An Intelligent Head Posture Recognition Pillow

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Abstract— The position and posture of the head during sleep can reflect the quality of sleep and overall health. As an important component of bedding that supports the head during sleep, pillows have gained attention from researchers due to their potential to monitor head posture through a variety of sensing means. This paper proposes a non-wearable sleep posture recognition system based on microphones and speakers integrated into the pillow. Two speakers and four microphones are utilized as sound sources and receivers to identify the position and posture of the human head on the pillow. To monitor posture, the pillow is divided into five areas to detect positions related to supine and lateral positions. Due to the pressure exerted by the head on the pillow, the inner latex material of the pillow will be deformed. At the same time, the microphones will be squeezed, changing the characteristics of the sound received. After analyzing the features of the collected data, fully connected neural network is used for classification. The position and posture of the human head on the pillow corresponding to the sound fragment can be predicted by the similarity measurement calculated from the features. The method achieves a posture recognition accuracy of 91.1% and a position recognition accuracy of 98.3%. In conclusion, this study creatively demonstrates the feasibility of identifying the position and posture of the human head on the pillow using speakers integrated into the pillow as a sound source. This method can be combined with hypnotic music in practical applications, making it highly promising in relieving insomnia and improving sleep quality.

1. INTRODUCTION

Sleep plays a very important role in human daily life. In the field of sleep monitoring, sleep posture recognition is an important content. Sleep posture recognition can help maintain a healthy cervical spine and is crucial for preventing pressure sores [1] and obstructive sleep apnea [2]. With the addition of alerts, it also supports caregivers in better caring for patients who have been bedridden for long periods of time, providing therapeutic value in a range of areas. Currently, the standard in terms of sleep disorder diagnosis is an overnight Polysomnogram (PSG) [3]. However, PSGs are expensive and limited by the specialized equipment. Invasive techniques also have a great impact on the subjects' sleep.

Non-invasive sleep posture monitoring can be divided into two categories, wearable and non-wearable, according to the way to capture the state of human bodies. Wearable methods place sensors on the body, such as wrists, ankles, and chest. [4] investigated a wearable sleep system consisting of three wearable inertial sensors on the trunk and forearms. [5] presented a smartwatch-based system that leverages the built-in accelerometer to monitor the respiratory rate and body position. [6] used three devices worn on the ankles and chest in both a simulated and real-world setting. The downside of wearable methods is that the sensor must be worn on the body, which might cause discomfort. Non-wearable methods include the use of FSR sensors [7], infrared sensors [7], millimeter-wave radar [8], dense flexible sensor array and printed electrodes [9], as well as other sensors built into beds and pillows. [10, 11] developed a non-obstructive multiple ultra-wideband radar sleep posture recognition system. These might not be practically fulfilled by the current systems because of cost, privacy concerns, and the interference with sleep.

In this paper, a non-wearable sleep posture recognition system based on microphones and speakers built into the pillow is proposed. The pillow inner deforms under the pressure of the human head, changing the sound received by the microphones from the speakers. Thus, the position and posture of the human head can be monitored. After feature analysis of the collected sound data, fully connected neural network is used for classification, which included five areas of position and two common postures, supine and lateral. This method only requires simple and cheap equipment, and meets the need of privacy protection. The sensors are built into the pillow and do not interfere with sleep. The speakers can gently play hypnotic music, bringing people a better sleep experience and improve the quality of sleep. At the same time, the detection of sleep position and posture can maintain a high accuracy. This work provides a new solution for using non-wearable sensors to monitor sleep position and posture.

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2. SYSTEM DESIGN

2.1. Latex Pillow Inner

In this work, the acoustic properties of latex are a very important factor. It was found that the sound transmission loss (STL) and sound absorption coefficient (SAC) performance is directly proportional to the thickness and density of the latex foam samples [12]. In all cases, the STL value of the foam with a low average pore area was higher than that of the foam with a high average pore area. The structure of the voids and pores of the latex foams acts as the transmission medium of acoustic energy. Low average pore area may lead to stronger resistance to sound-wave transmissibility, resulting in a higher STL value. This is consistent with previous research [13], which found that a larger surface area per unit volume leads to more energy loss due to friction. The results indicated that the smaller the pore size, the higher the acoustic resistance. [14] also found that densely packed foam cell structures increased airflow resistivity, trapping and dissipating sound waves within the foam cell structures. It can be concluded that the density of latex foam plays a vital role in absorbing the propagation of sound waves.

