e-Glass: A Wearable System for Real-Time Detection of Epileptic Seizures

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***Abstract*—Today, epilepsy is one of the most common chronic diseases affecting more than 65 million people worldwide and is ranked number four after migraine, Alzheimer's disease, and stroke. Despite the recent advances in anti-epileptic drugs, one-third of the epileptic patients continue to have seizures. More importantly, epilepsy-related causes of death account for 40% of mortality in high-risk patients. However, no reliable wearable device currently exists for real-time epileptic seizure detection. In this paper, we propose e-Glass, a wearable system based on four electroencephalogram (EEG) electrodes for the detection of epileptic seizures. Based on an early warning from e-Glass, it is possible to notify caregivers for rescue to avoid epilepsy-related death due to the underlying neurological disorders, sudden unexpected death in epilepsy, or accidents during seizures. We demonstrate the performance of our system using the Physionet.org CHB-MIT Scalp EEG database for epileptic children. Our experimental evaluation demonstrates that our system reaches a sensitivity of 93.80% and a specificity of 93.37%, allowing for 2.71 days of operation on a single battery charge.**

I. Introduction and Related Work

Epilepsy represents one of the major neurological health issues affecting more than 65 million people worldwide [1]. It is the fourth most common chronic disorder after migraine, stroke, and Alzheimer's disease [2]. Despite substantial progress in the efficacy and tolerance of anti-epileptic drugs, one-third of the epileptic patients continue to have seizures [3].

Epilepsy is characterized by intermittent seizures caused by disturbances in the electrical activity of the brain [1]. These seizures can last from seconds to minutes and can range from an impaired consciousness, automatic movement, up to severe convulsions of the entire body. Impaired consciousness may lead to driving accidents, drowning, as well as other serious injuries [4]. This contributes to a severe reduction in the quality of life and psychosocial functioning. The unpredictable nature of seizures can be life-threatening with a 2–3 times higher mortality rate in these patients than in the general population [5]. Furthermore, the most severe seizures, especially when occurring at night, can result in sudden unexpected death in epilepsy (SUDEP) [6]. Epilepsy-related causes of death account for 40% of mortality in high-risk groups of people with epilepsy [7]. In order to reduce morbidity and mortality due to epilepsy, real-time patient monitoring is essential for alerting family members and caregivers to administer prompt emergency medication and assist a person at the time of a seizure.

In the medical community, the standard procedures commonly used for epileptic patient monitoring are performed based on the video-EEG (v-EEG) [8]. v-EEG takes place in hospitals over several days and it involves the acquisition of the audio signal using a microphone, the video recording of the patient using a camera, the brain electrical activity using electroencephalography (EEG), as well as the electrical activity of the heart using electrocardiography (ECG). Considering the unpredictability of seizures, it is not possible to monitor patients on a long-term basis, due to the highly intrusive nature of these procedures.

With the currently flourishing era of embedded computing, wearable technologies are opening up new opportunities for real-time epileptic seizures monitoring. These new ultra-low energy portable devices overcome the limitation of medical equipment for real-time and long-term patient monitoring. In particular, the portability of these devices allows real-time remote patient monitoring on a daily basis. Ambulatory real-time patient monitoring allows hospital physicians to access patient information remotely and, hence, prevent further patient state deterioration by early detection of epileptic seizures.

The most popular wearable system for the detection of epileptic seizures consists of EEG head caps with embedded electrodes for measuring the electrical activity of the brain [9]. The placement of electrodes is based on the international 10-20 system [10], [11]. In [12], a new scheme for epileptic seizure detection based on approximate entropy and discrete wavelet transform analysis of 100 EEG channels has been proposed. Furthermore, different approaches that use artificial neural networks for epileptic seizure detection based on EEG signals are reported in the literature [13]. Nevertheless, all these methods use EEG head caps that are cumbersome and uncomfortable as they require from 23 to 256 wired electrodes to be placed on the patient's scalp. The majority of epileptic patients refuse to wear these caps due to negative effect of social stigma they are facing in their daily lives [14].

In order to alleviate the negative impact of social stigma on patient's daily life, several studies have been conducted to reduce the number of EEG electrodes needed for epileptic seizure detection. For instance, in [15], the authors use two different montages with reduced number of electrodes for automatic multimodal detection of epileptic seizures: eight electrodes in forehead montage, and seven electrodes in posterior montage. However, the proposed solution is still intrusive and, hence, the problem of social stigma persists.

