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Signature recognition using probabilistic neural network

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ABSTRACT

The signature of each person is different and has unique characteristics. Thus, this paper discusses the development of a personal identification system based on it is unique digital signature. The process of preprocessing used gray scale method, while Shannon Entropy and Probabilistic Neural Network are used respectively for feature extraction and identification. This study uses five signature types with five signatures in every type. While the test results compared to actual data compared to real data, the proposed system performance was only 40%.

I. Introduction

Identification is an important process to recognize and distinguish one thing with others; it can be animals, plants, and humans. This identification can be done by recognizing the human natural characteristic, known as biometrics. The characteristics are physiological and behavioral characteristics. The first characteristic is relatively stable and consists of fingerprints, hand silhouette, distinctive facial, iris pattern, or the eye retina. On the other hand, signature, speech patterns, or typing rhythm are the example of the behavioral characteristic.

The signature is widely used as an identification system against a person. It can be defined as an image of the visual representation of an object. Furthermore, the image is a visual representation of an object after suffering various transformations of data from various forms of numerical sequence. The introduction of the signature can be done through the stages of the conversion of the image into a numeric vector, image processing for quality improvement, prior to further processing stages numerically, including the use of Artificial Neural Network (ANN) for classification. Classification or identification features that are closely related to be reviewed.

This research focus on how to apply entropy method and Probabilistic Neural Network in the image of the signature that can accurately recognize a person's identity. The goal of this research is to apply the method of entropy and Probabilistic Neural Network to be able to recognize a person's identity only by utilizing his signature.

II. Literature Review

A. Probabilistic Neural Network

Probabilistic neural network (PNN) proposed by Specht in 1990 [1][2] as an alternative to back-propagation neural network. PNN has several advantages, namely the one iteration training process and the Bayesian based solution. The main advantage using PNN is its easy and fast training process. The input value is the training result instead of the weight. Weights were never changing, except the new vectors were inserted into the matrix of weights during the training process [3]. PNN structure, Fig.1, has four constituent layers: input layer, layer pattern, summation layer, and decision layer [4].

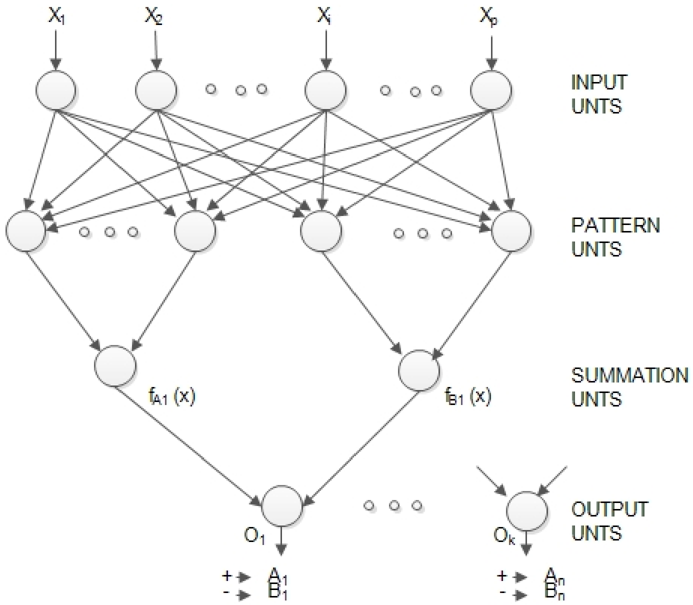


Fig. 1. Structure of PNN [4]

Constituent layers are described as follows:

1) Input Layer

The input layer is the composed of input *xk* characteristic value that will be classified in one of the classes of *n* class.

2) Pattern Layer

In the pattern layer carried dot (dot product) between the input *x* and the weight vector *xA*, namely *ZA = x Xai*, *ZA* then divided by bias (σ), which is specified and subsequently included in the function Parzen, namely *g(x) = exp(-x)*. Thus, the equation used in the pattern layer is (1).

$$g(x) = \exp\left(-\frac{(x-x_{Ai})^T(x-x_{Ai})}{2\sigma^2}\right) \quad (1)$$

Xai states with training vectors to class-*A* sequence-*i*.

