Emotion Detection from Natural Walking

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Abstract

Emotion identification, which aims to determine a person's affective state automatically, has immense potential value in many areas, such as action tendency, health care, psychological detection and human-computer (robot) interaction. In this paper, we provide a novel method for identifying emotion from natural walking. After obtaining the three-axis acceleration data of wrist and ankle recorded by smartphone, we run a moving average filter with different window size w, then cut actual data into slices. 114 features are extracted from each slice, and principal component analysis(PCA) is used for feature selection. We train SVM, Decision Tree, Multilayerperception, Random Tree and Random Forest classification models, and compare the accuracy of emotion identification using different datasets (wrist vs. ankle) in different models. Results show that acceleration data from ankle has better performance in emotion identification than wrist. Among different models, SVM has the highest accuracy, 90.31% when differ anger from neutral, 89.76% when differ happy from neutral, and 87.10% when differ anger from happy. The model for identifying anger/neutral/happy yields the best accuracy of 85%-78%-78%. The results show that we could identify peoples emotional states through the gait of walking with high accuracy.

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

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1. Introduction

Nonverbal signals can provide additional cues for identifying a person's emotion and intention, which can be used to improve human-machine interaction or health state detection. Identifying a person emotion states automatically is a challenging task. Traditionally, emotion detection is based on facial expressions, or linguistic and acoustic features in speech, which inevitably encounter high complexity in image or audio. 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 natural walking. In recording, 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, such as GPS, light sensors, acceleration sensors and gravity sensors. Some of these sensors, with substantial computing power and high precision in small sizes, can not only complementarily make the phone more intelligent, but also provide new opportunities for data acquisition and mining.

In this paper, we use the acceleration sensor in smartphone to collect data of natural walking. When collecting, participants are instructed to attach two smartphones(Samsung I9100G) to one wrist and one ankle separately, and to walk several minutes naturally. However, raw accelerometer data recorded by smartphone has gravity component. To acquire actual motion accelerometer data, we have to eliminate gravity component recorded by gravity sensor. After actual data is preprocessed by moving average filter with different window size w, it is cut into slices by sliding slice window. Then, we extract 114 features from above each actual data slice. These features including time-domain feature, frequency-domain feature, power feature and distribution feature. We use Principal Component Analysis (PCA) for feature selection. We compare classifi-

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cation performance of different models, including SVM, Decision Tree, Random Forest, Multilayerperception and Random Tree, and looking for differences in the performance of these models, especially the difference in w.

This work has a wide range of applications. It can generate daily, weekly or monthly emotion profile reporting 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, this work can also be 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 provide a new data preprocess method, especially in eliminating burr and noise, and improve 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 are several theories about emotion category.. Ekman's basic emotions, including 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.

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Be only shown 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]. Specifically, 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 also 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 states change rapidly even in a short walking, not to mention complex activity in body movement. Many factors could 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 just 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 had improved accuracy rates. 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 features 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

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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 moving filter windows(w).

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 natural walking, 59 healthy young adult participants(female = 32) were recruited from University of Chinese Academy of Sciences(UCAS). This study is supported by Institute of Psychology, Chinese Academy of Sciences(approval number: H15010) 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 is used, because we can 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. After signed the consent form, each participant wore one smartphone on one wrist and the other on one ankle, and stand in front of the starting line. Once the participant was ready, the host started two APPs to start recording, and used one Tab to record the

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time stamp during the whole experiment. The participant was asked to walk naturally back and forth in demand area for about two minutes. Then the host stopped subject walking and recorded the end time by the Tab. Each participant was asked to report her/his current emotion state with a score from 1 to 10. For the first-round experiment, the emotion score of anger was recorded. For the second-round, happy score was acquired instead. Then the participant watched one emotional film clip[9][1] for emotion priming. After finishing watching the clip, the participant was asked to walk naturally back and forth again in demand 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 finishing the clip.

The second-round experiment was conducted after at least three hours (if the internal is too small, the participant's emotion arousal might be influenced by the first clip). 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 state on a scale of 1 to 10. We acquired the activity acceleration data from the smartphones, and the time stamp data from the Tab. Then we 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 ,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 the clip). Every part contains one minute's raw accelerometer data. For the first two minutes' walking, we just used the last one

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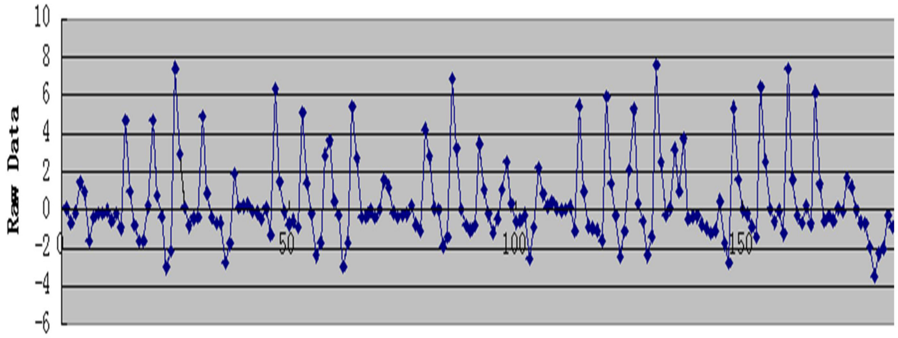

Figure 1: One raw accelerometer data of X-axis from ankle

minute's data before the film clip, for the participant might walk more steadily than that in the first minute. The actual accelerometer data we want to acquire is equal to $SensorLa - SensorGra$. Since noise and burrs may exist in the data, we run preprocessing on above actual accelerometer data, by moving 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. The size w is adjustable as well. 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 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 could make wave smoother, it also might throw away the key undulatory information of the data. Therefore, we just set w 3 and 5 for any further preprocessing.

