# Emotion detection from Natural walking

Emotion identification aims to automatically determine person's affective state, which has immense potential value in action tendency, health care, psychological detection and human-computer(robot) interaction. In this paper, we propose a novel method of identifying emotion from natural walking. After obtaining the three-axis acceleration data of wrist and ankle recorded by smartphone, we run a sliding average filter with different window size *w*, then cut actual data into slices. We extract 114 features including time-domain, frequency domain, power and distribution features from each slice, then use principal component analysis (PCA) for feature selection. We train SVM, Decision Tree, Multilayerperception, Random Tree and Random Forest classification models, and compare the accuracy on datasets of wrist and ankle with respect to different *w*. The performance of emotion identification on acceleration data of ankle is better than wrist. Among them, SVM yields the best accuracy of 90.31% for anger vs.neutral, 89.76% for happy vs.neutral, and 87.10% for anger vs.happy. The model for identifying anger/neutral/happy yields the best accuracy of 85%- 78%-78%. The results show that it is capable of identifying personal emotional states through the gait of walking.

PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

# Emotion Detection from Natural Walking

Liqing Cui[†‡], Shun Li[†‡], Tingshao Zhu[†♯*]

[†] *Institute of Psychology, Chinese Academy of Sciences*

[‡] *The 6th Research Institute of China Electronics Corporation(National Computer System Engineering Research Institute of China)*

[♯] *Institute of Computing Technology, Chinese Academy of Sciences*

**Abstract**

Emotion identification aims to automatically determine person's affective state, which has immense potential value in action tendency, health care, psychological detection and human-computer(robot) interaction. In this paper, we propose a novel method of identifying emotion from natural walking. After obtaining the three-axis acceleration data of wrist and ankle recorded by smartphone, we run a sliding average filter with different window size $w$, then cut actual data into slices. We extract 114 features including time-domain, frequency-domain, power and distribution features from each slice, then use principal component analysis (PCA) for feature selection. We train SVM, Decision Tree, Multilayerperception, Random Tree and Random Forest classification models, and compare the accuracy on datasets of wrist and ankle with respect to different $w$. The performance of emotion identification on acceleration data of ankle is better than wrist. Among them, SVM yields the best accuracy of 90.31% for anger vs.neutral, 89.76% for happy vs.neutral, and 87.10% for anger vs.happy. The model for identifying anger/neutral/happy yields the best accuracy of 85%-78%-78%. The results show that it is capable of identifying personal emotional states through the gait of walking.

*Keywords:* `Sensor mining, emotion identification, smartphone, accelerometer sensor`

*Corresponding author

*Preprint submitted to Elsevier* *September 22, 2015*

## 1. Introduction

Nonverbal signals are observed to deliver additional cues for a person's emotion and intention, which can be used to improve human-machine interaction or health state detection. It is a very challenging task to identify person's affect state automatically. Traditionally, emotion detection is based on facial expressions, linguistic and acoustic features in speech. Psychological studies on visual analysis of body movement show that human movement differs from other movements, because it is the only visual stimulus we have experience of both perceiving and producing[2][18]. In this paper, we propose a method of identifying human's emotion from walking. To record natural walking, we only acquire the accelerometer data of person's wrist and ankle by built-in sensors of smartphone.

Nowadays, smartphone has already become an indispensable communication tool in daily life. It always integrates many powerful sensors, including GPS, light sensors, acceleration sensors and gravity sensors, etc. Some of those sensors, with advantages of small size, substantial computing power and high precision, can not only complementarily make the phone more intelligent, but provide new opportunities for data acquisition and mining.

