2016.

[4] Ismi Amalia, "pengenalan citra tanda tangan menggunakan gray level co-occurrence matrix (glcm) dan probabilistic neural network (PNN)," *Teknologi*, vol. Vol. 14, pp. 29–34, 2014.

[5] I. P. S. Handika, I. A. Giriantari, and A. Dharma, "Perbandingan Metode Extreme Learning Machine dan Particle Swarm Optimization Extreme Learning Machine untuk Peramalan Jumlah Penjualan Barang," vol. 15, no. 1, pp. 84–90, 2016.

[6] R. M. Haralick and K. Shanmugam, "Textural Features for Image Classification," 1973.

[7] M. Madhu and R. Amutha, "Face Recognition using Gray level Co-occurrence Matrix and Snap Shot Method of the Eigen Face," vol. 2, no. 6, pp. 482–488, 2012.