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EMOTION RECOGNITION FROM HEART RATE VARIABILITY USING A HYBRID SYSTEM COMBINED WITH A HIDDEN MARKOV MODEL AND POINCARE PLOT

Abstract

The best emotion recognition system based on physiological signals with a simple operatory should have higher accuracy and fast response speed. This paper aims to develop an emotion recognition system using a novel hybrid system based on Hidden Markov Model and Poincare plot. For this purpose, an electrocardiogram from the MAHNOB-HCI database was used. A novel feature extraction from a hybrid system combining Hidden Markov Model and Poincare plot was presented. The authors extracted time and frequency domain features from heart rate variability, and used two central hybrid systems, the Support Vector Machine/ Hidden Markov Model and the Hidden Markov Model/ Poincare Plot. Finally, the support vector machine was used as a classifier to classify emotions into positive and negative. The proposed method showed a classification accuracy of 95.02 ± 1.97 % overall. Also, the computing time of the method is around 163 milliseconds. The key of this paper is in the use of hybrid machines to improve accuracy without high computation time. This method can be used as a real-time system due to the low computation time and can be developed in many fields, such as medical examination and security systems.

1. 1. INTRODUCTION

Emotion is a crucial part of human life. It is described as a series of subjective cognitive experiences and can affect the status of humans physiologically and psychologically. Emotions are convoluted biological processes related to the human physiological system, controlled by the autonomic nervous system (ANS). Although many primary emotion states have been proposed, there are two main categories for emotion states: positive emotion and negative emotion (Bulagang et al., 2020). Recognizing an emotional state is challenging because of many interrelated, objective, and subjective factors. In recent years, the pace of

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development of human-machine interfaces has been raised. Among these developments, computer-based human emotion recognition system (ERS) has not been an exception. However, this research area needs to be mature, and a comprehensive ERS has yet to reach total capacity (Tawsif et al., 2022; Mauss & Robinson, 2009).

The main aim of ERS is optimum performance through a simple operatory with high accuracy and fast response speed. Researchers have employed various emotion elicitation protocols, feature extraction techniques, and classification methods to develop an ERS. Many studies have used diverse induction techniques to stimulate emotions, like visual paradigms, auditory stimulation, real-life experiences, computer games, recall, and imagery (Tawsif et al., 2022; Kim & Andre, 2008). However, to reach an optimum ERS, the crucial elements are evaluation methods of emotions and feature extraction and selection. Various methods of evaluating emotions have been established in many studies. These methods include facial and speech expressions, gestures, and physiological signals (Park & Kim, 2011). All the mentioned techniques have some benefits and shortcomings. However, among all the modalities, physiological signals have attracted researchers in recent years. Physiological signals can be retrieved from the ANS and are not prompted consciously or intentionally. In other words, in contrast to facial ERS, a person cannot mask their emotions, and physiological signals can reflect emotional changes with high precision. Many physiological signals have been employed for emotion recognition and classification (Tawsif et al., 2022; Kim et al., 2004). One of the most frequently used physiological signals is Electroencephalogram (EEG). Many research papers have already reported using EEG signals for emotion classification. Although previous works using EEG have demonstrated high classification accuracy, ERS based on EEG suits for clinical use due to the operatory time-consuming. As regards easy operation, electrocardiography (ECG) is the best physiological signal. Also, psychological studies increasingly support the link between ECG and emotional responses. Electroencephalogram signal reveals the electrical activity of the heart over a period of time. Moreover, ECG can provide helpful details in recognizing emotional states. Electroencephalogram signals consist of some related parameters used for emotion recognition. Among these parameters, heart rate variability (HRV) has been considerably used in recent years to classify emotions (Shaffer & Ginsberg, 2017; Zhu et al., 2019).

Heart rate variability is a heart rate fluctuation known for an accurate and spontaneous reflection of many physiological responses. Moreover, HRV provides vital information about the interaction between sympathetic and parasympathetic ANS activity. Investigating variations in a series of RR intervals is known as HRV analysis, enabling a non-invasive method to determine the emotional state. The crucial aspect of using HRV for emotion recognition is feature extraction. Many feature extract approaches have been used in emotion recognition research. In early studies, standard features were divided into time and frequency dominant ones (Zhu et al., 2019). These studies reported 61.8 to 78.4 % accuracy for ERS. Standard features are a linear method, while HRV is naturally chaotic; thus, extracting features from nonlinear approaches is needed. Recent studies have employed some nonlinear methods and reported higher accuracy (Bulagang et al., 2020; Hoshi et al., 2013; Shaffer & Ginsberg, 2017). The systematic nonlinear methods used to extract features for ERS are the Poincare plot and Poincare Complex Correlation Measure (PCCM) (Guzik et al., 2006; Hoshi et al., 2013). Although using the PCCM showed higher accuracy than the Poincare plot, the PCCM requires a process that can be slow and that cannot be quickly accelerated using parallel computation. In effect, the computation time is spent computing the PCCM that is not spent when generating the Poincare plot, but the Poincare plot shows a different accuracy (Burby et al., 2021). Therefore, there is a need to find an approach that uses a Poincare plot and reaches high accuracy. In previous studies, usually one feature extraction approach has been employed. But hybrid systems have recently been proposed in other fields like speech recognition (Stadermann & Rigoll, 2004). One feature extraction method used recently in the hybrid system is the hidden Markov model (HMM). Hidden Markov Model based techniques are popular and have been applied in many domains, including the medical field. Previous studies using HMM to recognize emotion have been limited and reported low accuracy.