In this paper, we propose e-Glass, a wearable ultra-low energy system that uses four EEG electrodes embedded and hidden in the temples of glasses for real-time epileptic seizure detection. Concretely, the main contributions of this paper are:

1) A wearable system for reliable detection of epileptic seizures in real time that reaches a sensitivity of 93.80%

This work has been partially supported by the MyPreHealth research project (Hasler Foundation project no. 16073).

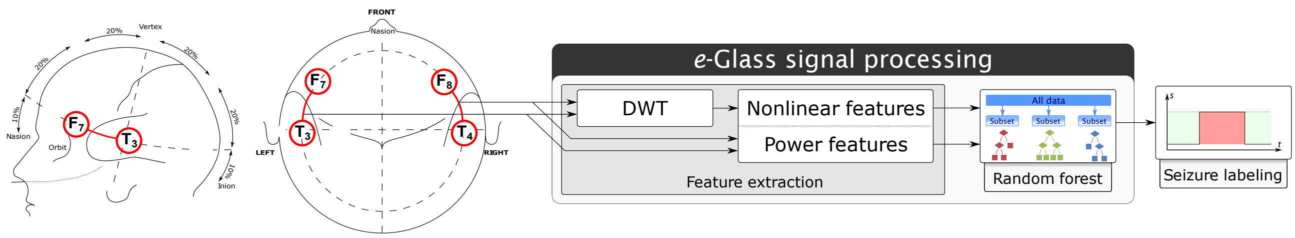

Fig. 1. The overall flow of e-Glass

and a specificity of 93.37%, allowing for 2.71 days of operation on a single battery charge.
2) Validation on CHB-MIT database (Physionet.org [16]).
3) Evaluation of energy consumption and battery lifetime of our proposed e-Glass system.

The remainder of this paper is organized as follows. In Section II, we propose our real-time system for epileptic seizure detection with limited number of electrodes. Experimental setup along with the evaluation of energy efficiency and performance of our system are presented in Section III. Finally, in Section IV, we conclude that our proposed system monitors epileptic seizures with high classification performance and limited number of EEG electrodes on a long basis.

II. Real-Time Methodology for Epileptic Seizure Detection

In this section, we propose e-Glass, a wearable system for real-time epileptic seizure detection. The overall flow of our proposed system is shown in Fig. 1, and it consists of two main phases: feature extraction (Section II-A) and classification (Section II-B). Each of these steps is thoroughly explained in the following subsections.

A. Feature Extraction

In order to capture the complex, non-stationary, and nonlinear nature of EEG signals, we extract various entropy measures along with several power features.

1) Nonlinear Features Extraction: When using entropy measures for epileptic seizure detection, it has been shown that applying a discrete wavelet transform (DWT) as a pre-processing step improves the detection rate for more than 20% [12]. Therefore, we decompose EEG signals down to level seven using a DWT. In particular, we use Daubechies 4 (db4) wavelet basis function. The value of sample entropy is calculated from detail wavelet coefficients at level 6 and 7, whereas the rest of the nonlinear features are calculated from detail wavelet coefficients at levels 3, 4, 5, 6, and 7 for different values of input parameters.

