

Apply Fuzzy Vector Quantization to Improve The Observation-Based Discrete Hidden Markov Model --An example on electroencephalogram (EEG) signal recognition

Shing-Tai Pan

Department of Computer
Science and Information
Engineering
National University of
Kaohsiung
Kaohsiung, Taiwan R.O.C.
stpan@nuk.edu.tw

Sheng-Fu Liang

Department of Computer
Science and Information
Engineering
National Cheng Kung
University
Tainan, Taiwan R.O.C.
sfliang@mail.ncku.edu.tw

Tzung-Pei Hong

Computer Science and
Information Engineering
National University of
Kaohsiung
Kaohsiung, Taiwan R.O.C.
tphong@nuk.edu.tw

Jian-Hong Zeng

Computer Science and
Information Engineering
National University of
Kaohsiung
Kaohsiung, Taiwan R.O.C.
mafiajerry@msn.com

Abstract—This paper applies fuzzy vector quantization (FVQ) to the modeling of observation-based Discrete Hidden Markov Model (DHMM) and then to improve the speech recognition rate for the Mandarin speech. Vector quantization based on a codebook is a fundamental process to recognize the speech signal by DHMM. A codebook will be first trained by K-means algorithms using Mandarin training speech. Then, based on the trained codebook, the speech features are quantized by the fuzzy sets defined on each vectors of the codebook. Subsequently, the quantized speech features are statistically applied to train the model of DHMM for the speech recognition. All the speech features to be recognized should go through the FVQ based on the fuzzy codebook before being fed into the DHMM model for recognition. Experimental results in this paper shows that the speech recognition rate can be improved by using FVQ algorithm to train the model of DHMM.

Keywords- Fuzzy Vector Quantization, EEG signal, Discrete Hidden Markov Model

I. INTRODUCTION

Recently, the Hidden Markov Model (HMM) is applied in many applications for prediction due to its statistic properties [1]. It is especially successful on the automatic speech recognition (ASR). According to the type of the probability distributions used in HMMs, HMMs can be categorized as Continuous Hidden Markov Model (CHMM) and Discrete Hidden Markov Model (DHMM). The DHMM provides more stable recognition results and faster training with the recognition accuracy that is no less than CHMM. Therefore, the DHMM is adopted in this paper. The codebook for the feature quantization of the target signal will be recognized plays an important role on the training of DHMM model. A well-trained codebook will enhance the total performance of

the recognition systems. In the past, the features are quantized by a codebook trained by K-means algorithm. This winner-take-all algorithm can not perform well on vector quantization, since multiple level of an element in some vectors exists in many applications. Consequently, the fuzzy vector quantization is used improve the performance of the vector quantization. Many research shows that the fuzzy vector quantization outperform VQ [2]. Besides, the relative works of fuzzy vector quantization, e.g. the fuzzy clustering [3-4] and fuzzy data retrieval systems [5] also demonstrate the benefit of fuzzy quantization method.

Besides, sleep is very importance to human's health. Humans spend averagely about 7 to 8 hours a day on sleep, which is equivalent to one third of our lifetime. At night, an 8-hour sleep contains about 4 to 5 sleep cycles and each cycle lasts about 90 minutes with different stages including light sleep (Stages 1 & 2), deep sleep (Slow Wave Sleep) and rapid eye movement (REM). The deep sleep stages become shorter as sleep cycle progresses. In human physiology, a good deep sleep (SWS) stage can help with physical recovery; as well, a good rapid eye movement (REM) stage can improve one's learning abilities and memories. Sleep diseases, such as insomnia and obstructive sleep apnea, seriously affect patients' quality of life. Without restrictive criteria, the prevalence of insomnia symptoms is approximately 33% in the general population. Obstructive sleep apnea affects over 2% of adult women and 4% of adult men [6]. These sleep issues may cause daytime sleepiness, irritability, depression, anxiety or even death.

For the diagnosis of sleep issues, all night polysomnographic (PSG) recordings, including electroencephalogram (EEG), electrooculogram (EOG) and electromyogram (EMG), are usually taken from the patients and the recordings are scored by a well-trained expert

according to the Rechtschaffen & Kales (R&K) rules presented in 1968. According to the R&K rules, each epoch (i.e., 30 s of data) is classified into one of the sleep stages, including wakefulness (Wake), non-rapid eye movement (stages 1-4, from light to deep sleep) and non-rapid eye movement (NREM).

