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Automated Class-based Compression for Real-Time Epileptic Seizure Detection

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***Abstract*—The emergence of next generation wireless networking technologies has motivated a paradigm shift in development of viable mobile-Health applications for ubiquitous real-time healthcare monitoring. However, remote healthcare monitoring requires continuous sensing for different biosignals and vital signs which results in generating large volumes of data that requires to be processed, recorded, and transmitted. In this paper, we propose our vision for the benefits of leveraging edge computing for enabling automated real-time epileptic seizure detection. In particular, we propose an adaptive classification and data reduction technique that reduces the amount of transmitted data, according to the class of patients, while enabling fast emergency notification for the patients with abnormality. Using such an approach, the patient data aggregator can automatically reconfigures its compression threshold based on the characteristics of the gathered data, while maintaining the required application distortion level. Our results show the excellent performance of the proposed scheme in terms of classification accuracy and data reduction gain, as well as the advantages that it exhibits with respect to state-of-the-art techniques.**

***Index Terms*—Seizure detection, Edge-based classification, EEG signals, mobile-Health, feature extraction.**

I. Introduction

The rapid advances in Wireless Body Area Network (WBAN), edge computing, and wireless communication technologies facilitate implementing efficient-remote healthcare services, or known as ubiquitous healthcare [1]. Such emerging technologies has boosted the evolution of traditional healthcare into Smart healthcare services. This vision of enhancing traditional healthcare systems can significantly help in a variety of pre-hospital emergency care situations and for patients that are located in geographically remote areas. Furthermore, the advances in Internet of Things (IoT) and edge computing is expected to inspire fundamental transformations for the healthcare industry.

In this context, there is a prompt progress in the field of mobile-health (m-health) systems [2] that leverage the wide range of mobile technologies (such as smartphones, tablets, and portable health devices) to provide continuous-remote healthcare monitoring [3]. However, neurologically-oriented m-health applications are still challenging, due to the need of recording, processing and wireless transmission of large volumes of data to ensure the quality of healthcare services. For instance, in Intensive Care Unit (ICU) EEG monitoring system, samples of EEG along with video recording should be stored and accessed remotely for correlating clinical activity with EEG pattern. This can result in generating 8-10 GB per patient per day [4], which obviously sets a significant load on the system design in terms of processing capabilities, storage space, and transmission power.

Thus, reducing the amount of transferred data originating from sensing nodes and selecting the most appropriate network interface for transmission is essential [5]. This is also important considering that m-health systems typically consist of several battery-operated devices that should run for a long time without replacement. A promising approach in this context is performing in-network processing on the raw data before their transmission. Number of biosignal compression algorithms were proposed in the literature [6], which vary in the lossiness, computational complexity, and waveform transformation (e.g., Discrete Wavelet Transform (DWT), Autoencoders, vector quantization, discrete cosine transform, etc.). In [7], the authors presented lossless/near-lossless compression algorithms for multichannel biomedical signals using information theory and signal processing tools through leveraging the spatial and temporal redundancies in biomedical signals. However, the intensive computational complexity of such techniques might turn the in-network processing on battery-operated devices impractical [8][9][10]. Furthermore, non of the aforementioned work has considered the characteristics of the gathered data, or the class of the patient before compression, in order to adapt the proposed compression techniques based on the class of the data and application's requirements.

In this paper, we argue that leveraging autonomy and intelligence of the network edge can significantly enhance energy consumption, latency, and emergency response time for mobile-health applications through moving classification and adaptive compression tasks to the edge node. Thus, our main contributions can be highlighted as follows.

1) Propose a highly accurate classification scheme using low-complexity classifier at the network edge.
2) Develop an automated class-based compression

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technique that maintains application Quality of Service (QoS) requirements (i.e., signal distortion and classification accuracy) taking into consideration the characteristics of the data, while saving a significant amount of energy at the edge. To the best of our knowledge, performing class-based data reduction at the network edge to minimize the transmission energy, while maintaining applications' QoS requirements has not been studied before.

