# A Study on Sleep Position Recognition of Body Pressure Image based on KPCA and SVM

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*Abstract*—**Sleep is an important part of life, and sleep position recognition is an important indicator which reflects sleep quality, warns diseases and prevents pressure sores. Actually, sleep quality is usually related to the body pressure, which affects muscle comfort and blood circulation during sleep. However, in order to regulate the body pressure, one vital step is to recognize the sleep position. Body pressure is a common indicator of the recognition of sleep position. This investigation put forward a body pressure recognition method combining with kernel principal component analysis (KPCA) and support vector machine. The feature extraction based on KPCA can well solve the nonlinear separable problems as well as dimension reduction processing of PCA, and reduce the system's complexity. Compared with the image recognition method and computer vision recognition method, it realized a higher recognition accuracy at a lower cost. Ultimately, the recognition accuracy of six common sleep positions reached 96.5%.**

***Keywords—Flexible pressure sensor, Kernel principal component analysis, Sleep algorithm, Sleep quality, Sleep position recognition, Support vector machine***

## I. INTRODUCTION

In the process that we sleep seven to nine hours a day on average, our body repairs itself and grows. People who suffer from mental pressure, fatigue, memory decline are usually related to a bad sleep quality [1]. The sleep stage division is also a supplementary method to detect many diseases such as insomnia, cardiovascular diseases and cerebrovascular diseases [2]. The poor sleep quality and the disorder of sleep stage will lead to many mental disorders like depression [3]. Therefore, sleep plays a very important role in people's normal life and medical auxiliary diagnosis. As an important indicator of sleep quality, sleep position has been widely studied in the fields concerning medical diagnosis and the treatment of sleep disorders [4]. Meanwhile, sleep position greatly affects sleep apnea and pressure distribution in various parts of the body. Side-lying position can alleviate the sleep disorders of patients with mild and moderate sleep apnea [5]. AMBROGIO found that chronic respiratory insufficiency, to some extent, is associated with the body's sleeping posture. If you sleep poorly for a long time, it may even lead to apnea [6]. Oxenburg and Silverberg made a further research on sleep related breathing disorders (SRBD) and sleep position [7]. All of these authors believed that patients with respiratory problems should avoid sleeping on their backs. If the body bears an excessive pressure during sleep, insufficient blood supply, poor blood circulation, spine deformation and other symbols will appear, affecting sleep health and sleep quality. However, the sleep position wasn't monitored for a long period of time to ensure that the pressure is distributed in an appropriate manner. Therefore, there is an urgent need for sleep position recognition, and non-contact sleep position recognition is the basis of influencing sleep position during sleep.

At present, some methods for sleep position recognition have already been proposed. For example, computer vision technology is used to monitor the sleep process without interference, and image segmentation technology is adopted to recognize sleep positions after extracting the features of target contour, such as shape, color, texture, etc. [8]. However, such methods, which might concern the privacy issues, are prone to be interfered by the environmental factors such as light. Pressure sensor technology is utilized to perceive the pressure distribution of the human body in a non-interference manner. Meanwhile, with an average recognition rate of 90.8%, the method based on BEMD [9] (Body-Earth Mover's Distance) is adopted to recognize sleep positions according to the pressure difference distribution map in horizontal and vertical directions. However, this method requires to cover the pressure sensors on the entire bed, thus the hardware cost is high and the technology is complex.

Robert Grimm and Sebastian Bauer et al from the University of Erlangen-Nuremberg took the advantages of range image (RI) and pressure image (PI) to obtain the information about the patients' position, orientation and posture in the nursing bed [10]. This method can be divided into three stages. The first step is about determining the patients' position and orientation in nursing bed. The second step concerns the recognition of the patients' sleep position through classification algorithm. Finally, the complete body postures can be obtained based on the recognized orientation and posture by matching body hinged model of RI/PI. In the sleep position recognition stage, the average recognition rate of this method using range image was 79.4%, and the average recognition rate of the method using pressure image was 95.5%.