Consequently, in this paper, the recognition of the sleep stage form EEG signal is used as an example to demonstrate the improvement of DHMM by FVQ.

II. FVQ AND DHMM

This paper introduces the proposed fuzzy vector quantization for the features used to train DHMM through a well trained codebook.

A. Fuzzy Vector Quantization

In order to train the DHMM model, a codebook should be set up first. In the codebook, feature vector must be classed as by vector quantization [1]. The K -means algorithm is adopted to train the codebook at head. Then, combing the fuzzy set, the codebook is arranged as a fuzzy codebook and all the features in training phase and in testing phase will be fuzzy vector quantized through the fuzzy codebook. Suppose a set of real numbers are expressed as $\{v_1, v_2, \dots, v_n\}$ in which $v_i \in R$ and the corresponding fuzzy set is expressed as

$\{u_i(x) | i = 1, 2, \dots, n\}$, where $\sum_1^n u_i(x) = 1, \forall x \in R$. The

triangular fuzzy set is depicted in Fig. 1. It is noted that since the elements of the codebook are not uniformly distributed in the domain of the speech signal after the training by K -means algorithm, the triangular fuzzy set is not symmetric in this application. The membership function in Fig. 2 is described as [2]:

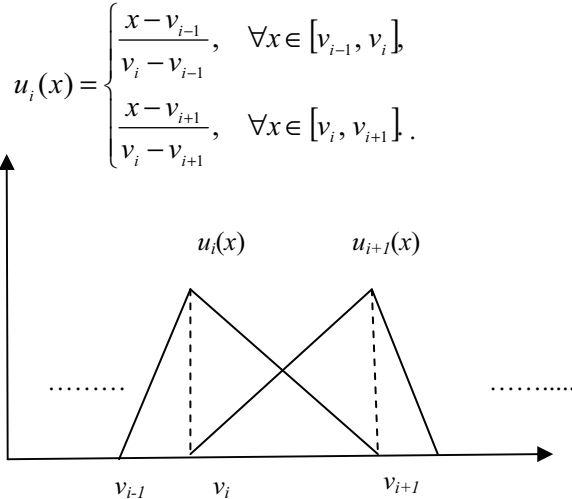


Fig. 1 Fuzzy set corresponding to each element of codebook

B. Discrete Hidden Markov Model (DHMM)

The DHMM is a double layers random process. The transfer of hidden states will correspond to the transfer of observations. Each model of DHMM can describe a specific signal to be recognized. The features of a signal are the observations used to estimate the hidden states. The target signal can be recognized by calculating the probability of the DHMM model. The model with highest probability in all DHMM models represents the most possibility of the recognized signal corresponding to the model [1].

In this section, the DHMM model is denoted as

$$\lambda = \{A, B, \pi, S, V\} \quad (1)$$

in which

$S = \{s_1, s_2, \dots, s_N\}$ is the hidden state;

$V = \{v_1, v_2, \dots, v_M\}$ is the output set of the DHMM model;

$A = \{a_{ij}\}, a_{ij} = P(q_t = s_j | q_{t-1} = s_i)$ is the probability matrix of state transfer;

$B = \{b_j(k)\}, b_j(k) = P(o_t = v_k | q_t = s_j)$ is the probability matrix of transfer out from each states;

$\pi = \{\pi_i\}, \pi_i = P(q_1 = s_i), 1 \leq i \leq N$ is the initial state probability;

$O = \{o_1, o_2, \dots, o_T\}$ is the observation sequence;

$Q = \{q_1, q_2, \dots, q_T\}$ is the state sequence.

As for the training of the DHMM model, the matrices A, B , and π are randomly generated initially. Then, the matrices are updated by the following algorithm.

$$state_t = \arg \max_{0 \leq i \leq 6} \alpha_t(i) \quad (2)$$

in which $state_t$ is the best estimated hidden state at time t ; $\alpha_t(i)$ is the probability for i th guessed state at time t according to A, B , and π . Moreover, the matrices A and B are trained as follows.

