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Original Article

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Innovative Measures of Verhulst Diagram for Emotion Recognition using Eye-Blinking Variability

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Abstract

Background: The human body continuously reveals the status of several organs through biomedical signals. Over time, biomedical signal acquisition, monitoring, and analysis have captured the attention of many scientists for further prediction, diagnosis, decision-making, and recognition. Recently, building an intelligent emotion recognition system has become a challenging issue using the application of signal processing. Frequently, human emotion classification was proposed utilizing the internal body status in dealing with affective provocations. However, external states, such as eye movements, have been claimed to convey practical information about the participant's emotions. In this study, we proposed an automatic emotion recognition scheme through the analysis of a single-modal eye-blinking variability.

Methods: Initially, the signal was transformed into a 2D space using the Verhulst diagram, a simple analysis based on the signal's dynamics. Next, some innovative features were introduced to characterize the maps. Then, the extracted measures were inputted to the support vector machine (SVM) and k-nearest neighbor (kNN). The former classifier was evaluated with three kernel functions, including RBF, linear, and polynomial. The latter performances were examined with different values for k. Moreover, the classification results were assessed in two feature-set partitioning modes: a 5-fold and 10-fold cross-validation.

Results: The results showed a statistically significant difference between neutral/fear and neutral/sadness for all Verhulst indices. Also, the average values of these characteristics were higher for fear and sadness than those of other emotions. Our results indicated a maximum rate of 100% for the fear/neutral classification. Therefore, the suggested Verhulst-based approach was supremely talented in emotion classification and analysis using eye-blinking signals.

Conclusion: The novel biomarkers set the scene for designing a simple accurate emotion recognition system. Additionally, this experiment could fortify the territory of ocular affective computing, and open a new horizon for diagnosing or treating various emotion deficiency disorders.

Keywords: Verhulst diagram; Human emotion recognition; Eye-blinking; Dynamics

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Introduction

The human body continuously reveals several organs' status (its state or behavior) through biomedical signals. Over time, biomedical signal acquisition, monitoring, and analysis have captured the attention of many scientists. Physicians and researchers are quantifying these signals for disease prediction and diagnosis decisions,[1] emotion recognition,[2] mental assessment,[3] human identification,[4] and the like.

Intelligent emotion recognition refers to the automated process of human emotion classification utilizing computerized and smart algorithms. Currently, these systems are also frequently used in diagnosing emotional disorders, human-computer interfaces, affective computing, and robotics.[5] Different methodologies have been proposed to analyze the bio-signals in a multi/single-modality or multi/single-channel manner.[6] Commonly, in an affect recognizer, the following signals are evaluated, the central nerve activity like an electroencephalogram (EEG), and the peripheral nerve/organ activity through electrocardiogram (ECG), electromyograms (EMG), heart rate variability, skin conductance, and photoplethysmography.[2,7-10] They all represent the internal body status in dealing with affective provocations. External states, such as eye movements, have been claimed to convey valuable information about the participant's emotions.[11,12] Information from multiple sources is often integrated with the goal of increasing classification accuracy.[6] Consequently, the design of a multi-channel/modality system is needed. However, these systems are not economical in terms of financial and computational costs and information processing speed. Moreover, the multi-sensor attachment to the body interferes with people's ordinary activities. Therefore,

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providing a single-channel/single-modality system with acceptable performance remains a challenging issue.

Until now, most of what scientists have learned about bio-signal activities have been gained using the theory of linear system. In former endeavors for biomedical signal processing, some conventional time-domain, statistical, morphological, and spectral measures have been recruited. However, researchers recently concluded that these signals are not stationary and produce random and nonlinear behavior.[13] Therefore, conventional measures cannot handle the bio-system dynamics, and a number of chaotic measures have been presented. Correlation dimension, embedding dimension, Lyapunov exponents, and entropy indices are some instances frequently examined in the literature. All of them provide an overall insight into the signal's trajectory in the reconstructed state space. In contrast, other algorithms, such as phase space-based measures and Poincaré plots, systematically characterize the shape of trajectories.[14,15]

After characterizing the signal, a class label (a target emotion) should be assigned to the features by the classification module. Among a wide range of machine learning algorithms,[16-22] support vector machine (SVM) and k-nearest neighbor (kNN) are the most widely used approaches in emotion recognition.[6]

