International Journal of Technology (2011) 1: 56-64
ISSN 2086-9614

IDENTIFICATION OF SIGNATURES TRANSMITTED OVER RAYLEIGH FADING CHANNEL BY USING HMM AND RLE

Djamhari Sirat[1], Arman D. Diponegoro[1], Leni N. Hidayati[1], Filbert H. Juwono[1*]

[1]*Department of Electrical Engineering, Faculty of Engineering*
Universitas Indonesia, Depok 16424, Indonesia

(Received: December 2010 / Revised: December 2010 / Accepted: January 2011)

ABSTRACT
The Hidden Markov Model (HMM) is a frequently used tool in scientific research for recognizing pattern. This study discusses signature recognition using HMM where the signature image is transmitted from the remote station to the headquarter office by wireless because the remote station was not provided by the original signature as a reference. Generally, the transmission of radio communication has been corrupted with Additive White Gaussian Noise (AWGN) over the Rayleigh fading channel. To reduce the number of bits in the bitstream, the signal prior to transmission was compressed by means of run-length encoding (RLE), also known as source coding. The signature image detected from the receiver was processed in the computer using the HMM. The successful rate of recognition was 0-36% without compression and 60-76%with compression.

Keywords: Hidden Markov Model (HMM); Rayleigh fading; Run-Length Encoding (RLE)

1. INTRODUCTION
Image transmission is important in interactive image communication, especially in remote surveillance, electronic shopping, telebrowsing, and database access (Hou et al., 2004). The applications of image transmission over wireless channels require sufficient design of coding and image compression subject to the limited bandwidth and transmitted energy. One of the compression methods suited for image transmission is run-length encoding (RLE), which delivers a simple algorithm and is used in many applications, such as the fax machine (Frejlichowski & Lisaj, 2008).

Signature identification is used in many applications, including check and credit card validation, security systems, certificates, and legal statements. Signature identification cannot be classified as common pattern recognition since one's signature varies by age, time, habits, current mental and psychological state, and practical conditions (Hou et al., 2004). Signature identification consists of a learning stage and a testing stage. The aim of the processing stages is to create a reference file for calculating the similarity between the test image and the database image. The importance of biometric identification has recently escalated due to the increase of electronic commerce. Signature identification is broadly developing as a method of biometric identification. An identification method often used is the Hidden Markov Model (HMM). Some researches about signature identification have been proposed as in (Hou et al., 2004) and (Wada & Hangai, 2007). However, the researches do not discuss about identification of transmitted signatures.

[*]Corresponding author's email: filbert@ee.ui.ac.id, Tel. +62-21-7270078 Fax. +62-21-7270077

In this study, the signatures were transmitted over wireless channel and RLE coded before identification and we use HMM as the identification method. HMM is a statistical identification method, i.e., it classifies the pattern based on feature extraction and the statistical model is used to build the pattern. By using HMM, it is expected that processing time will be faster. The RLE is used for compressed the signature image. In this paper, we use the terms “identification” and “recognition” interchangeably.

The digital signature is used as the object. A digital image is a two-dimensional pattern that is yielded from an analog image (Gonzales & Woods, 1992). Image processing can be defined as a process to enhance image quality by using various techniques that transform an image into another image for easier interpretation.

A digital image can be represented by a matrix. The values of the matrix constituent elements are called pixels, while the position of elements in rows and columns are represented as the coordinates (x, y) in the image. The function, f(x, y), is the intensity of the image in coordinates (x, y) (See Figure 1). Every pixel has a digital value that can be represented by the actual image.

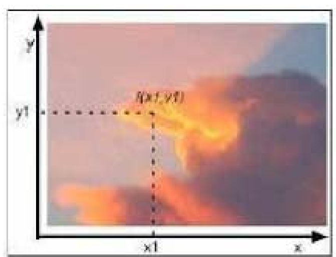

Figure 1 An example of digital image (Wada & Hangai, 2007)

2. PROPOSED SYSTEM

The proposed system is shown in Figure 2.