Therefore, the aim of this study is to develop an ERS by combining HMM and Poincare plot as a hybrid system based on the analysis of HRV. In particular, the authors concentrate on positive and negative emotions to reach an ERS based on HRV with high accuracy and fast response speed by creating a hybrid HMM/Poincare system, which could be easily carried on every environment and application.

To sum up, in this paper, following two contributions are made: (i) the development of a novel hybrid system that contains the Hidden Markov Model and Poincare plot for heart rate variability to recognize positive and negative emotion as a practical emotion recognition system, and (ii) demonstration that the combination of HMM and Poincare chart increases accuracy and reduces calculation time in emotion analysis.

The rest of this paper is organized as follows. The next session details the algorithm's proposed techniques and methods. Section 3 presents the evaluation results and compares them with the different models. Section 4 discusses and compares the results with other studies. Finally, Section 5 summarizes this study.

2. MATERIAL AND METHODS

2.1. Study design

This study proposed the six steps algorithm of emotion recognition, including two main hybrid systems.

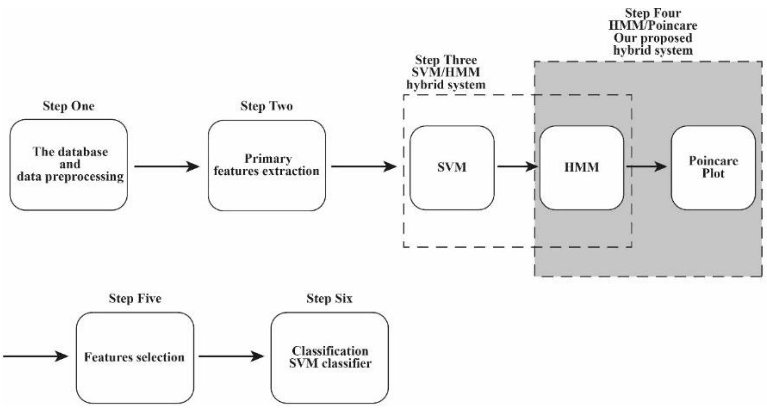

Fig. 1. Block diagram of the proposed algorithm of emotion recognition system based on heart rate variability. SVM= Support vector machine, HMM= Hidden Markov Model

The first step was to collect the recorded ECG from the database and preprocess the signals. In the second step, primary features were extracted in the time and frequency domain from HRVs. In the third step, a hybrid system containing a support vector machine (SVM) and HMM was employed to optimize and maximize the distance between the two classes. In the fourth step, a new hybrid system was suggested by combining HMM and Poincare plot to extract new features. In the fifth step, secondary features were selected. Finally, in the sixth step, SVM as a classifier was used to classify different emotional states in the two-class of the positive-negative model. The block diagram of the ERS algorithm is shown in Fig. 1.

2.2. First step: The database and data preprocessing

This study used MAHNOB-HCI database. MAHNOB-HCI database is recorded by Soleymani et al. (2012) for affective stimuli to recognize emotions and implicitly label research. The multimodal setup was arranged for synchronized recording of face videos, audio signals, eye gaze data, and physiological signals. The recorded physiological signals include EEG, galvanic skin response, temperature, respiratory, and also ECG signals. Twenty-seven participants from both genders took part in two separate experiences related to emotional stimuli. In the first experiment, participants watched 20 emotional videos and self-reported emotions they felt. In the second experiment, short videos and images were shown once without any tags and then with correct or incorrect tags. Agreement and disagreement with the displayed tags were assessed by the participants (Soleymani et al., 2012). The database is made available to the academic community via a web-based system. ECG signals were recorded using three sensors attached on the participants' body. Two electrodes were placed on the chest's upper right and left corners below the clavicle bones and third electrode was placed on the abdomen below the last rib. All ECG signals are stored using Biosemi data format (BDF). All files were converted to MAT format and administration of this study were done in MATLAB software.

