Comparing Features from ECG Pattern and HRV Analysis for Emotion Recognition System

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Abstract— **We propose new features for emotion recognition from short ECG signals. The features represent the statistical distribution of dominant frequencies, calculated using spectrogram analysis of intrinsic mode function after applying the bivariate empirical mode decomposition to ECG. KNN was used to classify emotions in valence and arousal for a 3-class problem (low-medium-high). Using ECG from the Mahnob-HCI database, the average accuracies for valence and arousal were 55.8% and 59.7% respectively with 10-fold cross validation. The accuracies using features from standard Heart Rate Variability analysis were 42.6% and 47.7% for valence and arousal respectively for the 3-class problem. These features were also tested using subject-independent validation, achieving an accuracy of 59.2% for valence and 58.7% for arousal. The proposed features also showed better performance compared to features based on statistical distribution of instantaneous frequency, calculated using Hilbert transform of intrinsic mode function after applying standard empirical mode decomposition and bivariate empirical mode decomposition to ECG. We conclude that the proposed features offer a promising approach to emotion recognition based on short ECG signals. The proposed features could be potentially used also in applications in which it is important to detect quickly any changes in emotional state.**

Keywords—affective computing, bivariate empirical mode decomposition, empirical mode decomposition, spectrogram, Hilbert transform.

I. Introduction

Features for emotion recognition system relying on ECG signals are usually derived based on standard Heart Rate Variability (HRV) – variation of time interval between heartbeats – analysis, which often requires at least 5 minutes length or several hours of ECG signals [1]. These features are thus most suitable for affect recognition where emotional states do not vary much. However, it is not suitable for emotion tracking applications where emotions change rapidly within a short periods of time. Emotion tracking based on short-time ECG signal analysis could be useful in such applications as biofeedback systems in computer games, monitoring of human-to-human interaction in psychological studies and emotional reactions to varying stimuli in psychiatric studies related to affective communication disorders.

As suggested in [2], Ferdinando, Ye, Seppänen, and Alasaarela [3] have applied the standard HRV analysis to ECG from the Mahnob-HCI database to obtain features for emotion recognition. The achieved accuracies were 42.6% and 47.7% for valence (it measures the degree of pleasantness as one of dimensional emotion variables) and arousal (it measures the degree of activeness as one of the dimensional emotion variables) respectively, on a 3-class problem (low-medium-high). However, since ECG signals in the Mahnob-HCI database vary between 35 and 117 seconds in length, they may be too short for standard HRV analysis [1].

Agrafioti, Hatzinakos, and Anderson [4] proposed Hilbert instantaneous frequencies and local oscillation of intrinsic mode functions (IMFs) as features for emotion detection system after applying the bivariate empirical mode decomposition (BEMD) to ECG. The BEMD is more robust in analyzing ECG signal than the original empirical mode decomposition (EMD) as shown in [5] by solving uniqueness and mode mixing problems in the EMD. It uses a synthetic ECG as imaginary signal to guide the sifting process.

In this study, we propose new features, i.e. statistical distributions of dominant frequencies (DFs) from IMFs and their first difference after applying the BEMD to short-time ECG, to emotion recognition. The proposed features were tested using ECG signals from the Mahnob-HCI database. The results are compared to emotion recognition using features from HRV analysis on the same database. We also calculated features based on the statistical distribution of instantaneous frequencies (IFs) and their first difference after applying EMD and BEMD as a comparison to the proposed features.

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II. Materials and Methods

A. ECG Signals and the Signal Processing

This study used the ECG signals from the Mahnob-HCI database, which contains data recorded from 27 subjects (11 males and 16 females) watching videos and images. The system recorded 32-channel EEG, peripheral physiological signals (ECG, temperature, respiration, skin conductance), face and body videos using 6 cameras, eye gaze, and audio. All recordings were precisely synchronized, allowing researchers to study multimodal emotional responses. ECG signals were recorded at 256 Hz [2].

Our experiments used the same data as in [3]. This data is available under the Collections of the Mahnob-HCI database identified by Selection of Emotion Elicitation. Originally, the number of samples was 513, but sample from session 2508 must be discarded, because visual inspection showed it to be corrupted. Thus, the total number of data was 512.

The recorded ECG contains baseline and response data, the former being unstimulated and the latter stimulated ECG. In addition, the database provides a synchronization signal to separate the two. Our experiments only employed ECG signals recorded during the stimulated phase.

