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Use of spontaneous blinking for application in human authentication

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ABSTRACT

Contamination of electroencephalogram (EEG) signals due to natural blinking electrooculogram (EOG) signals is often removed to enhance the quality of EEG signals. This paper discusses the possibility of using solely involuntary blinking signals for human authentication. The EEG data of 46 subjects were recorded while the subject was looking at a sequence of different pictures. During the experiment, the subject was not focused on any kind of blinking task. Having the blink EOG signals separated from EEG, 25 features were extracted and the data were preprocessed in order to handle the corrupt or missing values. Since spontaneous and voluntary blinks have different characteristics in terms of kinematic variables and because the previous studies' control setup may have altered the type of blink from spontaneous to voluntary, a series of statistical analysis was carried out in order to inspect the changes in the multivariate probability distribution of data compared to the previous studies. Statistical significance shows that it is very likely that the blink features of both voluntary and involuntary blink signal are generated by Gaussian probability density function, although different than voluntary blink, spontaneous blink is not well discriminated with Gaussian. Despite testing several models, none managed to classify the data using only the information of a single spontaneous blink. Thereby, we examined the possibility of learning the patterns of a series of blinks using Gated Recurrent Unit (GRU). Our results show that individuals can be distinguished with up to 98.7% accuracy using only a reasonably short sequence of involuntary blinking signals.

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1. Introduction

Since biometrics offers a much secure and feasible way for human authentication, they have been utilized widely in recent years. Due to the fact that biometrics like fingerprint, facial features, voice and iris are exposed to the external world, they can be spoofed and reused, which makes them vulnerable [19,13].

Numerous studies proposed using EEG-based authentication, for unlike the other biometrics, it is not directly exposed to the external world and is less likely to be scammed and regenerated [4]. First time in 1999, Poulos et al. introduced EEG-based individual authentication, achieving 72% to 84% correctly recognized instances [23]. Using EEG signals, Pham et al. was able to classify gender and age of subjects with an accuracy of 97% and 91%, respectively [22]. Ashby and colleagues investigated on low-cost EEG individual authentication during a mental imagery task [6]. Using support vector machine (SVM), they achieved a classification accuracy of 97.6%.

Recently, the use of blinking EOG signals has been considered by researchers in applications including bioemtrics and communications [26–29]. Abo-Zahhad et al. designed an experiment in which 25 subjects were asked to make 10 blinks during eight sessions and EEG signals were recorded using a single electrode device [3]. Using a Gaussian classifier on the 23 extracted features from blink data, they found that blinking EOG signals have unique patterns for each individual and thus, was able to distinguish between subjects with a precision of 97% [24]. In another work [4] conducted by the same authors, a multi-level hybrid authentication system was proposed which utilize both fusion of EEG and EOG signals. The use of Linear Discrimination Analysis (LDA) allowed the authors to increase the classification accuracy by 6% achieving a maximum accuracy of 97% in the process. Although the results are promising, we question the possibility of the results being impacted by the experimental setup (where the subjects were

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asked to blink voluntarily) since, the kinematic variables of voluntary and spontaneous blinking are quite different [9,20]. Moreover, low number of subjects might have influenced the classification results. Inspired by Abo-Zahhad and his colleagues, Wu et al. [25] conducted a study to develop a multi-task authentication system. Combining EEG and spontaneous EOG signals with face rapid serial visual presentation (RSVP), they were able to achieve an average accuracy of 97.6%.

Unlike the previous studies in which voluntary blinking or a mixture of EEG and involuntary EOG signals were used, here we investigate the feasibility of using only spontaneous blinking (natural blinking) signals [4,3,25]. Furthermore, putting no constraints on subjects' natural blinking function and gathering signals during a variety of random emotions, we tackle the existing difficulty of classifying imbalanced, dependent and not identically distributed random variables which has been eliminated or diminished in other studies. We also study the nature of spontaneous blinking signal in terms of the probability density function and the distinguishability of its attributes in the feature space. The main contribution of this work is to investigate the natural eye blinking activities as a mean to identify individuals with quite a reasonable accuracy.

2. Materials and methods

2.1. EEG data acquisition

EEG data were recorded using Emotiv EPOC, a 14-channel wireless headset [1] with sampling frequency of 128 Hz, to create two distinct datasets for two different experimental setups: 1) subject watching a video clip [21] and 2) subject is asked to like or comment to a series of images shown on a computer screen. The wet electrode Emotiv EPOC has 16 channels located at positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 with P3 and P4 as the two reference channels, arranged following the standard international 10–20 system. However, it is important to mention that although the EEG recorder has 14 channels, the data of only one channel (fp1) were used for extracting the blinking data, statistical analysis and classification task.

