Sleep Stages Classification by CW Doppler Radar Using Bagged Trees Algorithm

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***Abstract*—The quality of sleep has a great impact on health and life quality. A classification of sleep stage is very important for managing the quality of sleep. This paper presents a method for classifying sleep stages based on the bagged trees classifier with a continuous-wave (CW) Doppler radar. In the experiment, a subject was asked to sleep all night with polysomnography (PSG) to get the labels of the nine features extracted from the radar signals. Four kinds of tree classifiers were selected as the machine learning algorithm to classify wakefulness, rapid eye movement sleep (REM), light sleep and deep sleep. A 10-fold cross-validation procedure was used for testing the classification performance. Compared to PSG results, the bagged trees classifier has the best classification accuracy rate among the four classifiers. Using appropriate parameter of the base learner, the accuracy rate can be improved to 78.6%.**

***Index Terms*—sleep stage, CW Doppler radar, bagged trees algorithm, feature extraction**

I. Introduction

Sleep plays an important role in our daily life. The quality of sleep has a great impact on human immune system and cognitive function. it was not until recently that sleep found its role in several medical problems. Sleep disorders increase the risk of accidents, psychiatric disorders, cardiovascular diseases and obesity [1]. Usually we divide an overnight sleep into four stages as wakefulness, rapid eye movement sleep (REM), light sleep (NREM1 and NREM2) and deep sleep (NREM3) [2]-[4].

The gold standard for evaluating the sleep stages is polysomnography (PSG). However, during a PSG test, many sensors are needed to be attached to on the human body. Therefore, it is expensive and very uncomfortable for daily use. For participants, it is difficult to maintain the normal sleep route. As a result, the data received from the PSG cannot accurately reflect the sleep quality of the subject. Thus, it is important to provide a convenient method to monitor sleep, and accurately recognize sleep stages.

Some researchers have attempted to use non-contact monitor methods, such as video, phones and biomedical radar, to overcome these challenges [5]-[7]. Considering the privacy concern and high-cost, video and phones still have limitations compared to biomedical radar. Based on the non-contact detection technology, biomedical radar can monitor real-time vital signs information (such as respiration, heartbeat and body movement) of the measured target. It has the advantages of less susceptible to environmental factors and good accuracy. Also biomedical radar can provide a comfortable and non-invasive way for people to monitor sleep. There are some researches about biomedical radar in sleep stages. F. Lin et al. [8] had some researches about using a Doppler radar-based sensor to build a sleep status recognition framework. However they only focused on activities classification including on-bed movement, bed-exit and breathing but did not have the classification of sleep stages. Pallin et al. [9] and Hashizaki et al. [10] reported results of 2-stage (sleep / wakefulness) classification with the biomedical radar but did not provide any details of the method that they used.

In this paper, to address the limitations of PSG and classify more sleep stages with non-contact monitoring system, we used a continuous-wave (CW) Doppler radar based on machine learning using the bagged trees algorithm to classify the four stages as wakefulness, REM, light sleep and deep sleep. The remaining sections of this paper are organized as follows: Section II discusses the theory of Doppler radar in non-contact detection and feature extraction based on the signal from the Doppler Radar. Section III introduces the algorithm of the bagged trees and compares the classification result with the other three decision tree in different splits. In Section IV, we perform a set of experiment and analyze the experimental results. Finally, we conclude the paper and describe future work in Section V.

II. Theory

A. Theory of Doppler Radar Vital Signs Detection

The CW Doppler radar can be used to detect respiration, heartbeat and body movement. It transmits a single tone signal to the human body. When the radio wave reaches the human body, the displacement information of the chest wall which is associated to the respiratory and heartbeat movements will be modulated into the signal in the form of phase shift. And the energy information is correlative to the body movement signal.