In the preprocessing step, we applied two steps to the ECG signals: noise reduction and RR interval detection. The ECG signals are often distorted due to some issues, which make exact R detection difficult, so it needs to eliminate artifacts and noises. To achieve that, IIR-notch filter, moving averaging filter, and discrete wavelet transforms filter. These filters were used to remove power line interference, eliminate and reduce the high-frequency components, adjust the baseline, smooth the signals, and remove motion artifacts. In RR interval detection, ECG signals were segmented into a series of one-minute windows to extract RR intervals. The RR interval, the time between two consecutive R-waves of the ECG QRS signal (and its inverse, HR), is a function of the intrinsic properties of the sinus node, as well as autonomic influences. Two derivative operators were applied to detect the R peak. The applying of each derivative operator led to suppressing the P and T waves and enhancing the QRS, emphasizing the R peak slope. When the candidate RR intervals were detected, the inaccurate RR intervals were eliminated and refined the RR intervals, and at the end, the HRV was analyzed. Database is summerized in Table 1.

Tab. 1. MAHNOB-HCI database content summary (Soleymani et al., 2012)

Participants and modalities	
Number of participants	30, 13 male, 17 female (26.06 ± 4.39 years)
Recorded signals	32-channel EEG (256Hz), 3-channel ECG (256Hz), Peripheral physiological signals (GSR, Temp, RESP), Face and body video using 6 cameras (60f/s), Eye gaze (60Hz) and Audio (44.1kHz)
Recorded ECG signals	513 recorded, 33, 34 and 35 channel (only 35th channel were used)
Emotional responses to videos (Experiment 1)	
Number of videos	20
Selection method	Subset of online annotated videos
Self-report	Emotional keyword, arousal, valence, dominance, predictability
Rating values	Discrete scale of 1-9
Implicit tagging (Experiment 2)	
Number of videos and images	28 images and 14 videos
Dataset	Pictures from flickr (www.flickr.com), and short videos showing human actions
Self-report	Agreement with the displayed tag

2.3. Second step: Primary features extraction

In primary features extraction, we used time and frequency domain analysis. In time domain analysis, we employed mean RR interval (mean-RR), mean heart rate (mean-HR), standard deviation of RR interval (SDNN), square root of the mean squared differences between successive RR interval (RMSSD) and number of successive RR interval differed by > 50 ms (pNN50). In frequency domain analysis, we measured absolute power bands. Absolute power is calculated as ms squared divided by cycles per second (ms2/Hz).

Tab. 2. The extracted features of the HRV from time-frequency analysis

Analysis	**Parameter**	**Description**
Time domain	mean-RR	Mean RR interval
	mean-HR	Mean heart rate
	SDNN	Standard deviation of RR interval
	RMSSD	Square root of the mean squared differences between successive RR interval
	pNN50	Number of successive RR interval differed by > 50 ms
Frequency domain	VLF	Absolute power of the very low frequency (0.0033–0.04 Hz)
	LF	Absolute power of the low frequency (0.04–0.15 Hz)
	HF	Absolute power of the high frequency (0.15–0.4 Hz)
	LF/HF	Ratio of the LF and HF

Absolute power of the very low frequency (VLF), absolute power of the low frequency (LF), absolute power of the high frequency (HF) and ratio of the LF and HF (LF/HF) were measured. All these features were used to in two hybrid system (SVM/HMM and HMM/Poincare) to extract new non-linear features. Table 2 represents features measured from time and frequency domain analysis.

2.4. Third and fourth steps: Hybrid systems

In this study, two hybrid systems were used. The first one is SVM/HMM hybrid system that transforms the SVM results to a class posterior probability that is then used in the HMM computation. The SVM/HMM could decrease the errors to further improve the results. The second hybrid system is HMM/Poincare combination. The HMM/Poincare hybrid system was introduced to extract new non-linear features for achieving high accuracy as well as fast response speed. The concept of each component in hybrid systems is then presented.