3) The proposed schemes are evaluated through simulation discussing the tradeoff between transmitted data length and signal distortion. Our results show the gain provided by our solution, and its ability to obtain high energy reduction and classification accuracy for normal/abnormal EEG patterns.

The rest of the paper is organized as follows. Section II describes the system model. Section III presents the proposed edge-based classification and compression schemes. Section IV provides our simulation results, while Section VI concludes the paper.

II. System Model

In this paper, the wireless EEG monitoring system shown in Figure 1 is considered. We consider epileptic seizure detection as an application of EEG-based diagnosis. EEG signal is the main source of information on brain electrical activities [11]. Also, it is carrying valuable information between discriminating healthy subjects and patients diagnosed with epileptic disease. In our model, the Patient Data Aggregator (PDA) gathers EEG data from the patient using an EEG Headset [12]. The PDA continuously collects, processes, and forwards physiological data to the M-Health Cloud (MHC). The main modules considered at the PDA are Feature Extraction (FE), Edge-based Classifier (EC), and adaptive Class-based Compression (CbC) of the EEG data.

For implementing an automated epileptic detection system, we propose the following tasks at the PDA:

1) Transforming EEG data into frequency domain using the Fast Fourier Transform (FFT). This step assist in better analysis of EEG signal characteristics to improve classification process and enables our CbC scheme.
2) Extracting frequency-domain features, which are informative, non-redundant, and pertinent epileptic to seizure detection.
3) Performing a low-complexity classification technique using extracted feature in order to differentiate between normal/abnormal EEG signals.
4) Compressing data before transmission leveraging a reconfigurable or adaptive compression threshold that is varying based on the identified class.

Accordingly, we can reduce transmitted data size by compressing the data, while retrieving the original data at the MHC without affecting application's QoS requirements. At the MHC, signal reconstruction, knowledge discovery, storage, and further sophisticated analysis can be done to evaluate the patient's status.

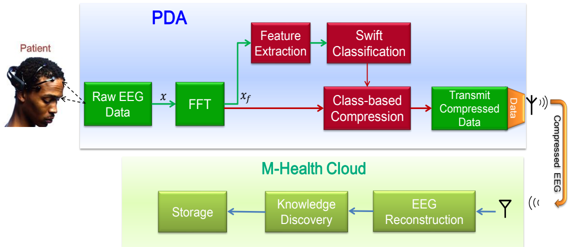

Fig. 1. System model under study.

III. Classification and Compression

In what follows, we propose an efficient, low-complexity and automated epileptic seizure detection system. The proposed system provides a class-based compression scheme taking into account the EEG characteristics of the generated traffic, and patient's status.

A. Feature Extraction

The first step in our procedure is generating the Frequency Features (FF) through transforming the gathered EEG data into the frequency domain using FFT [13]. FFT is considered as a classic frequency analysis method with complexity $O(N \log N)$. The main advantage of leveraging FF is their immune to signal variations resultant from electrode placement or physical characteristics of patients [14]. As shown by the signal behavior in Figure 2, the normal/abnormal EEG classes under study demonstrate different mean, median, and amplitude variations after FFT. Furthermore, it is crucial to consider as relevant features the Root Mean Square (RMS) to distinguish between seizures and non-seizure events, and Signal Energy (SE). RMS and SE are good signal strength estimators in different frequency bands. We therefore select the following five frequency features:

Mean absolute value

$$\mu = \frac{\sum_{k=1}^{N} |x_f(k)|}{N} \tag{1}$$

Median

$$M = \begin{cases} |x_f(\frac{N+1}{2})|, & \text{if } N \text{ is odd} \\ \frac{|x_f(\frac{N}{2})| + |x_f(\frac{N}{2}+1)|}{2}, & \text{if } N \text{ is even} \end{cases} \tag{2}$$

Peak absolute value

$$P = \max(|x_f|) \tag{3}$$

Root mean square

$$R = \sqrt{\frac{1}{N} \sum_{k=1}^{N} |x_f(k)|^2} \tag{4}$$

Signal energy

$$E = \sum_{k=1}^{N} |x_f(k)|^2 \tag{5}$$

where $|x_f|$ is the absolute value of input EEG signal x after FFT, and N is the number of samples, namely $N = 4096$ samples.

