A peer-reviewed version of this preprint was published in PeerJ on 26 July 2016.

View the peer-reviewed version (peerj.com/articles/2258), which is the preferred citable publication unless you specifically need to cite this preprint.

Zhang Z, Song Y, Cui L, Liu X, Zhu T. 2016. Emotion recognition based on customized smart bracelet with built-in accelerometer. PeerJ 4:e2258
https://doi.org/10.7717/peerj.2258
Emotion recognition based on customized smart bracelet with built-in accelerometer

Zhan Zhang, Yufei Y Song, Liqing Cui, Xiaoqian Liu, Tingshao Zhu

**Background.** In recent years, artificial intelligence (AI) has become an important issue, in which, how to make computers understand the thinking of human being is one of critical topics. If computer could perceive and respond to person's non-verbal language such as emotions, the communication between human beings and computers will be more friendly and naturally. So, more and more researchers are paying attention to realize human daily emotion recognition based on wearable sensor signals, which could be applied in many applications of health care and Human-Computer-Interaction (HCI).

**Methods.** In this paper, we propose an emotion recognition method, which is based on customized smart bracelet with built-in accelerometer. Those bracelets can be worn on people's ankle and wrist. Firstly, the acceleration data of ankle and wrist are obtained when person is walking naturally. Considering the original acceleration data is noisy and variable, the Moving Average Filter is used to eliminate noise. Besides, walking can be regarded as the repetitive movement of legs and arms, so the collected acceleration data may be redundant. Through analysis, we design a sliding window to divide the whole data into several data slices of the same size, and let the neighboring slices be partially overlapped. In the subsequent operations, each data slice would be taken as one sample. This process can not only avoid high computational requirement caused by redundancy data, and can also expand the number of samples. For each data slice, 114 relevant features for emotion recognition are extracted. Then, Principal Component Analysis (PCA) is applied to select effective attributes. Finally, we built the emotion recognition classifier based on Weka software platform. Taking the same attributes as input, we compared the performance of emotion recognition among some classical classifiers, including Support Vector Machine (SVM), Decision Tree, Random Tree and Random Forest.

**Results.** The classification accuracy is used to evaluate the effectiveness of our proposed emotion recognition method. Overall, SVM outperforms the other classifiers. The two-category classification accuracies of neutral-anger, neutral-happiness and happiness-anger are 91.3%, 88.5% and 88.5% respectively. The accuracy of multi-category classification among neutral, happiness and anger is 81.2%.

**Discussion.** In the comparative experiments, the recognition rates of different emotion
states are all above 81%. It is concluded that gait is capable to reveal affective state of minds.
Emotion recognition based on customized smart bracelet with built-in accelerometer

Zhan Zhang¹, Yufei Song², Liqing Cui², Xiaoqian Liu², Tingshao Zhu²,³

¹ School of Computer and Control Engineering, University of Chinese Academy of Sciences, Beijing, China
² Institute of Psychology, Chinese Academy of Sciences, Beijing, China
³ Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China

Corresponding Author:
Tingshao Zhu²,³
16 Lincui Road, Chaoyang District, Beijing, 100101, China
Email address: tszhu@psych.ac.cn

Xiaoqian Liu²
16 Lincui Road, Chaoyang District, Beijing, 100101, China
Email address: liuxiaoqian@psych.ac.cn
ABSTRACT

**Background.** In recent years, artificial intelligence (AI) has become an important issue, in which, how to make computers understand the thinking of human being is one of critical topics. If computer could perceive and respond to person’s non-verbal language such as emotions, the communication between human beings and computers will be more friendly and naturally. So, more and more researchers are paying attention to realize human daily emotion recognition based on wearable sensor signals, which could be applied in many applications of health care and Human-Computer-Interaction (HCI).