Motion artifact is removed by subtracting the smoothing signal from the original signal [2]. Later, a notch filter is used to remove power line interference. The final stage of signal pre-processing is to scale down the amplitude such that the amplitude is close enough to the synthetic ECG signal.

Fig. 1 shows the block diagram of the system. Feature extraction starts from an ECG analysis using the BEMD [6], which requires a complex value signal. Reference [4] used a synthetic ECG signal, generated based on the model developed by McSharry, Clifford, Tarassenko, and Smith [7], as the imaginary part and the original ECG signal as the real part. The imaginary part must be synchronized to the real one.

R wave events (see Fig. 1), detected using Pan-Tompkins method [8], are used to synchronize the synthetic signal to the original one. It is recommended to use a one-cycle ECG signal as a template, see Fig. 2, and centering this template on each detected R wave event. The template is generated at 60 beat per minute with default values for the other parameters. This method is faster than generating a one-cycle ECG signal for each detected R wave event. Since the time lapse between two consecutive R wave events varies, the joins between two consecutive templates will not be smooth. However, this is not a big problem as soon as the discontinuity is small, which can be achieved by setting the start and end of the template very close to zero.

Although there is no guarantee of obtaining a complete PQRST wave of the ECG signal at the beginning of the original signal, the R wave event may still be present. For this reason, we insert 256 (sampling frequency in Hz) zeros at the start of synthetic signal. After placing a template on all detected R wave events, we discard the first 256 samples. Fig. 3 shows the original ECG signal and the synchronized synthetic ECG signal. As expected, the figure demonstrates that the joints between two consecutive templates are not smooth. In addition, the first ECG signal cycle only shows the S and the T wave signal. Since there is no R wave detected, this part needs to be skipped.

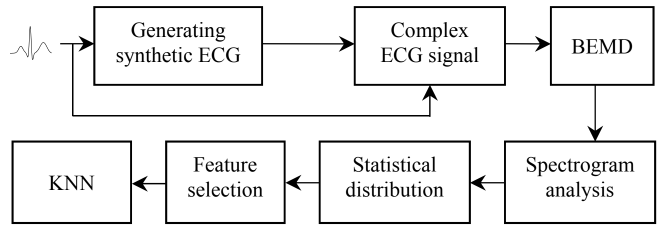

Fig. 1. Block diagram of the system

Since the length of the ECG signals varies, each ECG signal is divided into 5 seconds segments. The preliminary experiment showed that a 5 seconds signal provides appropriate number of IMF (this number depends on signal length and a longer signal produces more IMFs). Each segmented signal is subjected to the BEMD analysis, resulting in 5-6 IMFs plus residual as in [4].

Karagianis and Constantinou [9] observed that the first three IMFs of EMD tend to preserve information from the QRS complex of ECG signals. Agrafioti, Hatzinakos, and Anderson [4] also claimed the same fact for the IMFs from BEMD. Based

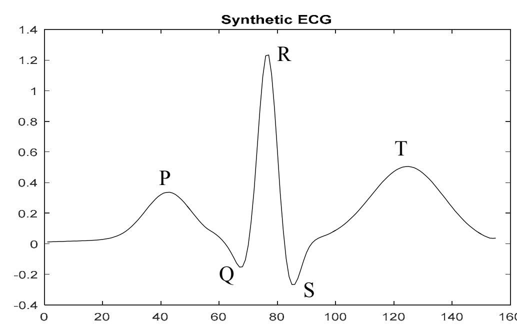

Fig. 2. A single cylce ECG signal as template

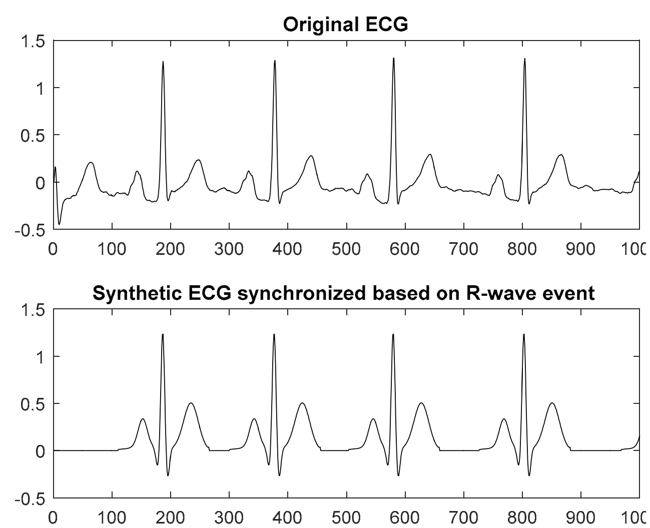

Fig. 3. Synchronized synthetic ECG signal with its original ECG signal

on those claims, we also processed the first three IMFs only to get the features.