In the first experimental setup, each subject was seated in front of a computer monitor to watch a synthetic video clip of 6 min 43 s long comprised of three different categories of small movie clips that can arise three different emotions in the subject. The video clip and the overall experiment procedure is the same as that of [21].

For the second experiment, We downloaded 150 advertisements (images) from Google by searching with keywords like ad (s), advertisement(s), popular ads, etc. Then we filtered out 30 images as per the following criteria: a)10 images which will be more prone to be liked by females (cosmetics, women's shoes, skin/hair care products, etc.); b) 10 images which will be more prone to be liked by males (cars, cigarettes, speakers, men's shoes, etc.) and c) the remaining 10 ads which was gender independent (food, chocolates, mobile phones, tourism, etc.).

The images may have stimulated a range of emotions in participants, simulating the variety of ordinary emotions an individual may experience in his daily life and can affect the blink's properties [7,11]. The task was easy to do and did not require a high level of concentration. For each of the 30 images, subjects had only two options: either they could hit the "Like" or the "Next" button. If after hitting the "Like" button someone wished to undo it, they could do that via clicking the "Like" button again before moving onto the next image. Once they moved onto to the next image, they could not return back to previous image. The whole experimental procedure took about 10 min from device setup to stimulus presentation. A 21.5-inch LED monitor with a refresh rate of 60 Hz was used for this purpose. We collected EEG data, video recording of the participant using a web-cam and video recording of the screen.

Prior to the study, subjects signed informed consent forms only after reading and agreeing to it. The minimum, maximum, standard deviation and mean age of the subjects were 19, 28, 1.80 and 22.10 respectively.

The whole process flow of the method used in this work has been illustrated in 1.

2.2. Preprocessing and feature extraction

BLINKER, a freely available MATLAB toolbox, has been used to extract the eye blink signals from recorded EEG signals [16]. Although we had 14-channels of EEG recordings from EMOTIV, we used only AF3 (equivalent to Fp1 electrode of Neurosky) channel's EEG sequence as input to BLINKER to extract eye blinks since AF3 (or Fp1 of Neurosky) electrode position is the closest to eye for potential blink detection. In addition, another purpose of using only AF3 channel is the fact that, we only need a single channel EOG recording for human authentication, not necessarily it has to be EEG recording, it could simply be an EOG recorder. This choice would also help us to compare with other existing studies who used a single-channel EEG recorder such as Neurosky (Fp1).

This subsection describes the process how the plugin BLINKER works. This algorithm takes any time-series EEG data as input, irrespective of whether preprocessed or not, whether single or multichannel, and whether with reference EOG channel or not. Thus, regardless of input signal type, it uses the same technique for initial blink detection and calculation of preliminary blink parameters such as blink start and end times. The input sequence is band-pass filtered between 1 and 20 Hz prior to blink detection. Then the algorithm determines the intervals during which the signal is more than 1.5 times the standard deviation above the overall mean (> 1:5std + mean). It only considers the potential blinks that are longer than 50 ms and at least 50 ms apart from each other. This algorithm is able to eliminate many small eye movements without eliminating many actual eye blinks. The major blink features that can be extracted using this toolbox are blink rate, blink duration, maximum and minimum amplitudes of blinks, and velocity measures. The process flow of the blink extraction is shown in 2.

Our final cohort consists of nearly 2000 blink instances of 46 subjects. Number of instances for each participant is different, forming an imbalanced dataset. This number varies between 17 up to 162 blinks depending on subject. For each blink 25 features, based on the proposed blink properties by Kleifges et al. [16], were extracted with the purpose of investigating on the discriminative information of original blink signal. Among these features, the amplitude of positive and negative blink signal and their derivatives (posAmpVelRatioBase, PeakMaxTent and PeakMaxBlink), duration of positive and negative pulse (durationBase, durationZero and durationTent), position of positive and negative peak from onset of positive and negative pulse (durationHalfBase, durationHalfZero and durationHalfBase), have the same definitions as in [3]. Fig. 3 shows an example of blink EOG signal and some of its attributes. Missing values is a common phenomenon in real world problems. The K-Nearest Neighbors Imputation (KNNI) [5]

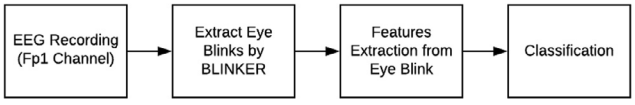


Fig. 1. Simple process flow of the whole method used in this research.