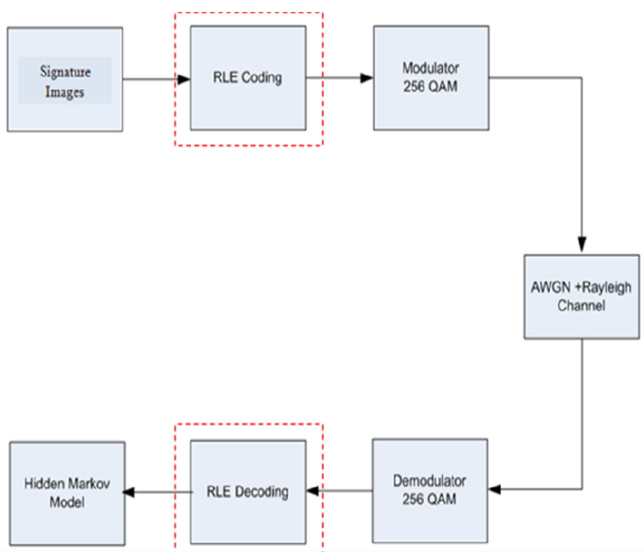

Figure 2 The system for signature identification

The digital signature was sent to HMM identifier over AWGN Rayleigh channel. In this study we will compare the recognition system with and without using RLE. In general, the aim of compression are:

- reduce the volume of the transmitted data
- reduce the bandwidth needed for transmission and the storage required (speech, audio, video).

The RLE compression algorithm is explained as follows. If the data *d* occurs *n* times in the input stream, then the data will be changed to *nd*. The data that occurs *n* times is called the run length of *n*, this compression is termed run-length encoding (RLE). The repeated occurrence is called the “run.” The amount of repetition is called the “length of the run.” An example of RLE compression of an 8-bit bitmap grayscale image is:
Original Data: 12 12 12 34 55 55 55 55 11 11 11 11 11 34 34 34
Encoded Data: (3,12) (1,34) (4,55) (5,11) (3,34)

The flat fading Rayleigh channel can be modeled as (Zhang & Gulliver, 2009) :

$$y = hx + n \tag{1}$$

where y is the received symbols, h is the complex Gaussian parameter with mean of ‘0’ and variance of σ^2, x represents transmitted symbols, and n is Additive White Gaussian Noise (AWGN).

Five signatures images were used as input, and each signature was transmitted 10 and 20 times to obtain 50 and 100 transmitted (noisy) signature images, respectively. These images were used as training images in the database. The effect of AWGN and the fading channel is shown in Figure 3. The effect of RLE compression in transmitting the image over a Rayleigh fading channel is shown (Figure 4 and 5).

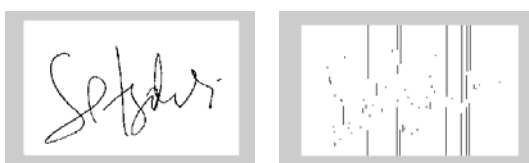
(a) (b)

Figure 3 Signature images transmitted over (a) AWGN channel (b) Rayleigh fading channel

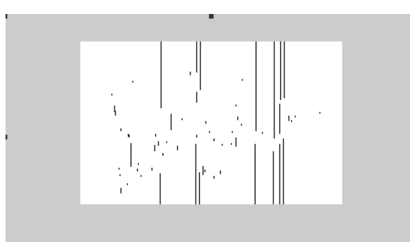

Figure 4 Received RLE-compressed signature image transmitted over Rayleigh fading channel

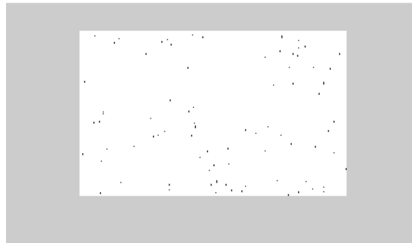

Figure 5 Received non-RLE-compressed signature image
transmitted over Rayleigh fading channel

3. HIDDEN MARKOV MODEL (HMM)

The block diagram of the process to identify the digital signature using HMM is shown in Figure 6.