From the first three of IMFs, several dominant frequencies (DFs) are estimated using spectrogram analysis with a window-size parameter of 30, 50, 100, 150, 200, 250 and 300 samples and an overlap range of 10% to 90% (with 10% steps). Using window-size lower than 30 samples might result less than 5 IMFs as it was not occurred in most of the other signals. On the other hand, window-size larger than 300 samples produced low accuracies.

At this stage, the idea is to locate frequencies with the highest power spectral density (PSD), and the end result is six DFs: three from 1st IMF, two from 2nd IMF, and one from 3rd IMF as Agrafioti, Hatzinakos, and Anderson [4] got six IFs from the first three IMFs. Of note, the algorithm detects the peaks of the PSD for each time instance. The number of peaks is related to which IMF is being processed and a corresponding frequency is stored for each detected peak. A series of frequencies with the highest peak is considered an DF. All six DFs from each segment belonging to the same ECG signal are joined to obtain the six DFs of that ECG signal.

The proposed new features are based on the statistical distribution of DFs and their first difference: mean, standard deviation, median, Q1, Q3, IQR, skewness, kurtosis, percentile 2.5, percentile 10, percentile 90, percentile 97.5, maximum, and minimum, resulting 168 features (84 features from original DFs, known as *feature1*, another 84 from 1st difference of DFs, known as *feature2*, and combining *feature1* and *feature2* results *feature12*). Next, a sequential forward-floating search process is applied to select the best features. Most discriminant features vary from 2 to 28, depending on whether valence or arousal is recognized and the parameters used in spectrogram analysis.

We also calculated features represented by statistical distribution of IFs of IMFs and the first difference as the results of EMD and BEMD analysis to ECG signals. The IF is calculated for each IMF with (1) [4], where d(t) is the IMF and H[ ] is the Hilbert transform. Both EMD and BEMD are also based on each 5-second segment of ECG signal as explained before. Each IMF contributes one series of IF and all IFs and their first difference are subject for 14 items in statistical distribution representation, resulting 84 features. After a sequential forward-floating search process, the number of significant features vary from 2 to 23, depending on the emotion label, i.e. valence and arousal. The idea is to compare the strength of features from DFs and IFs for emotion recognition. The reported accuracies are the best performance among them.

$$
\begin{aligned}
z(t) &= d(t) + jH[d(t)] \\
z(t) &= y(t)e^{j\theta(t)} \\
IF &= \frac{1}{2\pi}\frac{d\theta(t)}{dt}
\end{aligned}
\tag{1}
$$

B. Emotion Classification

As classifier, we use the k-nearest neighbor (KNN), for it was computationally feasible for a smartphone, with limited resources, which is the ultimate target platform, to solve 3-class problem (low-medium-high) for emotions in valence and arousal.

The 512 samples were divided into a training, testing and validation part, with the validation set consisting of 20% of the entire sample space. The rest of the data was used to train and test the classifier with 10-fold cross validation. For each K (the number of nearest neighbor) from 1 to 50, there were 100 repetitions with a random sampling of data to the training, testing and validation set. Final accuracies were calculated as average over the repetitions. In addition, the leave-one-subject-out (LOSO) validation was applied to different subjects to attain a subject-independent assessment of classifier accuracy [10].