In most previous studies on eye blinking evaluation, facial expression detection has been used in pre-defined/controlled laboratory conditions. In these experiments, face images are generally applied to the standard camera. Processing in these systems is subject to many factors, such as masking or wearing glasses, camera alignment, head pose, individual discrepancies of participants, and differences in intentional versus spontaneous expression.[23] To deal with these constraints, a signal-based system can be proposed instead of an image-based system, where eye-blinking is roughly calculated using an electrooculogram (EOG). Encouraged by the benefits of employing nonlinear features and EOG-based eye-blinking, the present study was intended to propose an innovative quantifier for the trajectory's shape of a bio-signal. Precisely, we examined the Verhulst diagram of the eye-blinking variability. Previously, there has been no attempt on evaluating Verhulst map of any bio-signal during emotion excitation. In addition, a single-modality eye movement scheme was presented in merely one experiment for emotion recognition.[24] The eye activity of sixty women during the positive and negative inducements was analyzed using statistical and low-level measures. Then, SVM was applied, which achieved a maximum accuracy of 66%.

We have previously used geometry-based features of the phase space of biological signals in emotion recognition. In a former study,[25] the high-dimensional phase space of the EEG signal was reconstructed. Then, we reduced it to three dimensions using principal component analysis. Finally, the obtained 3D phase space was quantified using polar indices. The use of 62 brain channels resulted in high computational complexity and a time-consuming model. We also attempted to propose an emotion recognition system utilizing eye-blinking data.[26] We introduced novel polar-based indices of the lagged Poincare plots, where the optimum lag was estimated using mutual information. A maximum average accuracy was 84.17%. Although the quantification of the Poincaré plot is straightforward, estimating the optimal delay can be time-consuming and dependent on the estimation method adopted. Currently, we explored the proficiency of eye-blinking variability as an emotional state's clue. For the first time, we envisioned extracting the dynamics of eye-blinking for an emotion recognition system using novel Verhulst diagram-based measures.

The research outline is as follows. First, we describe the signal sets. Second, we elucidate the Verhulst diagram and delineate the suggested indices. Machine learning algorithms and classification strategies are also introduced. To close, the results and conclusions of the study are presented.

Material and Methods

The data of 15 volunteers were analyzed while affective video clips were presented, which were offered by the SEED-IV benchmark dataset.[12] Data were selected in which emotions were induced with audio-visual stimuli because this type of motivation has been used in many emotion recognition studies.[6-7,11-12,16-17,20-22] The clips were projected to derive sad, neutral, happy, and fearful emotions. It was assumed that the music videos correctly prompt the target emotions in the individual. First, the Verhulst diagram of the signals was drawn. To characterize each map, we proposed four innovative measures. These features were fed to the classifiers. Here, the performances of two popular conventional classifiers, including kNN and SVM, were evaluated and compared. Moreover, we evaluated the effect of classifier parameters on the results. The presented human emotion recognition scheme is shown in Figure 1.

Data

The SEED-IV database,[12] which provides universally available eye-movement data, has been analyzed in this experiment. The eye-movement signals were recorded from seven men and eight women. All participants were healthy participants aged 20-24 years. To maintain the procedure constancy over time, each of them contributed to the test in three dissimilar sessions on different days. Ultimately, the recordings of 45 data were achieved.

The protocol was designed to excite sad, neutral, fearful, and happy reactions using video clips. 72 film clips were presented. Each video was shown only once to avoid repetition. Each video lasted about two minutes. Six trials for each target emotion were offered per session. A sample trial included a five-second indication for starting, a two-minute video exhibition (stimuli), and a 45-second self-appraisal (self-assessment). Figure 2 schematically explains the experimental procedure. SMI ETG eye-tracking glasses, was used to record eye movements.

The current study examined the eye-blinking of all patients in all sessions. Figure 3 exhibits a data illustration of the target emotions. Here, the time interval between closing and opening the eyes is called blinking duration. The inter-blinking time intervals were considered eye-blinking variability for each target's emotional state.