2.4.1. Support vector machine

Support vector machine (SVM) was first introduced by Vapnik and used to find an optimal classifier for a linear separate problem by structural risk minimization (SRM), but SVM can be used for non-linear classification (Cortes & Vapnik, 1995). Since the real-world problems, like physiological signals, are not linearly separable, the main reason of the success of SVM is the ability to handle non-linear problems by a kernel function. The output of a SVM is a distance measure between a test pattern and the decision boundary. SVM learns to discriminate one class from all other classes. Having K class it needs K SVM with output $f_q(x), q = 1, \dots, K$, which can be transformed into posteriors by using the described method of Platt for each SVM. But, in this study SVM was used for each class (positive and negative emotion) to eliminate the data in a class that can reduce the accuracy that tend to a pairwise classification. The combination of SVM and HMM provides a notable advantage. The advantage added by SVM/HMM is the maximum margin principle. This method contributes to improved classification accuracy through higher homogeneous data. We trained one SVM for each feature in both classes. There is no clear relationship with the posterior class probability $p(y = +1|x)$ that the pattern x belongs to the class $y = +1$. The transformation of the SVM class distances to probabilities is done by applying a sigmoid function to each of the SVM outputs. Platt proposed an estimate for this probability by fitting the SVM output f(x) with a sigmoid function

$$p(y = +1|x) = g(f(x). A. B) \equiv \frac{1}{1 + exp(A\, f(x) + B)} \tag{1}$$

The parameters A and B of eq. (1) are found using maximum likelihood estimation from a training set p_i, t_i with $p_i = g(f(x_i. A. B)$ and target probabilities $t_i = (y_i + 1)/2$. Since SVMs are binary classifiers we use a one-versus-one approach to come to a multiclass classifier. This approach is to be preferred over the one-versus- rest approach as it aims to learn the solution to a more specific problem, namely, distinguishing between one class from one other class at a time. Pairwise classification is a class binarization procedure that converts a multi-class problem into a series of two-class problems, one problem for each pair of classes. For this pairwise classification we need to train $K(K-1)/2$ SVMs, where in our case K=2.

For each SVM we used the method of Platt to get pairwise class probabilities $\mu_{ij} \equiv p(q_i|q_i\ or\ q_j, X)$ of the class (HMM state) q_i given the feature vector X, and that X belongs to either q_i or q_j . These pairwise probabilities were transformed into posterior probability $p(q_i|X)$ by:

$$p(q_i|X) = 1\Bigg/\left[\sum_{j=1, j\neq i} \frac{1}{\mu_{ij}}\right] \tag{2}$$

Finally, the posteriors $p(q|X)$ have to be transformed into emission probability $p(X|q)$ (needed for the HMM) by using Bayes' rule:

$$p(X|q) \propto \frac{p(q|X)}{p(q)} \tag{3}$$

The HMM computed their state-dependent likelihoods by using the probabilities from all SVMs. The a-priori probability of class q is estimated by the relative frequency of the class in the data training(Krüger et al., 2005; Stadermann & Rigoll, 2004).

2.4.2. Hidden Markov model

An HMM is a discrete-time Markov Chain, whose states are hidden. It attempts to model a process where a sequence of events occurs and intrinsic pattern exists. In Markov model, the production of any sequence is described by transition probability $p\left(w_j(t+1)\middle|w_i(t)\right) = a_{ij}$. This means that a_{ij} is the time-independent probability of having state w_j at step time t+1 given the state w_i at time t. We set the number of states of the Markov Chain to two in order of reflect of level of emotions, positive and negative. Our HMM is a two-state model. A particular sequence of visible symbol as $v^T = \{v_1, v_2, \dots, v_T\}$. Thus, in any state w there is a probability of emitting a particular visible state v_k, and the probability is $p\left(v_k\middle|w_j\right) = b_{jk}$. The connection between the hidden state and the observable symbols represents the probability of generating a particular observed symbol, given the Emission matrix that the Markov process is in a particular state. This matrix contains the probability distribution of observable symbols given a particular hidden state. We constructed one two-state HMM for each feature and extracted the observed time series of each feature in two states(Liu et al., 2015; Akbulut et al., 2020). Fig.2. shows the scheme of a Hidden Markov Model with two states of emotion. Our HMM approach defined two states corresponding to two observed variable states. One observed variable state is considered the positive class (1) and, the other state is considered the negative class (0) and The sigmoid function, which provides prediction values and experimental observation in the range [0,1]. All HRV produced an experimental observation sequence and prediction value with a length of 80, such as the experimental observation sequence O = [1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1] and prediction value P = [1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1]. Moreover, we estimated the Oscillation approach to limit distribution of the Markov chain. From the point of view of deterministic dynamics, complex eigenvalues indicate the existence of an unstable periodic time series. This dynamic approach provides conditions that guarantee a limiting distribution and describes the rate at which the transition probability can fit on the Poincare section as a dynamic system in phase space, requiring a prior setting of the number of clusters. Table 3. shows the result of the Oscillation approach to limit distribution for Markov Chain numbers 50, 60, 70, and 80.