III. Results

Table I and II shows the best result from grid search based on the DFs for arousal and valence respectively. A range of the best accuracies with similar values, see highlighted cell, are

TABLE II. Results from Grid Search for Arousal

		Window size (samples)						
		30	***50***	***100***	***150***	***200***	***250***	***300***
Overlap (%)	***10***	55.9 ± 5.9	53.6 ± 7.8	56.2 ± 7.5	54.7 ± 7.3	55.8 ± 7.6	58.3 ± 6.8	57.8 ±6.9
	20	55.9 ± 7.0	53.4 ± 7.8	57.2 ± 7.2	54.7 ± 7.0	59.0 ± 7.3	54.2 ± 7.6	56.6 ± 7.0
	30	56.5 ± 6.2	49.6 ± 7.1	58.8 ± 6.8	57.0 ± 6.9	58.5 ± 6.8	60.8 ± 7.8	57.8 ± 7.1
	40	60.0 ± 7.1	53.9 ± 8.0	53.8 ± 6.7	52.6 ± 8.0	57.1 ± 7.5	59.0 ± 6.8	55.1 ± 7.1
	50	57.0 ± 6.0	52.6 ± 7.3	57.0 ± 7.1	54.5 ± 6.9	55.3 ± 6.5	54.1 ± 7.5	58.2 ± 6.8
	60	54.5 ± 6.1	50.6 ± 7.6	56.1 ± 6.2	52.3 ± 7.7	51.8 ± 6.6	53.4 ± 8.2	55.7 ± 6.4
	70	55.8 ± 7.1	53.1 ± 6.8	56.3 ± 7.2	53.7 ± 7.3	51.8 ± 6.6	56.3 ± 7.4	58.0 ± 6.7
	80	55.5 ± 7.5	54.3 ± 7.3	54.2 ± 8.3	55.3 ± 6.9	56.1 ± 7.2	53.2 ± 7.1	56.1 ± 7.2
	90	55.2 ± 6.4	53.3 ± 7.1	54.3 ± 7.9	53.5 ± 8.0	57.8 ± 7.9	56.1 ± 6.1	55.6 ± 6.8

TABLE I. Results from Grid Search for Valence

		Window size (samples)						
		30	***50***	***100***	***150***	***200***	***250***	***300***
Overlap (%)	***10***	50.6 ± 7.2	47.1 ± 8.0	52.7 ± 7.7	48.8 ± 6.9	51.9 ± 7.6	54.5 ± 6.0	55.5 ± 7.0
	20	50.0 ± 7.7	49.1 ±7.8	55.1 ± 6.8	50.8 ± 7.1	55.3 ± 7.4	53.6 ± 8.1	51.4 ± 6.7
	30	47.9 ± 6.6	48.9 ± 6.8	51.8 ± 7.5	57.5 ± 7.3	52.4 ± 8.2	56.7 ± 7.6	55.0 ± 6.2
	40	50.1 ± 7.6	52.0 ± 7.5	54.3 ± 7.2	47.8 ± 7.5	52.1 ± 7.2	53.3 ± 6.7	51.8 ± 7.6
	50	50.0 ± 6.9	48.7 ± 6.7	52.9 ± 7.5	49.6 ± 7.5	54.3 ± 6.7	53.6 ± 7.8	52.3 ± 6.9
	60	44.0 ± 7.5	51.5 ± 7.4	51.5 ± 7.7	48.0 ± 7.8	52.1 ± 6.8	47.2 ± 8.0	49.8 ± 7.0
	70	48.2 ± 7.7	51.6 ± 7.4	53.4 ± 6.8	49.4 ± 8.0	51.2 ± 7.9	52.0 ± 8.3	55.7 ± 6.8
	80	45.6 ± 7.6	53.7 ± 7.9	52.8 ± 8.2	50.2 ± 8.5	52.2 ± 7.2	53.4 ± 7.1	49.7 ± 7.8
	90	46.8 ± 8.3	51.5 ± 6.5	50.1 ± 6.0	49.3 ± 6.7	51.3 ± 7.4	51.4 ± 6.9	50.5 ± 8.3

subjects for the Law of Large Numbers to reveal the true values as the repetition becomes larger. The results are summarized in Table III with the confusion matrices. According to the confusion matrices, the KNN worked well for low class of both valence and arousal.

Table IV presents a performance comparison between features based on HRV analysis [3] and the ones based on the proposed method using the same database. With the proposed features, accuracy for both valence and arousal increased by about 12%, indicating the superiority of this approach.