In this paper, we use acceleration sensor in smartphone to identify emotion based on natural walking. To collect accelerometer data, the participants are instructed to attach two smartphones(Samsung I9100G) to their wrist and ankle separately, then walk several minutes naturally. The raw accelerometer data recorded by smartphone has gravity component, and we acquire the actual accelerometer data by using the data from gravity sensor. After a sliding average filter with different window size $w$ and data slice cut by sliding slice window, we extract 114 features from actual accelerometer data. These features include time-domain, frequency-domain, power and distribution features. We utilize Principal Component Analysis (PCA) for feature selection. On the one hand, we compare classification performance of SVM, Decision Tree, Random Forest,



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

Multilayerperception and Random Tree. On the other hand, we also want to find whether the performance of these models may differ on different $w$.

This work has a wide range of applications. It can generate daily, weekly or monthly emotion profile to report how the emotion changes over time. Besides, we can embed the models into smart bracelet to record activity data and identify real-time emotion. In addition, data can be also used for personal health by offering a timely feedback like having some exercise or entertainment.

To summarize, our research has two main contributions.

- We acquire actual accelerometer data from wrist and ankle in natural walking, and find the relevance between one's walking activity and her/his current emotion.
- We propose a new data preprocess method, especially in eliminating burr and noise, and have improved performance of emotion identification distinctly.

The rest of this paper is organized as follows. Section 2 summarizes related work about identification of emotion by walking. Description of database, data preprocessing and feature extraction are presented in Section 3. Section 4 describes the results of the trained models and the performance of trained models for experiment. In section 5, we discuss our methods and summary our work. Finally, the paper ends with a conclusion in Section 6.

## 2. Related Work

In psychology, there exists several models to categorize emotions. Ekman's basic emotions, which are anger, disgust, fear, sadness and surprise, and the dimensional pleasure-arousal-dominance(PAD) model are widely used in automatic emotion recognition[8][15]. The PAD model spans a 3-dimensional space with the independent and bipolar axes pleasure, arousal and dominance. An affective state is described as a point within this state space.



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

By showing only body joints on black background, the observers were able to recognize the gender or a familiar person by walking[7]. In Montepare's study, he found that people can identify emotions from walking gaits[13]. It is reported that people can recognize sadness and anger much easier than pride. Pollick quantified expressive arm movements in terms of velocity and acceleration, and confirmed that velocity and acceleration are important in recognizing emotions[14]. Crane and Gross illustrated that emotion recognition is not only depended on gesticulatory behavior, but associated with emotion-specific changes in gait kinematics. In their study, they identified some activity features, including velocity, cadence, head orientation, shoulder and elbow range of motion, as significant parameters which are affected by emotions[6].

In fact, emotion changes rapidly even in a short walking, not to mention complex activity in body movement, and these factors may influence the accuracy of identification. Janssen investigated the recognition of four emotional states by artificial neural nets. The accuracy is 99.3% in average based on walking patterns for intra-individual recognition, but for inter-individual, accuracy is about 50%. Karg had applied different methods such as Principal Component Analysis(PCA), Kernal PCA(KPCA) and Linear Discriminant Analysis(LDA) into kinematic parameters of person-dependent recognition and inter-individual recognition to compare results and improved accuracy rate. LDA in combination with Naive Bayes leads to an accuracy of 91% for person-dependent recognition of four discrete affective states based on observation of barely a single stride[1]. In [10], PCA is used for feature selection, and the best accuracy is achieved by Naive Bayes with 72% for the four emotions which are sad, neutral, happy and angry during natural walking.

A general survey of analytical techniques for clinical and biomechanical gaits analysis is given in[4][5]. It mainly refers to classification of clinical disorders, though the methods for feature extraction can be also taken for psychological gaits analysis. Dimension reduction techniques such as KPCA improves recognition of age in walking[16]. The performance comparison of Principal Component Analysis (PCA) and KPCA is discussed in[3]. Martinez and Kak found that



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

PCA can perform much better on small size of training sets[12].

In this paper, we extract relevant time-domain, frequency-domain, power and distribution features from kinematic acceleration data set to identify human emotion. We collect actual accelerometer data from wrist and ankle to build emotion identification models, and compare the identification accuracy with different sliding filter window.