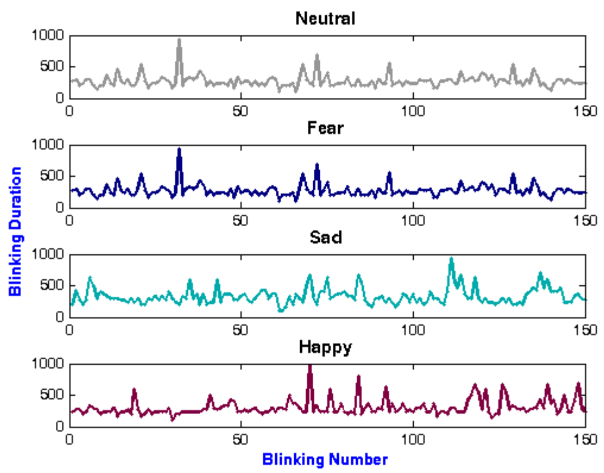

Figure 3. Eye-Blinking Signals in Neutral, Fear, Sad, and Happy Emotions (session 2, volunteer 8)

Verhulst Diagram

Verhulst diagram is a two-dimensional graph. It is also acknowledged as a "*cobweb plot*".[27] Often in dynamic

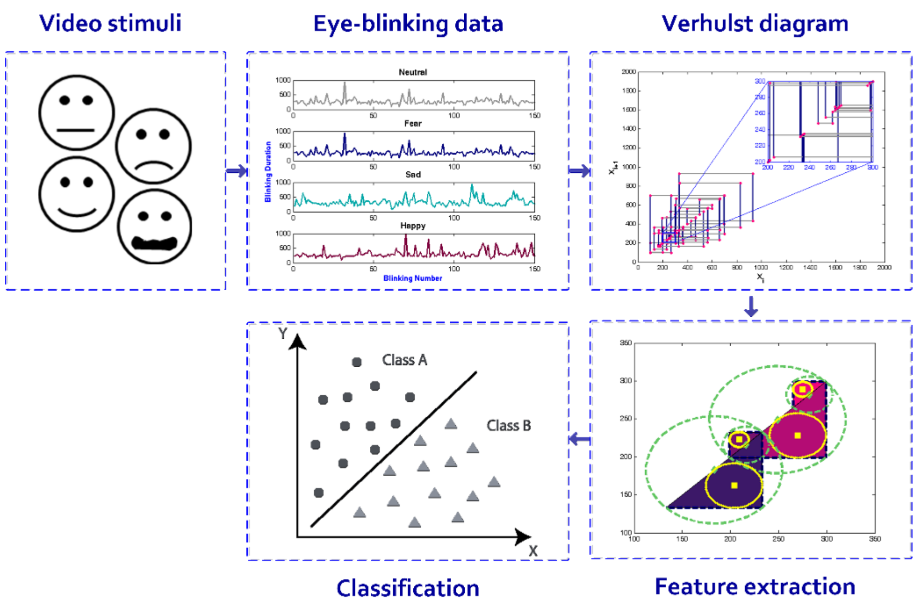

Figure 1. Proposed Framework

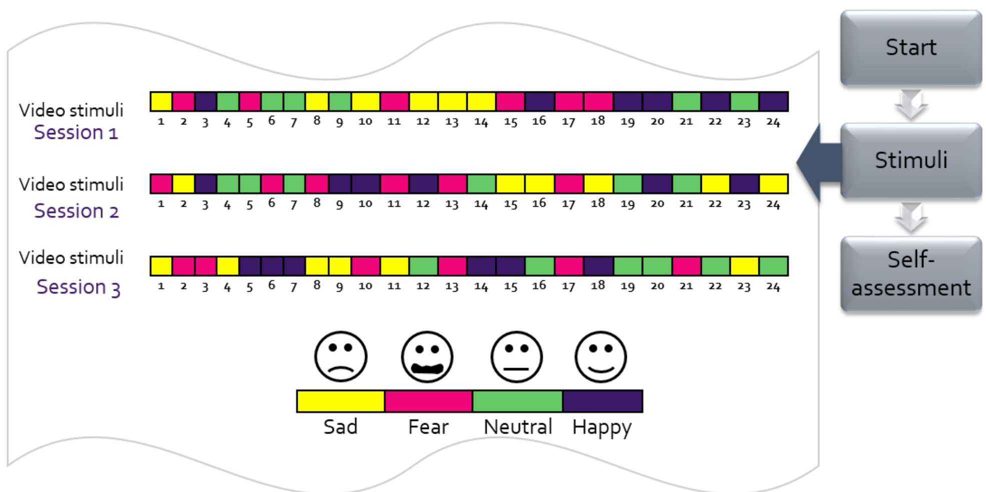

Figure 2. The Emotion Inducement Protocol

mathematical systems, this visual tool is used to screen the behavior of 1D repetitive functions qualitatively.