**Methods.** In this paper, we propose an emotion recognition method, which is based on customized smart bracelet with built-in accelerometer. Those bracelets can be worn on people’s ankle and wrist. Firstly, the acceleration data of ankle and wrist are obtained when person is walking naturally. Considering the original acceleration data is noisy and variable, the Moving Average Filter is used to eliminate noise. Besides, walking can be regarded as the repetitive movement of legs and arms, so the collected acceleration data may be redundant. Through analysis, we design a sliding window to divide the whole data into several data slices of the same size, and let the neighboring slices be partially overlapped. In the subsequent operations, each data slice would be taken as one sample. This process can not only avoid high computational requirement caused by redundancy data, and can also expand the number of samples. For each data slice, 114 relevant features for emotion recognition are extracted. Then, Principal Component Analysis (PCA) is applied to select effective attributes. Finally, we built the emotion recognition classifier based on Weka software platform. Taking the same attributes as input, we compared the performance of emotion recognition among some classical classifiers, including Support Vector Machine (SVM), Decision Tree, Random Tree and Random Forest.

**Results.** The classification accuracy is used to evaluate the effectiveness of our proposed emotion recognition method. Overall, SVM outperforms the other classifiers. The two-category classification accuracies of neutral-anger, neutral-happiness and happiness-anger are 91.3%, 88.5% and 88.5% respectively. The accuracy of multi-category classification among neutral, happiness and anger is 81.2%.

**Discussion.** In the comparative experiments, the recognition rates of different emotion states are all above 81%. It is concluded that gait is capable to reveal affective state of minds.

Keywords: Emotion recognition, customized smart bracelet, accelerometer, HCI, SVM

1 INTRODUCTION

The communication between human beings and computers will be more friendly and naturally if computer could perceive and respond to individual’s non-verbal language such as emotions. The earliest definition of emotion was given by James, the father of American psychology. In his article published in 1984, he believed that emotion is a feeling of physical changes, which lead to emotional perception. Any emotion is associated with certain physical changes, which include facial expression, muscle tension and visceral activities[7]. Lazarus considered emotion is the combination of physiological disturbance, affect, and action tendencies which are no need to show[18]. Several emotion recognition approaches have been proposed, and made a certain progress. According to the characteristics used in emotion recognition, these methods could be classified as: facial expressions based, linguistic based, physiological parameter based, gesture based and body motions-based[16].
Many psychological studies supported that emotions are expressed in walking[15]. In this paper, we focus on emotion recognition based on gait. Compared with the state-of-the-art methods, utilizing customized smart bracelet make the application of emotion recognition is more convenient in daily life.

In this paper, a novel emotion recognition method based on the acceleration data of wrist and ankle is proposed. The acceleration data for emotion recognition is obtained by customized smart bracelet with built-in accelerometer, which can be worn on wrist and ankle when person is walking. Our proposed method could recognize three different kinds of human emotions: happiness, anger and neutral state. And the performance of our method is outstanding. This method consists of data collection, data preprocessing, feature extraction and classification. Firstly, we use customized smart bracelet to record acceleration data. Then, we utilize Moving Average Filter to remove noise in data preprocessing. In the process of feature extraction, a sliding window is designed to divide the data into several slices with uniform size. For each slice, 114 features are calculated and effective attributes are selected by PCA in feature extraction. Finally, we build standard classifiers with default parameter by Weka software (Waikato Environment for Knowledge Analysis, a popular suite of machine learning software which contains a collection of machine learning algorithms for data mining tasks), and test the classification model using 10-fold cross-validation.

The outline of the paper is as follows. Section 2 summarizes related work about emotion recognition in walking. Section 3 describes our method in detail, including data collection, data preprocessing, feature extraction and classification. Results are presented in Section 4 and discussed in Section 5. The paper ends with a conclusion in Section 6.

2 RELATED WORK

Because the appearance of emotions is diverse, versatile and elusive in daily life, there is no general agreement on a standard definition of emotion. Through a series of studies, Ekman found that certain emotions appeared to be universally recognized, and classified six emotions as basic: anger, disgust, fear, happiness, sadness, and surprise. The dimensional pleasure-arousal-dominance(PAD) model is widely used in automatic emotion recognition [5][17].

Many psychological studies indicated that emotions can be expressed in walking and recognized by human observers. Montepare et al.[15] pointed out that different affects could be identified from the trait and diversity of walking style. Besides, sadness and anger are easier to be identified by human observers. In addition, Michalak et al.[14] supported that sadness and depression are reflected in walk. Crane and Gross[3] indicated that emotion are associated with physical movements. They have identified velocity, cadence, head orientation and the motion range of shoulder and elbow as significant physical parameters which affected by emotions.