The essential elements of the sleep position recognition of human body pressure are recognition and classification. SVM is suitable for dealing with the classification problem of small samples, and it has many advantages such as high dimensions and strong generalization. It is successfully used in the fields of prediction, pattern recognition, image recognition, and recognition, etc. [11]. However, there is a certain correlation between each pixel and the contiguous ones in sleep position recognition of human body pressure image. For example, the more the pixels are, the larger the dimensions of data are. Moreover, the pressure value of pixels is non-linearly separable for sleep position recognition. On the other hand, the method based on kernel principal component analysis (KPCA) is better than the method based on PCA in terms of the feature extraction of nonlinear problems under the dimension reduction processing of PCA [12]. Therefore, this paper proposed an algorithm based on KPCA and SVM to process human body pressure image and recognize sleep positions. Theoretically, it should be possible to achieve the optimal sleep position recognition accuracy with a lower cost and less system complexity.

## II. METHODS

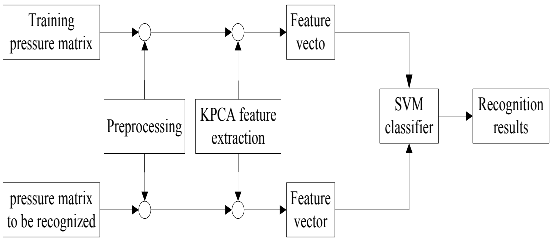



Fig. 1 Algorithm framework

Figure 1 shows the framework diagram of the algorithm in this paper, which mainly included the image preprocessing of the data. The algorithm mainly conducted some image filtering processing of a two-dimensional matrix, and the matrix was then converted into a column vector, after which the characteristic quantity was extracted through KPCA. Subsequently, the extracted feature vector conducted a dimension reduction for the original data as the input of SVM. After the completion of all the parameter training processes of the support vector machine, the model precision evaluation was conducted to verify the data.

### *A. Overview of support vector machine (SVM)*

Support vector machine (SVM) is not only a part of the statistical theory but also a common classification method. SVM method was developed from the optimal surface under linear separable conditions. The figure shows two types of two-dimensional linear separable conditions. H is classification line, while H1 and H2 are the points closest to the classification and parallel to the classification in the two types of samples. Besides, the distance between them is called the classification margin. In a D-dimensional space, the equation of the classification can be expressed as [13] Equation (1).

$$w^T X + b = 0 \quad (1)$$

If it is linearly separable, for the sample set $(x_i, y_i)$,i=1,2,…m, $x \in R^n$,$y \in \{+1,-1\}$, it meets

$$y_i[w^T X + b] - 1 = 0, \quad i = 1,2, \dots m \quad (2)$$

where the closest margin between the two types is $\frac{2}{||w||}$. If we want the biggest classification margin, it means that $||w||^2$ is the smallest. Therefore, under the constraints of Equation (3)

$$y_i[w^T X + b] - 1 \geq 0, \quad i = 1,2, \dots m \quad (3)$$

the minimum of the function in Equation (4)

$$\Phi(w) = \frac{1}{2}||w||^2 \quad (4)$$

is obtained. Then the condition minimum is obtained by using Lagrange multiplier. Assume Equation (5) [14].

$$L(w, b, a) = \frac{1}{2}||w||^2 - \sum_{i=1}^{n} \alpha_i \{y_i[w \cdot x_i + b] - 1\} \quad (5)$$

In Equation (5), $\alpha_i > 0$ is the Lagrange coefficient. Being set as 0, partial derivatives of *w* and *b* are calculated, respectively. In this way, the above optimal classification problem can be transformed into a simple dual problem, namely, under the constraint condition in Equation (6)

$$\sum_{i=1}^{n} y_i \alpha_i = 0 \quad (6)$$

the maximum of the function is Equation (7)

$$\max_{\alpha} \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \quad (7)$$

$$\text{s.t.} \qquad \alpha_i \geq 0 \; i = 1,2, \dots m \quad (8)$$

$$\sum_{i=1}^{n} y_i \alpha_i = 0 \quad (9)$$

Finally, the classification function can be expressed as Equation (10).

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{m} \alpha_i y_i (x_i \cdot x) + b\right) \quad (10)$$

### *B. Multiclass SVM*

Decomposition method is to decompose multiclass problems into a series of two-category classification problems, so as to directly adopt standard two-category SVM. In the recognition stage, voting is utilized to determine the category to which it belongs. There are different combinations when transforming multiclass problems into two-category ones, mainly including 1-a-a (one-against-all, OAA method) and 1-a-one (one-against-one, OAO method). The limitations of these methods is the lack of direct and comprehensive considerations of the problems.