Assume eye-blinking data points as $X_0, X_1, \ldots, X_N$, where N is the data length. The following steps are typically performed to draw a Verhulst diagram.

1. The identity line (x = y) is drawn.
2. The first sample of the signal in the phase space (PS) is determined.
3. A line horizontally from this point to the identity line is drawn (in grey).
4. A vertical line from the sample on the identity to the data PS curve is drawn (in navy blue).
5. For all number of PS points, the preceding steps are repeated.

Note that, for each iteration, vertical, horizontal, and diametrical lines intersect a triangle. Moreover, there were some repeated elements in the signals. For further processes, we preserved the unique values in the signals and repeated values of the same element were removed. An example Verhulst diagram for an eye-blinking variability is demonstrated in Figure 4.

In the following stage, we quantified the diagram. Based on the resulting triangles on the map, four measures were defined.

1. The triangle area was calculated separately and added to each other (AR).
2. The triangle perimeter was calculated separately and added to each other (PR).
3. The triangle circumradius was considered separately (equation (1)) and added to each other (CR).

$$CR_i = \sqrt{\frac{a^2b^2c^2}{(a+b+c)(-a+b+c)(a-b+c)(a+b-c)}} \qquad (1)$$

where i shows the triangle number and a, b, and c are the triangle's sides.

5. The triangle inradius was considered separately (equation (2)) and added to each other (IR).

$$IR_i = \sqrt{\frac{(-a+b+c)(a-b+c)(a+b-c)}{4(a+b+c)}} \qquad (2)$$

Four measures are presented in Figure 5.

Classification

k-Nearest Neighbor

kNN is a non-parametric and supervised machine learning (ML) algorithm used to classify an element into a set.[28] It handles the sorting task utilizing the proximity of other members in the set (training examples), while the distance calculation is definite. The new sample is classified based on the proximity of the nearest k members in the feature space.

In this paper, the classification performance was evaluated for different K (k) values, comprising 2, 5, 8, and 10.

Support Vector Machine

SVM is a supervised ML algorithm. Customarily, it deals with a binary classification problem. Assuming the groups are linearly separable, the algorithm discovers the maximum marginal hyper-planes to distinguish the sets. Once samples are not linearly separable, a kernel function portrays them to a larger dimension so that they can be linearly detached. As a result of mapping input measures into a high dimensional space, a more trivial task is demanded to separate data compared to the basic input measures. An iterative learning operation produces the most encouraging hyper-plane with the maximum margin between the sets. Finally, the ultimate boundaries over the data groups will be sketched by the hyper-planes with maximum margin. A more considerable distance between hyper-planes and data elements in different groups depicts a higher performance.

This research evaluated the proficiency of different kernel functions, including the linear, radial basis (RBF),

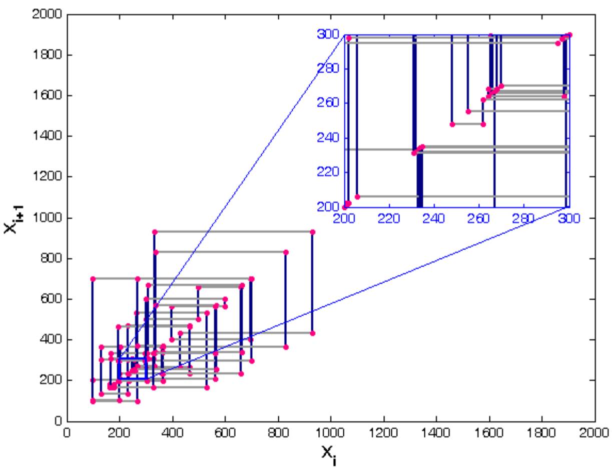

Figure 4. The Verhulst Diagram of an Eye-Blinking Variability (session 2, subject 8)