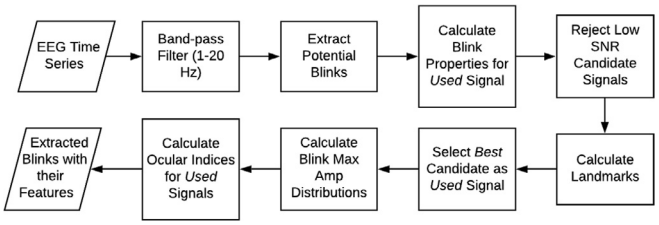


Fig. 2. Process flow of the BLINKER tool to extract eye blinks from EEG time series (adopted from [16]).

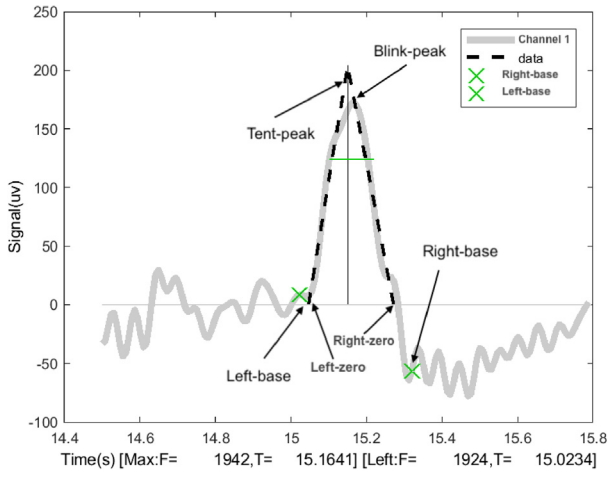


Fig. 3. An example of extracted blink signal and some of its features.

with Euclidean distance function was applied to handle the missing values. Using this method, the missing data of each blink are imputed by considering K nearest instances which are most similar to the instance of interest. In order to select a subset of features that carries the most relevant information and centralizing the statistical analysis on variables which matter the most, the Random Forest [10] algorithm was used. As illustrated in Fig. 3, the three most important subset of features are: the maximum amplitude of the blink, length of the interval in seconds between successive blink peaks and maximum height of the tent peak.

In the next section, the aptitude of Gaussian classifier for classifying spontaneous blink signal, as it was proposed in [3], is investigated. Afterward, several models were examined aiming to find the best one for classifying the data using the information carried by a single blink signal. Finally, the use of information in arbitrarily sequences of blinks for human recognition is examined.

2.3. Gated Recurrent Unit (GRU)

Gated Recurrent Unit (GRU) [12] is an extension of traditional Recurrent Neural Networks (RNNs) which aims to solve the vanishing gradient problem and is capable of handling variable-length sequence as input by having a recurrent hidden state. Let's consider a vector of blinks $X = (X_1, X_2, X_3, \ldots, X_t)$. Given this series of blinks, the GRU updates the recurrent hidden state h_t^j by

$$h_t^j = \left(1 - z_t^j\right) h_{t-1}^j + z_t^j \tilde{h}_t^j + b_h \tag{1}$$

where h_t^j, h_{t-1}^j and $\tilde{h}_t^j$, are the activation of GRU at time t, the previous and candidate activation, respectively. The update gate z_t^j decides how much the unit should be updated which is computed by

$$z_t^j = \sigma(W_z X_t + U_z h_{t-1} + b_z)^j \tag{2}$$

where W, U are parameter matrices and σ is the logistic sigmoid function. The candidate activation is computed by

$$\tilde{h}_t^j = tanh(WX_t + U(r_t \odot h_{t-1}))^j \tag{3}$$

where r_t is a group of rest gates and $\odot$ is element-wise operation. Parameters Parameter b_h and b_z are bias vectors. The choice of GRU is based on the fact that in comparison with Long-short Term Memory unit (LSTM) [14] it needs less parameters and its advantage over RNNs in terms of faster convergence and having better solutions [12]. One the other hand, GRU RNN is similar to the LSTM RNN, although with less external gating signal in the Eq. (1). Assume that the cell state is n-dimensional and the input signal is m-dimensional. The total parameters in LSTM RNN are equal to $4 \times (n^2 + nm + n)$ while the number of parameters for GRU RNN is equal to $3 \times (n^2 + nm + n)$. This means that GRU needs less parameters in comparison with LSTM.

Several different architectures of GRU have been proposed to reduce the number of the parameters even more [30]. These architectures basically retain the architecture of Eq. (1) and focus on variation in the structure of the gating signals in Eq. (2). In the first variant called GRU1 each gate is computed using only the previous bias and hidden state.

$$z_t^j = \sigma(U_z h_{t-1} + b_z)^j \tag{4}$$

This way, the number of parameters is reduced by $2 \times nm$.