The trained parameter $\bar{a}_{ij}$ of a_{ij} and $\bar{b}_j(k)$ of $b_j(k)$ is described as

$$\bar{a}_{ij} = \frac{n(u_{ij})}{n(u_{i\bullet})} \quad (3)$$

$$\bar{b}_j(k) = \frac{n(u_{\bullet j}, o = v_k)}{n(u_{\bullet j})} \quad (4)$$

in which

u_{ij} is the event that the state s_i transfer to s_j ;

$u_{i\bullet}$ is the event that the state s_i transfer to other states;

$u_{\bullet j}$ is the event that enter the state s_j ;

$n(u_{ij})$ is the number of times that s_i transfer to s_j ;

$n(u_{i\bullet})$ is the number of times s_i transfer to other states;

$n(u_{\bullet j})$ is the number of times that enter the state s_j ;

$n(u_{\bullet j}, o = v_k)$ is the number of times that the observation v_k occur when enter the state s_j .

The number $n(u_{\bullet j}, o = v_k)$ is obtained through the fuzzy codebook as follows. Suppose that the features are classified into n classes by K -means algorithm, i.e., the trained codebook is expressed as $CB_{n \times m} = \{FK_1, FK_n, \dots, FK_n\}^T$ where $FK_i \in R^m$ is the center vector of i th class. The fuzzy degree contribute to the number $n(u_{\bullet j}, o = v_k)$ for each feature $f \in R^m$ is computed as $u_i(v_i + \|FK_i - f\|)$ for $n(u_{\bullet j}, o = v_i)$ and $u_i(v_{i+1} - \|FK_{i+1} - f\|)$ for $n(u_{\bullet j}, o = v_{i+1})$. This tactic is not only used for the training phase of the DHMM model but also for the testing phase of the speech recognition. In this paper, the strategy of using DHMM to recognize the signal is that we train first DHMM model λ for each corresponding signal by fuzzy codebook. Then, in testing phase, the tested signal features which is viewed as a sequence of observation O are fed into each DHMM model. The highest probabilities are found from computing the probability for all models by using the following equation:

$$P(O | \lambda) = \sum_{all Q} P(O, Q | \lambda) \quad (5)$$

$$= \sum_{q1, q2, \dots, qT} \pi_{q1} \cdot b_{q1}(o_1) \cdot a_{q1q2} \cdot b_{q2}(o_2) \cdot a_{q2q3} \cdots a_{qT-1qT} \cdot b_{qT}(o_T).$$

Figure 2 shows the processes for the training of the fuzzy codebook and DHMM model. Besides, the speech recognition process also can be found in the figure.

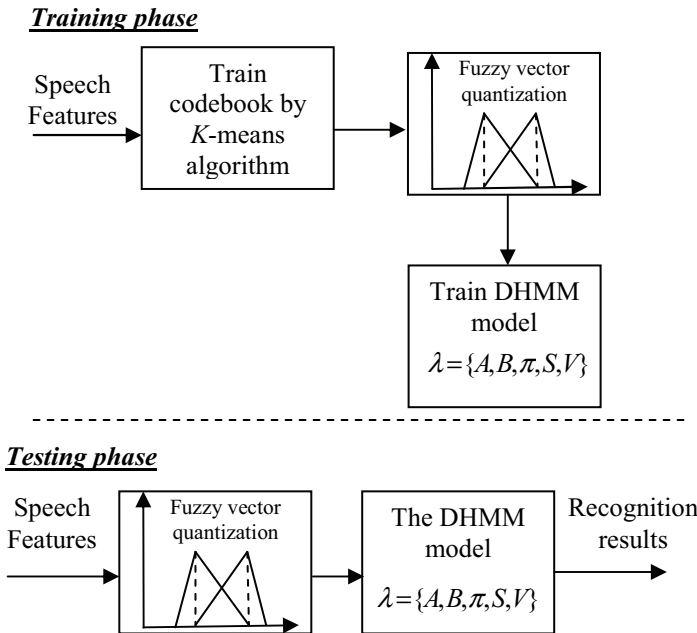


Fig. 2 Strategy of the proposed FVQ on speech recognition by DHMM

III. SLEEP STAGE AND EEG

The main purpose of this section is to enable the understanding of the basic elements of sleep stages. First, we introduce polysomnography, which includes electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG) [7]. Then, we introduce the classification of sleep stages used in the R&K rules, and explain why we adopte the new sleep staging classification.

Polysomnography (PSG) is a multi-parametric test used in the study of sleep, as well, it is used as a diagnostic tool in sleep clinical trials. The test result is called a polysomnogram. Polysomnography is a comprehensive recording of the biophysiological changes that occur during sleep. The PSG monitors many body functions including brain activities (Electroencephalogram), eye movements (Electrooculogram), muscle activity or skeletal muscle activation (Electromyogram) and heart rhythm (Electrocardiogram) during sleep [8].

Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. The sleep analysis, the EEG, is based on the characteristics of brain activities, and it can be divided into several different frequency bandwidths. The main EEG frequency bandwidths are given below in Table 1 [9]:

Table 1 Various signals in EEG [9]

Type	Frequency (Hz)	Waveform
Delta	0 – 4 Hz	
Theta	4 – 8 Hz	
Alpha	8 – 13 Hz	
Beta	13 – 30 Hz	

Electrooculogram (EOG) is the resulting signal of a technique for measuring the resting potential of the retina. Eye movements are usually measured by placing pairs of electrodes either above and below, or to the left and right of the eye [10]. If the eye is moved from the center position towards one electrode, this electrode realizes the positive side of the retina, and the opposite electrode realizes the negative side of the retina. Consequently, a potential difference occurs between the electrodes. Assuming that the resting potential is constant, the recorded potential is a measurement for the eye

position [11]. In this paper, we use one EOG feature to recognize mainly the REM stage.

Electromyogram (EMG) is a technique for evaluating and recording the electrical activities produced by skeletal muscles. In sleep analysis, the electrodes are typically placed on the chin of the subject. The impulse (action potential) for muscle activation begins from the central nervous system, and it reaches the muscle via the spinal cord and the motor neuron. The action potential can be measured as EMG signals [12]. From the EMG signal, we will be able to tell whether the subject has entered deep sleep, and whether his muscles are in a relaxed state. In this paper, we will use three EMG features to recognize mainly the Wake stage.

3.1 Sleep Stages

In this subsection, we introduce the manual sleep staging rules by R&K rules and new sleep stage by AASM. Furthermore, the Mov stage which is used in previous research is included in this study and will be explained later.

2.2.1 Manual Staging Rules

The standard of manual sleep staging is R&K rules, which is proposed by Rechtschaffen and Kales in 1968 [13]. According to R&K rules, the stages are scored epoch-by-epoch in 20-30 second intervals. Then, the sleep is divided into six stages: stage wake(Wake), stage 1(S1), stage 2(S2), stage 3(S3), stage 4(S4), and stage rapid eye movement (REM). The details of each stage in R&K rules are described as follows [14].

Stage wake (Wake):

There is a low voltage (10–30 μ V) and mixed frequency (2-7 Hz) EEG during wakefulness. Possible features are alpha (8-13 Hz) activity in EEG and relatively high tonic EMG, about > 50% of the epoch.

Stage 1 (S1):

S1 is characterized by low voltage, mixed frequency EEG with the highest amplitude in the 2-7 Hz range. The vertex sharp waves may occur, and their amplitude can reach the value of about 200 μ V. The alpha activity is less than 50% of an epoch.

Stage 2 (S2):

S2 is characterized by wave-pattern sleep spindles (12–15 Hz), K-complexes (sharp negative waves) and the absence of slow waves. The duration of these patterns should be a minimum of 0.5 second. If the time duration between two succeeding occurrences of sleep spindles or K-complexes is less than 3 minutes, this epoch is scored as S2, otherwise it is scored as S1.

Stage 3 (S3):

S3 is characterized by the presence of a minimum of 20-50% delta waves ranging from 0.5-2 Hz EEG and having a peak-to-peak amplitude > 75 μ V. Sleep spindles and K-complexes may occur during S3.

Stage 4 (S4):

S4 has the same attributes as S3, 0.5-2 Hz EEG and amplitude > 75 μ V. The only difference is the delta waves are more than 50% of an epoch.

Stage REM (REM):

REM shows low voltage and mixed (2-7 Hz) frequency of EEG similar to S1. Sawtooth wave patterns in EEG is often present. Moreover, EMG reaches the lowest level in this stage. In 2007, the American Academy of Sleep Medicine (AASM) group decided the new stage name terminology as follow: Stage W (Wakefulness), Stage N1 (NREM 1 sleep), Stage N2 (NREM 2 sleep), Stage N3 (NREM 3 sleep), Stage R (REM sleep). It is noted that NREM is non-REM stage, which consists of three stages N1, N2 and N3 [15]. The stages N1 and N2 are equivalent to S1 and S2 in the R&K rules respectively, and are light sleep. The stage N3 is equivalent to the stage that combined S3 and S4 in the R&K rules. Because the characteristics of the two stages S3 and S4 are much similar, in order to facilitate simplicity and accuracy of sleep staging, AASM group hence decided to combine stages S3 and S4 as N3. Stage N3 is also called deep sleep, or slow wave sleep (SWS) stage. The term SWS is used for revealing the physical meaning of this stage, therefore, in this paper, we adopt the five stages classification: Wake, S1, S2, SWS, and REM.