## 3. Methods

The proposed emotion identification method based on three-axis acceleration sensor and gravity sensor embedded in smartphone comprises the following three steps: 1) data acquisition and pre-processing, 2) feature extraction, and 3) training and testing. At the last step, we train several classification models and evaluate their performance.

### *3.1. Participants*

To identify emotion from gaits patterns, 59 healthy young adult subjects(female = 32) were recruited to participate in this study from University of Chinese Academy of Sciences(UCAS). This study was approved by Institute of Psychology, Chinese Academy of Sciences and written informed consent were obtained from all subjects prior to their participation. Our project employed two SAMSUNG I9100G and one SAMSUNG Tab as platform(Android operation system, because we can program and develop APP on Android system in smartphone and Tab to access raw data from accelerometer sensor and gravity sensor, and record time series). The sampling frequency of sensor is 5Hz , which records one piece of data per 200ms.

The experiment was conducted on a fixed rectangle-shaped area(length:about 6m,width:0.8m), marked on the floor with red lines. Each participant signed the consent form, and wore one smartphone on wrist and the other on ankle, standing in front of the starting line. When the participant was ready, the host started two APPs on smartphones to start recording, and used one Tab to



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

record the time stamp across the whole experiment. The participant conducted natural walking back and forth in this area for about two minutes. The host stopped subject walking, and recorded the end time by the Tab. Each participant was asked to report her/his current emotion score on a scale of 1 to 10. For the first-round experiment, the host recorded the score of participant's anger. For the second-round, happy score was acquired instead. The participant was then required to watch one emotional film clip[9][1] for emotion priming. After watching the clip, the participant was asked to walk back and forth in above area for about one minute, just as did before. Each participant was asked to report his/her current anger score and recall the anger score after watching film clip. To avoid any influence on emotional priming, we didn't ask participant to report her/his emotion score immediately after watching the clip. At least three hours later (if the internal is too small, the participant's emotion arousal might be influenced by the first clip), the participant was allowed to conduct the second-round experiment. The procedure is the same as the first-round experiment except that the participant watched the happy film clip[9], and report her/his happy emotion on a scale of 1 to 10. We acquired the activity acceleration data from the smartphones, and the time stamp data from the Tab. We then cut and aggregate activity accelerometer data of each participant from smartphone according to the time stamp recorded by the Tab.

### *3.2. Data Preprocessing*

We acquired two groups of sensor data in which one is for wrist, and the other is for ankle. Each group includes raw accelerometer data set($SensorLa$) and gravity data set($SensorGra$). One sample raw data of X-axis from ankle is shown in Figure. 1.

According to time stamp recorded, we cut every participant's walking data into two parts(before and after watching the clip). Every part contains one minute's raw accelerometer data. For two minutes' natural walking, we just

[1]in submission



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

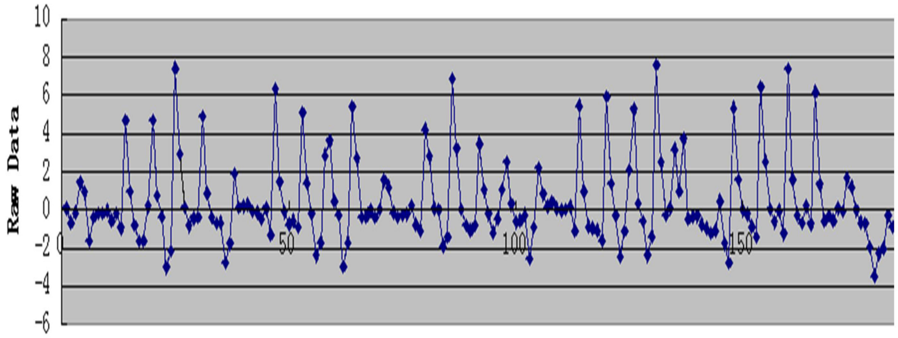


Figure 1: One raw accelerometer data of X-axis from ankle

kept the last one minute's data before watching, as the participant might walk more steadily than in the first minute. To get the actual accelerometer data, we just use $SensorLa - SensorGra$. Since noise and burrs may exist in the data, we then run preprocessing on actual accelerometer data, by sliding average filter window as below:

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

The filter uses a series of raw discrete time signal as input, and outputs average signal for each sampling point, in which $w$ is adjustable. In this paper, we just try to set $w = 3, 5$ just as did in [11].

