In-Network Data Reduction Approach Based On Smart Sensing

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***Abstract*—The rapid advances in wireless communication and sensor technologies facilitate the development of viable mobile-Health applications that boost opportunity for ubiquitous real-time healthcare monitoring without constraining patients' activities. However, remote healthcare monitoring requires continuous sensing for different analog signals which results in generating large volumes of data that needs to be processed, recorded, and transmitted. Thus, developing efficient *in-network* data reduction techniques is substantial in such applications. In this paper, we propose an in-network approach for data reduction, which is based on fuzzy formal concept analysis. The goal is to reduce the amount of data that is transmitted, by keeping the minimal-representative data for each class of patients. Using such an approach, the sender can effectively reconfigure its transmission settings by varying the target precision level while maintaining the required application classification accuracy. Our results show the excellent performance of the proposed scheme in terms of data reduction gain and classification accuracy, and the advantages that it exhibits with respect to state-of-the-art techniques.**

***Index Terms*—Mobile-Health system, Fuzzy data reduction, EEG signals, conceptual learning, wavelet compression.**

I. Introduction

Wireless remote healthcare monitoring services can significantly enhance traditional healthcare systems, especially in a variety of pre-hospital emergency care situations and for patients that are located in geographically remote areas [1]. Advances in wireless communication and sensor technologies have facilitated the implementation of effective mobile-health (m-health) systems, without constraining patients' activities [2]. However, neurologically-oriented m-health applications are still very challenging, as they require recording, processing and wireless transmission of large volumes of data. For instance, high-quality EEG devices can consist of up to 100 electrodes. The sampling rate at each electrode can be as high as 1000 samples/s, which, representing each sample by 2 bytes, results in a data rate of 1600 kbps per single patient. This clearly puts a significant load on the system design in terms of storage space, processing capabilities, and transmission power.

Accordingly, reducing the amount of data originating from sensing nodes is essential for such systems. This is particularly true considering that m-health systems typically consist of several battery-operated devices that need to run for a long time without replacement. Thus, a promising approach is to perform local in-network processing on the raw data before their transmission. This can be done by compressing the gathered data, or by transmitting only some features of the signals that are pertinent to the specific application [3]. Existing solutions taking either one of these approaches [4][5][6] vary in the lossiness, computational complexity, and the waveform transformation that is applied (e.g., discrete cosine transform (DCT), vector quantization, and repetition count compression methods [4]). However, the intensive computational complexity of such techniques might make the in-network processing on battery-operated devices impractical.

In this paper, we focus on EEG signal, which is the main source of information on brain electrical activity and plays an important role in the diagnosis of several brain disorders (such as epileptic disease, brain death, tumors, and stroke) [7]. EEG signal also plays a primary role in Brain Computer Interface (BCI) applications [8]. In this context, we propose a fuzzy data reduction technique to obtain the most representative EEG samples and neglecting redundant ones without loss of knowledge. To this end, we use fuzzy Formal Concept Analysis (FCA), which has been recently developed and applied in many fields such as learning, knowledge acquisition, and information retrieval [9][10][11]. In FCA, crisp binary data is represented as a two-entry table in a *(object, property)* relational database, whose cells take value either 0 or 1 according to whether the object has a certain property or not. If the properties are represented in a fuzzy way, the table cells will contain the degree to which these properties relate to the objects (e.g., 'high', 'medium', 'low'). (More details and related work in FCA and Fuzzy theory can be found in [12][13][14].) We exploit this formalism to identify the most related non-redundant samples, such that the association rules extracted from such data are identical to the ones that can be

This work was made possible by GSRA grant # GSRA2-1-0609-14026 from the Qatar National Research Fund (a member of Qatar Foundation). The findings achieved herein are solely the responsibility of the authors.

extracted from the original dataset. We call this approach *smart sensing*, since instead of transmitting the whole sensed data to the receiver side, we reduce the amount of data originating from sensing nodes and transmit only the most discriminant samples. To the best of our knowledge, performing fuzzy data reduction at the transmitter side to obtain and transmit the most representative samples of EEG data has not been studied before. The proposed scheme is evaluated through simulation and compared to different data reduction techniques, discussing the tradeoff between transmitted data length and classification accuracy. We remark here that aspects purely related to wireless transmission and channel characterization are not within the scope of this paper; the reader is referred to [15] for such work.

The rest of the paper is organized as follows. Section II describes the system model. Section III presents the proposed smart sensing scheme, while Section IV introduces adaptive DWT-based compression and frequency-domain feature extraction. Section V shows our performance evaluation and, finally, Section VI concludes the paper.