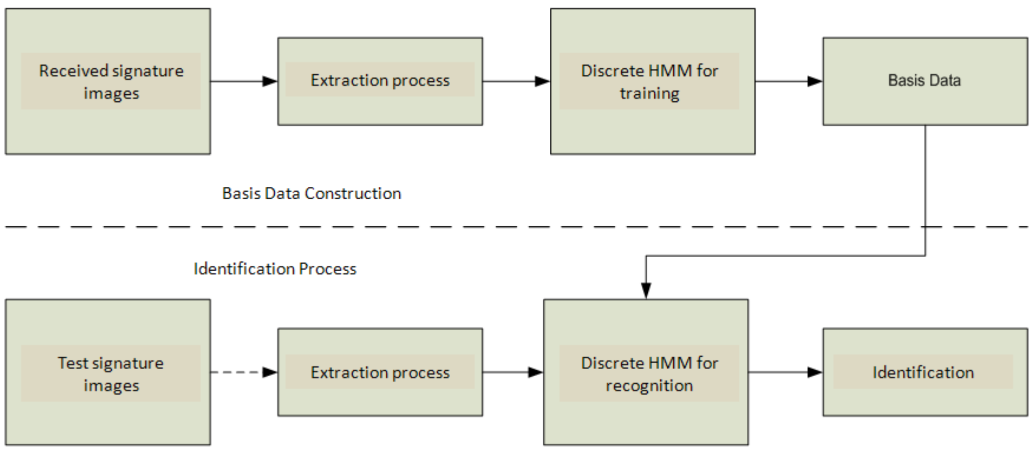

Figure 6 Block diagram of HMM identification

The signature image is segmented where each segmentations is formed as sample point that collected in cluster. The process is called vector quantization (VQ) (Figure 7). One of the methods of collecting the sample points by means of LBG. Each cluster is represented by a centroid or codeword. The collection of all codewords is known as the codebook. The distance between vectors to the nearest codeword is called VQ Distortion.

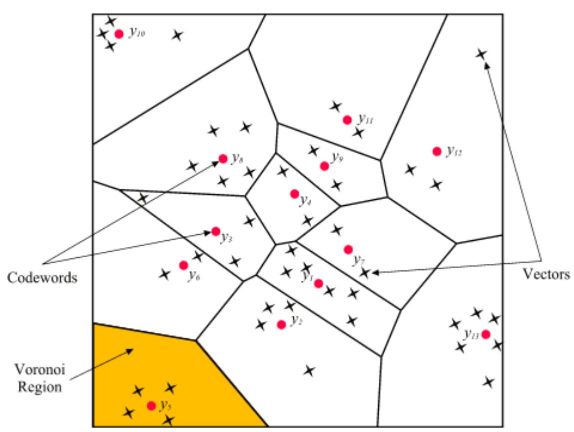

Figure 7 VQ mapping (Anonym, 2005)

The HMM is a statistical model from a system identified as the Markov process, with unknown parameter values. Values of the hidden parameters are determined based on the observable parameters. The determined parameters can then be used for further analysis, such as pattern recognition. A HMM is assumed to be the simplest dynamic Bayesian network. The calculation of the conditional probabilities can be formulated by using the Bayes rule:

$$P(B|A)=\frac{P(A|B)P(B)}{P(A)} \tag{2}$$

where $P(A)$ is the prior probability of A, $P(B)$ is the prior probability of B, $P(A|B)$ is the conditional probability of A, given B, and $P(B|A)$ is the conditional probability of B given A.

In a general Markov model, the state can be observed directly. Thus, the probability of state transition is the only parameter. In a Hidden Markov Model, the states cannot be observed directly. The observable ones are the variables influenced by the states. Every state has a probability distribution of output tokens that probably occur. Therefore, the sequence of the tokens gives information about the sequence of the states. Parameters of the probability from a HMM are:

- x : state
- y : probable observation
- a : probability of state transition
- b : probability of state occurrence

Use of the topology model is essential to obtain sufficient results in the learning and verification phase. In the discrete model, there are two dominant factors (Rabiner, 1989); the number of the states used and the number of transitions between states. In the signature, the left-to-right discrete model is commonly used since Latin handwriting moves from left to right.
A method to identify a HMM is by observation of the pattern of the transition matrix (A) from the Markov chain. The common pattern is the ergodic pattern, i.e., every state is fully connected (Figure 8) with N = 5 states. This model has a_{ij} values between 0 and 1.