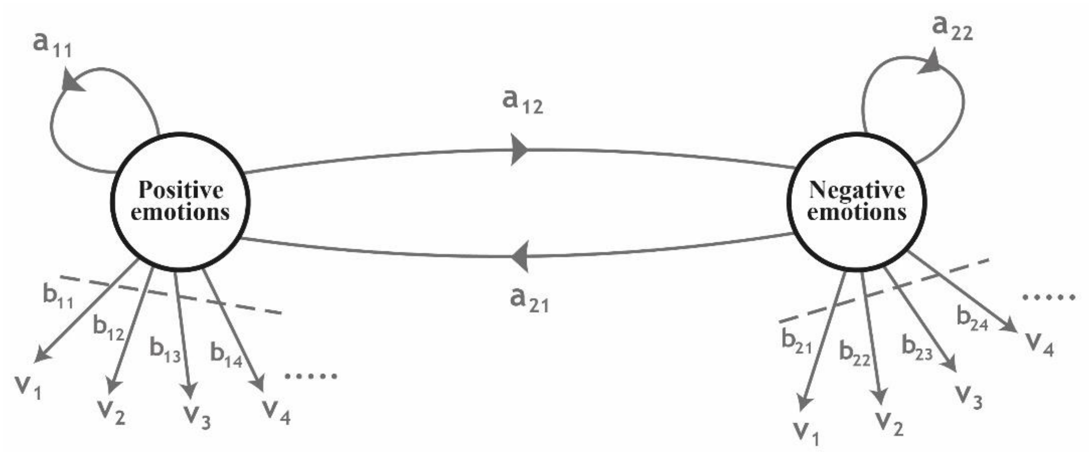

Fig. 2. The scheme of Hidden Markov Model two district states positive emotions and negative emotions (w_i), and a_{ij} their transition probabilities. v_k repesnens the emitted symbols at each state and b_{ik} shows their respective probility of appearing at each distcrete state. The dashes lines represent the seperation between the observable and hidden part of the model

Tab. 3. The Oscillation approach to limit distribution

Markov Chain	First layer	Second layer	Third layer
50	0.3500	0.1521	1.3236
60	0.3502	0.1522	1.3212
70	0.3446	0.1497	1.3247
80	0.3448	0.1498	1.3223

2.4.3. Poincare plot

As mentioned before, the Poincare plot is one of many methods employed in the analysis of HRV. The Poincare plot is a geometrical representation of a RR time series constructed by plotting successive RR interval on a 2D phase space. In a typical Poincare plot, the duration of the current cardiac beat (RR_i) is shown on the x-axis, whereas the duration of the subsequent beat (RR_{i+1}) is shown on the y-axis. Thus, the plot can describe each point in (RR_i, RR_{i+1}) space. In the Poincare plot, the scatter points can be fitted to an ellipse. The half minor axis (SD1) and the half major axis (SD2) of the ellipse are the most important quantitative indicators. SD1 describes the short-term variability of HRV, which reflects the parasympathetic activity, while SD2 represents to the long-term dynamics of HRV, which reflects the overall variability. The SD1 and SD2 are derived from the correlation and mean of the RR interval time series(Hoshi et al., 2013; Wang et al., 2022). In this study, we used Poincare plot and measured these descriptors for the observed time series from dynamics of Oscillation to limit distribution of Markov chain of each feature in two states from output of HMM to extract new features that suggested by this study. To achieve this, as mentioned in section 2.4.2, the estimation of the kernel transition matrix K is only by counting the transitions between states and converting them into probabilities. Moreover, considering the quasi-periodicity of the pointed processes, some oscillatory behavior could be expected for the Markov chains estimated from the reconstructed attractors. Thus, the final state of the process depends on the length of the recorded time series, and it will not tend to some states notoriously more than others (Arias-Londoño & Godino-Llorente, 2015). The Poincare section as a three-dimensional space was converted to a two-dimensional point cloud to evaluate Poincare plot parameters. This 2D point cloud was considered a Poincare plot that provided a condition to measure standard deviations.

2.5. Fifth step: Features selection

After extracting new functions from HMM/Poincare, those that can improve accuracy as well as response time were selected. Thus, the final features of Poincare plot were SD1, SD2 and the ratio SD1/SD2 from the mean-RR observation time series of Oscillation limit distribution output from HMM and also VLF from HMM. Table 4 shows the new features were used in this paper.

Tab. 4. New extracted features from the HMM/Poincare hybrid system

Analysis	Parameter	Description
Features of Poincare from mean-RR observation time series output from HMM	SD1	Minor axis of the ellipse from Poincare plot
	SD2	Major axis of the ellipse from Poincare plot
	SD1/SD2	Axis ratio
Features from HMM	VLF	Absolute power of the very low frequency (0.0033–0.04 Hz)

2.6. Sixth step: Classification

When the proper features were selected, the classifier was employed to identify emotional states in the two states model of positive and negative. The support vector machine was used to classify the emotional states. As we described SVM, SVM creates a separator hyper plan that has been tried to maximize the distance between the samples of different classes, choosing a separator hyper plan with the highest boundary. We have two classes, positive and negative, and SVM separated between these two classes. Fig.3. represents the signal behavior of HRV estimated from our system compared to the real HRV.