In the second variant, GRU2, the gate is computed using only the previous hidden state which reduces the parameters of GRU by $2 \times (nm + n)$.

$$z_t^j = \sigma(U_z h_{t-1})^j \tag{5}$$

The third variant, which has the least number of parameters, uses only bias and reduces the parameters by $2 \times (nm + n^2)$.

$$z_t^j = \sigma(b_z)^j \tag{6}$$

Rahul et al. [30] analyzed the performance of these variants in comparison with the original GRU and reported that the first and second variants perform almost as good as original GRU while the third variant lags in performance. Since in this work the main goal is to achieve the best possible performance, the original GRU is used to measure the accuracy of the model.

2.4. Potential use of Gaussian classifier

We survey the adequacy of Gaussian classifier for classifying single involuntary blink signal by analyzing the multivariate distribution of features used both in [3] and the current study. As mentioned above, the most important features are the duration of positive pulse, the amplitude of positive peak of first derivative, amplitude of negative peak of first derivative and the position of positive peak from the onset of positive pulse (see Fig. 4). Thereby, we show the statistical results only for these features, although, the results are valid for other variables as well. By showing that all the features are generated by a Gaussian density function, we conclude that both voluntary and spontaneous blinking signal are generated by multivariate Gaussian density function. The distribution of each variable was extracted for each individual and was compared to the others in terms of the type of distribution, mean and variance. As illustrated in Fig. 5, Gaussian distribution is the best fit for the amplitude of positive peak as one of the most important features.

In order to quantify the distance between empirical and the cumulative distribution function of Gaussian as the reference distribution and to decide about the goodness of its fit, the Kolmogorov-Smirnov test [17] was constructed by using the

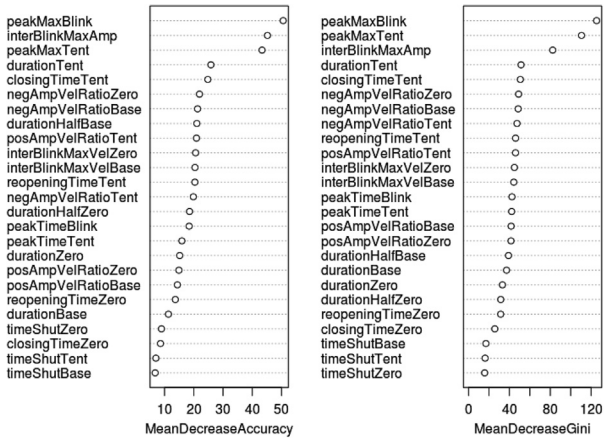


Fig. 4. Variable importance.

critical value associated with a significance level $\alpha = 0.05$. As shown in Tables 1, the probability associated with the critical value K_α of multivariate distribution of empirical data being generated by Gaussian distribution is not significant, resulting in the rejection of the null hypothesis. Considering the p-value of Kolmogorov-Smirnov test for all the features across all the subjects, we confirm that the generative function of blinking data follows a Gaussian density function. Here we discuss the possibility of using Gaussian classifier for human authentication as it was proposed in [3] for voluntary blinking. Let $f_1(x), f_2(x), \ldots, f_n(x)$ be the probability density function associated with $p \times 1$ vector random variables X for populations π_i populations. Each instance i must be assigned to one of the π_n. Let R_n be the n th critical regions where the instance is assigned to. Having highly overlapped regions among π_n populations, as it is observable in Fig. 6, causes a high error rate in classification of instances using Gaussian classifier. This result is valid for all the 25 existing variables in dataset of spontaneous blinks' signal. This shows that although the signal of both voluntary and spontaneous blinking is generated by a Gaussian function, considering the high classification rate achieved in [3], we may conclude that for involuntary blinking, the distribution of data is not as separable as it is for voluntary blinking. Therefore, other models ought to be examined in order to find the best classifier.