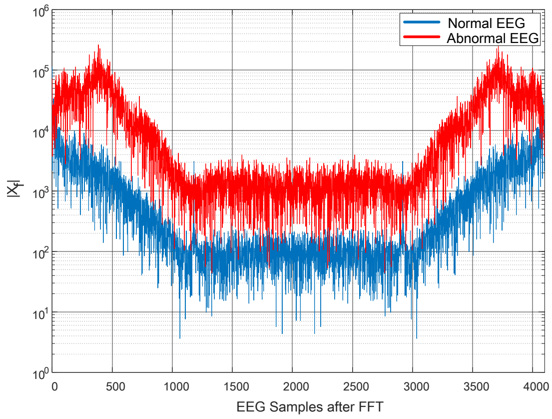

Fig. 2. Normal/Abnormal EEG signals after FFT.

B. Edge-based Classification

The second step in our procedure is proposing a reliable, edge-based classification algorithm for epileptic seizure detection. We leverage the extracted frequency features to perform an initial classification on normal/abnormal EEG patterns at the network edge (i.e., PDA). The advantages of such classifier is two-fold. First, by knowing the data class at the transmitter, we can enhance the performance of our compression technique through increasing/decreasing compression threshold without violating distortion threshold imposed by the application. Second, in case of emergency, a quick alert and notification can be initiated based on this EC, which saves significant delays resulting from transmitting then classifying the data at the MHC.

The fundamental question now is: How can we obtain a simple yet accurate classification rule using generated FF to differentiate between normal/abnormal EEG patterns? First, we define a classification indicator λ that combines generated FF as follow

$$\lambda = \mu + M + P + R + E. \tag{6}$$

Second, we define a classification rule using the obtained λ to detect the abnormal pattern of the sensed EEG data, where λ will represent the condition part of the rule, while the status of the patient S will represent its consequent part. Accordingly, we obtain through our experiments the following classification rule

$$S = \begin{cases} \text{Normal}, & \text{if } \frac{\lambda}{\alpha} \leq \gamma \\ \text{Abnormal}, & \text{if } \frac{\lambda}{\alpha} > \gamma \end{cases} \tag{7}$$

where α is a scaling factor, and γ is the classification threshold that is obtained during an offline training phase based on classification indicator values for different signals behavior, as will be shown in the simulation results. This classification rule will be exploited to obtain the status of the patient at the PDA to be used in our class-based compression scheme.

C. Adaptive Class-based Compression

The third step in our procedure is developing an adaptive class-based compression technique through controlling the transmitted data size based on patient's status (i.e., class of the data). After transforming the collected EEG data into the frequency domain, the FFT returns N complex numbers (coefficients) corresponding to the N input samples. However, the generated spectrum is conjugate even (i.e., two-sided spectrum); the magnitude spectrum is symmetrical (see Figure 3). Leveraging such EEG signal characteristics in the frequency domain, we can transmit one-sided spectrum, thus the output after the FFT will be $N/2$ complex coefficients. Furthermore, the coefficients that are below a predefined threshold δ can be discarded without much signal quality loss. Accordingly, by properly adjusting such a threshold we can control the length of the output data generated from CbC and, thus, the compression ratio of the CbC.

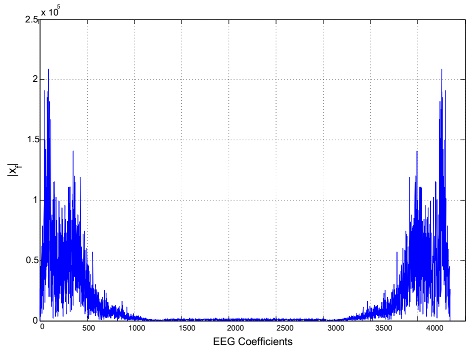

Fig. 3. An example of abnormal EEG signal coefficients after FFT.

At the receiver side, the reconstruction and data recovery can be applied using IFFT to retrieve the original signal. To quantify the difference between the original and the reconstructed signal, the signal distortion is evaluated as

$$D = \frac{\|x - x_r\|}{\|x\|} * 100, \tag{8}$$

where x is the original signal, and x_r is the reconstructed one.