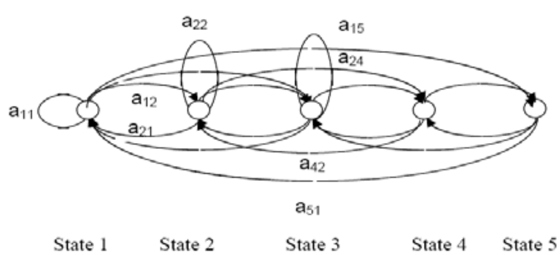

Figure 8 HMM’s state diagram with 5 states (Rabiner & Juang, 1993)

The HMM parameters can be written as $\lambda=(A,B,\Pi)$ where:

- The parameter A is expressed in a matrix of M x M, where M is the number of existing states. The transition matrix in Figure 3 consists of 5 states; every state has 5 transition relations. Parameter A can be written in matrix form as :

$$A=aij=\begin{pmatrix} a11 & a12 & a13 & a14 & a15 \\ a21 & a22 & a23 & a24 & a25 \\ a31 & a32 & a33 & a34 & a35 \\ a41 & a42 & a43 & a44 & a45 \\ a51 & a52 & a53 & a54 & a55 \end{pmatrix} \tag{3}$$

- The parameter B is called the probability of state, which is the probability of occurrence of a state in a sequence of existing states. It is written as the column matrix of M x 1, where M is the number of all existing states. For example, if there are 5 states, then the matrix B is represented by the following equation.

$$B = \left(b1 \quad b2 \quad b3 \quad b4 \quad b5\right)^T \tag{4}$$

- The parameter $\prod$ is initial probability, or the probability of occurrence of a state in the beginning. As with parameter B, this parameter is also written as a column matrix of M x 1, where M is the number of states. If there are 5 states, then the parameter can be expressed by the following equation.

$$\Pi = \left(c1 \quad c2 \quad c3 \quad c4 \quad c5\right)^T \tag{5}$$

The probability of observation $P(O)$ can be obtained from all of the above parameters. Function of probability of O is shown by the equation:

$$P\left(O\right) = \sum_{i=1}^{N} P\left(A_{ij}\right) * P\left(B_i\right) \tag{6}$$

where $P\left(A_{ij}\right)$ is the probability of the matrix A's element in row i and column j and $P\left(B_i\right)$ is the probability of matrix B's element in row i.

The next process is identification. The identification process is divided into two stages: database construction and identification itself. Three phases in database construction are: labeling, codebook construction, and HMM construction. Preprocessing processes, such as cropping and reshaping, are applied to the input signature image before constructing the database.

In the labeling process, each image of a signature to be registered on the database was labeled according to the name of the person. For example, the signature of "Setyahadi" was given Label1; signature of "Siska" was given Label2, and so on. The label name will be the output on the process of signature identification.

In our program, three inputs were the sequence number of the label (index), the amount of data entered into each label (training), and the label name. The term "training" refers to the learning process by the system. Number of training was filled with the desired number and name of the label was filled in accordance with the signature name entered in the database.

After the labelling process, the next step was to merge all labels into a codebook file. In addition, the vector quantization process was carried out.

Codebook sizes used were 32, 62, and 128 bits. The three codebook sizes were used for comparison to see which codebook value was most accurate in the process of signature identification. The number of iterations is the number of repetitions performed in the process of determining the centroid to obtain sufficient precision. We observed that the greater the number of iterations, the more precise the location of the centroid. However, a high iteration codebook significantly slows the codebook construction process. In our study, we used a value of iteration of 10.

4. RESULTS AND ANALYSIS

Tests were carried out on 5 signature images (shown in Figure 9). Each image was then transmitted over the channel and some variations of the signatures resulted.

Figure 9 Signatures used in this paper

The process of testing performed used variations in codebook size and the number of training transmission that were generated from repeated transmissions of the image. In the identification process, the log of probability was observed to identify the image. We used 10 training transmissions and a codebook size of 32.

Table 1 Results of identifying signatures with and without RLE

No.	Names	Results without RLE	Results with RLE
1	Setyahadi	**Solih**	Setyahadi
2	Siska	**Yudi**	Siska
3	Solih	**Setyahadi**	Solih
4	Suyanto	**Siska**	Suyanto
5	Yudi	**Siska**	**Suyanto**
6	Setyahadi	**Yudi**	Setyahadi
7	Siska	**Suyanto**	**Solih**
8	Solih	**Yudi**	Solih
9	Suyanto	**Solih**	**Setyahadi**
10	Yudi	**Siska**	Yudi
11	Setyahadi	**Solih**	Setyahadi
12	Siska	**Solih**	Siska
13	Solih	**Setyahadi**	**Suyanto**
14	Suyanto	**Siska**	Suyanto
15	Yudi	**Solih**	Yudi
16	Setyahadi	**Solih**	Setyahadi
17	Siska	**Yudi**	Siska
18	Solih	**Yudi**	Solih
19	Suyanto	**Solih**	**Siska**
20	Yudi	**Suyanto**	Yudi
21	Setyahadi	**Suyanto**	Setyahadi
22	Siska	**Yudi**	Siska
23	Solih	**Yudi**	**Siska**
24	Suyanto	**Yudi**	**Setyahadi**
25	Yudi	**Suyanto**	Yudi