3. Results and discussion

Each instance of a blinking signal was labeled with a unique ID representing the individuals. These labels were then considered as the class of each blink and were used in classification task to identify each subject using the extracted features from each signal. Several algorithms from a variety of classification approaches including kernel methods, tree, distance-based and Bayesian models were tested and the accuracy of each one were compared to the others. For all the classifiers cross-validation with 10 folds was used. K-Nearest Neighbors, as a distance-based algorithm, with $K = 9$, leaf size of 30 along with Euclidean distance measure had the worst accuracy with 28%. The best result, on the other hand, was achieved by Multilayer Perceptron with 42.4%, having learning rate set to 0.001, momentum for gradient descent update equal to 0.9 and 500 iterations. Random Forest, as a tree model, with gini criterion, maximum depth of 4 and 8 trees per forest has classification accuracy of 29%. Support Vector Machine (SVM) with linear

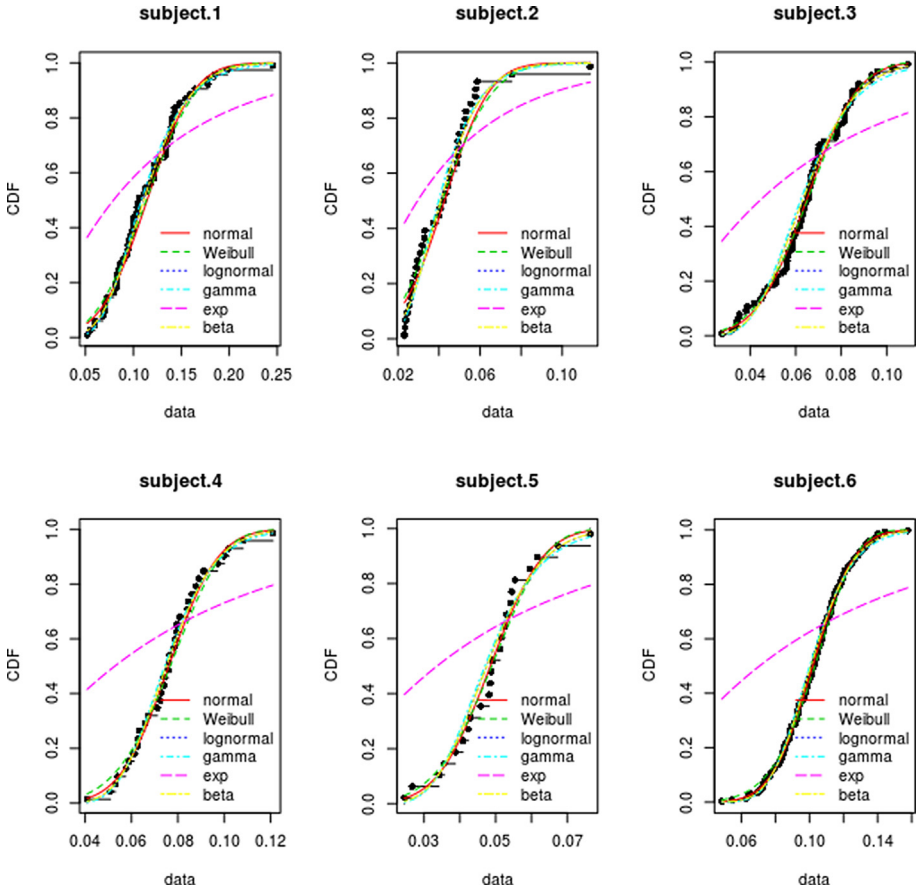


Fig. 5. The Q-Q plot of the amplitude of positive peak of six randomly selected subjects for the amplitude of positive peak.

Table 1
The Kolmogorov-Smirnov test results of 6 randomly chosen subjects for the duration of positive pulse (top left), amplitude of positive peak of first derivative (top right), amplitude of negative peak of first derivative (bottom left) and the position of positive peak from the oneset of positive pulse (bottom right).

	$D_{n,\alpha}$	p-value
1	0.14913	0.1515
2	0.12363	0.6238
3	0.10247	0.4452
4	0.20151	0.1075
5	0.13532	0.7717
6	0.076773	0.8901
1	0.18052	0.399
2	0.074364	0.9772
3	0.063843	0.9165
4	0.21212	0.06707
5	0.089928	0.9804
6	0.078665	0.8449
1	0.108	0.4753
2	0.16047	0.2667
3	0.10615	0.3741
4	0.17544	0.1934
5	0.083467	0.991
6	0.11116	0.4496
1	0.10021	0.5705
2	0.13378	0.4811
3	0.083546	0.6733
4	0.085402	0.9353
5	0.11412	0.8788
6	0.10067	0.5754