Figure.2 presents the ankle wave signal with respect to $w = 3$, and the undulating signal has become smoother than raw data shown in Figure. 1..

For $w = 5$ as shown in Figure. 3, the signal becomes more smoother than that of $w = 3$ in Figure. 2.

It is very obvious that $w$ plays a key role in data preprocessing. But if $w$ is too high, it may eliminate some minor changes in the data. Though it makes wave smoother, we may lose key undulatory information of the data. Therefore, we just set w 3 and 5 for any further preprocessing.

Since the sampling frequency is 5Hz, i.e., the APP can access accelerometer data five times per second and write it into database. A few minutes can accumulate hundreds of pieces of records, these records are too much to deal

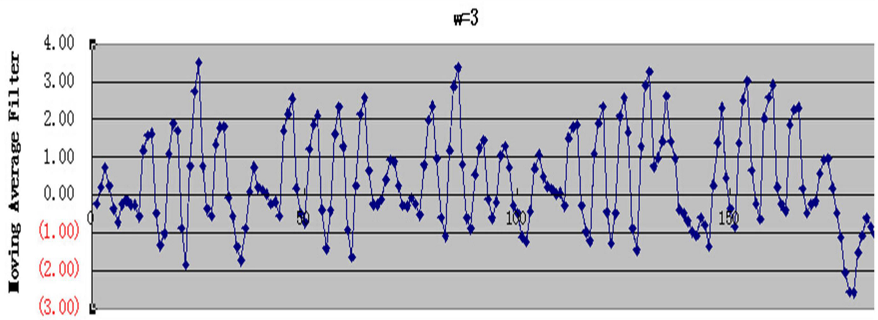


Figure 2: One raw accelerometer data of X-axis from ankle is processed by sliding average filter window $w = 3$

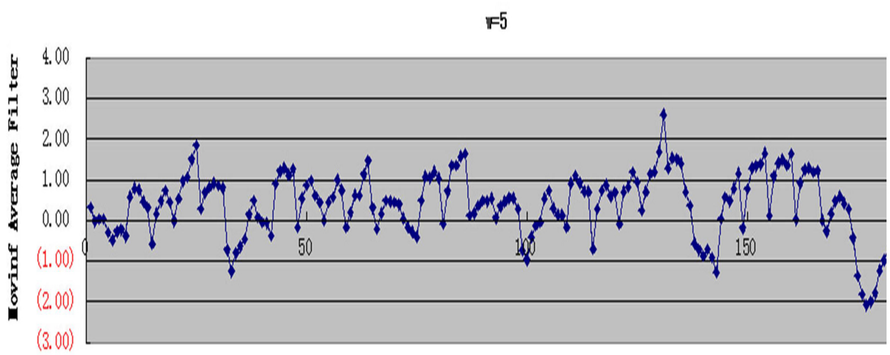


Figure 3: one raw accelerometer data of X-axis from ankle is processed by sliding average filter with $w = 5$

with and extract features timely. We use sliding slice window to cut data into slices, and the size of sliding window may be quite different, which is 128 in this paper, and the coverage ratio is 50% [17], as shown in Figure. 4.