The question now is: How can we obtain the threshold δ? It is well-known that, for lossy compression techniques, there is always a tradeoff between increasing compression ratio and decreasing distortion. Hence, it is crucial to maximize compression ratio, for saving energy consumption, without violating application QoS requirement (i.e., distortion). To consummate this, we propose an Automated

Seizure Detection (ASD) algorithm. This algorithm enables the PDA to automatically update its compression threshold, hence the compression ratio, based on the class and the characteristics of the gathered data such that it can satisfies application distortion constraint. Leveraging the extracted FF, ASD algorithm can detect normal/abnormal EEG classes, hence updates threshold δ as follows:

$$\delta = \begin{cases} \mu \cdot \frac{\lambda}{\alpha} \cdot \zeta, & \text{if } S \text{ is Normal} \\ \mu \cdot \frac{\lambda}{\beta} \cdot \zeta, & \text{if } S \text{ is Abnormal} \end{cases} \tag{9}$$

where ζ is an optional tuning parameter for a user to increase/decrease compression ratio, α and β are normalizing parameters for normal and abnormal EEG pattern, respectively. The main steps of the proposed ASD algorithm are summarized in Algorithm 1.

Algorithm 1 Automated Seizure Detection (ASD)

Input:
  x: Collected EEG signal.
Compute x_f.
From x_f, generate frequency features using equations (1)-(5).
Compute λ, as in (6).
if $\frac{\lambda}{\alpha} \leq \gamma$ **then**
  Normal EEG pattern detected.
  Update the value of δ as in (9).
else
  Abnormal EEG pattern detected, generate emergency notification signal.
  Update the value of δ as in (9).
end if
Compress and transmit x_f using obtained δ.

We remark here that leveraging the proposed edge-based classifier with CbC enables the PDA to obtain the best threshold that can be used at the CbC based on the class of the data, while satisfying application QoS requirements. Unlike the other threshold-based techniques that neglect the class of the data and define a threshold taking the conservative approach (i.e., fixing the value of the threshold corresponding to the maximum-obtained distortion for normal EEG pattern), which decreases the obtained compression ratio for abnormal EEG pattern, or using greedy approach (i.e., fixing the value of the threshold corresponding to the maximum-obtained distortion for abnormal EEG pattern), which results in high distortion for normal EEG pattern, as will be shown in simulation results. Thus, using the proposed ASD algorithm, the PDA can automatically reconfigure its compression ratio based on the characteristics of the gathered data through adjusting its threshold, hence, saves a significant amount of transmitted data while maintaining distortion constraint.

IV. Simulation Results

In our simulation, the EEG dataset in [15] is used. We considered three sets, denoted A,B, and E, each containing 100 EEG records of 23.6-sec duration and sampling rate 173.61 Hz. Sets A and B (i.e., normal class) represent healthy subjects with eyes opened (A) and closed (B), respectively, while set E (i.e., abnormal class) originated from EEG archive of presurgical diagnosis and contained seizure activity.

First, We assess the performance of the proposed edge-based classifier, and illustrate the effect of γ on the obtained Classification Accuracy (CA). Figure 4 shows the effectiveness of the proposed classification indicator λ to differentiate between normal/abnormal EEG classes. Thus, by properly adjusting the value of the classification threshold γ[1], the PDA can obtain very high CA. Figure 5

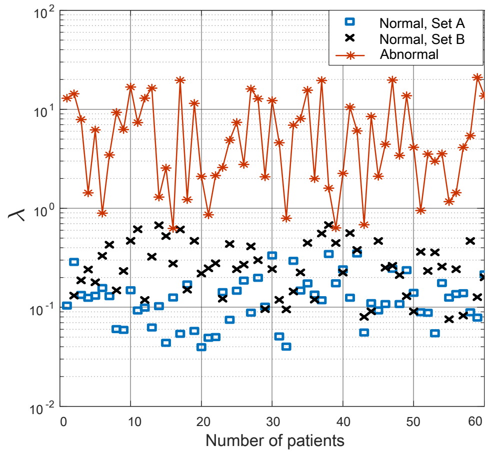

Fig. 4. Classification indicator behavior for normal/abnormal EEG patterns.