II. System Model

In this paper, we consider epileptic seizure detection as an application of EEG-based diagnosis. EEG signal is the main source of information carrying valuable information describing epileptic seizure status. The dynamic characteristics of EEG signals are used to differentiate between healthy subjects and patients diagnosed with epileptic disease. We consider the wireless EEG monitoring system shown in Figure 1, where the Personal/Patient Data Aggregator (PDA) collects data from the sensors, possibly processes it, and forwards it to the M-Health Cloud (MHC). The latter can further process the data and store it. We remark here that the presented data reduction techniques can be implemented at the sensor or at the PDA level, in order to reduce the size of the transmitted data, as well as at the MHC level with the aim to reduce the amount of data to be stored and facilitate the data retrieving process.

The main modules considered in this model are amplifier and sampling, smart sensing component, Discrete Wavelet Transform (DWT) compression, Feature Extraction (FE) components, quantization, and encoding of the quantized data. Herein, we implement three different options at the transmitter: *(i)* sending raw EEG data without processing, *(ii)* compressing and forwarding EEG data, or *(iii)* sending EEG features (i.e., frequency-domain features). In feature extraction, we start from the initial-gathered data and obtain values (features) that are informative, non-redundant, and pertinent epileptic to seizure detection. In this paper, we consider Frequency-Domain Features Extraction (FD-FE) by transforming EEG data into frequency domain, and forwarding the whole or part of this data to the receiver side based on the required classification accuracy and power consumption. The drawback of FE techniques is their irreversibility: we cannot retrieve the original data at the receiver side. In the case of Compression-based Reduction (CBR), we apply the DWT-based compression with reconfigurable or adaptive compression ratio to control the size of the transmitted data. The disadvantage of such lossy compression technique is that at the receiver side a decompression technique should be implemented to retrieve the data, and the reconstructed signal will have some distortion compared to the original one. In the proposed Smart Sensing (SS) approach, instead, we obtain and transmit the most representative non-redundant data without loss of knowledge. In other words, we save in transmitted data size by neglecting redundant data, while sending original-discriminant samples. At the MHC, according to the transmitted data, signal reconstruction, feature extraction, classification and distortion evaluation can be performed to evaluate the patient's status.

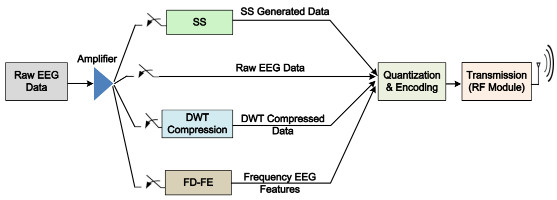

Fig. 1. System model under study.

We leverage the EEG dataset in [16] considering three classes of patients, namely, Healthy, Non-active, and Active. Class *Healthy* represents healthy subjects, class *Non-active* represents non-active patients diagnosed with epileptic disorder, while class *Active* represents patients with active epileptic seizure, as shown in Figure 2. Each class in the considered dataset contains data that refer to 100 patients (rows), and for each patient there are 4096 samples (columns).

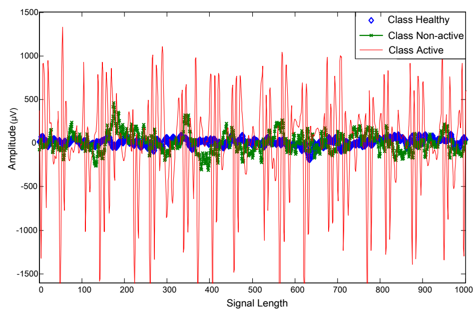

Fig. 2. Three classes of EEG signal in the time domain.

III. Smart Sensing Data Reduction Approach

The fundamental question here is the following: How can we obtain the most representative EEG samples that minimize data size without incurring in any knowledge loss? By knowledge we mean the set of association rules that can be extracted from the initial data. To answer the above question, we propose a *smart sensing* approach that leverages fuzzy data reduction. Specifically, we exploit FCA to identify the samples that can be removed from the initial fuzzy binary context, at a given precision level δ, and transmit only the samples that are representative of the whole set.

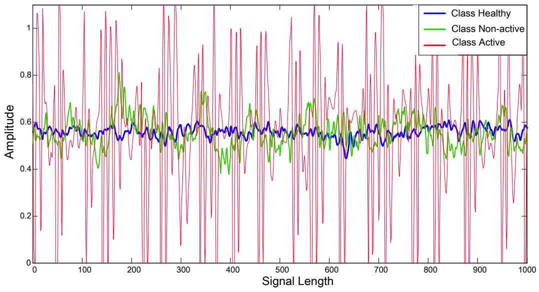

Fig. 3. Fuzzification of the original EEG signal.