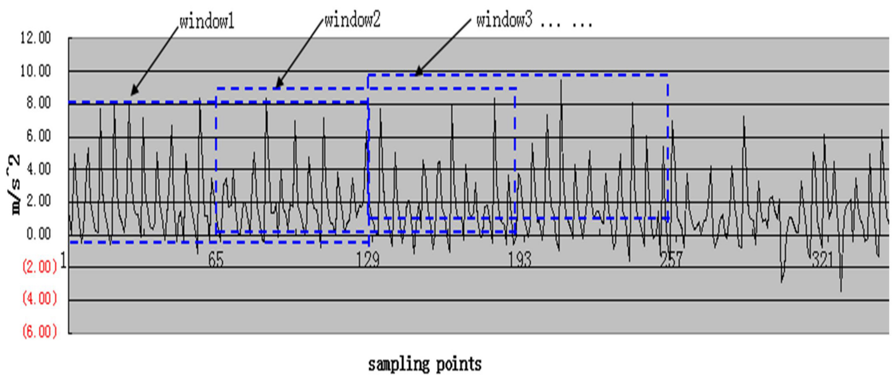


Figure 4: Slice sliding window to cut accelerometer data

### 3.3. Feature Extraction

Participant's walking has a great difference in behavioral pattern, including gesture gait and speed. Besides, each participant's data has various length. In this paper, we extract time-domain feature, frequency-domain feature, power feature and distribution feature from each slice. Time-domain feature is directly computed from the data. Distribution feature includes each axis's standard deviation, kurtosis, skewness and correlation coefficient (every two axes). Standard deviation reflects the degree of dispersion within one slice. Kurtosis shows the flat or sharp degree of top of frequency distribution curve. Skewness coefficient describes the characteristics of deviating symmetry degree for certain distribution. Frequency-domain feature includes the first 32 amplitude coefficients of FFT(Fast Fourier Transformation). Each amplitude coefficient represents the size of the corresponding low frequency signal. As for power feature, Power Spectral Density (PSD) is the power per unit of bandwidth. Means of PSD is the size of average power per unit of bandwidth. Standard deviation of PSD shows the degree of dispersion in terms of power.

In summary, each axis of slice produces 38 features. Totally, we extract $1*(38*3)$ features from each data slice, and extract features from all slices from one participant, and we aggregate all these feature matrices into one feature matrix.

The value of these features may vary dramatically, in case some important features with small values are ignored while training the model, which may seriously affect the identification results. To avoid it, we run Z-score normalization on all features.

In general, high dimension of feature vector increases computational complexity, and there exists much redundant information. In order to reduce the dimension of feature vectors, and obtain the best description of the different behavior and the best classification characteristics, dimension reduction is an essential step. Here, we take the feature matrix aggregated from all subjects as PCA's input, and make components account for 0.95.

## 4. Results

For train sets we get from wrist and ankle with different w($w = 3, 5$) in the two rounds of experiment, for the first-round, we labelled each sample with "natural" or "anger" after PCA, then we trained models in Weka. Similarly, for train sets got in the second-round, we labelled each with "neutral" or "happy", then trained models.

### *4.1. Anger Emotion Identification*

In first-round experiment, we acquired accelerometer data from wrist and ankle. After a series of procession, we utilized diverse kinds of classification algorithms to train models in Weka with default parameters and standard 10-fold cross validation, including SVM(model parameters: -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 -seed 1), J48(model parameters:-C 0.25 -M 2), Random Tree(model parameters: -K 0 -M 1.0 -V 0.001 -S 1), Multilayerperception(model parameters: -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H

a) and Random Forest(model parameters: -I 10 -K 0 -S 1 -num-slots 1). Decision Tree(J48) model is explained easily and fast, but Random Forest can inspect impact between features. For SVM, it not just outstrips Multilayerperception in linearity and nonlinearity, but has a good performance to deal with high dimension data.

The results of identification with $w = 3$ on wrist and ankle are shown in Table. 1.