In recent years, machine learning methods have been applied in assistant therapeutic equipment for patients with gait disorders, identity recognition based gait, and human motion identification[6][10]. Before training model, dimension reduction is often considered. Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPCA), Linear discriminant analysis (LDA) are all effective dimension reduction methods. The performances of PCA and KPCA are compared in[2]. Martinez and Kak showed that if the number of samples in training set are smaller, PCA can outperform LDA[13]. In [19], KPCA was used to improves the performance of age classification model based on walking[19]. Michelle and Robert employed Principal Component Analysis (PCA) and Fourier Transformation to realize data reduction, and classified four emotions utilizing Naive
Bayes, 1-Nearest Neighbor and SVM respectively. Best classification accuracy 72% is achieved when using Naive Bayes [11]. Janssen et al. figured out the emotion recognition method from walking based on artificial neural nets[8].

In this paper, we propose a novel emotion recognition method. Firstly, we use customized smart bracelet with built-in accelerometer to collect acceleration data of wrist and ankle when person is walking. Then, in order to improve the performance of emotion recognition, Moving Average Filter is deployed to eliminate noise before extracting relevant features from acceleration data. Finally, several classical classification methods are used to construct emotion classification model.

3 METHODS

3.1 Data Collection

In order to obtain the acceleration data of ankle and wrist when person is walking in neutral, anger and happiness respectively, we used customized smart bracelet with built-in accelerometer to collect data. The bracelet could record x, y and z axis acceleration data five times per second, and the acceleration data are stored in memory in the data format which could be read by software. We designed two experiments to collect the acceleration data of different emotions. The first experiment is conducted to collect the acceleration data of ankle and wrist when person is walking in neutral and anger state respectively. The second experiment is done when person is neutral and happy respectively. We recruited 123 healthy participants (45 females, 78 males) and they are all students of University of Chinese Academy of Sciences (UCAS).

In order to ensure that there is no interference, the experiments were proceeded in an enclosed classroom. And a special rectangle with width 1 meter and length 5 meter was fixed with red mark on the floor. We used a SAMSUNG Tablet PC to record time. Every experiment consists of two procedures. Before the experiment got started, all participants were asked to read the consent letter. Two customized smart bracelets with built-in accelerometer were worn on each participant’s right ankle and right wrist. Take the first experiment as example, the process of experiment are introduced in detail. Firstly, the participants were required to walk back and forth in the special rectangle for two minutes, and the instructor used the Tablet to record start and end times of the walk. In the second procedure, the participants were required to see a short emotional film clip[9], which could make them anger. After watching the film clip, the participants were asked to walk back and forth in the same special rectangle for about one minute again, and the instructor used the Tablet to record start and end times of walk.

In second experiment, two procedures were as same as the first experiment except that, in second procedure, the participants would watch different short emotional film clip[9], which could make them happy. The interval of two experiments was more than four hours ensure that the participant’s emotion were not influenced by the film clip given in the first experiment.

After every participant finished both experiments, the acceleration data were read from bracelet’s memory and stored in .txt file. Then the acceleration data of first and second procedure are divided based on timestamp. Both of two experiments were supported by Institute of Psychology, Chinese Academy of Sciences.

3.2 Data Preprocessing

Acceleration data collected by customized smart bracelet may contain noise and blur caused by the vibration in walking. For denoising and improving recognition rate, for each axis of acceleration
data, we used Moving Average Filter to make the data more smoother. Moving Average Filter is a well-known low-pass filter for discrete time signals, which is defined as

\[
Output[i] = \frac{1}{w} \sum_{j=0}^{w-1} Input[i+j]
\]  

The \textit{Input} represents that original three-axis acceleration data collected by customized smart bracelet with built-in acceleration sensor, and the \textit{Output} represents the export of Moving Average Filter. The parameter \(w\) is the window size of Moving Average Filter. The value of \(w\) is the key in the preprocessing of original acceleration data. In this paper, we set \(w \in \{3,5\}\)\[4][12].

The sampling frequency of customized smart bracelet is 5 per second, and during one minute, 300 set records could be obtained. Each set record consists of the acceleration data of axis \(x, y\) and \(z\). Walking can be taken as a process of behavioral repetition, so the data collected over a long period of time may be redundant. Considering the 300 records is huge and it is time-consuming for feature extraction in computing, we designed a sliding window to divide the acceleration data into several slices with uniform size. Through this step, the number of samples could be expanded. In this paper, the size of sliding window is 128. The sliding step is set as 64 to ensure that the overlapping ratio is 50%\[4][20].