kernel and tolerance factor equal to 0.001 had the second best result with 42.2% accuracy. Finally, Gaussian classifier and Linear Discrimination Analysis achieved 37% and 35% classification rate respectively. Since, the number of participants were different in the previous researches, we analyzed the results with different number of subjects in order to find its impact on accuracy. Depending on the model, it was observed that an increase of number of subjects from 31 (number of subjects participated in [4]) to 46 can decrease the classification rate up to 40%. More specifically, for LDA and Gaussian classifier suggested by Abo-Zahhad et al. [3], we observed a decrease of accuracy by 28% and 20% respectively. As depicted in Fig. 7 none of the tested models manages to distinguish individuals using the information of a single spontaneous blink with high accuracy. Since, this study has almost half of the same features as that of [3,25], using their models for voluntary blinking reduces the likelihood of having a similar high accuracy for our spontaneous involuntary blinking dataset or for a mixture of EEG and EOG signals. Nevertheless, since no feature score was reported in [3], there is a possibility that the most relevant variable subset reported in the current study has less importance in [3,25] thus, making it necessary to carry out further investigations in terms of the sequence of blinks. To do so, the individuals' blinking data were ordered sequentially and then were fed to the GRU. For optimizing the model we trained it for a maximum of 256 epochs using the Adam optimizer [15] with a learning rate of 0.00005 and the training is stopped if the validation loss does not decrease for two consecutive epochs. The dropout probability was set to be equal to 0.5. The batch size and embedding dimension were both set to 64. The dataset was split randomly, 70% into the training set and 30% into the test set. A sliding window with different sizes was used to create sequential instances of a series of blinks and then each series related to each individual was labeled with a unique ID. The classification task is then identifying the individual (which is represented with a unique ID) using the predicted ID for a sequence of blinks. A sequence of 2,4,6 and 8 blinks (2b, 4b, 6b, 8b) with 1 to 3 hidden layers (1 l-3 l) was tested. As it is illustrated in Fig. 8, as the number of hidden layers and blinks in a sequence are increased, the classification rate becomes more accurate and the median rate gets closer to the third quartile. When number of hid-

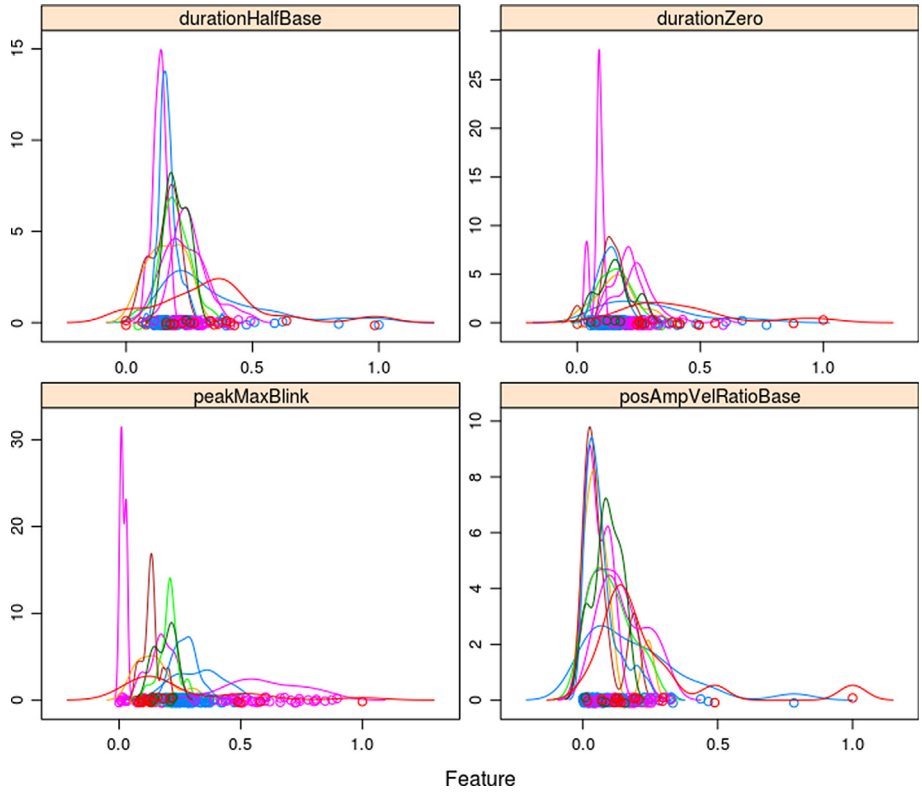


Fig. 6. The distribution of four most important features for ten randomly selected subjects.

