Offline Signature Recognition using Back Propagation Neural Network

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Abstract
　　The signature recognition is a difficult process as it requires several phases. A failure in a phase will significantly reduce the recognition accuracy. Artificial Neural Network (ANN) believed to be used to assist in the recognition or classification of the signature. In this study, the ANN algorithm used is Back Propagation. A mechanism to adaptively adjust the learning rate is developed to improve the system accuracy. The purpose of this study is to conduct the recognition of a number of signatures so that can be known whether the recognition which is done by using the Back Propagation is appropriate or not. The testing results performed by using learning rate of 0.64, the number of iterations is 100, and produces an accuracy value of 63%.

Keywords: back propagation, image, neural network, signature recognition

1. Introduction
　　AADFG The signature is one of identification tools of each individual because each person has a signature characteristic that distinguishes one person to another. The signature often used to authenticate a document, such as financial documents, business ownership, and others. By the growing importance of the signature function in everyday life, some people often have forged the signatures, especially for crimes. Even, the intricate and complex signature also still have threats to be forged by others [1]. It would be very detrimental to parties who have the signature and some other related parties.

　　To avoid the occurrence of the crime falsification of signatures, the signature recognition is needed to be done. The signature recognition performed may include two main objectives, namely to know the owner of a particular signature and determine whether a signature is genuine or fake. A signature verification system must be able to detect the falsification of signatures, and at the same time avoiding the rejection of the original signatures [2]. There are two types of signature recognition, namely the online and offline recognition. The online recognition using dynamic features such as stylus pen movement, velocity, acceleration, and pressure of the pen as a function of time (time series). While the offline recognition using static features such as a scanned signature image [3]. There are six major components contained in the signature recognition system, namely the acquisition of the signature data, the data preprocessing, feature extraction, feature selection, classification and evaluation of recognition results [4].

　　The signature recognition can be done by applying certain algorithms, such as Neural Network. The signature recognition using Multi-Layer Perceptron is one example of research using Neural Network algorithm. Multi-Layer Perceptron (MLP), which is one of a Neural Network algorithm and also the traditional classification techniques, compared with Support Vector Machine (SVM) to perform the offline signature recognition. There are two types of representation used, namely using the feature vector created by the geometric characteristics and using bitmap from the signature image that has been normalized as a feature vector. SVM proven capable of providing high accuracy that is equal to 71% in conducting signature recognition, outperformed the MLP [5]. A Neural Network algorithm which is often used for the signature recognition is Back Propagation [1], [6-8]. It is because Back Propagation easy to implement, and can maintain the efficiency of the network. Back Propagation algorithm minimizes error in the output by making adjustments to the weights in the network.

Traditional Back Propagation has several drawbacks, such as the learning process requires a long time to achieve convergence, besides also the solution obtained may be stuck in a local optimum [9]. The learning process is strongly influenced by the selection of the learning rate. A large learning rate may cause the method leaps a targeted solution. In contrast, the learning rate that is too small causes the learning process becoming longer and the computing time is often can't be well received. This study offers a solution to overcome the weakness of Back Propagation by applying an adaptive learning rate in the learning process. An adaptive learning rate works by lowering the learning rate value at the time of the resulting error value has not changed in several iterations. With the decrease of the learning rate, the learning process will be slow so it is expected the final results that will be given closer to the actual results.

2. Back Propagation

Back propagation is a kind of supervised learning in which output of the network compared with the expected target in order to obtain the output error, then the error is propagated back to repair the network weights in order to minimize the error [10]. Back propagation algorithm consists of three layers as shown in Figure 1. In Figure 1, the function of the input layer is to receive input signals from the outside, the hidden layer describes the relationship between the input layer and the output layer, and the function of the output layer is to release the output signal to the outside [11]. The number of hidden layers used affects the accuracy value [12].
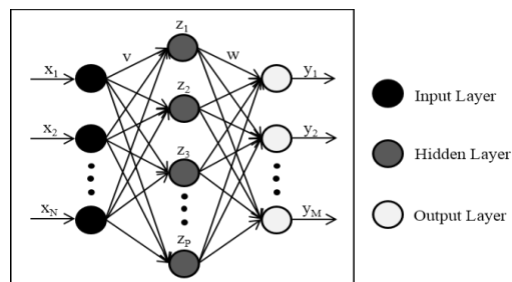

Figure 1. Back Propagation Neural Network

Back propagation algorithm has three training stages, namely feed forward, back propagation, and weight update. In feed-forward stage, the input pattern is counted forward from the input layer to the output layer. While in back propagation stage, each unit of the output receiving the target pattern which associated with the input pattern to calculate the error value. The error will be propagated backwards. The weight update stage is used to reduce the errors that occur by doing repairs weights.