AS the sampling frequency is 5Hz, i.e., the APP can access accelerometer data five times per second and write it into database. Since few minutes can accumulate hundreds of pieces of records, it is a big work to deal with these

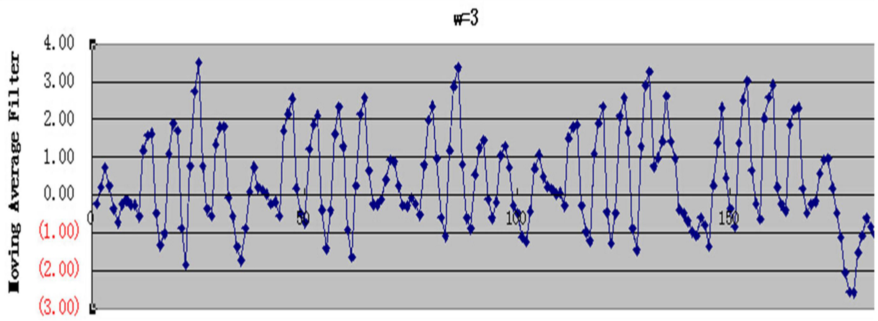

Figure 2: One raw accelerometer data of X-axis from ankle is processed by moving average filter window $w = 3$

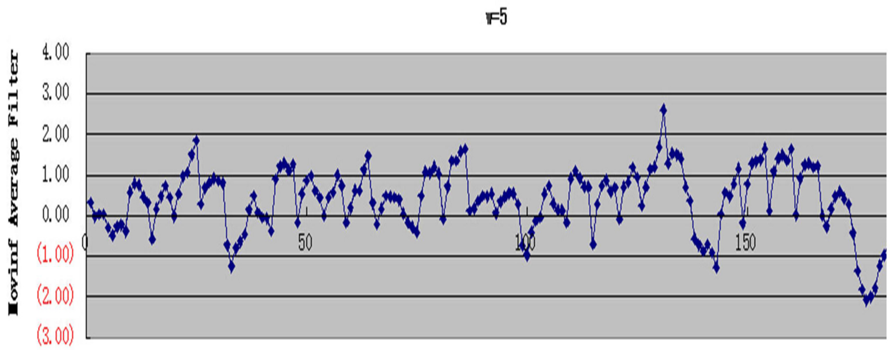

Figure 3: one raw accelerometer data of X-axis from ankle is processed by moving average filter with $w = 5$

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

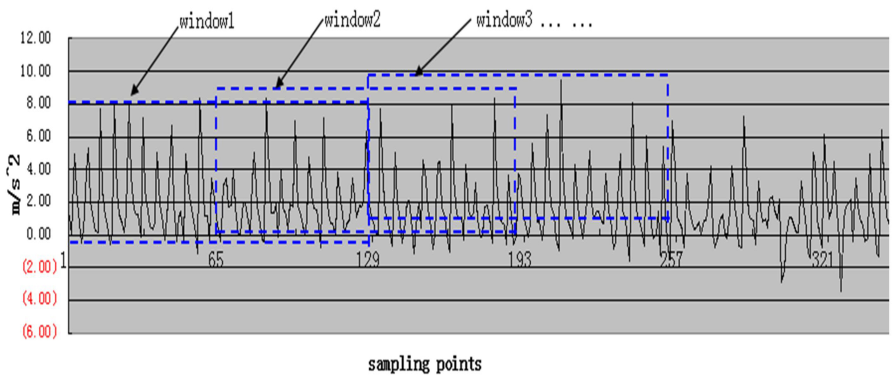

Figure 4: Sliding slice window to cut accelerometer data

3.3. Feature Extraction

Participants walking have great differences in behavioral patterns, including gesture gait and speed. Besides, the length of different participants data is various.. 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 front 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.

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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, then we aggregate all these feature matrices into one feature matrix.

The value of these feature could vary dramatically. To avoid important features with small values being ignored while model training, which may seriously influence identification accuracy, we run Z-score normalization for all features. After that, high dimension of feature vectors computational complexity increases, and information become much more redundant. In order to reduce the dimension of feature vectors, and acquire the best description of the different behavior and the best classification characteristics, dimension reduction is an essential step.

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 "neutral" 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 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

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impact between features. For SVM, it not just outstrips Multilayerperception in linearity and nonlinearity, but also 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.

The results show that emotion priming by watching video clips really works. And the emotional arouse, shown by the change of their reported emotion scores, have significant influence on their gaits. 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 hands is more complex than ankles when walking. There is much noise which is not easily filtered out from data.

In fact, when we set $w = 5$, the results we obtained change dramatically, as shown in below Table 2.

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.

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The results show that for $w = 5$, 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.

4.2. Happiness Emotion Identification

In second-round experiment, the way we obtained accelerometer data 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 and 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 models. The ankle accuracy reaches 87.65% on average. 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 when $w = 5$

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

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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 is significant difference between person's gaits under different emotions. Besides, 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.

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%

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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%

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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 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(moving average filter window size) have an significant effect on the accuracy of identification. We find that when w becomes greater, the sequence is smoother in time-domain. But if w is too big, it may ignore any tiny changes and lead to the performance of the models decrease. 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 emotion states identification (anger-happiness) is relatively easy, whose accuracy reaches 87.10%. For identifying anger/neutral/happy, the best accuracies for each state are 85%, 78% and 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%. In 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 capably represent one person's gait characteristics. The results are much more credible

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as well.

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 to wrist and ankle. After data preprocessing, we extract 114 features from each slice. We test four learning models in Weka with default parameters 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 window. Both anger and happy can be recognized 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 considerations and improvements are required. That includes how the size of sliding slice window 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 filter windows, and we will try more advanced machine learning algorithms.

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