#### *1) 1-a-a*

The one-against-all (1-a-a) method takes the sample of certain category as one category, and regards the whole composed by all other categories as another category to form a two-category problem. In the decision-making process, this method takes the category with the maximum output value of the classifier function as the prediction category, therefore this identification strategy is called the maximum strategy. However, for this classification algorithm, its generalization ability is very poor, and its training time is proportional to the number of training sample categories k. When the number of training samples is large, training is difficult. In particular, 1-a-a method will result in an uneven training set (if the categories are not uniform, the negative samples in each category classifier will be much more than the positive samples), and its recognition accuracy for small samples is relatively low.

*2) 1-a-1*

With other various categories, each category composes a two-category problem, and k categories construct a total of $C_k^2$two-category SVM. Similar to 1-a-a pattern, the training sample also needs to change the category label accordingly. When predicting, the sample passes through all two-category SVM and gets $C_k^2$recognition results. The category of the test sample is determined by the voting method, namely, among k (k-1) / 2 classification functions, the category which appears mostly is the final prediction category. The disadvantage of this method is that the classification function increases rapidly with the increase of the number of categories, which slows down the prediction process. However, it is shown in the literature that 1-a-a algorithm usually has a higher classification accuracy.

### *C. Feature extraction based on KPCA*

Kernel function method is to use non-linear Φ to map x to high-dimensional feature space F, and then in the high-dimensional space, dimension reduction technology of PCA is carried out, with the purpose to eliminate the correlation between various characteristic quantities. The mapping data is processed centrally to meet the requirements [15]in Equation (11).

$$\sum_{i=1}^{m} \Phi\left(X_i\right) = 0 \quad (11)$$

In Equation (11), m is the number of training samples, and its corresponding covariance can be calculated as Equation (12).

$$C = \frac{1}{m}\sum_{i=1}^{m} \Phi(x_i)\Phi(x_i)^T \quad (12)$$

Through finding the eigenvalues and feature vectors of the covariance matrix C, λ is eigenvalues, $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_n$, the cumulative contribution rate of the previous i principal components is Equation (13).

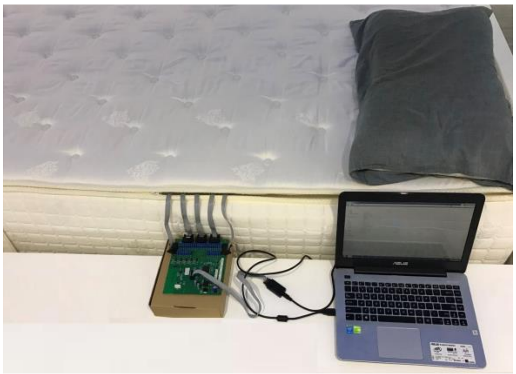
$$\omega = \sum_{i}^{n} \lambda_i \Big/ \sum_{1}^{n} \lambda_i \quad (13)$$

Through selecting appropriate I, the cumulative contribution rate is about 90%, which means a less information loss and a great reduction of dimension.

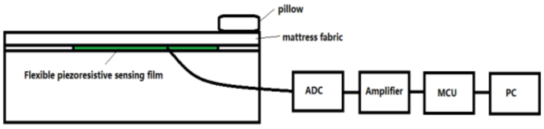
## III. Experiments and Results

### *A. Sensing system and image acquisition*

This paper adopted flexible piezoresistive array sensor whose pixel was 64 × 32, and the maximum test pressure of single sensor was 500N. The sensor converted analog pressure signals into digital signals with a resolution of 512, and output the pressure data as a two-dimensional matrix F [64] [32]. The sensing membrane covered an area of about 100cm*60cm, which was distributed in the area from shoulder to lower hip to thigh. Figure 2 (a) showed the pictures of the sensor and hardware system; and Figure (b) showed the schematic diagram of the mattress structure and the hardware block diagram. The sensing membrane was located below the mattress' fabric layer, from the shoulder to the thigh area. This is because the head is on the pillow, and the data which is decomposed by the force of the pillow has a larger distortion. At the same time, the data is greatly determined by the pillow's material, hardness, thickness and so on. Furthermore, cruses usually have a small characteristic quantity due to a small weight, thus removing the sensors laid on above shoulders area and below thigh area is conductive to reduce the cost and the complexity of data processing. Moreover, the pressure distribution in the shoulders, torso, hips and thighs is crucial to the recognition of sleep positions.