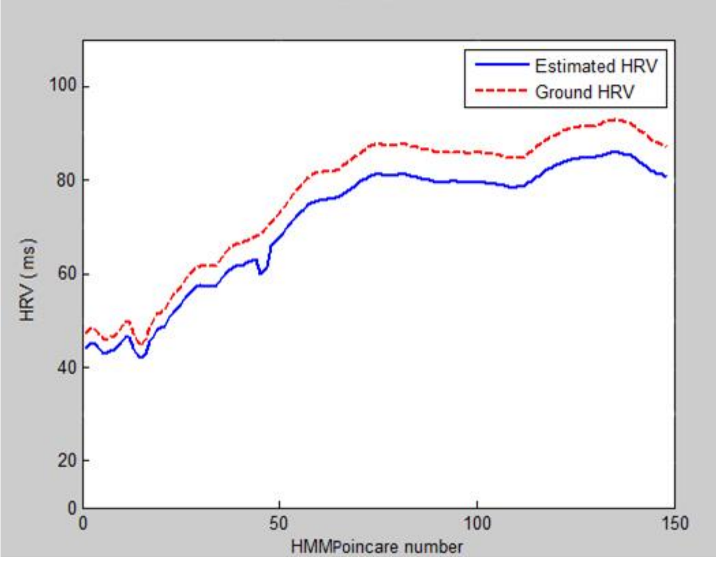

Fig. 3. Comparison of the estimated HRV and real HRV based on our system HMM/Poincare. The figure is obtained from MATLAB output

3. RESULTS

This study classified the emotional state by applying a new hybrid system (HMM/Poincare) as a feature extractor and an SVM as a classifier. First, nine features of HRV were extracted from time-frequency domain analysis in two classes (positive and negative). The authors applied HMM/Poincare system for all features and extracted new features. They then used four features to classify emotion states. The authors classified whether an emotion was positive or negative. They demonstrated that happiness and calmness belong to the positive class, while other emotions belong to the negative class. In this section, the result of the accuracy and the computing meantime of the hybrid system was presented. The results of a comparison between the suggested method and other previous approaches, which were evaluated separately, are then presented.

The performance of the proposed methodology is reported by two values, accuracy and response time. The accuracy of the authors' system was 94.33 ± 1.67 % for positive emotions, 95.71 ± 1.89 % for negative emotions, and 95.02 ± 1.97 % overall. The accuracy of the HMM/Poincare system is shown in Table 5. Also, Fig.4. indicates the overall accuracy in 20 iterations. The mean response time to computing for our ERS hybrid system was 163 milliseconds. The result showed that the proposed method achieves highly accurate performance with high response speed, so it can be implemented in real time.

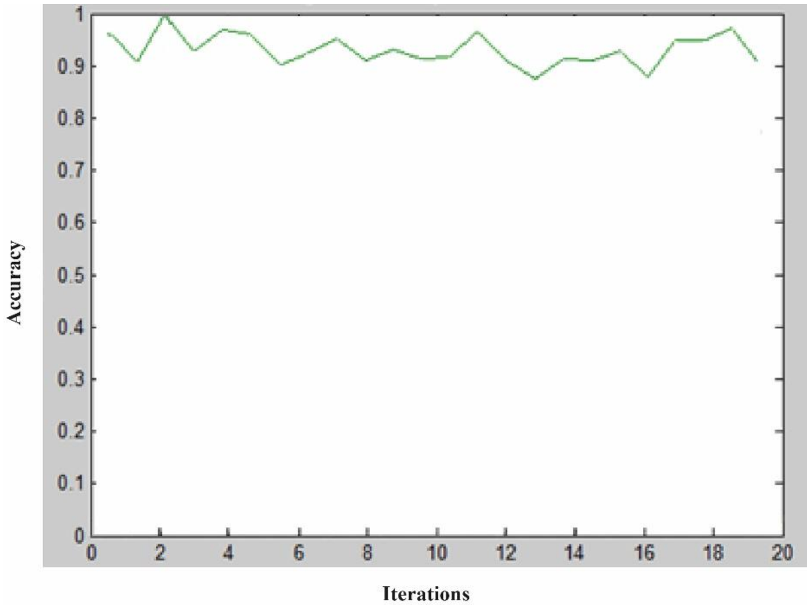

Fig. 4. Overall accuracy of our proposed approach in 20 iterations. The figure is obtained from MATLAB output