IV. SLEEP STAGE BY OBSERVATION-BASED DHMM

In observation-based DHMM, the DHMM are modeled for each sleep stage. Therefore, there are five DHMM models corresponding to each sleep stage. The transition for each DHMM model is illustrated in Fig. 3. The hidden states are arbitrarily defined in this strategy. The features become the observation codes via vector quantization. For the DHMM $\lambda = (A, B, \pi)$, A is the probability matrix of the transference from one hidden state to another hidden state. The matrix B is the probability matrix of the observation of a hidden state. The matrix π is the probability of the hidden state at the beginning. In this strategy, we focus on the probability of the five DHMM models, corresponding to the five sleep stages for a feature vector (observation). The DHMM model with maximum probability among all models is distinguished, and the corresponding sleep stage is the estimated stage for the feature vector. This strategy is shown in Fig. 4. In the Fig. 4, P_{Wake} , P_{S1} , P_{S2} , P_{SWS} and P_{REM} are the probability of the five DHMM models for feature vectors calculated from a 30-second sample of a sleep stage, corresponding to the five sleep stages Wake, S1, S2, SWS and REM, respectively.

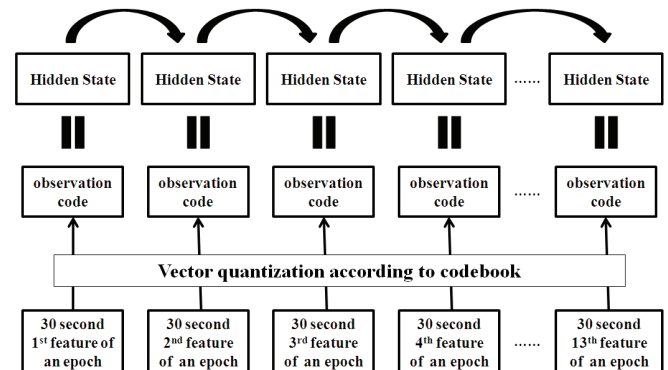


Fig. 3 DHMM for sleep staging.

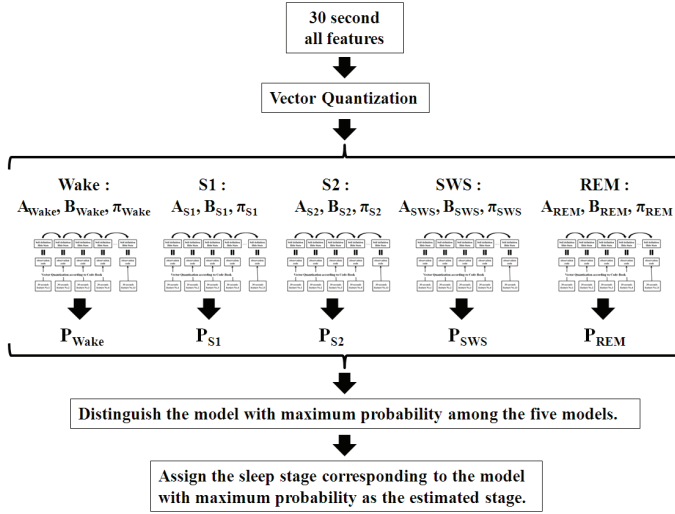


Fig. 4 Strategy of observation-based DHMM sleep staging.

Based on the above discussion, the sleep staging procedure by observation-based DHMM is then summarized as follows.

Procedure of observation-based DHMM sleep staging

- Step 1. Train codebook by K -mean method.
- Step 2. Generate five DHMM models by finding (A, B, π) of the corresponding sleep stages.
- Step 3. Generate the observation codes by quantizing the feature vectors based on the codebook.
- Step 4. Calculate the probability of all sleep models using the corresponding (A, B, π) .
- Step 5. Choose the model with the highest probability among all of the sleep models for the feature vector and assign the corresponding sleep stage as the estimated sleep stage.
- Step 6. Repeat Steps 3 to 5 until all the feature vectors of the epochs are completed.