### 3.3 Feature Extraction

To figure out the hidden characteristic and universality of acceleration data and improve classification accuracy, the relevant features are extracted in temporal domain, frequency domain and temporal-frequency domain from acceleration data\[4\] respectively. We conduct the same procedure of feature extraction for each data slice. In the following presentation, we take one data slice as an example.

#### 3.3.1 Temporal domain Feature

For each axis, we calculate the skewness \(S'\), kurtosis \(K'\) and standard deviation of data \(\sigma'\), in which, \(t \in \{x,y,z\}\) denotes the label of different axes. Besides, the correlation coefficient is calculated between every two axes.

The skewness measures the asymmetry of the probability distribution of data. It is defined as

\[
S' = \frac{\frac{1}{n} \sum_{i=0}^{n-1} (x'_i - \bar{x'})^3}{\left(\frac{1}{n} \sum_{i=0}^{n-1} (x'_i - \bar{x'})^2\right)^{\frac{3}{2}}}
\]  

in which, \(x'_i\) is \(t\) axis acceleration data, \(t \in \{x,y,z\}\), and \(n\) denotes the length of a slice data. The \(\bar{x'}\) is mean of \(t\) axis data, \(t \in \{x,y,z\}\).

The kurtosis \(K'\) measures the flatness of the probability distribution, which is defined as

\[
K' = \frac{\frac{1}{n} \sum_{i=0}^{n-1} (x'_i - \bar{x'})^4}{\left(\frac{1}{n} \sum_{i=0}^{n-1} (x'_i - \bar{x'})^2\right)^2}
\]
The standard deviation $\sigma^t$ is a measurement used to quantify the extent of variation or dispersion of the data, which is defined as

$$\sigma^t = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} (x^t_i - \bar{x}^t)^2}$$

In which, $\sigma^t$ represents standard deviation of $t$ axis data, $t \in \{x, y, z\}$.

The correlation coefficient defines a quantitative measure of the relationships between correlation and dependence, that is the statistical relationships between two random variables or observed data, or the statistical relationships among three or more, and which is defined as

$$P_{t_1, t_2} = \frac{Cov(t_1, t_2)}{\sigma_{t_1} \sigma_{t_2}}$$

$$Cov(t_1, t_2) = E[t_1 - E(t_1)][t_2 - E(t_2)]$$

The $P_{t_1, t_2}$ represents Pearson Correlation Coefficient between axes $t_1$ and $t_2$ ($t_1 \in \{x, y, z\}, t_2 \in \{x, y, z\}, t_1 \neq t_2$). The $Cov(t_1, t_2)$ is the covariance between every two axes. $E(t_1)$ is the mean of $t_1$ axis data, and so is $t_2$.

### 3.3.2 Frequency domain Feature

Frequency domain feature is extracted by transforming the acceleration data from temporal domain to frequency domain. For each axis, we calculate the mean and standard deviation of Power Spectral Density (PSD) as frequency domain features respectively. PSD is the power unit of band. The mean of PSD represents the size of average power per unit of bandwidth, and the standard deviation of PSD represents the degree of dispersion in terms of power.

### 3.3.3 Temporal-frequency Feature

Because temporal domain feature and frequency domain feature may be not comprehensive, more and more studies are trying to combine both of temporal domain information and frequency domain information and extract temporal-frequency feature which could represent the characteristics of temporal domain and frequency domain synchronously. Fast Fourier Transform (FFT) is an algorithm, which could convert the signal from its original domain (often temporal or spatial) to another form of representation in frequency domain. The formula is defined as

$$X^t_k = \sum_{j=0}^{n-1} x^t_j e^{-i2\pi k^j} \quad k = 0, \cdots, 31$$

In which, $i$ is the sign of complex number. For each axis, we conduct FFT to the temporal feature and select the front 32 amplitude coefficients as the temporal-frequency feature.