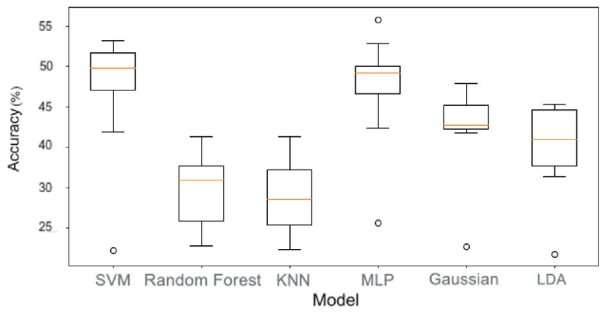


Fig. 7. Boxplot of classification accuracy of six different classifiers.

den layers is set to 4 or more layers, the improvement in classification rate is not significant. Since the classes are not completely balanced, accuracy, micro-average of precision and recall were used to evaluate the performance of the classifier.

$$Micro\ precision = \sum_{i}^{n} \frac{TP_i}{TP_i + FP_i} \tag{7}$$

$$Micro\ recall = \sum_{i}^{n} \frac{TP_i}{TP_i + FN_i} \tag{8}$$

$$Accuracy = \sum_{i}^{n} \frac{TP_i + TN_i}{TP_i + TN_i + FN_i + FP_i} \tag{9}$$

where: TP = True positive; FP = False positive; TN = True negative and FN = False negative. The results show that a sequence of 8 blinks carries enough information for each individual to be classified with 98.7% accuracy, 97.5% micro average precision and 97% micro average recall. A series of 7 and 6 blinks on the other hand, are classified with 96.1% and 97.8% accuracy, 97.5% and 95.2% precision, and 96.8% and 94.1% recall, respectively.

Confidence interval can be presented in order to estimate the reliability of the results as follows:

$$z\sigma = error \pm const \times \sqrt{(error \times (error - 1)/n)} \tag{10}$$

where σ is the standard deviation and *const* is the confidence level. By setting the confidence level to 1.96, there is a 95% likelihood that the true classification error is 0.018± 0.006 for the unseen population.

The interpretation of the model is done based on the unified approach suggested by [18]. As shown in Fig. 9 (left) the length of the interval between successive blink peaks, maximum amplitude of the blink and maximum height of the tent peak are the most relevant features in the current model and the features of the first four blinks of each sequence have the most contribution in increasing the classification rate. Nevertheless, for this model,

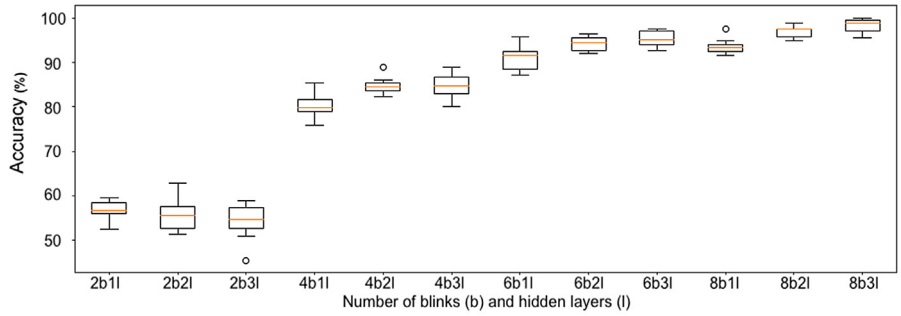


Fig. 8. Boxplot of classification accuracy of GRU with variation in number of hidden layers and number of blinks in each sequence.