depicts the obtained CA using our classifier with changing γ while considering 300 EEG records (200 for normal EEG signals, and 100 for abnormal EEG signals). At low γ, the classifier tends to consider most of the normal EEG signals as an abnormal signals, which results in maintaining low CA. However, by adjusting the value of γ, the classifier obtains high CA. The results show that, the proposed classifier could achieve 98.3% CA with the optimal-obtained γ, which is around 0.65. Accordingly, we could efficiently detect the emergency case (i.e., abnormal EEG signals) with very high accuracy using the proposed edge-based classifier.

Next, we assess the performance of the proposed CbC technique compared to threshold-based Discrete wavelet transform (DWT) technique [16]. In general, by increasing the compression ratio η, the distortion increases for both CbC and DWT. However, in CbC, at the same compression ratio, we could maintain less distortion than DWT (see Figure 6). It is worth also mentioning here that through varying the Daubechies families, or decomposition levels of the DWT, it can maintain less distortion, however, it comes at the expense of increasing the computational

[1]We remark here that γ can be obtained during an offline training phase leveraging the values of λ for different EEG classes.

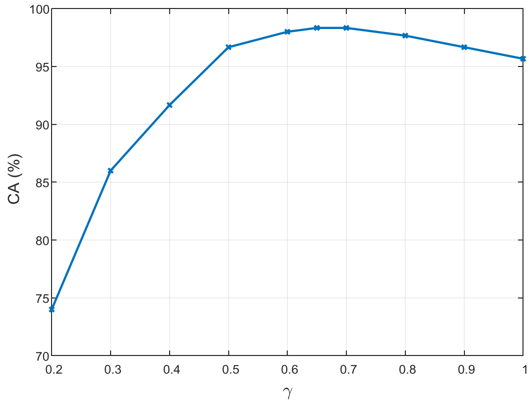

Fig. 5. Effect of varying γ on obtained classification accuracy.

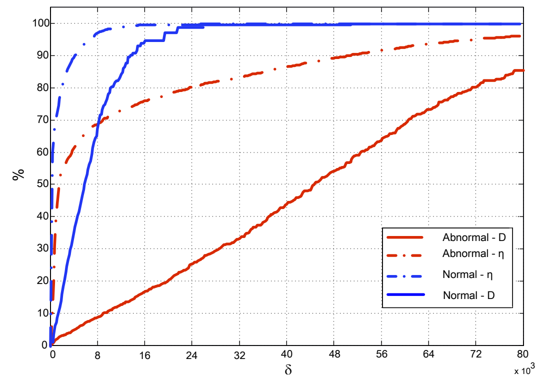

Fig. 7. Effect of varying the threshold δ on c_r and PDR for different EEG classes.

complexity, which may not be acceptable for such battery-operated devices. Furthermore, we remark here that for the same compression ratio, the value of the distortion varies based on the class of the data. Thus, by knowing the class of the data at the PDA, it can increase its compression ratio while maintaining the required distortion threshold. It is clearly illustrated in Figure 7. As mentioned, in our CbC technique we control the transmitted data length by changing the threshold δ: as δ increases, η increases, at the expense of increasing the distortion. As shown in Figure 7, at the same δ, the distortion D and η vary according to the EEG class. Hence, to obtain the optimal η that maintains application distortion threshold, the PDA should properly adjust δ based on the detected EEG class. Thus, it is important to have an initial-swift classifier at the PDA to obtain the proper compression threshold based on the class of the data.