### 3.3.4 Feature selection

For each slice, we have extracted 38 attributes in each axis from temporal domain, frequency domain and temporal-frequency domain. So we could obtained $38 \times 3$ attributes from one data slice in
total. Considering the high-dimensional feature vector is redundant, efficient dimension reduction is required before applying different classifiers. We used Principle Component Analysis (PCA) to realize feature selection, and the attributes which could satisfy accumulative contribution rate be up to 95% are selected finally.

Classification

With the help of Weka platform, we built several classical emotion recognition classifiers and compared the performances of them. Decision Tree (model parameter: J48 -C 0.25 -M 2) is a simple and widely used classifier. It is easy to understand and is able to handle both numerical and categorical data. But if the structure of decision tree is too complicated, the model may be overfitting and the result of classification would be very poor[1]. Support Vector Machine (SVM) (model parameter: LibSVM -S 0 -K 2 -D 3 -G 0.0 -R 0.0 -N 0.5 -M 40.0 -C 1.0 -E 0.001 -P 0.1 -model E:\Weka-3-7 -seed 1) is a kind of supervised learning method, which are usually used for classification and regression analysis. In this paper, SVM outperforms than other classifiers. Random Forest (model parameter: RandomForest -I 10 -K 0 -S -num-slots 1) could overcome the shortcomings of decision trees about overfitting. Random Tree (model parameter: RandomTree -K 0 -M 1.0 -V 0.001 -S 1) is a tree or a tree-map which is established by random process. In order to construct reliable and stable model, we utilized standard 10-fold cross-validation to build the classification model. The performance of each classifier is evaluated according to classification accuracy $Q$ (which could also be called emotion recognition rate in this paper), which is definition by Equation 7.

$$Q = \frac{\text{The number of samples which are classified correctly}}{\text{The total number of samples}}$$ (7)

4 RESULTS

4.1 Anger Emotion Identification

For recognizing anger and neutral emotion, we collected acceleration data of ankle and wrist in the first experiment. Then, moving Average Filter was used to eliminate noise, and PCA was utilized for feature selection. Finally, based on Weka software, we constructed several classical classifiers with default parameter for emotion classification.

We built classification models based on LibSVM, Decision Tree, Random Forest and Random Tree respectively. when $w \in \{3, 5\}$, the classification accuracy of all classifiers are shown in Table 1 and Table 2 respectively.

Table 1. The emotion recognition results between anger and neutral when $w = 3$

| Joint  | LibSVM | DecisionTree | RandomForest | RandomTree |
|--------|--------|--------------|--------------|------------|
| wrist  | 86.0%  | 76.2%        | 71.1%        | 65.7%      |
| ankle  | 72.5%  | 64.2%        | 63.8%        | 64.3%      |

The LibSVM classifier outperforms the other classifiers with classification accuracy $Q = 91.3\%$, when $w = 5$ and using the acceleration data of wrist. For every classifier, the performance using
Table 2. The emotion recognition results between anger and neutral when \( w = 5 \)

| Joint  | LibSVM | DecisionTree | RandomForest | RandomTree |
|--------|--------|--------------|--------------|------------|
| wrist  | 91.3%  | 83.8%        | 82.8%        | 69.8%      |
| ankle  | 71.3%  | 61.5%        | 62.3%        | 61.9%      |

Acceleration data of wrist is better than that using data of ankle. When using the acceleration data of wrist, for the same classifier, the classification accuracy \( Q|w = 5 \) is higher than \( Q|w = 3 \).

4.2 Happiness Emotion Identification

We conducted the second experiment to collect acceleration data of wrist and ankle for distinguishing between happiness and neutral emotion. After data preprocessing and feature extraction, we built standard classifiers in the same way. The classification results using \( w = 3 \) and \( w = 5 \) are shown in Table 3 and Table 4 respectively.

Table 3. The emotion recognition results between happiness and neutral when \( w = 3 \)

| Joint  | LibSVM | DecisionTree | RandomForest | RandomTree |
|--------|--------|--------------|--------------|------------|
| wrist  | 88.5%  | 77.8%        | 64.9%        | 61.0%      |
| ankle  | 80.9%  | 73.1%        | 65.7%        | 63.0%      |

Table 4. The emotion recognition results between happiness and neutral when \( w = 5 \)

| Joint  | LibSVM | DecisionTree | RandomForest | RandomTree |
|--------|--------|--------------|--------------|------------|
| wrist  | 78.2%  | 67.7%        | 63.1%        | 62.3%      |
| ankle  | 71.7%  | 62.4%        | 61.5%        | 62.6%      |

When using the acceleration data of wrist and \( w = 3 \), LibSVM performs best with \( Q = 88.5\% \). Under the same conditions, the classification accuracy of LibSVM \( Q|w = 5 \) = 78.2\%, which is also relatively higher than others. Comparing all the results of anger emotion recognition and happiness emotion recognition, the highest recognition rate of anger is 91.3\%, and the highest recognition rate of happiness is 88.5\%. It is concluded that anger is easier to be identified than happiness.