When the head rests on the pillow, pressure of different sizes is exerted on different parts of the latex pillow due to different sleeping positions and postures. On the one hand, it leads to the deformation of latex and change the density and pore structure of local latex. On the other hand, it also leads to the sound from the built-in speaker in the process of transmission to the built-in microphone by different sound resistance which changing the characteristics of the sound. Meanwhile, due to the good sound absorption coefficient and noise reduction coefficient of latex, external sounds such as ambient noise, talking, and snoring have almost no effect on the experimental results. However, when the head is resting on the pillow, the latex squeezes and produces a slight noise. The variation in noise captured by the four microphones is one of the crucial factors in determining sleep position and posture.

2.2. Hardware System

The size of pillow used in this work is 720 mm×410 mm×115 mm. The outer surface material of the pillow is knitted fabric, and the pillow inner material is composed of more than 80% latex and memory foam, with an overall net weight of 1500g. An incision is made in the pillow 70 mm from the bottom which is cut crosswise to a depth of 250 mm, forming a cross-section inside the pillow, as shown in Figure 1. The speakers and microphones are attached here firmly. The length of the pillow is divided into five parts by four microphones, with each part being 144 mm long. The two speakers are separately located in the middle of the two microphones. The tape used to mark the boundaries of the five areas is attached to the part of pillow near the neck. When the subject is lying on an area on the pillow, the head and the neck must between the two boundaries of the area. The specific structure is shown in the Figure 1.

(a) (b)

Figure 1: (a) Cross-section of the pillow. (b) Placement of the built-in speakers and microphones in the pillow inner.

Speakers and microphones are connected to Personal Computer (PC). The sound played by the speakers in the PC is selected, and the sound signal received by the microphones is transmitted back to the computer for data processing and classification.

3. EXPERIMENTAL INVESTIGATION

The experiment involves five areas with a length of 144 mm, equally divided from left to right on the pillow. The two postures involved are supine and lateral, as shown in Figure 2.

There are two kinds of sounds played by the speakers, one is sound with a fixed frequency of 200 Hz, and the other is soft hypnotic music. The volume is adjusted to a level that can be heard

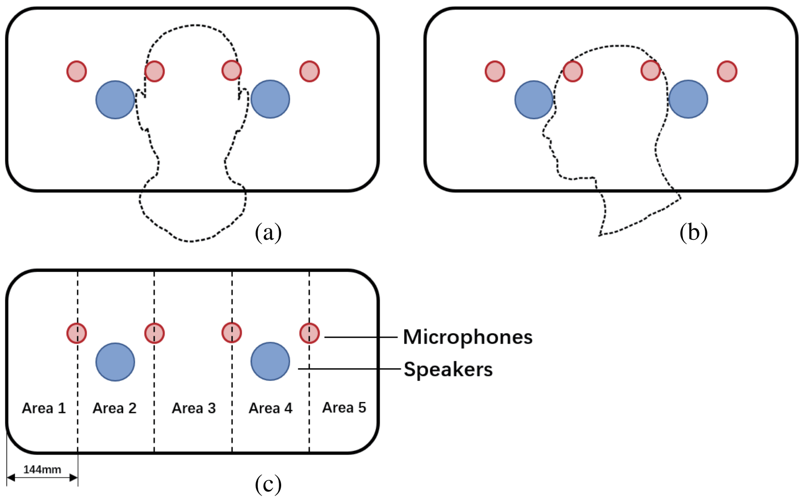


Figure 2: (a) Supine position. (b) Lateral position. (c) Division of the five areas of the pillow.

when the subjects are lying on their back in the center of the pillow. When subjects adopt different sleeping positions and postures, it affects the transmission of sound in the pillow, and these effects and changes are received and processed through the microphones, and then transmitted to the PC.