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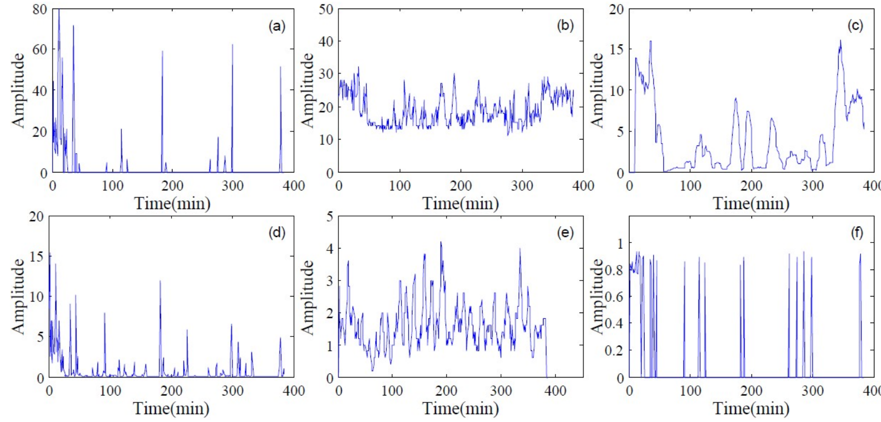

Fig. 1. Six features extracted from the respiration signal including (a) Movement signal (b) Respiration per minute (RPM) (c) Variance of respiratory rate for whole night (d) Amplitude difference accumulation (ADA) (e) REM parameters (f) Deep parameters.

The transmitted signal can be assumed as:

$$T(t) = \cos[2\pi f t + \varphi(t)] \tag{1}$$

where f is the carrier frequency and φ is the phase noise. Compared to the transmitted signal, the received signal has a time delay $\tau = \frac{2d(t)}{c} = \frac{2d_0+2x(t)}{c}$, where d_0 is the fixed distance between the radar and the human body, $x(t)$ is the displacement of the chest wall. So the echo of the radar can be written as:

$$\begin{aligned} R(t) &= T(t-\tau) \\ &= \cos[2\pi f(t - \frac{2d_0 + 2x(t)}{c}) + \varphi'(t)] \\ &= \cos[2\pi f t - \frac{4\pi f d_0}{c} - \frac{4\pi f x(t)}{c} + \varphi'(t)] \end{aligned} \tag{2}$$

where $\varphi'(t) = \varphi(t - \frac{2d_0}{c} + \frac{2x(t)}{c})$.

In order to obtain the phase shift information, we perform frequency mixing between $T(t)$ and $R(t)$ to generate two quadrature base band signal which can be formulated as:

$$B_I(t) = \sin[\theta + \frac{4\pi x(t)}{\lambda} + \Delta\varphi(t)] \tag{3}$$

$$B_Q(t) = \cos[\theta + \frac{4\pi x(t)}{\lambda} + \Delta\varphi(t)] \tag{4}$$

where $\Delta\varphi(t) = \varphi(t) - \varphi(t - \frac{2d_0}{c})$ is the residual phase noise and $\theta = \theta_0 + \frac{4\pi d_0}{\lambda}$ is the constant phase related to the nominal distance d_0. As shown in (3) and (4), the vital signs information can be acquired by arc-tangent method.

$$\phi(t) = \arctan(\frac{B_Q(t)}{B_I(t)}) = \theta + \frac{4\pi x(t)}{\lambda} + \Delta\varphi(t) \tag{5}$$

Considering that the respiratory and heartbeat signals are distributed in different frequency sections, we can get them through two filters. And the energy of the respiratory signal can reflect the information of the body movement.

B. Feature Extraction

In this paper, the sleep data from all night are divided into successive epochs. Each epoch is 60 s, and nine features are extracted from it. Six features were extracted from the respiratory signal and the other three from the heartbeat signal. Features were extracted directly from the analyzable part.

1) Body movement signal: During sleep, with the occurrence of body movement, the body movement monitoring is essential for the detection of sleep. We combine the energy spectrum method with the root mean square error (RMSE) method to determine body movement. The initial values of them are set to 0, and then the energy and RMSE within 10 seconds window are calculated. When they are both larger than the threshold values, this window is determined to occur a body movement. The body movement signal is presented in Fig. 1(a).

2) Respiration per minute (RPM): In this paper, we use peak detection to calculate the REM. The peak detection is the second derivative of the respiratory signal, the first derivative is zero, the second derivative less than zero is the respiratory signal peak, and we need to remove the pseudo peaks in the calculation. The range of respiratory rate of a healthy adult is 0.13Hz-0.4Hz, therefore the peaks out of this range are discarded. Then we extract the effective peak points per minute as the number of breathing. The RPM all night is shown as Fig. 1(b).

3) Variance of respiratory rate: Variance is a measure of a random variable or set of data in probability theory. As shown in Fig. 1(c), variance of respiratory rate can reflect the rate of change for the whole night. We can learn that the variance becomes larger with the increasing of the respiratory rate. So variance is an important parameter to determine REM. To reflect the change in the number of respiration, we calculate a variance within a five-minute window.