V. SLEEP STAGE BY OBSERVATION-BASED DHMM

In our experiment, we use the signals measured from three EEG channels (C3, F3, and P3), EMG and EOG to generate the features for training and testing. The sleep data used in the experiments are collected from twenty subjects and are numbered from No. 1 to No. 20 for convenience. The 158 hours of sleep data are recorded, and then used to train seventeen subjects and test three subjects. There are three different combinations of the training and testing set, named Set 1, Set 2 and Set 3, are used in this experiment and are listed in Table 2.

Table 2 Former class with three testing subjects.

Combination sets	Training subjects	Testing subjects
Set 1	{No. 1 ~ No. 20}/{Testing subjects}	No. 10, No. 14, No. 17

Set 2	{No. 1 ~ No. 20}/{Testing subjects}	No. 3, No. 9, No. 20
Set 3	{No. 1 ~ No. 20}/{Testing subjects}	No. 5, No. 12, No. 19

Table 3 shows the recognition rates of the proposed various tactics which are designed based on the DHMM without FVQ while Table 4 is those with FVQ. A more detail comparison on the recognition rate of each sleep stage and means for the three sets Set 1, Set 2 and Set 3 are depicted in Fig. 5 – Fig. 8. These figures reveal that the DHMM with FVQ performs much better than DHMM without FVQ. This verify that the proposed FVQ on DHMM is efficient.

Table 3(a) Recognition rate for Set 1 by DHMM without FVQ

DHMM without FVQ (Set 1)						
R&K		Wake	S1	S2	SWS	REM
mean: 78.35%	Wake (%)	79.17	8.33	6.25	6.25	0
	S1 (%)	5.44	12.72	48.44	4.17	29.22
	S2 (%)	0.43	2.89	81.05	11.57	4.06
	SWS (%)	0.33	0.56	7.35	91.75	0
	REM (%)	0.53	9	27.74	0.47	62.26

Table 3(b) Recognition rate for Set 2 by DHMM without FVQ

DHMM without FVQ (Set 2)						
R&K		Wake	S1	S2	SWS	REM
mean: 76.75%	Wake (%)	74.22	8.69	2.56	9.54	4.99
	S1 (%)	5.67	7.04	36.77	1.42	49.09
	S2 (%)	0.28	2.34	82.36	5.68	9.33
	SWS (%)	1.95	0.57	18.02	78.19	1.27
	REM (%)	0.40	5.26	19.37	0.21	74.77

Table 3(c) Recognition rate for Set 3 by DHMM without FVQ

DHMM without FVQ (Set 3)						
R&K		Wake	S1	S2	SWS	REM
mean: 79.11%	Wake (%)	62.15	6.42	10.76	1.91	18.75
	S1 (%)	4.44	5.93	43.43	3.70	42.49
	S2 (%)	0.37	1.72	82.03	8.72	7.17
	SWS (%)	0.61	0.66	8.06	90.35	0.31
	REM (%)	0	4.63	19.30	0.89	75.22

Table 4(a) Recognition rate for Set 1 by DHMM with FVQ

DHMM with FVQ (Set 1)						
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R&K		Wake	S1	S2	SWS	REM
mean: 86.64%	Wake (%)	97.92	0	2.08	0	0
	S1 (%)	14.72	10.45	39.39	0	35.44
	S2 (%)	0.35	0.21	88.56	8.47	2.41
	SWS (%)	0.65	0	5.01	94.34	0
	REM (%)	0.75	3.79	14.47	0.47	80.52

Table 4(b) Recognition rate for *Set 2* by DHMM with FVQ
DHMM with FVQ (Set 2)

R&K		Wake	S1	S2	SWS	REM
mean: 81.96%	Wake (%)	94.66	0.92	3.49	0	0.93
	S1 (%)	18.03	5.65	31.15	0	45.17
	S2 (%)	0.21	0.36	87.57	3.80	8.06
	SWS (%)	1.73	0.86	12.66	84.75	0
	REM (%)	0.34	3.14	17.17	0.13	79.22

Table 4(c) Recognition rate for *Set 3* by DHMM with FVQ
DHMM with FVQ (Set 3)

R&K		Wake	S1	S2	SWS	REM
mean: 84.36%	Wake (%)	65.97	17.19	10.42	2.78	3.64
	S1 (%)	7.17	7.29	43.55	0	41.99
	S2 (%)	0	0.22	87.86	9.77	2.15
	SWS (%)	0.20	0.16	5.57	94.07	0
	REM (%)	0	1.16	16.04	0.47	82.33