A subject-independent classification experiment was conducted using the leave-one-subject-out (LOSO) validation process, in which one subject at a time is left out of the training set to test the classifier. These experiments were conducted on the basis of Tables III with final accuracies were the average over individual performances. Table V gives a summary of this experiment, indicating that a good performance level can be achieved for both valence and arousal. Confusion matrices revealed that the proposed features worked well for low class from both valence and arousal but not for medium and high classes as in 10-fold cross validation. Results from [3] and the 10-fold cross validation experiment in this paper show that the classifier for arousal achieves higher accuracy than that for valence, but this is not the case for the LOSO validation

This study also compared the results to features from EMD and BEMD analysis to ECG. Table VI and VII present the summary of these experiment with 10-fold cross and LOSO validations with various number of IMFs involved for both valence and arousal respectively. For both validations method, features from DFs after BEMD analysis outperformed the ones from IFs from EMD and BEMD. In addition, the accuracies were close to [3], see also Table III. Table VIII and IX compare the experiments for 10-fold cross and LOSO validations for all features analysis respectively.

IV. Discussions

The proposed features improve the accuracy to classify emotion in valence and arousal for 3-class problem: from 42.6% to 55.8% for valence and from 47.7% to 59.7% for arousal in 10-fold cross validation. Generally, it increases the accuracy around 12%. It is a huge step for this database compared to [2] and [3]. Moreover, the proposed features are applicable for short time ECG signal which the standard HRV analysis fails. This is the main contribution of this study for emotion recognition system.

Window-size parameter in spectrogram analysis from 30 to 300 samples gives small difference for most performance in valence but not for arousal. Generally, small overlap offers better accuracy than the large one does, see highlighted cells in Table I and II. Large overlap gives more detail frequency content analysis but it looks like not suitable for ECG signal as each part in P, Q, R, S, and T waves have different frequency characteristic, e.g. QRS complex contains higher frequency among the others. Using large overlap may join part of the signal containing different frequency characteristic and it degrades the performance.

TABLE III. Results After Applying Law of Large Numbers (10-fold cross validation)

Valence **150 samples, 30% overlap**	**Arousal** **250 samples, 30% overlap**
55.8 ± 7.3	59.7 ± 7.0

	0	1	2
0	76.6	13.9	9.5
1	38.8	44.7	16.5
2	37.9	18.5	43.6

0: low, 1: medium, 2: high

	0	1	2
0	73.2	17.9	8.9
1	44.5	46.1	9.4
2	29.9	13.8	56.3

0: low, 1: medium, 2: high

TABLE IV. Performance Comparison Based on the Mahnob-HCI Database using Features in HRV Analysis and the Proposed Method

	Reference [3]	**Current approach**
Feature calculation method	Standard HRVanalysis	Dominant frequencies based on BEMD analysis
Classifier	SVM (RBF kernel)	KNN (Euclidean distance)
Valence	42.6%	55.8%
Arousal	47.7%	59.7%

TABLE V. Subject-independent (LOSO) Validation

Valence **150 samples, 30% overlap**	**Arousal** **250 samples, 30% overlap**
59.2 ± 11.4	58.7 ± 9.1

	0	1	2
0	81.6	11.0	7.4
1	35.6	46.2	18.2
2	37.4	19.0	43.6

0: low, 1: medium, 2: high

	0	1	2
0	75.9	18.3	5.8
1	48.6	43.6	7.8
2	40.4	11.9	47.7

0: low, 1: medium, 2: high

TABLE VI. Summary of Experiment with Features Based on IFs from EMD Analysis

	10-fold cross validation		**LOSO validation**	
	Valence	***Arousal***	***Valence***	***Arousal***
1 IMF	41.8 ± 8.0	46.6 ± 6.7	42.2 ± 12.3	47.0 ± 0.0
2 IMFs	43.6 ± 7.4	47.1 ± 7.4	42.7 ± 13.1	46.3 ± 10.4
3 IMFs	45.3 ± 7.1	45.1 ± 7.4	45.4 ± 13.0	45.9 ± 11.0

TABLE VII. Summary of Experiment with Features Based on IFs from BEMD Analysis

	10-fold cross validation		**LOSO validation**	
	Valence	***Arousal***	***Valence***	***Arousal***
1 IMF	40.9 ± 8.7	44.7 ± 7.9	40.6 ± 9.4	46.4 ± 11.8
2 IMFs	43.5 ± 7.4	45.4 ± 7.4	41.2 ± 7.2	45.9 ± 13.3
3 IMFs	45.6 ± 6.8	46.6 ± 6.8	41.6 ± 10.6	43.8 ± 10.0