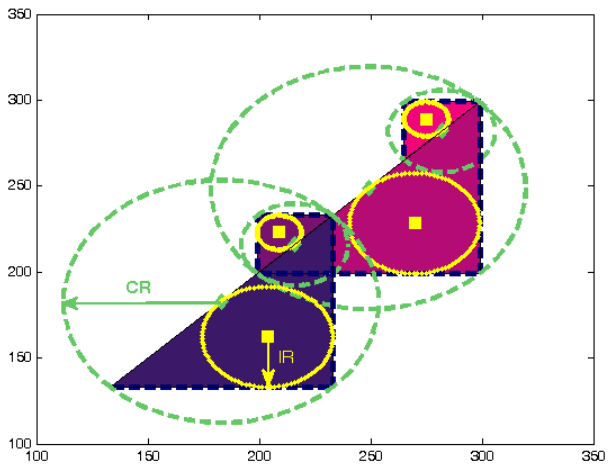

Figure 5. The Suggested Verhulst Map Measures for Four Triangles

and polynomial functions.

Consider F as the feature set. Normalization was performed before involving the measures in the classifier.

$$Normalized\ F = 2\left(\frac{F - F_{min}}{F_{max} - F_{min}}\right) - 1 \quad (3)$$

Five and ten-fold cross-validation (CV) approaches were applied to calculate the accuracy (AC), specificity (SP), sensitivity (SE), and F1 score of the classifiers. The classification algorithms were executed twenty times using a 5-fold and 10-fold CV.

Statistical Analysis

An analysis-of-variance (ANOVA) test was done with post-hoc Tukey honestly significant difference (HSD) to examine considerable differences between contradictory emotional conditions.

For ANOVA, the following assumption should be satisfied. Each category contains independent random samples from a normal distribution. Therefore, a Lilliefors test was conducted for the null hypothesis at the 5% significance level to assess whether the attribute originates from a normal distribution, against the possibility that it does not derive from such a distribution. Following the ANOVA, post-hoc Tukey HSD was performed as a multiple comparison procedure to conclude which means are meaningfully different from each other.

All simulations were implemented in MATLAB R2014a (The MathWorks®).

Results

Table 1 shows the variations of PR, AR, CR, and IR measures in different conditions. The table also provides information about statistical differences, provided with ANOVA test with post-hoc HSD, between the groups.

The average AR value is about 2.13×10^6 for fear, which dropped to about 1.5×10^6 for other states. The highest average PR value was 3.6×10^4, achieved for fear. The maximum average CR and IR values were 7.45×10^3 and 3.08×10^3, respectively, both of which were obtained for fear. The table indicates the higher mean values of all biomarkers for fear compared to the other groups. The second higher values of the indices belong to the sad state. However, significant statistical differences have been discovered between neutral/fear ($P<0.05$ and $F>8.3$) and neutral/sad ($P<0.05$ and $F>4.4$) for all Verhulst indices.

The maximum performance values of the machine learning algorithms have been provided in Figure 6.

Using a 5-fold CV partitioning strategy, the highest accuracy was obtained for N/F discrimination, where an accuracy of about 90% was obtained. The corresponding sensitivity and specificity of the model was 100%. The second-best classification accuracy was obtained for the N/S classification. In this case, the sensitivity was about 90% and specificity of the model was 100%. As the figure shows, the accuracy of the classifiers has increased for a 10-fold cross-validation partitioning strategy. A maximum classification accuracy of 100% was obtained for F/N and H/N classification. For both, the sensitivity and specificity of the classifier were 100%. The maximum recognition rate was achieved using SVM with the

Table 1. Mean and Standard Deviation of the Verhulst Measures and the Statistical Test Results Between the Emotions