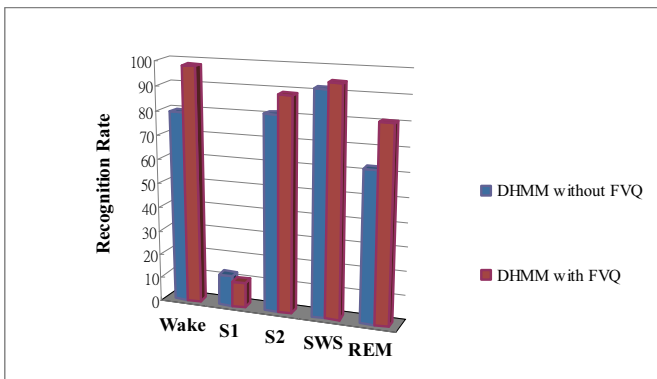


Fig. 5 Recognition rate on each sleep stage for Set 1

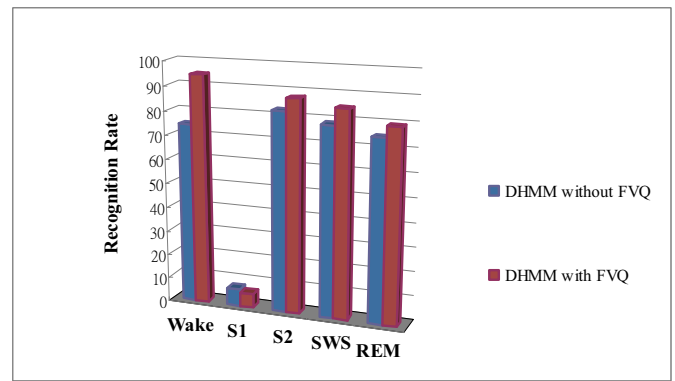


Fig. 6 Recognition rate on each sleep stage for Set 2

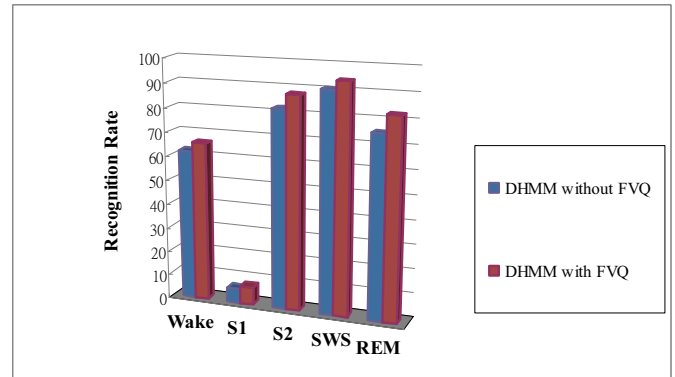


Fig. 7 Recognition rate on each sleep stage for Set 3

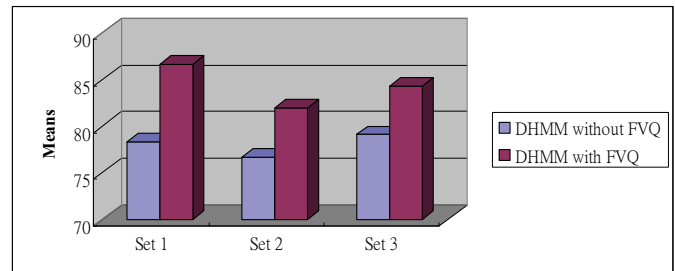


Fig. 8 Means of recognition rate for Set 1, Set 2 and Set 3

VI. CONCLUSIONS

The fuzzy vector quantization (FVQ) had been used on the modeling of Discrete Hidden Markov Model (DHMM) to improves the recognition rate for the sleep stages based on EEG, EOG and EMG signals. First, a codebook was trained by *K*-means algorithms. Based on the trained codebook, the features are quantized by the fuzzy sets defined on the trained codebook. Subsequently, the quantized features are used to the modeling of DHMM for the sleep stage recognition. All the features should go through the FVQ based on the fuzzy code book before being fed into the DHMM model for recognition. Experimental results reveal that the speech recognition rate can be improved by using FVQ algorithm to train the model of DHMM.

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