From Table 1, we notice that the system without RLE yielded completely incorrect signature identifications. From 25 tests, 25 faults resulted. Table 1 also shows the results for the same system using RLE compression; only 7 faulty identifications resulted. Table 2 and 3 show the overall accuracies in terms of the number of training transmission and the codebook size.

Table 2 System's accuracy (without RLE)

Number of training transmission	*Codebook*	Accuracy [%]
10	32	0
10	64	28
10	128	36
20	32	24
20	64	28
20	128	28

Table 3 System's accuracy (with RLE)

Number of training transmission	*Codebook*	Accuracy [%]
10	32	72
10	64	76
10	128	64
20	32	72
20	64	64
20	128	60

If the number of training transmissions is fixed and the codebook size is varied from 32 to 128, we observed that the level of accuracy tends to decline as codebook size and training numbers increase. The greatest accuracy (76%) was obtained when the size of the codebook was 64 and the number of training was 10 (Table 4).

The level of accuracy in the fading signature images is strongly influenced by the number of training. Decrease in percent accuracy on a large number of codebooks is caused by fading channels which have variations of random noise so that a larger codebook size causes an increase in the number of codewords (centroids). An increase of centroids makes the quantization process more precise so that the mapping of data vectors can be in smaller distances, i.e., the VQ distortion is smaller. The large number of training transmissions creates similarity in the images so that the distance between centroids is closer and the identification process is more difficult.

From Tables 2 and 3, it is noted that the system for which RLE was not used had a much lower level of accuracy than the system that used RLE. This scenario occurred because the system using RLE produced a signature images that still had pattern, while the system not using RLE yielded irregular images without a pattern (Figure 4, 5). The probability of error (PE) also affects the accuracy of identification, as shown in Table 4. The system that used RLE achieved better PE than the system without RLE because the images with small PE were not easily recognized.

Table 4 Probability of error of the transmitted images

Signatures	Without RLE	With RLE
Setyahadi	0.9762	0.9677
Siska	0.9749	0.6785
Solih	0.9755	0.8072
Suyanto	0.9753	0.7682
Yudi	0.9755	0.9691

5. CONCLUSION

The experiment proved that the combination of HMM and RLE has ability to identify the digital signature transmitted over Rayleigh fading channel with accuracy between 60% and 76%.

6. REFERENCES

Anonym, 2005. *Two Dimensional Voronoi Diagram*, <http://www.eecs.ucf.edu/vector quantization/> [accessed on 20 April 2010].

Frejlichowski, D. & Lisaj, A., 2008. New Method of the Radar Images Compression for the Needs of Navigation in Marine Traffic, *In*: *Proceedings of Radar Symposium*, IEEE, pp 1-4.

Gonzales, R. & Woods, R., 1992. Digital Image Processing, *USA: Addison Wesley Publishing Co*.

Hou, W., Xiufen Y., Kejun W., 2004. A Survey of Off-line Signature Verification, *In: Proceedings of the 2004 International Conference on Intelligent Mechatronics and Automation*, August 2004, Chengdu, China.

Rabiner, L. R., 1989. A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition Proceedings, *IEEE* 77(2), 257-286.

Rabiner, L. R. & Juang, B. H., 1993. Fundamental of Speech Recognition, Englewood Cliffs, *N.J.: Prentice Hall*.

Wada, N & S. Hangai, 2007. HMM based Signature Identification System Robust to Changed of Signature with Time, *IEEE Workshop on Automatic Identification Advanced Technologies*, pp. 238-241.

Zhang, H. & A. Gulliver, 2009. A Channel Selective Approach to Wireless Image Transmission Over Fading Channels, *Proceedings of IEEE Pacific Rim Conference on Communication, Computers and Signal Processing*, pp. 720-724.