Table 1: The classification accuracy in different models when w=3

| Joint | SVM | DT | RF | MLP | RT |
|---|---|---|---|---|---|
| wrist | 90.03% | 56.25% | 62.21% | 63.92% | 58.81% |
| ankle | 90.31% | 71.31% | 64.49% | 59.38% | 59.94% |

DT : Decision Tree.

RF : Random Forest.

MLP : Multilayerperception .

RT : Random Tree.

From the above reults, the emotion priming by watching video clips really works. Participants reported emotion arouses according to own emotion score change which has a significant influence on her or his gait. In addition, both wrist and ankle have a relatively higher accuracy by SVM than other models. Meanwhile, the identification accuracy from ankle is higher than wrist. A possible reason is that the activity of hand is more complex than ankle when walking. There exists much noise which is not easily filtered out from data.

In fact, when we set $w = 5$, the results we obtained are of greatly significant difference, as shown in below Table 2.

The results show that with $w = 5$, the evaluation results of most above models have a little higher accuracy than the results of $w = 3$ except for SVM. The accuracy of wrist is still lower than ankle. We come to the same conclusion when $w$ is 3.

Table 2: The classification accuracy in different models when w=5

| Joint | SVM | DT | RF | MLP | RT |
|---|---|---|---|---|---|
| wrist | 84.61% | 54.99% | 59.54% | 58.97% | 52.99% |
| ankle | 87.46% | 74.07% | 65.81% | – | 62.68% |

- : invalid.

### 4.2. Happiness Emotion Identification

In second-round experiment, the way we obtained accelerometer data from wrist and ankle is the same as we did in the first-round experiment. After data preprocessing, we run several classification algorithms to train models in Weka. The classification results is shown in Table 3 with $w = 3$.

Table 3: The classification accuracy in different models when w=3

| Joint | SVM | DT | RF | MLP | RT |
|---|---|---|---|---|---|
| wrist | 89.76% | 61.19% | 61.49% | 58.51% | 61.19% |
| ankle | 87.65% | 74.93% | 67.46% | 61.19% | 62.39% |

From above results, we can find that the funny clip arouse participants' emotion so that their gaits have a significant difference, which makes it easy to differentiate the gaits before and after emotion priming. Just as shown in Table 1, ankle performs better to identify emotion than wrist on all above models. The ankle accuracy reaches 87.65%. Similarly, w has a great influence on classification accuracy in second-round experiment, as shown in Table 4.

Table 4: The classification accuracy in different models with $w = 5$

| Joint | SVM | DT | RF | MLP | RT |
|---|---|---|---|---|---|
| wrist | 83.73% | 63.88% | 58.20% | 51.94% | 62.69% |
| ankle | 87.65% | 85.07% | 70.45% | 54.32% | 60.60% |

Table 4 demonstrates that $w$ does influence emotion identification to some



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

extend. Comparing with other models, SVM has the best accuracy of 87.65% .

### 4.3. Emotions Identification

We aggregated data sets after emotion priming in both first-round experiment and second-round experiment, and respectively labelled them as "anger" and "happy". The accuracy of classification is shown in Table 5 and Table 6.

Table 5: Anger-happy classification accuracy in different models when w=3

| Joint | SVM | DT | RF | RT |
|---|---|---|---|---|
| wrist | 76.83% | 63.34% | – | – |
| ankle | 78.00% | 74.49% | 63.64% | 56.60% |

Table 6: Anger-happy classification accuracy in different models when w=5

| Joint | SVM | DT | RF | RT |
|---|---|---|---|---|
| wrist | 65.98% | 63.05% | 54.25% | 54.25% |
| ankle | 87.10% | 85.34% | 67.16% | 66.86% |

From above two tables, it is obvious that there exists significant difference between person's gaits under different emotions. SVM always performs better on ankle, reaching 87.10% to identify anger or happy with $w = 5$ than accuracy when $w$ is 3.