3. Methodology

The signature recognition process begins from preprocessing in the signature image data, and then performs feature extraction in that data, and Back Propagation is used to classify the signature data. The signature data used consists of 30 classes with 6 pieces of data for each class. In each class, 4 pieces of data be used as training data, 1 piece of data is used as the target data, and 1 piece of data is used as test data.

3.1. Preprocessing

Preprocessing is used to improve image quality. In general, the preprocessing stages are as follows:
1) Color Inversion

The image of the offline signature from the scanning result is an image with color format. The data is converted into grayscale format. Each color images composed from pixels, and each

pixel has a color matrix consisting of Red (*R*), Green (*G*), and Blue (*B*). The process of converting color images into grayscale using Equation (1) [6], [13].

$$Gray = (0.299 \times R) + (0.5876 \times G) + (0.114 \times B)$$ (1)

2) Noise Filtering

Noise is unwanted information that pollutes the image. Median filter is widely used for smoothing and restoring the image damaged by noise, so that other objects that interfere with the image can be eliminated. Median filter is a non-linear process that is useful for reducing noise of salt and pepper [6]. Noise of salt and pepper can ruin the image, namely pixels are damaged take maximum or minimum gray level. This type noise causes image quality to be bad [14].

3) Background Elimination

Some of the image processing algorithms requiring a separation of the object from the background image. The easiest method used to overcome this problem is image thresholding. This method is widely used in image segmentation. The thresholding process begins with selecting the threshold value T, then all pixels that have a value of less than or equal to T are given a value of 0, and all pixels that have a value greater than T is given a value of 1 [1].

4) Normalization

The dimensions of the signature image may vary as a result of irregularity the process of scanning and capturing images. The signature height and width of each person will vary; even the same person might produce a different signature size. The different signature size removed to obtain the standard signature size for all signatures. After the normalization process, all the signatures will have the same dimensions [6]. The normalization process is done by using Equation (2) and Equation (3).

$$x_i = \frac{x'_i - x_{\min}}{x_{\max} - x_{\min}} \times M$$ (2)

$$y_i = \frac{y'_i - y_{\min}}{y_{\max} - y_{\min}} \times M$$ (3)

x_i and y_i are the coordinates of the pixel of the normalized image, x_i' and y_i' are the coordinates of the pixel of the original image, and M is a dimension (width or height) normalized image.

5) Feature Extraction

Feature extraction is the process of analyzing an image so that it can be known a dominant feature to represent of the main features of the image [15]. Feature extraction using grid feature segmentation has been widely used to get the feature value. In the grid feature segmentation, feature extraction is done by dividing the image of the signature that has been normalized into a 3 × 3 grid as shown in Figure 2.

3.2. Classification using Back Propagation

In this study, the network architecture of Back Propagation that is used consists of 9 input layer, 2 hidden layer and 9 output layer as shown in Figure 3. In Figure 3, the input layer consisting of x_1, x_2, ..., x_9 is a grid feature value of a signature. The value of x_1 is a grid feature value in row 1 column 1, x_2 is a grid feature value in row 1 column 2, and so on until x_9 which is a grid feature value in row 3 column 3. The output layer is also composed of nine values, namely y_1, y_2, ..., y_9 which is the output values that will be compared with the output target so that can be known its class type.

The calculation process starts from the normalization process by using Equation (4).

$$x_{new} = 0.8 \times \frac{(x_{old} - \min)}{(\max - \min)} + 0.1$$ (4)
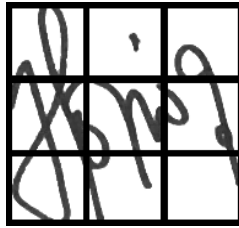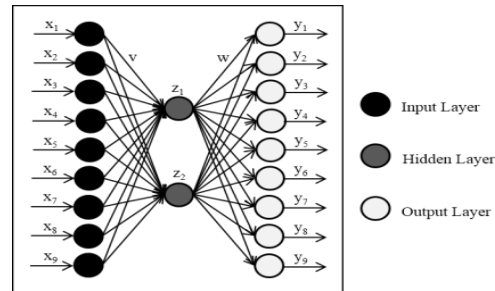
Figure 2. Grid Feature Segmentation Image   Figure 3. Back Propagation Neural Network Architecture

In the first stage, namely the stage feed-forward, the weight value *V* between the input layer with the hidden layer is formed randomly by value range [-1, 1] to obtain the results as shown in Table 1.