(a) Sensor and hardware system diagram




(b) Schematic diagram

Fig.2 (a) Scene graph of sensor and hardware system (b) Schematic diagram

### *B. Experimental process*

The original pressure images acquired by experimental setting and pressure collection usually contained the data deviation caused by noises and threshold setting. Most of the noises could be eliminated through median filtering, so as to make the contour of the images become more clear and smooth. Moreover, the gravity of the body was determined by extracting the peak value of each row of data in the images, and then the effective pressure was extracted. Finally, the images were conducted with a normalization processing to eliminate the influence of people with different weights on the pressure matrix.

After preprocessing, a new pressure matrix was acquired, and then the two-dimensional matrix was converted into a column vector. The pressure map of 60 people was collected in this investigation, including 30 men and 30 women, with their age ranges from 18 to 50, and the height ranges from 145 cm to 185 cm, while their weight ranges from 40 kg to 102kg. Each person followed a prescribed posture and could make a minor adjustment according to comfortability. The data about six common sleep positions were collected from each person, and a total of 360 data samples were collected. The data of 40 people were selected as the training data, while the data of other 20 people were as the test data.

People's sleep positions are diversified, but there are six common sleep positions, including supine, prone, left lying, right lying, left fetal lying and right fetal lying. Each sleep position corresponds to a different pressure regulation mode. For example, when people are supine, due to the bending curve of the spine, the pressure on the waist is generally smaller and has an insufficient support, therefore an adequate support should be provided for the waist. When people are lying on side, the pressure on shoulders and crotch increases, which requires a certain release and pressure transfer, so that the mattress can fit people's body and spine as much as possible. Figure 3 shows a brief diagram of 6 sleep positions: (a) supine, (b) prone, (c) left fetal lying, (d) left lying, (d) right fetal lying, and (f) right lying. The six sleep positions are labeled as S, P, LF, LL, RF and RL.

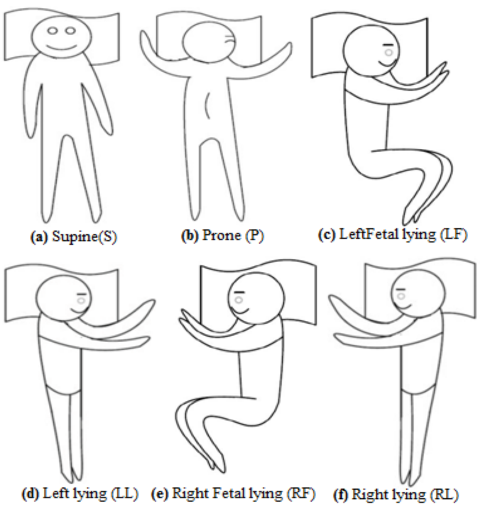



Fig. 3 Six common sleep positions

### C. Pressure image preprocessing and feature extraction

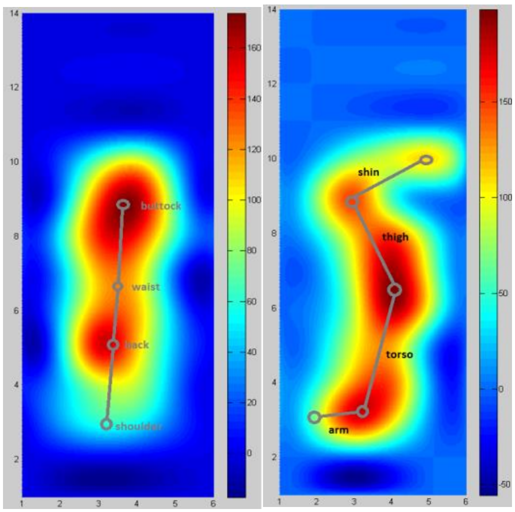
Gaussian Kernel Function was adopted in this paper, which means $k(x, y) = \exp(-||x - y||^2/\delta)$. Table I shows the contribution rate and cumulative contribution rate of the eigenvalues of various principal components based on KPCA. After the contrasting different accumulative contribution rates, it was concluded that the final contribution rate was 96% and the number of dimensions was 16.