- Sample entropy: Given a time-series $X = x(1), \ldots, x(N)$ along with the pattern length m and the criterion of similarity r [17], we define the following sequences $X_m(i)$:
$$X_m(i) = \{x(i), x(i+1), \ldots, x(i+m-1)\}$$
$$\forall i = [1, N-m+1].$$
Then, two patterns $X_m(i)$ and $X_m(j)$ are similar if the difference between any pair of corresponding measurements in the patterns is less than r:
$$|x(i+k) - x(j+k)| < r, \forall k = [0, m).$$
We define the set of all sequences of length m, X_m, along with the criterion function $C_{im}(r)$ as follows:
$$X_m = \{X_m(1), X_m(2), \ldots, X_m(N-m+1)\},$$
$$C_{im}(r) = \frac{n_{im}(r)}{N-m+1},$$
where $n_{im}(r)$ is the number of patterns in X_m that are similar to $X_m(i)$ excluding self-matches. The sample entropy is defined as:
$$SampEn(x, m, r) = \ln\left(\frac{C_m(r)}{C_{m+1}(r)}\right),$$
where we calculate $C_{im}(r)$ for each pattern in X_m, and we define $C_m(r)$ as the mean over $C_{im}(r)$. In this work, we use $m = 2$, and $r = k \cdot \mathrm{std}(signal)$, where $\mathrm{std}(signal)$ represents the standard deviation of a signal, and $k \in \{0.2, 0.35\}$.
- Permutation entropy: Given a time-series $\{x_t\}_{t=1,\ldots,T}$, where T is the length of the time-series, all possible $n!$ permutations are calculated [18]. The parameter π corresponds to the permutation type, whereas the parameter n represents the number of instances considered in order to estimate the permutation entropy (e.g., (x_i, x_j, $i \neq j$)), where $n = 2$, or (x_i, x_j, x_k $i \neq j \neq k$), where $n = 3$. For instance, for $n = 2$, π can take on only two values. Let us denote them by 01 or 10. If $x_t < x_{t+1}$, then $\pi = 01$, and if $x_t > x_{t+1}$, then $\pi = 10$. Hence, in case of $n = 2$, there are just two possible permutations, namely, 01 and 10. The relative frequency for type π is estimated as follows:
$$p(\pi) = \frac{\text{number of perms that have the type } \pi}{T-n+1}.$$
The permutation entropy of order $n \geq 2$ is defined as:
$$PE(n) = -\sum_{\pi} p(\pi) \log(p(\pi)).$$
In this paper, we compute the value of permutation entropy for $n \in \{3, 5, 7\}$.
- Renyi entropy: This entropy is calculated as follows [19]:
$$RE(q) = \frac{1}{1-q} \ln \sum p_i^q,$$
where $q \neq 1$, and p_i defines the total spectral power in i-th band.
- Shannon entropy: This entropy is the special case of Renyi entropy [19] for $q = 1$, namely:
$$SE = -\lim_{q \to 1} RE(q) = -\sum p_i \ln(p_i).$$
- Tsallis entropy: It is defined as in [19]:
$$TE(q) = \frac{1}{q-1}\left(1 - \sum p_i^q\right).$$

2) Power features: Epileptic seizures affect the distribution of EEG signal power in different frequency bands [20], [21]. The most commonly reported features extracted from EEG signals in the literature [22] rely on the spectral power of EEG signals in various frequency bands of the EEG, namely delta $[0.5, 4]$ Hz, theta $[4, 8]$ Hz, alpha $[8, 12]$ Hz, beta $[13, 30]$ Hz, gamma $[30, 45]$ Hz. We calculate the total and the relative EEG signal powers in the aforementioned frequency bands, as well as the relative EEG powers in the following bands: $[0, 0.1]$ Hz, $[0.1, 0.5]$ Hz, $[12, 13]$ Hz. These power features are extracted from raw EEG signals.

B. Classification Based on Random Forest

Random forest generates an ensemble of decision trees that are combined to produce an aggregate mode, which is more powerful than any of its individual decision trees alone [23]. However, one of the main disadvantages of using a single decision tree for classification purposes is its overfitting tendency. Nonetheless, combining different decision trees into an ensemble solves the problem of overfitting.

Each of the classification trees is constructed using a bootstrap sample of data. In particular, if our training set has M rows in the feature matrix, a bootstrap sample of data of size M is constructed by randomly picking one of the M rows of the dataset with replacement; hence, allowing the same row to be selected multiple times. This process is repeated M times resulting in a bootstrap sample of size M. This sample has the same number of rows as the training set, with possibly some rows from the training dataset missing while others occurring multiple times, just due to the nature of the random selection with replacement. For each of the bootstrap samples, we grow an unpruned tree (fully grown) [24]. At each node, we randomly select a subset of features and we choose the best split within this smaller subset.

To classify a new sample, each decision tree gives a classification decision. The forest chooses the classification decision that has the most votes among the other trees in the forest. Using bootstrap aggregation, as well as a random feature selection algorithm for growing each tree individually, results in a low-variance model and a robust outcome, as shown in our experiments in Section III. The highest classification accuracy of our system is obtained by random forest. However, our system is not classifier-dependent, hence, any other state-of-the-art classification algorithm can be used as well.

III. Experimental Setup and Results

In this section, we demonstrate the classification performance of our system using Physionet.org CHB-MIT Scalp EEG database. This database is described in Subsection III-A. Then, the target computing system of the e-Glass wearable platform on which we port our classification technique is explained in Subsection III-B. Next, the performance of our real-time detection algorithm is shown in Subsection III-C, and the energy consumption estimation is presented in Subsection III-D.