4.3 Emotion Identification between Happiness and Anger

We conducted emotion classification of anger against neutral in the first experiment, and happiness against neutral in the second one. In order to classify anger against happiness, we combined acceleration data of both experiments. The classification results of all classifiers when \( w = 3 \) and \( w = 5 \) are shown in Table 5 and Table 6 respectively.

When using the acceleration data of wrist, the performances of classifying anger against happiness are \( Q|w = 3 \) = 88.5\%, and \( Q|w = 5 \) = 82.5\%.
Table 5. The emotion recognition results between happiness and anger when \( w = 3 \)

| Joint | LibSVM | DecisionTree | RandomForest | RandomTree |
|-------|--------|--------------|--------------|------------|
| wrist | 88.5%  | 83.3%        | 73.8%        | 68.1%      |
| ankle | 79.1%  | 70.1%        | 65.3%        | 60.6%      |

Table 6. The emotion recognition results between happiness and anger when \( w = 5 \)

| Joint | LibSVM | DecisionTree | RandomForest | RandomTree |
|-------|--------|--------------|--------------|------------|
| wrist | 82.5%  | 72.9%        | 66.3%        | 63.1%      |
| ankle | 71.1%  | 60.4%        | 62.0%        | 60.9%      |

4.4 Emotion Identification among Anger, Happiness and Neutral

We had done several experiments of emotion recognition about neutral-anger, neutral-happiness and happiness-anger, and the highest classification accuracy of them are 91.3%, 88.5% and 88.5% respectively. In addition, we conducted the experiments about emotion recognition among anger, happiness and neutral when \( w = 3 \) and \( w = 5 \). Results of all classifiers are shown in Table 7 and Table 8. The highest emotion classification accuracy is 81.2%.

Table 7. Happiness, Anger and Neutral emotion recognition when \( w = 3 \)

| Joint | LibSVM | DecisionTree | RandomForest | RandomTree |
|-------|--------|--------------|--------------|------------|
| wrist | 79.6%  | 65.8%        | 59.0%        | 52.4%      |
| ankle | 68.6%  | 60.1%        | 53.2%        | 49.3%      |

5 DISCUSSION

For emotional states recognition from walking, our study mainly focus on the following aspects:

- Acceleration data of wrist and ankle collection
- Data preprocessing and feature extraction
- Comparison of different classification methods

In order to collect acceleration data from walking when a person is in the emotional state of anger, happiness and neutral respectively, we designed two experiments. The customized smart bracelet with built-in accelerometer is used to record the acceleration data. In experiments, we used anger and happy short video clips to make participants being in anger and happy when walking. After data collection, we utilized Moving Average Filter to eliminate noise with parameter \( w = 3 \) and \( w = 5 \). In order to reduce the computing-cost and expand the number of samples, a sliding window is designed to divide each data into several data slices of the uniform size. For each data slice, 114 relevant attributes are extracted and PCA is utilized for feature selection to improve the recognition rate. With the help of Weka, we constructed several classical classifiers for emotion
Table 8. Happiness, Anger and Neutral emotion recognition when $w = 5$

| Joint   | LibSVM | DecisionTree | RandomForest | RandomTree |
|---------|--------|--------------|--------------|------------|
| wrist   | 81.2%  | 70.6%        | 66.2%        | 56.6%      |
| ankle   | 62.3%  | 49.6%        | 52.4%        | 47.8%      |

recognition. The classification accuracies of happiness-neutral and happiness-anger using $w = 3$ are both better than that using $w = 5$, but the classification accuracy of anger-neutral, anger-happiness-neutral are higher when $w = 5$. The results show that different values of $w$ would influence the accuracy of emotion classification. Under the same conditions, for each classifier, the classification result using the acceleration data of wrist is better than that using the acceleration data of ankle. The best classification accuracies of anger-neutral, happiness-neutral, anger-happiness-neutral are 91.3%, 88.5%, 88.5% and 81.2% respectively. It is revealed that emotions could influence the gait.