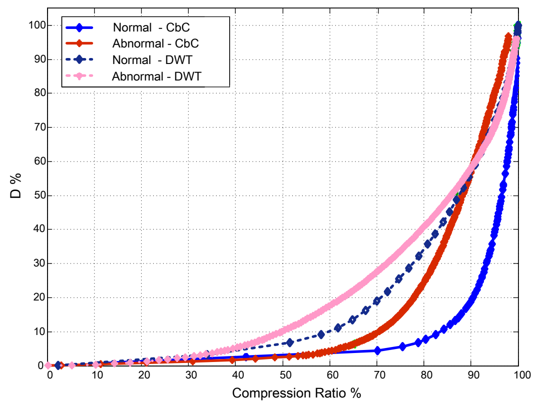

Fig. 6. Distortion variation with compression ratio for proposed CbC technique and DWT.

Finally, Figure 8 illustrates the main advantage of the proposed ASD scheme compared to fixed threshold compression scheme, and assesses the ability of our scheme to adapt to varying EEG records. In this figure, we present the average obtained distortion and compression ratio for each EEG set (i.e., set A, B, and E, respectively) over the time. Also, it is assumed that there is a constraint on the maximum obtained distortion, i.e., $D \leq 7\%$. We compare the ASD algorithm with two fixed threshold schemes: Conservative and Greedy compression schemes. In Conservative scheme, we consider that the threshold δ is fixed and identified using normal EEG class, such that the obtained distortion at normal EEG class is below the predefined distortion constraint. In Greedy scheme, δ is fixed such that the obtained distortion at abnormal EEG class is below the predefined distortion constraint. ASD algorithm obtains compression threshold δ taking into consideration the class and characteristics of the compressed data, unlike the other algorithms that consider fixed δ over the time. Thus, with changing collected EEG classes, ASD algorithm can reduce transmitted data size without violating distortion constraint. On the contrary, fixing δ at low value (as in Conservative approach) maintains distortion constraint at the expense of obtaining very low compression ratio for abnormal class. While fixing δ at high value (as in Greedy approach) achieves high compression ratio at the expense of violating distortion constraint for normal class (see Figure 8).

V. Conclusion

In this paper, a remote monitoring EEG system is considered. In particular, we proposed a class-based data reduction technique that can be used for epileptic seizure detection. The proposed technique is applied at the PDA level in order to reduce the amount of transmitted data. In this context, we proposed a highly accurate classification scheme for epileptic seizure detection using edge-based swift classifier. Using this classifier, we can obtain patient's state before transmitting its medical data. We found that, by obtaining the class of the data at the PDA, our solution is very effective in reducing the amount of data while maintaining the application distortion threshold. Our results also show that the proposed swift classifier and data reduction approach provides a high level of classification accuracy and data reduction that outperform the state-of-

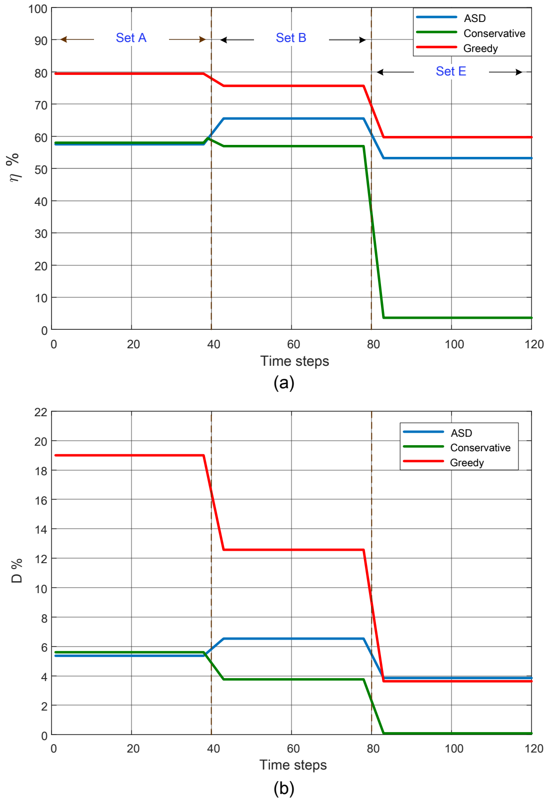

Fig. 8. Temporal evolution of the system performance, (a) compression ratio and (b) distortion, with varying EEG records.

the-art compression-based reduction, with the advantage of reconstructing the signal at the receiver side with minimum distortion.

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