Each combination of position and posture produces a four-channel time sequence of sound signals. Figure 3 shows a four-channel sound signal within 10 seconds when the frequency of sound source is 200 Hz, and the sleep posture of the subject is in a supine position lying on Area 4.

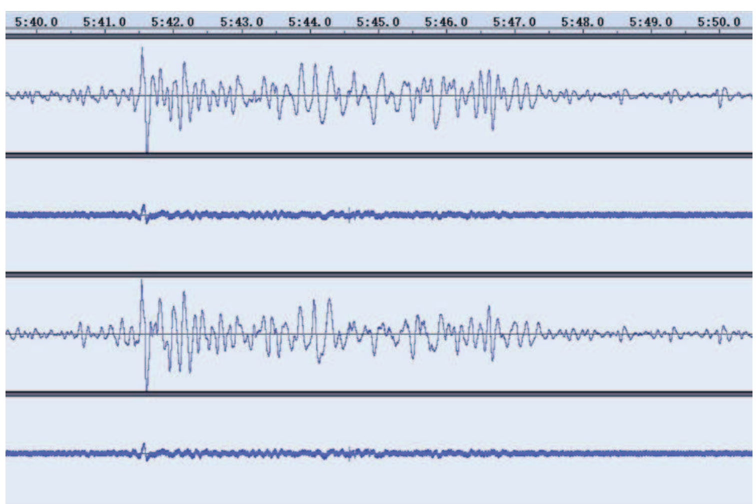


Figure 3: Four-channel sound signal within 10 s.

The time-domain signals can be used to characterize both time and frequency domains, making it possible to compare these positions and postures.

3.1. Experimental Data Source

Three sets of data were collected for the experiment, as shown in Table 1. The sound sources of the three data sets are as follows: no sound, 200 Hz fixed-frequency sound, and soft music. These sources are used to enhance the practical application effect of the classification model in different scenarios. For each sound source, the sound signal was collected when there was no one lying on the pillow. The sound signal was collected in ten scenes, with a combination of five areas and two postures. Each combination of position and posture was recorded for 120 seconds, with an overlap rate of 0.75. The reason for using these three sound sources is to consider the practical application value of the system proposed in this work. The built-in speaker can play users' preferred soothing sounds, such as soft music, low-frequency sounds, white noise, and more. Thus, these three typical sound sources were selected for data collection in order to improve the practical application effect of the final classification model in different scenarios.

Table 1: Summary of data sources.

Dataset	Sound Source	Types	Samples/type (time/sample)
1	No sound	10 combinations + control group	960 (0.5 s)
2	200 Hz	10 combinations + control group	960 (0.5 s)
3	Soft music	10 combinations + control group	960 (0.5 s)

3.2. Data Preprocessing

In order to realize sleep position and posture recognition, this paper proposes a deep learning method based on fully connected neural network. The collected data is first preprocessed in three steps: normalization, sliding window, and feature extraction in both time and frequency domains to provide input information for the neural network. The final output forms are Sleep Position ID and Sleep Posture ID. The specific process is shown in Figure 4.

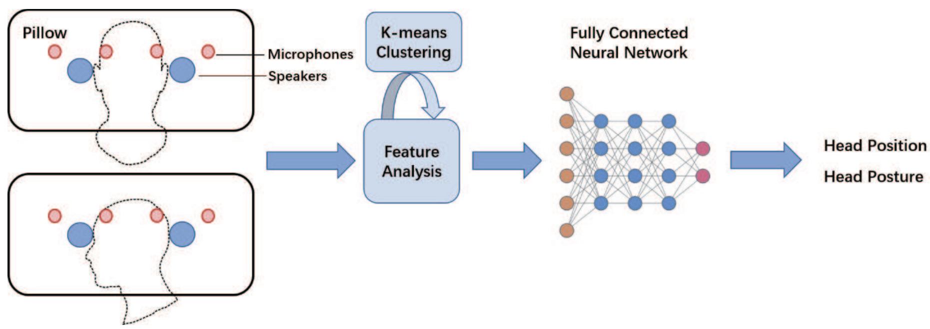


Figure 4: The process of sleep position and posture recognition.