4) Amplitude difference accumulation (ADA): Sleeping in NREM, the amplitude of respiratory signal is smoother and the frequency is slower than the REM. Body movement during the deep sleep period is almost none and the peaks of the

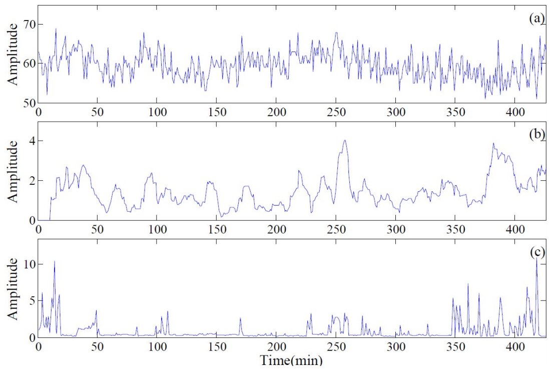

Fig. 2. Three features extracted from the heartbeat signal including (a) Beat per minute (BPM) (b) Variance of BPM for whole night (c) Amplitude difference accumulation (ADA) of the heartbeat signal

respiratory signal are in a steady state,

thus the accumulation of the difference in the peak value of the respiratory signal in every minute can effectively determine whether or not it is in deep sleep. The accumulation of respiratory signal peak difference is shown in Fig. 1(d).

5) REM parameters: The REM parameters (Fig. 1(e)) are defined as follows [11]:

$$Rem\left(k\right)=\frac{1}{2q+1}\sum_{i=-q}^{q}\left|R_K^{former}-R_{K+1}^{latter}\right| \tag{6}$$

where the R_K^{former} indicates the number of breaths in the first 30 seconds of the k-th minute, and the R_K^{latter} indicates the number of breaths in the second 30 seconds of the k-th minute. The difference of them represents the difference in the number of breaths at the k-th minute and the REM parameter during the REM period becomes larger.

6) Deep parameters: By medical knowledge we can see, during deep sleep stage, the amplitude of body movement signal becomes very small and frequency becomes low. therefore we extract the deep parameters to estimate deep stage. The deep sleep parameters (Fig. 1(f)) are defined as follows [11]:

$$D\left(k\right)=\frac{A_k^{body}}{A_k^{resplr}+A_k^{body}} \tag{7}$$

where A_k^{body} indicates the body movement signal during sleep, A_k^{respir} indicates the respiratory signal and $D(k)$ indicates the proportion of body movement signal in breathing. The value of $D(k)$ in the light sleep compared to the deep sleep will become larger.

7) Heartbeat signal parameters: The heart rate signal parameters extraction method is similar to that for the respiratory signal. We extract the heart rate (Fig. 2(a)), variance (Fig. 2(b)) and ADA (Fig. 2(c)) of the heart rate as the features.

III. Classification Algorithm

A bagged trees classifier was used in the experiment. The bagged trees classifier, which is an ensemble classifier, has high performance in many realistic tasks. It is the combination of the bagging algorithm and decision tree classifier [12]-[13].

Bagging is based on the bootstrap sampling. From the original data set, we choose m samples randomly as a training set to train the base learner. By repeating N times, we get those classifiers. The result is got from plurality vote, which is introduced as follow:

$$H\left(x\right)=c_{\underset{j}{arg\max}\sum\limits_{i=1}^{N}h_i^j(x)} \tag{8}$$

where h_i^j is the output that comes from the N classifier. The details about the bagging algorithm are shown in Algorithm 1.

Algorithm 1 Bagged Algorithm

Inputs:

Training Set $D=\{(X_1,y_1),(X_2,y_1),...,(X_m,y_m)\}$;

Base Learning Algorithm σ;

Traning Times N;

Iteration:

1: **for** $t=1,2,3,...,N$ **do**

2: $h_t=\sigma(D,D_{bs})$

3: **end for**

Output: $H\left(x\right)=\underset{y\in\mathcal{Y}}{arg\max}\sum\limits_{t=1}^{N}\mathbb{I}\left(h_t\left(x\right)=y\right)$

Decision tree classifier is the base learner. Usually one decision tree include a root, some interior nodes and leaf nodes. The leaf nodes correspond to decision results, other nodes correspond to the attributes A respectively and root has all samples. The maximum number of splits (MaxNumSplits) is the parameter which we can set. Specify the MaxNumSplits or branch points to control the depth of the decision tree.