Table 1. Initialization of the Random Weight Value *V*

Weight Value *V*	1	2
1	-0.40381	0.07308
2	-0.48845	0.33914
3	0.15812	0.26923
4	0.11826	-0.15217
5	0.22457	0.27711
6	-0.12251	0.11918
7	0.07559	0.10668
8	-0.02667	-0.33677
9	-0.03734	0.20783

Furthermore, the weight values *W* between the hidden layer and the output layer are also formed randomly by value range [-1, 1] to obtain the results as shown in Table 2.

Table 2. Initialization of the Random Weight Value *W*

Weight Value *W*	1	2
1	-0.27425	0.12881
2	0.10071	0.28467
3	0.24856	0.66037
4	0.04695	0.64814
5	-0.19445	0.27994
6	0.67675	0.38549
7	0.00937	-0.03055
8	0.62095	-0.03537
9	-0.24028	0.21428

In the next stage, the back propagation stage, the error value is calculated by comparing the results (output signal) to the value of the target pattern. The target pattern used in this example are $t_1 = 0.80071$, $t_2 = 0.58024$, $t_3 = 0.89418$, $t_4 = 0.76773$, $t_5 = 0.75140$, $t_6 = 0.67286$, $t_7 = 0.71311$, $t_8 = 0.75316$, and $t_9 = 0.55000$. The calculation of error results is as follows: $\delta_1 = 0.7788$, $\delta_2 = 0.00583$, $\delta_3 = 0.06143$, $\delta_4 = 0.03839$, $\delta_5 = 0.05718$, $\delta_6 = 0.00866$, $\delta_7 = 0.05422$, $\delta_8 = 0.04618$, and $\delta_9 = 0.01086$.

Once the error value known, the changes value in the weights *W* which is the weight of the output layer and the hidden layer are calculated so that they can be updated on the next data training process. Furthermore, the value changes of the weights *V* is the weight between the hidden layer and the input layer is also calculated.

The last stage is the weight update stage, which is updating the weights *V* and *W* on the network. In the testing process, the weight of *V* and *W* are obtained from the weight of *V* and *W* on the last line data in the last iteration in the training process. By using the test data, these weights are used to obtain the output value *y*. Denormalization process performed on the *y* value by using Equation (5).

$$y' = \frac{(\max - \min) \times (y - 0.1)}{0.8} + \min \tag{5}$$

4. Results and Discussion

Testing conducted to determine the parameters that are used in order to generate a high accuracy value. The testing that is performed consists of the segment number testing, the learning rate value testing, and the iteration number testing.

The segment number testing is done by using the parameters of learning rate are 0.64, the iteration number is 100, and the number of hidden layer is 3. The MSE value when using a single learning rate is 0.1579701, while the MSE value when using adaptive learning rate is 0.1579699. The segment number that is tested consisted of 2 × 2 grid, a 3 × 3 grid, and so on up to 50 × 50 grid. All kinds of segment number testing produce an accuracy value of 63%.

The accuracy results which is obtained has a small value because the preprocessing of image rotation is not performed, so that the sloped image signature with a certain degree will produce an output with the vastly different values and result in errors in the classification results.

5. Conclusion

Based on the testing that was done, it can be concluded that Back Propagation algorithm less suitable to solve the signature recognition problems. It is because the output is given by Back Propagation is a value, not a class, so the accuracy is found to be small. In addition, the stages are carried out on image preprocessing also greatly affect the accuracy of a given value.

In the next study, the image rotation will be added to the image preprocessing stage to increase the accuracy value. In addition, the use of other methods used in the extraction process features, such as circular grid segmentation can be used to determine whether the method can give better accuracy. To overcome an early convergence in the learning stage, a meta-heuristic algorithm such as genetic algorithm can be employed [16].

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