A. CHB-MIT Database

The used database contains EEG signals from children with refractory seizures. All recordings are collected from children (in the 1.5–22 age range). EEG signals are sampled at $fs = 256$Hz. In order to be able to evaluate the performance of our proposed system and the impact of the reduced number of electrodes, we consider multiple traces from 10 patients that are fully compliant with the standard acquisition protocol [11]. These traces include the total number of 55 seizures.

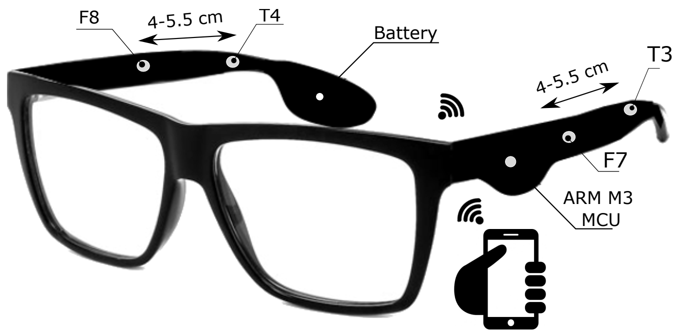

Fig. 2. e-Glass: a wearable system for real-time epileptic seizure detection

B. Target Platform

The proposed e-Glass wearable system is shown in Fig. 2. Our system acquires EEG signals from two electrode pairs: F_7T_3, and F_8T_4, shown in Fig. 1. The sampling frequency of acquired EEG signals ranges from 125 Hz up to 16 KHz with up to 16-bit resolution. Our system features an ultra-low power 32-bit microcontroller STM32L151 [25] with an ARM® Cortex®–M3, which can operate at a maximum frequency of 32 MHz. e-Glass contains a 570 mAh battery, as well as 48 KB RAM, 384 KB Flash, and several analog peripherals including a 24-bit ADC [26]. At the time of a seizure, a warning from e-Glass is sent to the caregivers through the communication with a mobile phone. For these purposes, we use Bluetooth low energy (nRF8001) [27].

C. Performance Evaluation of e-Glass

1) Classification Performance Metric and Cross-Validation: To evaluate the classification performance of our system, we consider both sensitivity and specificity metrics, as well as their geometric mean (gmean), which is the only correct average of normalized measurements [28]. These metrics are defined as follows:

$$sensitivity = \frac{tp}{tp + fn}, \quad (1)$$

$$specificity = \frac{tn}{tn + fp}, \quad (2)$$

$$gmean = \sqrt{sensitivity \cdot specificity}, \quad (3)$$

where tp, tn, fp, fn represent the number of true positive, true negative, false positive, and false negative, respectively.

We use a sliding window of four seconds with 80% overlap for extracting the features mentioned in Subsection II-A. Namely, we extract these features for both, seizure and seizure-free signal parts. In order to have balanced classes, the same number of seizure and seizure-free windows is used for each patient.

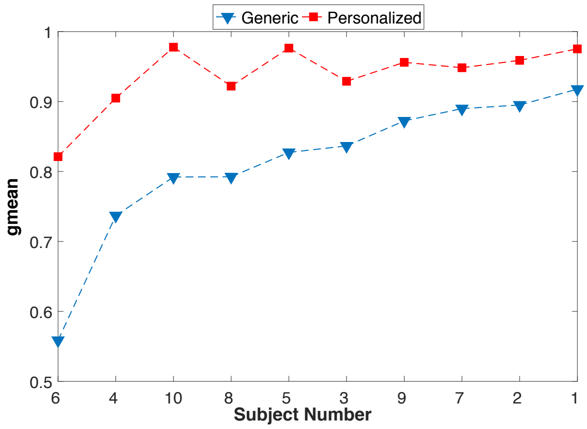

Fig. 3. Geometric mean (gmean) for personalized versus generic approach using four electrodes