Accordingly, we first convert the gathered EEG samples into a fuzzy binary context R by normalizing them with respect to their maximum value, as shown in Figure 3. A *fuzzy Binary context* (or fuzzy binary relation) is a fuzzy set given by the product of a set of objects, O, and a set of properties, P, i.e., $U = O \times P$, where U is called universe of discourse. If we apply our method at the MHC level (for efficient data representation and storage), the data gathered from different patients is represented as a fuzzy binary context by taking the set of patients as set of objects O, and the set of samples for each patient as the set of properties P. Instead, when the algorithm is executed at the PDA or sensor level with the aim to reduce the size of transmitted data, the sensed data for each individual patient is first divided into batches, with each batch containing a fixed number of samples. Then, a fuzzy binary context is obtained defining O as the set of batches, and P as the set of samples in each batch. Then, for each object, we verify whether this object is equivalent to any set of objects in the initial fuzzy binary context or not. The equivalent objects are removed so that a reduced output fuzzy context $\tilde{R}$ is obtained (see Algorithm 1).

In more details, we perform the following steps.

Step 1: For a given object x, find the set of equivalent objects S_x using function $h_\delta : B \to A$, with $B \subset P$ and $A \subset O$. Specifically, denoting by B the fuzzy set of properties associated to x, we identify S_x as the set of objects that satisfy the set of properties B, with precision level δ. More formally, $S_x = h_\delta(B) = \{y \in O | b \in P \Rightarrow \mu_B(b) \rightarrow_L \mu_R(y,b) \geqslant \delta\}$, where $\rightarrow_L$ denotes the Lukasiewicz implication [17], i.e., for $u, v \in [0,1]$, $u \rightarrow_L v = \min(1, 1-u+v)$, $\mu_B(b)$ is the degree of membership (weight) of property b, $\mu_R(y,b)$ is the degree of association between an object y and a property b.

Step 2: Find the minimum of the set S_x using $f(S_x) = \{b/\gamma | \gamma = \min\{\mu_R(y,b) | y \in S_x\}, b \in P\}$, where $f(S_x)$ is the fuzzy set of the properties shared by the objects in S_x.

Step 3: If for every property of the objects in S_x, the associated weight is smaller than the weight of the corresponding property of object x, then x can be removed. This means that object x can be replaced by the objects in S_x. A numerical example with $\delta = 0.7$ is illustrated in Figure 4, while the main steps of our SS algorithm are presented in Algorithm 1.

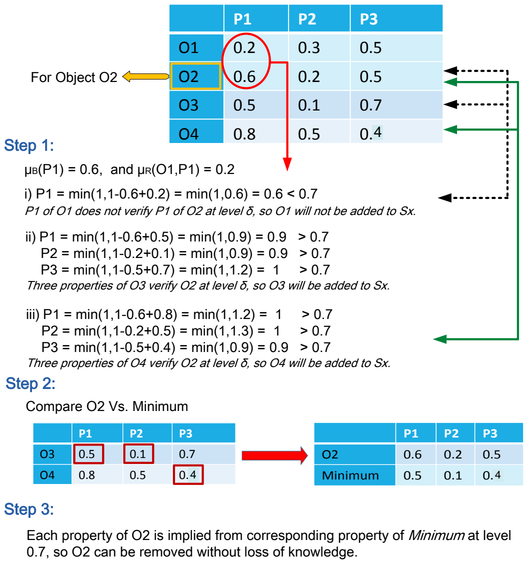

Fig. 4. An example of objects reduction using Lukasiewicz implications.

We remark here that: 1) Varying δ $(0 \leq \delta \leq 1)$ allows for the generation of a different number of fuzzy objects. The smaller δ, the more fuzzy objects are neglected, which results in less precision level. 2) Considering for example that the algorithm is executed at the sensor or PDA level, its computational complexity is $O(N \cdot K)$ where N is the number of original samples and K is the number of data batches that are created.

IV. Adaptive Compression and Feature Extraction Solutions

Several related works have explored the use of data reduction techniques on EEG signals, such as compression techniques, dynamic channel selection, and discontinuous recording [3]. However, the computational complexity needed for processing the signals and the resultant signal distortion can severely impact the classification performance. In this context, we consider two reduction schemes: CBR based on DWT compression, and frequency-domain feature extraction. We then use these as benchmark techniques and compare their performance to that of our proposed SS scheme.

Algorithm 1 Smart Sensing (SS) algorithm

Initialization:
R: initial fuzzy context,
$\tilde{R}$: output fuzzy context
δ: precision level
$\tilde{R} = R$
Data acquisition
Transform collected EEG samples into fuzzy binary context R
for all objects in R **do**
  Find the set of properties verified by the object x_i
  Find the set of objects S_x verifying the required values for the properties of x_i at precision level δ
  if the objects in S_x satisfy the same properties of x_i at precision level δ **then**
    Remove x_i from $\tilde{R}$
  end if
end for
Output:
Reduced output fuzzy context $\tilde{R}$.