Each combination of position and posture contains 4 time series channels, for each channel, first normalize and then map the results to the interval of $[-1, 1]$. The normalization formula can be expressed as follows:

$$x_{norm} = -1 + \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where $x_{\min}$ and $x_{\max}$ represent the maximum and minimum values in the original data, x is the original data, and x_{norm} represents the normalized data.

Due to the high sampling frequency of the sound signal in this experiment, sliding window was used to collect discrete samples from the time series. The window size in this work is set to 0.5 seconds with an overlap rate of 0.75, which converts each two-minute time series of each combination to 960 windows.

A series of 4×4 matrices can be obtained by calculating the cross-correlation coefficient for the four channels of each time series P_n. The formulas for calculating the cross-correlation coefficient are shown in Table 2. The k-means clustering of the matrix can obtain the category ID corresponding to each matrix. To determine the optimal number of categories (K), the K interval is set to $[0, 20]$, and for each K category, the sum of distances from each point in the cluster to the cluster center is calculated when the k-means clustering algorithm is used. To avoid overly fine category divisions, the value of K is set to 5, which corresponds to the inflection point of the loss curve. Then k-means clustering is performed to obtain the category ID corresponding to the matrix.

Each time series can obtain a spectrum Q_m by Fast Fourier Transform (FFT), so as to calculate the characteristics of the sequence in the time and frequency domains. Table 2 shows the available features, including eight time domain features and three frequency domain features: max, min, mean, standard deviation (std), median, energy, entropy, mean_freq, std_freq and center_freq. Here, $P_n = p_1, p_2, \ldots, p_n$ represents discrete samples of the time series, $Q_m = q_1, q_2, \ldots, q_n$ represents frequency domain sequences, and Q_m is calculated as the FFT of P_n. Each window contains a time series of 4 channels, each channel contains 10 features, and each window contains one corr ID, so the sample collected by a sliding window contains 41 features.

Table 2: Formulas of features.

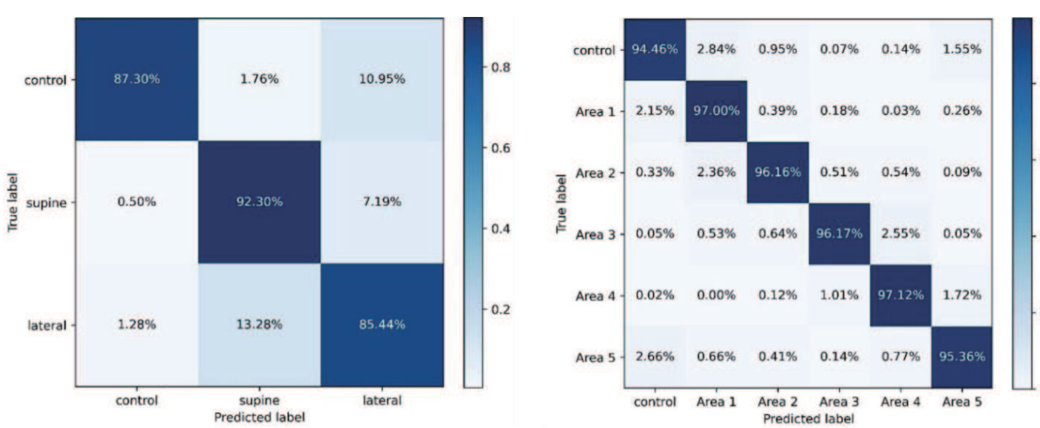
Features	Formula
max	The maximum of p_i
min	The minimum of p_i
mean	$\frac{1}{n}\sum_{i=1}^{n} p_i$
std	$\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(p_i-\bar{p_i})^2}$
median	The median of p_i
energy	$\frac{1}{n}\sum_{i=1}^{n} p_i^2$
entropy	$-\sum_{i=1}^{n} p_i \log p_i$
mean_freq	$\frac{1}{n}\sum_{i=1}^{n} q_i$
center_freq	$\frac{1}{n}\sum_{i=1}^{n} iq_i$
std_freq	$\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(q_i-\bar{q_i})^2}$
corr ID	$\frac{\sum_{i=1}^{n}(p_j-\bar{p_j})(p_k-\bar{p_k})}{\sqrt{\sum_{i=1}^{n}(p_j-\bar{p_j})^2}\sqrt{\sum_{i=1}^{n}(p_k-\bar{p_k})^2}}, j,k=1,2,3,4$ and k-means clustering