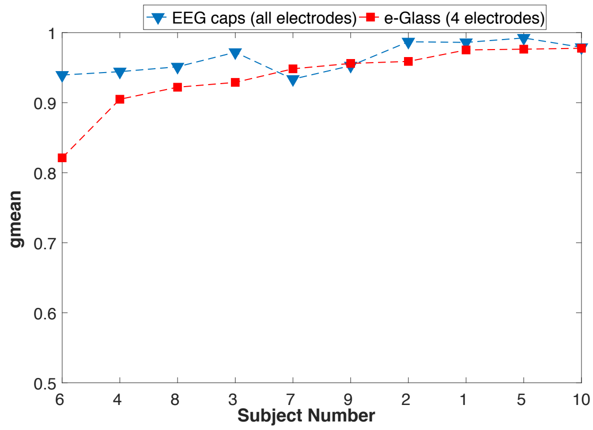

Fig. 4. Geometric mean (gmean) for personalized approach using EEG caps (all electrodes) versus e-Glass (four selected electrodes)

2) Personalized Versus Generic: In this section, we investigate the difference in terms of classification performance between the personalized and generic approach. Namely, the generic approach uses leave-one-out cross-validation scheme. Out of ten subjects, a single subject is retained for testing the model, and the remaining nine are used as training data. The personalized approach performs the classification based on the features extracted from different trials of one subject. Hence, this classification is done per subject. While splitting the data into training and test sets each trial is included into either the training set or the test set. First, we find the number of seizures for each patient. As we want to make sure that the test set contains at least one seizure, 30% of seizure data is put in the test set, whereas 70% goes to the training set. For instance, let us assume that patient A has had 6 seizures. Then, feature windows that correspond to two seizures are put in the testing set, whereas the remaining four seizure windows are put in the training test. We use all possible combinations of six seizures to select two at a time for test set. For each of these combinations, we split the rest of seizure-free data into training and test sets for all possible 70–30% splits. We report the value of gmean (Eq. (3)) for each subject in our personalized approach.

Fig. 3 shows the gmean across all subjects (vertical axis) for four electrodes used: F_7T_3, and F_8T_4 in Fig. 1. The geometric mean across all subject for the generic approach is 80.48% (sensitivity = 80.82%, specificity = 80.15%), whereas this value reaches 93.59% for the case of our personalized approach (sensitivity = 93.80%, specificity = 93.37%). In the best case, for patient 6 our approach improves the detection rate for 26.26%, as shown in Fig. 3. As we can infer from this figure, the personalized classification approach can adapt to significant inter-patient variations in EEG patterns. Thus, it achieves a higher classification performance.

3) EEG Caps Versus e-Glass: In this section, we compare the classification accuracy in case of the personalized approach for a different number of used electrodes. Fig. 4 shows the value of gmean for personalized approach using EEG caps (all available electrodes) versus the value of gmean obtained from e-Glass (four selected electrodes: F_7T_3, and F_8T_4). The geometrical mean across all subjects is 96.36% (sensitivity = 96.95%, specificity = 95.77%). and 93.59% (sensitivity = 93.80%, specificity = 93.37%) for all electrodes and for the subset of electrodes, respectively. As it can be observed from Fig. 4, using only a few electrodes it is possible to ensure a high degree of wearability without any major loss in classification performance. Even though there is a slight difference for subject number 7 in Fig. 4, this difference is within the expected statistic range since the number of trials for this subject is limited.

D. *Energy Consumption and System Lifetime Analysis*

Our proposed e-Glass system includes a 570 mAh battery, as previously discussed. Assuming that the EEG acquisition circuit is active all the time, we run our proposed algorithm for epileptic seizure detection every four seconds. The processing of a four-second window takes 3.08 seconds, which represents the latency of our system. Therefore, the CPU duty cycle of our system is 77%. This results in 65.15 hours of operation on a single battery charge. Thus, it allows for 2.71 days of continuous operation. Furthermore, e-Glass is designed to be an inconspicuous system that could enable patients to avoid the aforementioned social stigma of wearing EEG head caps.

IV. Conclusions

In this paper, we have presented e-Glass, a new wearable system for real-time epileptic seizure detection. Our experimental evaluation demonstrates that our personalized approach outperforms the generic approach in terms of classification performance reaching a sensitivity of 93.80% and a specificity of 93.37%, while allowing for 2.71 days of operation on a single battery charge. Furthermore, it also ensures the high degree of wearability without any major loss in terms of classification performance. This reduced set of electrodes overcomes the lack of portability of hospital equipment, as well as reducing the computational complexity, which further leads to a reduction in energy consumption. Thus, e-Glass can provide an early warning of epileptic seizures and promptly inform patient family members of preventive measures to avoid possible accidents during seizures and epilepsy-related death. Overall, e-Glass can significantly contribute to improvements in the patient's quality of life by reducing the socioeconomic burden of epilepsy.

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