3) Summation Layer

In summation layer, each pattern in each class is summed to produce a probability density function for each class. The equation (2) used at this layer.

$$p(\omega_A)p(x|\omega_A) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d N_A}\sum_{i=1}^{N_A} exp\left(-\frac{(x-x_{Ai})^T(x-x_{Ai})}{2\sigma^2}\right) \quad (2)$$

Where$\rho(\omega_A)$ is a probability of class A, $\rho(x|\omega_A)$ is a conditional probability of x given class A, x_{Ai} is i^{th} training vector of class A, d for the dimension of input vector, N_A for the number of training patter class A, and σ is bias.

4) Decision layer

In the decision layer, input *x* will be classified into class *A* if the value of *pA(x)* compared to other classes.

B. Signature Verification

Verification is a process of comparing a user's sample biometric against the previously stored reference to ascertain the person's identity while accessing the system. The process can be divided into two types, namely off-line and on-line signature classification [5].

Offline signature verification takes a signature image as an input that will be used later in the process. On the other hands, On-line captures the signature directly from the digitizer to generate dynamic values, such as coordinates and the time signature. The Off-line signature has a quite higher noise level compared to the On-line one. However, it also depends on the scanner and the used background paper. In terms of cost, it is cheaper than On-line. The Offline version is usually used in Indonesian banks, organizations and institutions.

C. *Digital Image*

Imagery can be generally defined as a function of an object light intensity in two dimensions *f (x, y),* where *x* and *y* express the spatial coordinates and the value *f* at any point *(x, y)* is proportional to the image gray scale (brightness), as shown on Fig. 2. Therefore, *f (x, y)* continuously express the degree of image intensity. In the field of image processing, the continuous image has been converted into a discrete form, both coordinates of space and light intensity.

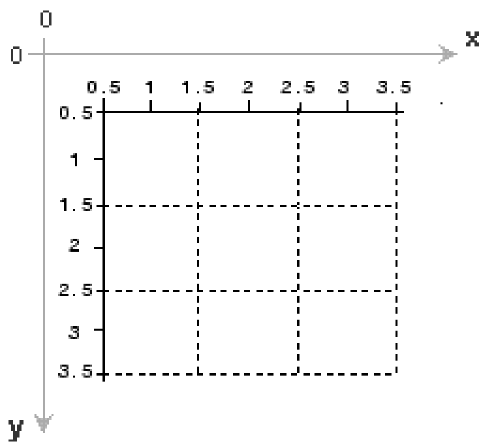


Fig. 2. Illustration image in Pixel Coordinate System [6]

Digital image *f (x, y)* can be envisioned as a two-dimensional matrix. The matrix index identifies the image point while the value is for the color level. That element is called image elements (picture elements), usually abbreviated as pixels, or pels.. Pixels can be defined as the smallest element of a digital image that determines the image resolution. In other words, smaller pixel may produce higher resolution. The digital image is a representation of the image in the discrete form in both coordinate and light intensity value. As illustrated in Fig. 3, a matrix of size N x M (row / height = N, columns / width = M), may represent a digital image.

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,M-1) \\ f(1,0) & f(1,1) & \dots & f(1,M-1) \\ . & & & \\ . & & & \\ . & & & \\ f(N-1,0) & f(N-1,1) & \dots & f(N-1,M-1) \end{bmatrix}$$

Fig. 3. Matrix digital image of N x M [2]

D. *Feature Extraction*

Feature extraction transforms input data into a set of features [7]. The purpose of feature extraction is to reduce the computational complexity and space dimensions. Applying the feature extraction to image recognition system may significantly affect the classification accuracy [8].

One technique that can be used to extract features of an image is Shannon Entropy, was developed around 1940 by Claude Shannon in the Bell labs. This term is used in the field of thermodynamics to mark a number of physics system disorders. This technique measures yhe data uncertainty in the discrete distribution [8]. The entropy H of a discrete random variable *X* as defined by (3).

$$H(X) = -\sum_{x \in X} p(x) \log_2 p(x) \quad (3)$$

H plays a major role in information theory to measure the information, choice, and uncertainty. It is a function of chance, with a member of the random number, *X*. The entropy value depends on the gray level intensity.

III. Results and Discussion

A. Analysis System

Signature Identification System is a digital signature based system for recognizing a person identity. The system consists of two steps: training and signature identification. Training model is obtained by processing the entire training data signature. The process is called preprocessing, converts an RGB image into a grayscale image. Afterwards, Shannon Entropy technique extracts the converted image into a more specific training model.

The second step is the signature identification. Here, preprocessing and feature extraction are also performed in the test data. Afterwards, PNN will used to calculate the distance between each test data and the training model. The shortest distance test data to a particular class will be identified as a member of that specific class.