Feature		Mean ± SD	Fear		Sad		Happy	
			P	F	*P*	F	*P*	F
AR	Neutral	$(1.28\pm1.18)\times10^6$	0.002 [a]	9.55	0.036 [a]	4.53	0.18	1.86
	Sad	$(1.83\pm1.25)\times10^6$	0.28	1.19	—	—	0.49	0.47
	Fear	$(2.13\pm1.43)\times10^6$	—	—	0.28	1.19	0.09	2.92
	Happy	$(1.64\pm1.32)\times10^6$	0.09	2.92	0.49	0.47		
PR	Neutral	$(2.39\pm1.77)\times10^4$	0.005 [a]	8.31	0.039 [a]	4.41	0.25	1.33
	Sad	$(3.21\pm1.9)\times10^4$	0.37	0.82	—	—	0.36	0.85
	Fear	$(3.6\pm2.17)\times10^4$	—	—	0.37	0.82	0.08	3.12
	Happy	$(2.84\pm1.89)\times10^4$	0.08	3.12	0.36	0.85		
CR	Neutral	$(4.96\pm3.67)\times10^3$	0.005 [a]	8.31	0.039 [a]	4.41	0.25	1.33
	Sad	$(6.64\pm3.94)\times10^3$	0.37	0.82	—	—	0.36	0.85
	Fear	$(7.45\pm4.49)\times10^3$	—	—	0.37	0.82	0.08	3.12
	Happy	$(5.88\pm3.91)\times10^3$	0.08	3.12	0.36	0.85		
IR	Neutral	$(2.05\pm1.52)\times10^3$	0.005 [a]	8.31	0.039 [a]	4.41	0.25	1.33
	Sad	$(2.75\pm1.63)\times10^3$	0.37	0.82	—	—	0.36	0.85
	Fear	$(3.08\pm1.86)\times10^3$	—	—	0.37	0.82	0.08	3.12
	Happy	$(2.44\pm1.62)\times10^3$	0.08	3.12	0.36	0.85		

[a] Tukey-Kramer significant differences.