TABLE I FEATURE TABLE AND CONTRIBUTION RATE

| KPCA principal components | Characteristic value | Contribution rate | Cumulative contribution rate |
|---|---|---|---|
| PC1 | 48.5 | 27.40 | 27.40 |
| PC2 | 34.6 | 19.54 | 46.94 |
| PC3 | 22.1 | 12.48 | 59.43 |
| PC4 | 18.2 | 10.28 | 69.71 |
| PC5 | 10.8 | 6.10 | 75.81 |
| PC6 | 8.2 | 4.63 | 80.45 |
| PC7 | 6.9 | 3.89 | 84.35 |
| PC8 | 4.6 | 2.59 | 86.94 |
| PC9 | 3.7 | 2.09 | 89.03 |
| PC10 | 2.8 | 1.58 | 90.62 |
| PC11 | 2.4 | 1.35 | 91.97 |
| PC12 | 2.1 | 1.18 | 93.16 |
| PC13 | 1.9 | 1.07 | 94.23 |
| PC14 | 1.4 | 0.79 | 95.02 |
| PC15 | 1.0 | 0.56 | 95.59 |
| PC16 | 0.8 | 0.45 | 96.04 |

### D. Experimental results

Figure 4 shows the heat map of the pressure distribution of the two sleep positions. Figure 4 (a) is prone (P), and Figure 4 (b) is left fetal lying (LF). According to the figures, the pressure distribution was more symmetrical when people were supine, and the force was mainly concentrated on the hips and back, while the pressure on the waist was smaller, leading to a lack of support. However, when people were lying on the side, the bending directions of various parts of the body, such as arms, trunk, thighs and cruses are evident, and it could be found that the pressure on shoulders and crotch became larger.




(a) Prone pressure (b) Side-laying pressure

Fig. 4 Heat map of prone and side-laying pressure

Table II shows the results of 20 groups of test data, and 40 groups of training data constructed the recognition hybrid matrix of 6 sleep positions after the SVM model. It could be seen that the accuracy of various sleep positions recognition ranges from 95% to 98%, with an average accuracy of about 96.5%. Table III shows the accuracy comparison of various algorithms for sleep position recognition at present, and it indicates that the accuracy of the algorithm based on KPCA-SVM was higher.

TABLE II HYBRID MATRIX OF SLEEP POSITION RECOGNITION

| | P | S | LF | LL | RF | RL | Recall |
|---|---|---|---|---|---|---|---|
| P | 96.8 | 2.7 | 0 | 0 | 0 | 0 | 96.8 |
| S | 1.5 | 95.2 | 0 | 0 | 0 | 0 | 95.2 |
| LF | 0 | 0 | 96.1 | 1.7 | 0.8 | 0 | 96.1 |
| LL | 1.0 | 1.2 | 2.1 | 97.4 | 0 | 0 | 97.4 |
| RF | 0 | 0 | 1.8 | 0.2 | 96.5 | 2.6 | 96.5 |
| RL | 0.7 | 0.9 | 0 | 0.7 | 2.7 | 97.4 | 97.4 |
| Precision | 95.7 | 95.6 | 97.1 | 96.8 | 96.5 | 97.4 | 96.5 |

TABLE III ALGORITHM ACCURACY COMPARISON TABLE

| Algorithm | Accuracy |
|---|---|
| The algorithm used in this investigation(KPCA-SVM) | 96.5% |
| SVM[16] | 94.1% |
| Hybrid Gaussian clustering algorithm[17] | 91.6% |
| Body-Earth Mover's Distance [18] | 91.2% |
| Fuzzy C-Means Clustering[19] | 88% |
| Pressure image sparse classifier [20] | 83.2% |

## IV. CONCLUSIONS

This paper presents the human body pressure image recognition method combining with KPCA and SVM. The feature extraction based on KPCA can well solve the non-linear separable problems as well as dimensional reduction processing of PCA, and it can reduce the complexity of the system. Compared with the image recognition method and computer vision recognition method, the algorithm used in this investigation realized a higher recognition accuracy with a lower cost. Moreover, the accuracy of recognizing six common sleep positions reached up to 96.5%.

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