Tab. 5. Accuracy of our proposed emotion recognition system for positive and negative emotions and overall

	Positive emotions	**Negative emotions**	**Overall**
Accuracy	94.33 ± 1.67 %	95.71 ± 1.89%	95.02 ± 1.97%

To get a better comparison, two other standard methods used to classify emotions in other literatures were run. First, nine features from the time/frequency domain analysis and SVM were used as classifiers, and second, features extracted only from the Poincare graph and SVM were used as classifiers. Using HMM and SVM individuals is rare. Other studies have employed HMM with classifiers like K-nearest neighbor, Multilayer perceptron, or Leave-one-out cross-validation. Their results also have not been highly accurate. So, the authors have not used HMM and SVM for comparison to their method. As Table 6. shows, the proposed hybrid system had a significantly higher accuracy than other approaches. The results indicated that our ERS system based on HMM/Poincare had high accuracy with a low computational cost.

Tab. 6. The accuracy of our method and two standard methods ran for comparison

Method	**Positive emotions**	**Negative emotions**	**Overall**
HRV + SVM	83.67 ± 1.53 %	84.05 ± 2.02%	83.86 ± 1.84%
Poincare + SVM	86.01 ± 1.42 %	87.11 ± 1.87%	86.56 ± 1.73%
Our Method	94.33 ± 1.67 %	95.71 ± 1.89%	95.02 ± 1.97%

HRV + SVM= Time-frequency analysis extracted features from HRV and SVM as a classifier. Poincare + SVM= features extraction from Poincare plot and SVM as a classifier.

4. DISCUSSION

In this study, the authors presented novel features from a hybrid system that provides an independent emotion recognition system based on ECG signal and HRV. The proposed method uses a hybrid approach to extract features from HRV, an HMM/Poincare hybrid model. Another hybrid system (SVM/HMM), which was used earlier to optimize and stabilize the system, was also used. This study aimed to develop an emotion recognition system that can be used in various practical applications to increase usability and reliability. ECG signals were used to ease the accessibility of the ERS and also simplify the operating model to instant recognition. The results show that this system could be high-performance and fast in emotion recognition.

This section compares the new proposed algorithm with other approaches to emotion recognition that use ECG signals. Many studies have attempted to find an efficient algorithm for an automatic emotion recognition system based on physiological signals. Many approaches have been employed to develop a reliable ERS. In early research, linear approaches were used to analyze HRV and extract features. In recent years, emotion recognition researchers have used non-linear methods to extract reliable features to achieve higher accuracy. Mikuckas and colleagues classified the emotion states by HRV with linear and non-linear feature extraction. They used eight linear features in the time domain, including SDNN, SDANN, RMSSD, SDNN index, NN50, and pNN50%. The frequency domain was HF, LF, and LF/HF. They also used non-linear features from the Poincare plot that was SD1 and SD2. Their total classification accuracy was 71%(Mikuckas et al., 2014). Bong et al. (2012) employed time domain features: HR, mean R peak amplitude, and mean RR intervals extracted from ECG. They classified emotions into two classes by K-nearest neighbor (KNN) and SVM. The best classification accuracy was 77.69 %, 61.48%, and 60.21% (Bong et al., 2012). Ferdinando et al. (2016) proposed features for emotion recognition to represent the statistical distribution of dominant frequencies from ECG signals using the MHANOB-HCI database. KNN is used to classify emotions in valence and arousal. They achieved an accuracy of 59.2% for valence and 58.7% for arousal (Ferdinando et al., 2016). In another study, Wiem and Lachiri (2017) recognized emotion using linear HRV features. They used the MAHNOB-HCI database and also SVM as a classifier. They achieved a classification accuracy of 64.23% in arousal and 68.75% in valence(Wiem & Lachiri, 2017). The results of the present work were successful in comparison to these related works. The proposed algorithm in this study had a significantly higher accuracy than linear and statistical models.