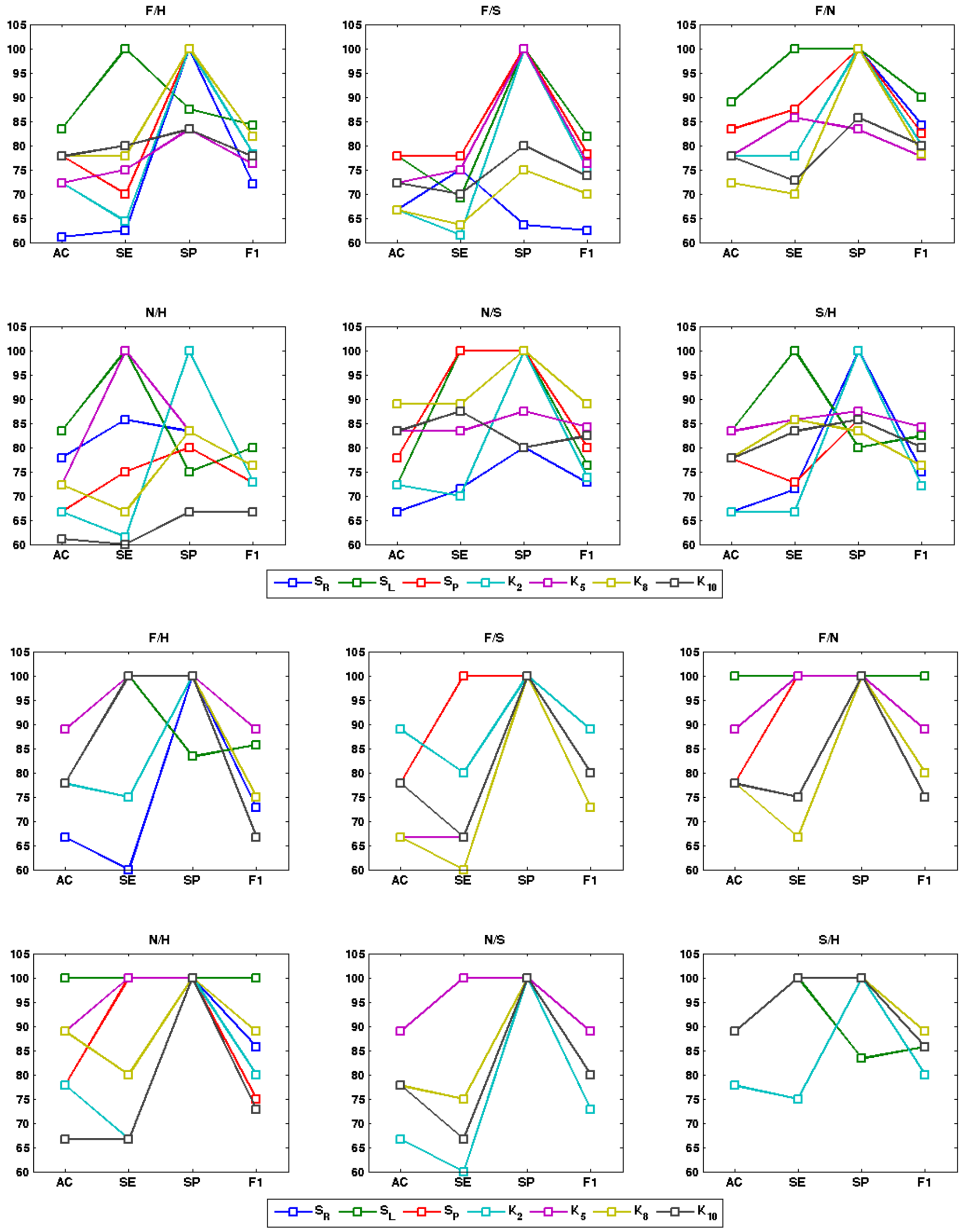

Figure 6. Binary Mode Classification Performances (a) a 5-Fold (b) a 10-Fold Cross-validation Partitioning Strategy. Note – S_R: SVM with RBF, S_L: SVM with linear, S_P: SVM with polynomial kernel function, K_2: 2-NN, K_5: 5-NN, K_8: 8-NN, and K_{10}: 10-NN. S: Sad, N: Neutral, H: Happy, and F: Fear

linear and RBF kernels. Other parameters extracted for classification evaluation reached 100% in F/N separation.

Discussion

In this study, we directed to evaluate the proficiency of the eye-blinking variability for human emotion recognition. To our knowledge, the current experiment is the first one to utilize eye-tracking characteristics/dynamics for emotion classification. A freely available eye-blinking of the SEED-IV database[12] was applied. A computerized emotion recognition system was proposed using some Verhulst diagram measures. As we know, no experiment has appraised Verhulst indices for bio-signal analysis. Four novel measures of the graph were proposed. In terms of feature analysis, our results indicated higher average values of the suggested biomarkers for fear. In addition, statistically significant differences were revealed between neutral/fear and neutral/sad. To discriminate emotions, two classification algorithms were evaluated, including the SVM and the kNN. The classifiers were adjusted by their parameters in two partitioning schemes, i.e. a 5-fold and 10-fold cross-validation. Outstanding performances were achieved. SVM outperformed the kNN in terms of higher performances. Also, notable results were achieved in a 10-fold cross-validation mode. A maximum accuracy rate of 100% was found for F/N and H/N discrimination using S_L and S_R. Other SVM parameters have reached 100% for F/N separation. The classification accuracy rates were higher for the 10-fold CV compared to the 5-fold CV. The highest recognition rate was about 90% utilizing a 5-fold CV for the N/F and N/S classification. The accuracy rates, in this case, fluctuated between 60 and 90%. On the contrary, utilizing10-fold CV, accuracy rates have increased to 67-100%. The F values fluctuated almost in the same range as accuracy. Generally, at least one classifier reached 100% specificity and sensitivity for both CV modes. Therefore, other performance parameters of the classifiers also emphasized the significance of the results.

Formerly, a multi-modal scheme for emotion recognition was proposed utilizing eye movements' characteristics and EEG.[12] For fear classification, the eye movements outperformed EEG. Our results are not in line with their conclusion, because it is definitely not possible to determine the separability of an emotional state. The authors also reported the best mean accuracy of about 70% using eye movement data, which received a much weaker rate compared to the results obtained from our algorithm. The performance of our framework has been considerably higher than that of the Lu et al[11] system. The maximum average recognition rate was 77.8% using eye-movement measures.[11]