6 CONCLUSION

This study focuses on emotion recognition from human gait. For this purpose, we recorded acceleration data of wrist and ankle while participants were walking. Based on acceleration data, emotion recognition model is constructed with the help of Weka platform. The recognition results of different kinds of emotion were all above 81%. It is concluded that emotion could be revealed from gait.

ACKNOWLEDGMENTS

The authors gratefully acknowledges the generous support from National High-tech R&D Program of China (2013AA01A606), National Basic Research Program of China(2014CB744600), Key Research Program of Chinese Academy of Sciences(CAS)(KJZD-EWL04), and CAS Strategic Priority Research Program (XDA06030800).

REFERENCES

[1] Bramer, M., Bramer, M., and Bramer, M. (2007). Principles of data mining, volume 131. Springer.
[2] Cao, L., Chua, K., Chong, W., Lee, H., and Gu, Q. (2003). A comparison of pca, kpca and ica for dimensionality reduction in support vector machine. Neurocomputing, 55(1):321–336.
[3] Crane, E. and Gross, M. (2007). Motion capture and emotion: Affect detection in whole body movement. In Affective computing and intelligent interaction, pages 95–101. Springer.
[4] Cui, L., Li, S., and Zhu, T. (2015). Emotion detection from natural walking. Technical report, PeerJ PrePrints.
[5] Ekman, P. and Friesen, W. V. (1986). A new pan-cultural facial expression of emotion. Motivation and emotion, 10(2):159–168.
[6] Han, J. and Bhanu, B. (2006). Individual recognition using gait energy image. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 28(2):316–322.
[7] James, W. (1884). Ii.-what is an emotion? Mind, (34):188–205.
Janssen, D., Schöllhorn, W. I., Lubienetzki, J., Fölling, K., Kokenge, H., and Davids, K. (2008). Recognition of emotions in gait patterns by means of artificial neural nets. *Journal of Nonverbal Behavior*, 32(2):79–92.

Jinjing Song, Guozhen Zhao, Y. X., Sun, X., and Ge, Y. (2015). A chinese emotional film clips database.

Kale, A., Sundaresan, A., Rajagopalan, A., Cuntoor, N. P., Roy-Chowdhury, A. K., Krüger, V., and Chellappa, R. (2004). Identification of humans using gait. *Image Processing, IEEE Transactions on*, 13(9):1163–1173.

Karg, M., Jenke, R., Kühnlenz, K., and Buss, M. (2009). A two-fold pca-approach for inter-individual recognition of emotions in natural walking. In *MLDM Posters*, pages 51–61.

Ma, L. (2013). Sensor-based activities recognition on mobile platform. Master’s thesis, Harbin Institute of Technology.

Martínez, A. M. and Kak, A. C. (2001). Pca versus lda. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 23(2):228–233.

Michalak, J., Troje, N. F., Fischer, J., Vollmar, P., Heidenreich, T., and Schulte, D. (2009). Embodyment of sadness and depression-gait patterns associated with dysphoric mood. *Psychosomatic medicine*, 71(5):580–587.

Montepare, J. M., Goldstein, S. B., and Clausen, A. (1987). The identification of emotions from gait information. *Journal of Nonverbal Behavior*, 11(1):33–42.

Peter, C. and Beale, R. (2008). *Affect and emotion in human-computer interaction: From theory to applications*, volume 4868. Springer Science & Business Media.

Russell, J. A. and Mehrabian, A. (1977). Evidence for a three-factor theory of emotions. *Journal of research in Personality*, 11(3):273–294.

Smith, C. A. and Lazarus, R. S. (1990). Emotion and adaptation.

Wu, J., Wang, J., and Liu, L. (2007). Feature extraction via kpca for classification of gait patterns. *Human Movement Science*, 26(3):393–411.

Xue, Y. and Jin, L. (2011). Discrimination between upstairs and downstairs based on accelerometer. *IEICE TRANSACTIONS on Information and Systems*, 94(6):1173–1177.