In Table 7, Table 8 and Table 9, anger-neutral-happy emotion confusion matrix for SVM shows that neutral emotion is easiest to be identified. When $w = 5$, Table 10 shows that anger is easiest to be identified.

Four confusion matrixes show that the affective state happy is easier to be misclassified as anger, similarly, anger is also easier to be misclassified as happy.

## 5. Discussion

In this paper, we use PCA for feature selection, and try different machine learning algorithms in Weka for training and testing different models. We have



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

Table 7: Anger-neutral-happy confusion matrix when $w = 3$ for wrist

| affect | anger | neutral | happy | acc |
|---|---|---|---|---|
| anger | 136 | 7 | 32 | 78% |
| neutral | 18 | 151 | 7 | 86% |
| happy | 43 | 8 | 115 | 69% |

Table 8: Anger-neutral-happy confusion matrix when $w = 3$ for ankle

| affect | anger | neutral | happy | acc |
|---|---|---|---|---|
| anger | 126 | 10 | 39 | 72% |
| neutral | 10 | 152 | 14 | 86% |
| happy | 31 | 10 | 125 | 75% |

Table 9: Anger-neutral-happy confusion matrix when $w = 5$ for wrist

| affect | anger | neutral | happy | acc |
|---|---|---|---|---|
| anger | 121 | 18 | 36 | 69% |
| neutral | 25 | 135 | 16 | 77% |
| happy | 57 | 17 | 92 | 55% |

Table 10: Anger-neutral-happy confusion matrix when $w = 5$ for ankle

| affect | anger | neutral | happy | acc |
|---|---|---|---|---|
| anger | 148 | 5 | 22 | 85% |
| neutral | 18 | 137 | 21 | 78% |
| happy | 17 | 20 | 129 | 78% |



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

tried to build models with different parameter settings, and run 10-fold cross validation for evaluation.

We extract 114 features from accelerometer data, then train models to identify person's emotion based on participant's gait. The experimental results presented above are quite interesting and promising, which demonstrates that there exists significant difference of walking under different emotion. Different $w$ values(sliding average filter window size) have an evident effect on the accuracy of identification. We find that while $w$ becomes greater, the sequence is smoother in time-domain. But if $w$ is too great, it may ignore any tiny changes which may decrease the performance of the models. Otherwise, small $w$ loses an evident moving smooth performance. When $w$ is 3 or 5, ankle has a better performance for emotion identification than wrist, with the accuracy of 90.31% in first-round experiment and 89.76% in second-round experiment. We infer that wrist has complex additional movement when people walk. Besides, two kinds of emotion(anger-happiness) is relatively easy to be identified, whose accuracy reaches 87.10%. For identifying anger/neutral/happy, it yields the best accuracy of 85%-78%-78%.

M. Karg and R. Jenke[10] presented two-fold PCA algorithm to make a four-emotion classification: angry, happy, neutral and sad. Their results indicate that the accuracy of angry prediction reaches 69% and 76% on happy by using Naive Bayes. In our work, we find SVM works the best, reaching 90.31%. For our experiment, since we obtain person's actual wrist and ankle accelerometer data, there is less noise involved. Due to that, all features that we extract represent one person's gait characteristics more accurately, the results are more credible.

## 6. Conclusion

This paper proposes to identify human emotion by natural walking. To do so, we obtained motion data by using accelerator sensors in smartphone attached on wrist and ankle. After data preprocessing, we extract 114 features from each slice. We have tested four learning models in Weka with default parameters



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015

and standard 10-fold cross validation, including SVM, Decision Tree, Random Tree and Random Forest. Among them, SVM classifier works best to identify personal affect.

The results of different trained models indicate that ankle data is more capable to reveal human emotion than wrist, with the best accuracy of 90.31%. The preprocess technique plays a key role in determining the performance of the model, especially the size of slice $w$. Both anger and happy can be recognizable from human's characteristics of natural walking, which reaches an accuracy of 87.10%. For identifying anger/neutral/happy, it yields the best accuracy of 85%-78%-78%.