IV. Experiments

A. Experimental Setup

The experimental setup is illustrated in Fig. 3. A male healthy subject was asked to lie on the bed to sleep all night with a digital-IF Doppler radar (2.4GHz, -7dBm transmitting power) located on the top of him. The distance between the radar and him is 0.8 meter. Meanwhile, the PSG, which collected nineteen sets of data, including: three channels for the EEG, three for the ECG, four for the EOG (including two channels for the reference signals), two for the chin muscle tone, four for the body movement signal, as well as oxygen, oronasal airflow and belly straps, was tied to the subject. The PSG classifies the sleep period into wake, REM sleep, light sleep (NREM1,NREM2) and deep sleep (NREM3). We used them as labels to train the features.

B. Experimental Result

We used four classifiers including bagged trees (the MaxNumSplits is 20), simple tree (the MaxNumSplits is 4), medium tree (the MaxNumSplits is 20) and complex tree (the MaxNumSplits is 100) to classify the sleep stages. The accuracy rates of the classifier were evaluated based on 10-fold

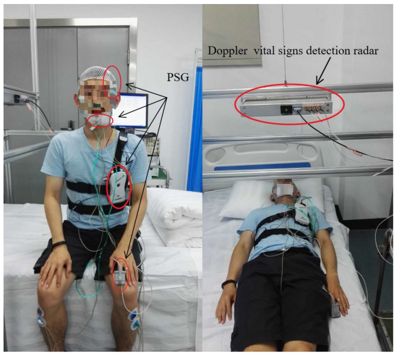

Fig. 3. Experimental setup.

TABLE I
THE ACCURACY RATES OF FOUR TREE CLASSIFIERS

Classifier	MaxNumSplits	Accuracy
Complex Tree	100	66.0%
Medium Tree	20	69.5%
Simple Tree	4	70.2%
Bagged Trees	20	76.5%

cross-validation. In the validation, the data sets were divided into ten folds randomly. Each time, nine folds were picked out as the trained folds for the classifier, and the remaining one was chosen as the test fold. This procedure was repeated for ten times and the final classification accuracy rate is defined as the average classification rates of the ten times.

Table I shows the classification accuracy rates of those classifiers. The accuracy rates are 66.0%, 69.5%, 70.2% and 76.5%. The bagged trees classifier shows the best classification accuracy rate. And in the decision tree classifiers (simple tree, medium tree and complex tree), we can see that the simple tree presents the best accuracy rate at 70.2%. It shows that the accuracy rate changes along with the changes of the MaxNumSplits.

Then, we changed the MaxNumSplits with different values (the MaxNumSplits = 1,2,3,...,20,50,100) to train the decision tree classifier repeatedly. Fig. 4 shows relationship between the accuracy and MaxNumSplits. The accuracy rates increases as the MaxNumSplits steps up. When the MaxNumSplits is 9, the accuracy rate reaches the peek at 72.3%. However, with the MaxNumSplits continues to increase, the accuracy begins to decrease. Therefore, we set the decision tree with the MaxNumSplit at 9 as the base learner of the bagged trees. When the MaxNumSplits sets to 9, the bagged trees classifier gains an accuracy of 78.6% which is better than the original result.

V. CONCLUSION

In this paper, a novel method to classify sleep stages based on bagged trees classifier in a CW Doppler radar is proposed. Nine features were extracted for four classifiers to classify the sleep stages. The experimental results show that the bagged trees classifier has the best accuracy and the MaxNumSplits is related to the accuracy. Finally an accuracy of 78.6% were achieved compared to the PSG result. Because sleep stages classification is an imbalanced task, we will focus on the research of new algorithm and features to overcome this problems and take more subjects to experiment in future work.

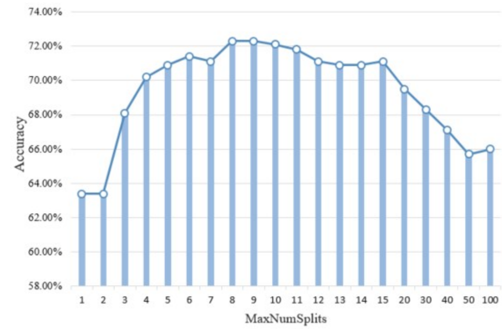

Fig. 4. The relationship between accuracy and MaxNumSplits.

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