B. Hand sign image

This study uses five types of signatures, each signature consist of 5 images. Those signatures are divided into training data and test data, consist of 4 and 1 of each type respectively. RGB image signatures have jpg format with the same pixel (591 x 709) with a total of 419 019 pixels. The pixels are selected randomly due to the space limit.

C. Pre-processing

Respondent's signatures are scanned to obtain signature images. Each pixel in the image of the signature has three values, that is R, G and B. The image must be converted into a grayscale image, an image with a pixel value between 0-255 or 1-256, before the feature extraction process. RGB image is converted into grayscale using (4).

$$grayscale = 0.2989 * R + 0.5870 * G + 0.1140 * B \quad (4)$$

Table 1 shows the grayscale value obtained from the average of the pixels of R (red), G (green), and B (blue).

Table 1. Grayscale value from the average of RGB pixel

252	**249**	**249**	**92**	**1**	**1**	**0**	**8**	**76**	**159**	**238**	**255**	**251**
252	254	230	27	13	29	28	5	0	1	68	191	250
252	254	228	30	24	209	232	161	96	31	2	12	89
252	253	234	23	23	235	255	255	253	231	130	44	4
254	252	237	28	10	171	255	252	255	255	255	241	139
252	254	249	86	0	128	255	251	255	255	255	255	255
252	252	254	176	8	54	239	253	255	255	255	255	248
253	250	252	233	30	10	171	255	255	255	255	254	251
255	254	255	255	100	0	108	255	254	252	253	253	254
255	255	255	255	185	18	33	225	255	253	251	253	255
255	255	255	255	255	92	0	128	255	251	253	253	255

D. FeatureExtraction

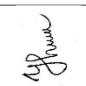
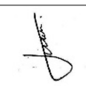
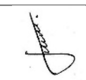
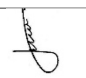
Entropy method is used to measure the characteristic of uncertainty information in the training data. Measurements carried out based on the histogram value information. Histogram change the image intensity values to form a uniform distribution. The grayscale histogram should be normalized to obtain the same degree on every gray pixel. Normalization obtained by changing the degree of a

Vol. 2, No. 1, March 2016, pp. 46-53

gray pixel with a new degree, created by a transformation function. Entropy calculation produces only one value for that image to obtain five entropy values as shown in Table 2.

Table 2. Entropy calculation

No.	Identity	Citra	Figure Citra	Entropy Value
1	A	1		0.208071
		2		0.256652
		3		0.211692
		4		0.259836
		5		0.255666
2	B	1		0.887653
		2		0.741031
		3		0.841124
		4		0.909576
		5		1.036420

No.	Identity	Citra	Figure Citra	Entropy Value
3	C	1		0.566040
		2		0.542834
		3		0.640784
		4		0.574318
		5		0.639530
4	D	1		0.428333
		2		0.346907
		3		0.373272
		4		0.370412
		5		0.436951
5	E	1		0.321452
		2		0.339263
		3		0.350978
		4		0.373102
		5		0.365274

E. Image Identification

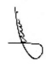
PNN classifies image data into its classes. Furthermore, the test data will be tested on a classification model. The test data is data that is not used in the learning process. Classification is done to classify the data in each class. The class consists of A class (class 1),B class (class 2), C class (class 3), D class (class 4) and E class (class 5). Data extraction results of each class are divided based on the data sharing scenario. Each sub-data consist of one image. Entropy values for the training data can be seen in Table 3.

Table 3. Entropy Values for Training Data

Sample Image -	Entropy Value
5^{th}	0.255666
10^{th}	1.036420
15^{th}	0.639530
20^{th}	0.436951
25^{th}	0.365274

PNN measures the distance of test data with each class in the training model. The data with the shortest distance will be identified as part of the class. The results of the test data classification can be seen in Table 4.

Table 4. Classification Result of Test Data

No.	Citra	Actual Class	Prediction Class
1		1	5
2		2	3
3		3	3
4		4	5
5		5	5

IV. Conclusion

This research applies entropy method and PNN classification to identify a kind of signature. The process of signatures identification begins with the image preprocessing stage. The preprocessing results are extracted using methods Shannon Entropy. To test the system, the data is divided into two training data and test data. The test data is classified using a probabilistic neural network. This research is still far from perfect. The entropy method and classification PNN less able to distinguish the type of signature; the system performance only reaches 40%. The system accuracy can be improved by adding segmentation process before the process of feature extraction, increase the number of image data, and improving the image before preprocessing.

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