However, further consideration and improvement is required. This includes how the size of sliding window slice influences the performance of identification, and whether it can also improve model's accuracy. We also intend to investigate how to void the overlap of neighboring values between two adjacent sliding windows, and we may try more advanced machine learning algorithms.

## References

[1] *A comparison of PCA, KPCA and LDA for feature extraction to recognize affect in gait kinematics*, Sept 2009.

[2] Christian Peter Russell Beale. Affect and emotion in human-computer interaction.

[3] L.J. Cao, K.S. Chua, W.K. Chong, H.P. Lee, and Q.M. Gu. A comparison of pca, {KPCA} and {ICA} for dimensionality reduction in support vector machine. *Neurocomputing*, 55(1C2):321 – 336, 2003. Support Vector Machines.

[4] Tom Chau. A review of analytical techniques for gait data. part 1: fuzzy, statistical and fractal methods. *Gait & Posture*, 13(1):49 – 66, 2001.

[5] Tom Chau. A review of analytical techniques for gait data. part 2: neural network and wavelet methods. *Gait & Posture*, 13(2):102 – 120, 2001.

[6] Elizabeth Crane and Melissa Gross. Motion capture and emotion: Affect detection in whole body movement. In AnaC.R. Paiva, Rui Prada, and RosalindW. Picard, editors, *Affective Computing and Intelligent Interaction*, volume 4738 of *Lecture Notes in Computer Science*, pages 95–101. Springer Berlin Heidelberg, 2007.

[7] JamesE. Cutting and LynnT. Kozlowski. Recognizing friends by their walk: Gait perception without familiarity cues. *Bulletin of the Psychonomic Society*, 9(5):353–356, 1977.

[8] Paul Ekman and WallaceV. Friesen. A new pan-cultural facial expression of emotion. *Motivation and Emotion*, 10(2):159–168, 1986.

[9] Yuexin Xiong Jinjing Song, Guozhen Zhao, Xianghong Sun, and Yan Ge. A chinese emotional film clips database.

[10] Michelle Karg, Robert Jenke, Kolja Kühnlenz, and Martin Buss. A two-fold pca-approach for inter-individual recognition of emotions in natural walking. In *MLDM Posters*, pages 51–61, 2009.

[11] Liang Ma. Sensor-based activities recognition on mobile platform. Master's thesis, Harbin Institute of Technology, 2013.

[12] Aleix M. Martinez and A.C. Kak. Pca versus lda. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 23(2):228–233, Feb 2001.

[13] JoannM. Montepare, SabraB. Goldstein, and Annmarie Clausen. The identification of emotions from gait information. *Journal of Nonverbal Behavior*, 11(1):33–42, 1987.

[14] Frank E Pollick, Helena M Paterson, Armin Bruderlin, and Anthony J Sanford. Perceiving affect from arm movement. *Cognition*, 82(2):B51 – B61, 2001.

[15] James A Russell and Albert Mehrabian. Evidence for a three-factor theory of emotions. *Journal of Research in Personality*, 11(3):273 – 294, 1977.

[16] Jianning Wu, Jue Wang, and Li Liu. Feature extraction via {KPCA} for classification of gait patterns. *Human Movement Science*, 26(3):393 – 411, 2007.

[17] Yang Xue and Lianwen Jin. Discrimination between upstairs and downstairs based on accelerometer. *IEICE TRANSACTIONS on Information and Systems*, 94(6):1173–1177, 2011.

[18] Z. Zeng, M. Pantic, G.I. Roisman, and T.S. Huang. A survey of affect recognition methods: Audio, visual, and spontaneous expressions. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 31(1):39–58, Jan 2009.



PeerJ PrePrints | https://dx.doi.org/10.7287/peerj.preprints.1384v2 | CC-BY 4.0 Open Access | rec: 23 Sep 2015, publ: 23 Sep 2015