Among research used Poincare plot and map, some studies have a reliable classification accuracy rate. Goshvarpour et al. (2017) used lagged Poincare indices to recognize the emotions from HRV. They extracted five geometrical indices that led to the probabilistic neural network applied to time-series classification. The maximum recognition performance rate was 97.45%. Although they achieved a high classification accuracy, the spending computation time is not specified (Goshvarpour et al., 2017). Baghizadeh and colleagues used a Poincare map for the RR, QT, and ST intervals from the ECG of the MOHNOB-HCI database. They extracted many features from different time series and frequency domains from the Poincare map and classified emotions in valence and arousal by three classifiers KNN, SVM, and MLP. Their result showed that the optimal features generated from the Poincare map of ST intervals achieved the best average accuracies, 82.17 ± 4.73 % for arousal and 78.07 ± 3.59 % for valence(Baghizadeh et al., 2020). Moharreri et al. (2018) used a method to stimulate emotion and record ECG. After that, they used the Poincare plot and heart rate asymmetry to extract features. They classified emotion by using IF-THEN rules and achieved 95.7%. The method proposed in this paper showed high accuracy and low computational cost compared to previous works using Poincare plots and maps (Moharreri et al., 2018). The resulting accuracy and speed of calculations can be explained by the fact that two-hybrid systems were used, which optimized the data and the classification process.

Unfortunately, according to our knowledge, the studies that used HMM to recognize emotion are limited. Akbulut et al. (2020) presented a method that uses HMM and HRV analysis. They evaluated their method on a comprehensive new dataset collected from 30 participants. The result showed that their method achieved an average accuracy of 88.6%. They used a hierarchical approach to classify emotions, where they first categorized the emotion as either positive or negative and then identified the exact emotion(Akbulut et al., 2020).

Tab. 7. A comparison of our proposed method and other studies in emotion recognition

Study	Analysis	Signal	Classifier	Maximum Accuracy
(Mikuckas et al., 2014)	Time-frequency domain, Poincare plot	ECG	NA	71%
(Bong et al., 2012)	Time domain	ECG	SVM, KNN	77.69%
(Ferdinando et al. 2016)	Statistical	ECG (MAHNOB-HCI database)	KNN	59.2%
(Wiem and Lachiri, 2017)	Time-frequency domain	ECG (MAHNOB-HCI database)	SVM	68.75%
(Goshvarpour et al., 2017)	Lagged Poincare indices	ECG	PNN	97.45%
(Baghizadeh et al., 2020)	Poincare Complex Correlation Measure	ECG (MAHNOB-HCI database)	SVM, KNN, MLP	82.17%
(Moharreri et al., 2018)	Poincare plot and heart rate asymmetry	ECG	IF-THEN	95.7%
(Akbulut et al., 2020)	HMM	ECG	LOOCV	88.6%
Our Method	HMM/Poincare hybrid system	ECG (MAHNOB-HCI database)	SVM	95.02%

ECG = Electrocardiogram, SVM = Support vector machine, KNN = K-nearest neighbor, PNN = Probabilistic neural network, MLP= Multilayer perceptron, LOOCV = Leave-one-out cross-validation, NA = Not available.

5. CONCLUSION

This article presents a novel and accurate method of emotion recognition using ECG based on HRV analysis. The key of the proposed method is the hybrid system based on combining HMM and Poincare plots to extract new features that enable accurate emotion recognition without requiring a large number of training processes which leads to low computational cost. Another hybrid system that incorporates SVM and HMM was also used, which optimizes the data to achieve high classification accuracy for this approach. The results indicated that using the proposed system achieved a classification accuracy of 95.02% and recall was 163 milliseconds.

The application of the emotion recognition system is very vast, from the medical and healthcare industry to marketing analysis and security systems. For instance, the method proposed in this article can be used for medical purposes. People with some disorders or disability (like elderly or autistic people) who cannot express their emotions can receive benefits from our ERS. Likewise, in the security system, this method can help reveal the emotions of people who intentionally want to mask their real emotions.

This study has some limitations that should be noted. First, this study developed a model based on two positive and negative emotions. The proposed method can be evaluated with more categories of emotions in the future. Second, the focus was on biomedical and practical purposes, rather than mathematical and research purposes. Accuracy and responsiveness were key to the development of this methodology. This approach contributed to the development of a fast and accurate algorithm. Thus, the proposed algorithm yielded practical results; meanwhile, some mathematical and visual results were missed. Third, statistical methods and features were not used in this model. Statistical features would have improved the results of the proposed method.

In future research, the authors plan to use the proposed method to recognize accurate emotions instead of two classes of emotions. Their ultimate goal is also to develop a model with an accurate emotion recognition system in application with a wearable ECG system. Moreover, the proposed hybrid system has the potential to be used and improved in future research. Two suggestions from this study for future research to improve the proposed method are (i) using a different dynamic sampling teq of Poincare inequality and Poincare constant to converge to a Markov chain instead of Poincare graph and section; (ii) using statistical methods and functions in the proposed algorithm.

Declaration of Computing Interest

The authors declare that they have no known computing interest that could influence the results.

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No finding was obtained for this study.

Availability of Data and Material

The database analyzed during this study are available on the MAHNOB-HCI tagging, https://mahnob-db.eu/hci-tagging/.

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