TABLE VIII. SUMMARY ALL EXPERIMENTS FOR 10-FOLD CROSS VALIDATION

Feature calculation method	HRV [3]	DF of BEMD (proposed features)	IF of EMD	IF of BEMD
Classifier	SVM	KNN	KNN	KNN
Valence	42.6%	55.8%	45.3%	45.6%
Arousal	47.7%	59.7%	47.1%	46.6%

TABLE IX. SUMMARY ALL EXPERIMENTS FOR LOSO VALIDATION

Feature calculation method	DF of BEMD (proposed features)	IF of EMD	IF of BEMD
Classifier	KNN	KNN	KNN
Valence	59.2%	45.4%	41.6%
Arousal	58.7%	47.0%	46.4%

According to the confusion matrices in Table III, the classifiers work well for low class of both emotions. However, this is not the case for medium and high class for valence and arousal. Mostly, the classifier tends to classify the input to low class.

LOSO validation, on the other hand, measures the performance of the model built by the classifier when new data is applied to the model for classification. Once the model can accommodate this new data, we can say that the model offers possibility as general model for a specific application. This kind of validation also keep the model from overfitting. As a model is built based on the parameter of the classifier and the features, it requires good tuning parameters and features. This study demonstrates that the proposed features is appropriate for general model which can accept new data.

For valence with LOSO validation, the thus achieved accuracy (59.2%) was slightly higher from that provided by 10-fold cross validation (55.8%). For arousal, moreover, accuracy in LOSO validation (58.7%) was similar to the corresponding value attained in 10-fold cross validation (59.7%). This fact is interesting, since in [2], [3], and in the 10-fold cross validation presented in this paper, the classifier for arousal outperformed the one for valence. Standard deviations in this validation were much larger, indicating large variations in accuracy between subjects.

When comparing the features from EMD and BEMD analysis with Hilbert transform to calculate instantaneous frequencies, the proposed features demonstrates better performance for all validation methods, see Table VIII and IX. For these experiments, the accuracies have no significant difference from the ones in [3] for 10-fold cross validation. We tested this conclusion for the statistical significance using t-test method with significance level 0.05. The p-values of valence and arousal for differences in the classification accuracies when using HRV based features and IF of EMD -based features are 0.16 and 0.31, respectively. These results show that there is no significant difference between the accuracies. Similarly, differences in the classification accuracies when using HRV based and IF of BEMD -based features, produced p-values for valence and arousal 0.14 and 0.18, respectively. These values also indicate that the differences of both accuracies are not significant.

The instantaneous frequency calculated with Hilbert transform is the average of frequencies in the signal of interest. Using spectrogram, it is possible to define certain number of dominant frequencies from the signal of interest [11].

V. CONCLUSIONS

This paper proposed new features for emotion recognition based on short ECG signals. The performance of these features were compared to the ones from standard HRV analysis of ECG signals from the same emotion recognition database, the Mahnob-HCI. For a 3-class problem (low-medium-high), the proposed features increased the performance reported in [3] from 42.6% to 55.8% for valence and from 47.7% to 59.7% for arousal, using 10-fold cross validation, see Table IV.

Accuracies based on LOSO validation also presents good results as it is close to the accuracies from 10-fold cross validation. It shows that the proposed features are independent from the subject. Using k-fold cross validation may lead to wrong conclusion about the classifier as the structure of the isolated data might be learnt based on the available data. This kind of validation is enough when the model is applied to data within certain scope.

The proposed features also showed superior over the features based on IFs of IMFs after applying EMD and BEMD analysis to the ECG signal in 10-fold cross and LOSO validations, compare Table III, V, VI, and VII. Hilbert transform results an instantaneous frequency as the average of frequencies in the signal of interest [11].

Since the proposed features use short, 5 second segments of ECG signals, they can be used to recognize emotions almost in real-time. Use of signal segments shorter than 5 seconds is unadvisable in BEMD analysis, because the number of IMF tends to be less than three and the computed features are not of good quality.

The proposed features may possess potential for building emotion tracking systems. Such systems could be useful for psychiatrics who want to monitor emotional changes of patients under medication. Psychologists are also interested to learn and monitor the dynamics of emotion of the subjects under evaluation. Moreover, emotion tracking systems could also be useful in smart cars, for example, to monitor the emotion of the driver in order to prevent accidents.

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