Deficit emotion recognition is one of the symptoms of some affect-related disorders, such as autism spectrum disorder (ASD), major depression, Parkinson's disease, oppositional defiant disorder (ODD), and conduct disorder (CD). On the other hand, eye movement abnormalities in company with emotional shortfalls have been pronounced in neurodevelopmental (like ASD and attention deficit hyperactivity disorder [ADHD]), neurological (like stroke and amyotrophic lateral sclerosis), and psychiatric disorders (like mood and psychotic disorders).[29] Some eye-tracking studies have been previously conducted to investigate the emotional facial recognition (like gazing behavior) of subjects suffering from these disorders.[30-34] The experiment of Bours and colleagues[30] revealed a decreased relative total fixation duration to the eyes in both the ASD and the ODD/CD for several emotional expressions. They also concluded the nominally significantly increased time to the first fixation on the eyes of fearful faces in the ASD and the ODD/CD. The potential of eye movements in showing specific relational memory impairment[33] and reaction time differences[34] in the context of emotional stimuli has been confirmed in major depression. Different eye movement patterns have been reported even in some diseases that do not have direct symptoms of emotional recognition defects. For example, a recently published study[35] reported different eye movement patterns when looking at affective faces in patients with focal epilepsy compared to healthy controls. A recent systemic review[36] revealed the prevalence of neurodevelopmental disorders in adolescents (under 18 years old) as follows: ADHD: 5–11%; ASD, 0.70–3%; communication disorders, 1–3.42%; intellectual disability, 0.63%; specific learning disorder, 3–10%; and motor disorders, 0.76–17%. It should be noted that there are extensive studies on specific neurodevelopmental disorders, and they are evaluated rarely as a whole. On the other hand, these outbreak rates are only for specific age groups and do not include other psychiatric and neurological disorders. Therefore, the broad spectrum of the population is estimated to suffer from these disorders. Consequently, the results of this study may be beneficial for the diagnosis and/or treatment of these disorders, and the necessity and importance of studying eye movements are confirmed in clinical evaluations.

The present study provided a low-cost (both computational and consumed time) emotion recognition system. Reaching promising results, the algorithm paved the way for the recognition of emotions through eye-blinking changes. However, it has some shortcomings that need to be addressed in the future: (1) A limited number of data recordings are available in the SEED-IV database. A richer dataset should be analyzed in future works to validate the algorithm, (2) A limited number of emotions have been classified in the current study. The number of emotional states we experience in daily life is considerably broader. Therefore, in the future, the performance of the presented algorithm should be evaluated in other emotional states, (3) The present algorithm was evaluated in the binary classification model; in future work, multi-class classification should be considered, and (4) We achieved the accuracy of 100% in separating F/N and H/N utilizing a simple SVM classifier. Implementing a more complex machine learning algorithm can be a solution to increase the number of accurately classified emotions.

Conclusion

In this paper, we introduced an innovative single-modality approach for emotion recognition using eye-blinking variability. The novelty of this article can be considered in both the use of single-modal eye-blinking signals and the feature extraction approach. For the first time, some indices were introduced to characterize the dynamics of the eye-blinking variability. In the proposed methodology, the signal was first converted into a Verhulst graph. Next, the proposed features were extracted and fed to the SVM and kNN algorithms. The SVM classifier was evaluated with three kernel functions, including RBF kernel, linear kernel, and polynomial kernel. The kNN performances were also examined with different values for k. Moreover, a 5-fold and a 10-fold CV was performed for partitioning the feature set. Then, the algorithm performances were assessed in a binary emotion classification problem, which achieved promising results. The results show that all Verhulst indices have higher mean values for fear against the other emotional groups. The second higher mean values of the attributes were for the sad. Significant statistical differences between neutral/fear and neutral/sad were obtained for all indices. The classification accuracy rates were higher for the 10-fold CV compared to the 5-fold CV, and SVM outperformed kNN. The maximum classification performances, AC, F1, SP, and SE, were obtained for F/N discrimination. These outstanding performances were likened to formerly reported findings regarding high recognition rates. The advocated algorithm can be extended for a forthcoming emotion recognition system based on eye-blinking variability.

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Competing Interests
The authors declare that they have no conflict of interest.

Ethical Approval
This article examined the SEED-IV database[12] which is freely available in the public domain. This article does not contain any studies with human participants performed by any of the authors." The study was approved by Shanghai Jiao Tong University Bio-X Institutes (No. 2017060).[12]

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