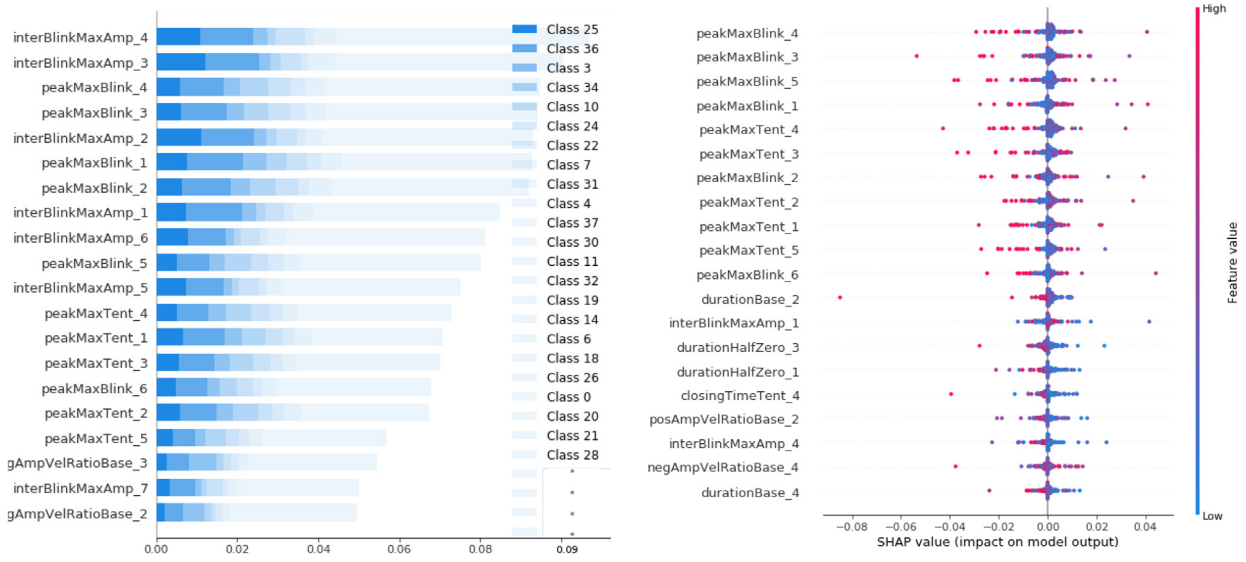


Fig. 9. The impact of features and their values on prediction accuracy. The index of each feature is related to the blink position in the sequence of instances.

Table 2
A comparison between the current work and the previous studies.

Author	Data Type	Number of subjects	ACC (%)
Abo-Zahhad et al. [3]	Voluntary blinking signal	25	97
Abo-Zahhad et al. [4]	Voluntary blinking signal, EEG gathered from a single channel	31	98.6
Abo-Zahhad et al. [2]	Voluntary blinking signal	40	93.7
Wu et al. [25]	Spontaneous blinking signal, EEG gathered from 16 channels	40	97.6
The current study	Only spontaneous blinking signal	46	98.7

as illustrated in Fig. 9 (right), the difference between the contribution of the most and less relevant features previously determined by Random Forest is not significant. Also, for all the features both negative and positive values result in a higher prediction yet, the impact of each of these values depends on each class.

Table 2 provides a comparison of our results against the baseline approaches. Since the previous studies used accuracy as a measure of performance, we use the same measure in our comparison. In comparison with the previous studies our method outperforms in terms of classification performance. Our method achieved a better accuracy in comparison with [4], although it is important to mention that the dataset used by Abo-Zahhad et al. [3] contains both EEG and EOG signals and the results were verified with significantly lesser number of subjects compared to the this work. Our method has also better accuracy compared to the other studies conducted by Abo-Zahhad et al. [3,2]. In these works only EOG signals were used although, the data acquired in the current study is related to spontaneous blinking and the experiment puts no restriction over the blinking task neither the quality nor the total number of blinks. Considering the number of individuals participated in [25], Wu et al. achieved a promising classification rate, however spontaneous blink signals along with EEG data were used in their work. On the contrary, our method achieved better accuracy just using EOG signals. Furthermore, they used 1500 data samples for each subject in the training phase while in our study an average of 50 samples (per subject) were fed to GRU for training. In terms of time cost, the method proposed by Wu et al. [25] performs better than our approach however, the authentication time is highly dependent on the experimental setup. On average, in our experiment subjects blinked 12.5 times per minute. This low blink rate may have been caused by the visual task performed by individuals during the data acquisition [8]. Hence, further experiments ought to be done in other conditions such as rest and conversation [8] so as to find the time cost of the current method during the other tasks where blinking rate is higher (an average of 25–30 blinks per minute). One may question the feasibility of using a sequence of blinks for user authentication in daily tasks such as having access to a computer, cellphone, etc. Here, the possible application of this method, considering our emphasis on using spontaneous blinking, involves continuous and long term individual authentication when he/she stays in a specific area (airport, restricted areas or even in a city). Also, it is worth mentioning that only the first authentication may take a longer time and once the user is identified the next authentication needs only a single blink.

4. Conclusion

In this paper, we investigated the use of spontaneous blink signal for human recognition. Data of 46 subjects were recorded during a picture visualization task. After preprocessing the data, 25 features were extracted. In the next step, the distribution of variables was analyzed to examine whether the generator function is the same for spontaneous and voluntary blinking. It was found that features are not distributed identically. Several models were tested with the purpose of finding the best classifier however, none managed to distinguish individuals with high accuracy. Thereby, the possibility of using a sequence model for human authentication was investigated and several sequences were tested. Although the best accuracy (98.7%) was achieved by feeding the information carried by a series of 8 blinks to Gated Recurrent Unit Neural Network, our method is capable of using even lesser number of blinks for accurate human authentication. For future works, the proposed method should be replicated during other tasks such as reading, rest and conversation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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