3.3. Fully Connected Neural Network

In this work, the seven-layer fully connected neural network is used to classify the calculated features. The first layer is the input layer, receiving the input of 41 features for each sample. The middle 5 layers are the hidden layer, and the last layer is the output layer. The input layer and the hidden layers are linear layers, and the output layer is a softmax layer. The softmax function converts the output value of the multi-classification into a probability distribution in the range of $[0, 1]$, with a sum of 1. To reduce the interference caused by overfitting, the Dropout rate is set to 0.2. The loss function is defined as the cross-entropy loss function. The classifier assigns the Adam optimizer [^kin] to update weights. The probabilities are calculated for one control group and 10 combinations of two defined gestures and 5 positions, using the softmax function. Finally, output the position ID and the posture ID. The learning rate is set to 0.0001.

4. RESULTS AND ANALYSIS

The dataset was randomly divided into training set (70%) and test set (30%). The final classification model has an accuracy of 91.1% for posture, an accuracy of 98.3% for position, and a total accuracy of about 88.2%. Figure 5 and Figure 6 shows the confusion matrix obtained from the test results. It can be seen that the trained model has a better classification effect on position, with an accuracy rate of more than 94.46% for each area. The classification of posture is slightly insufficient, and it tends to misclassify lateral as supine. In the classification of all combinations including the control group, the classification result of lateral combined with Area 4 is the most inadequate, with an accuracy rate of only 71.88%. The classification accuracy under the supine condition is significantly higher than that of lateral. This suggests that the model's ability to classify lateral is weaker than that of supine.



(a) (b)

Figure 5: (a) Confusion matrix of postures. (b) Confusion matrix of positions.

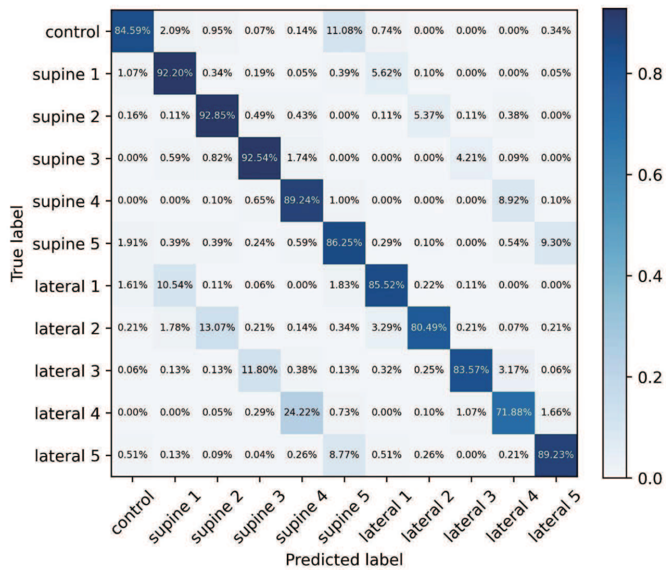


Figure 6: Confusion matrix of all results.

5. CONCLUSION

This paper proposes an intelligent head posture recognition pillow with built-in speakers and microphones. The pressure exerted by the head on the pillow affects the sound transmission from the speakers to the microphones, allowing the microphones to pick up changes in the sound signal. Thanks to the high sound absorption and noise reduction properties of latex, the pillow system can maintain a high accuracy rate even in noisy environments. It demonstrates the potential to monitor head position and posture through both its built-in speakers and microphones, as well as the properties of the latex material itself. Meanwhile, users can enjoy soothing sounds while using the pillow, providing additional benefits. This technology can be applied to sleep monitoring, smart home systems, and other fields.

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