A. DWT-based Adaptive Compression

Herein, we focus on threshold-based Discrete wavelet transform (DWT) approach for EEG data compression. The EEG signals are analyzed using one of the wavelet families (such as the Daubechies family), [18][19]. For an EEG signal x, we thus have:

$$x = \Psi \alpha_w \tag{1}$$

where Ψ is the wavelet family basis, and α_w is the vector of wavelet domain coefficients. In the multi-stage DWT, these coefficients are calculated recursively on multilevel wavelet decomposition (i.e., decomposition levels). Moreover, the computation of DWT involves filtering, where the wavelet filter length of the utilized wavelet family is obtained as $F = 2\kappa$, with κ being the wavelet family order. The computational complexity of such compression process, for an N-dimensional EEG signal, is calculated as:

$$C_{DWT} = F \cdot N \sum_{l=0}^{L} \frac{1}{2^l} \tag{2}$$

where L is the number of decomposition levels [18].

Using threshold-based DWT, the coefficients that are below a predefined threshold can be zeroed without much signal quality loss [20]. Accordingly, by properly setting such a threshold we can control the number of output samples generated from DWT and, thus, the compression ratio of the DWT. The compression ratio is evaluated as

$$C_r = 1 - \frac{M}{N} \times 100 \tag{3}$$

where M is the number of output samples generated after DWT, and N is the number of the original samples.

The encoding distortion is measured by the percentage Root-mean-square Difference (PRD) between the recovered EEG data and the original one, as

$$D_s = \frac{\|x - x_r\|}{\|x\|} * 100, \tag{4}$$

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

It is worth mentioning here that by leveraging such adaptive compression technique, the PDA can effectively reconfigure its transmitted data length by adjusting the encoder parameters to meet the constraints on energy consumption as well on the classification accuracy at the receiver side.

B. Frequency-Domain Feature Extraction (FD-FE)

Reliable, yet energy-efficient, epileptic detection can be also achieved by performing feature extraction (FE) and classification at the PDA level: instead of transmitting the raw/compressed EEG data, a set of epileptic-related features can be selected to be transmitted. However, a serious drawback of this approach is that raw data cannot be retrieved at receiver side, which may be unacceptable for some applications. Here we present a feature extraction technique in the frequency domain (FD), which we later compare to the SS scheme in terms of overall classification accuracy and feature vector length.

In FD-FE, the gathered EEG data is transformed into the frequency domain using Fast Fourier Transform (FFT) [21]. FFT is considered as a classic frequency analysis method with complexity $O(N \log N)$. In the frequency domain, we observe that the different EEG classes have different amplitude range (see Figure 5), which facilitates the classification task compared with the case of time domain analysis (see Figure 2).

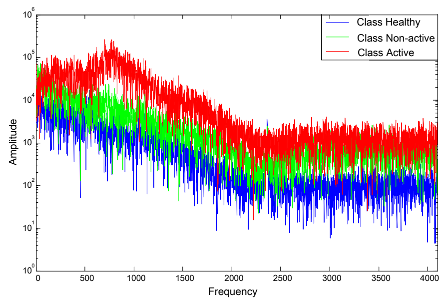

Fig. 5. Three classes of EEG signal in the frequency domain.

After that, the frequency spectrum of the EEG signal can be segmented into multi-subbands, each one has a certain number of frequency components. Different subsets of these sub-bands can be selected as feature vector [22]. Thus, if the spectrum is divided into s sub-bands, we will have 2^s different subsets that can be transmitted, which results in complexity $O(2^s)$. Typically, the EEG spectrum is segmented into five frequency sub-bands named α, β, σ, γ, and θ with frequency ranges $8-12$, $12-32$, $0.2-3$, >32, and $3-8$ Hz, respectively [23]. Thus, we can control the length of the transmitted data by sending different subsets of these frequency sub-bands: increasing the number of transmitted frequency subsets, the length of the transmitted data grows, which in turn increases energy consumption while maintaining high classification accuracy at the receiver side.

V. Performance Evaluation

A. Environment Setup

We consider 300 patients in our experiments. For each patient, 4096 samples are gathered. Then, either the sensor or the PDA decides to send the raw data, representative samples of the data using SS, some features of this data (i.e., frequency features), or compressed data, to the M-Health Cloud (MHC). The MHC evaluates the EEG feature extraction, classification and distortion so as to detect the status of the patients. WEKA explorer, with Random Forests classifier and cross validation, is used for classification at the MHC [24].

B. Simulation Results

As mentioned, in our SS algorithm we can control the number of transmitted samples by changing δ: as δ decreases, more fuzzy objects are eliminated, which results in less precision level and greater data reduction, as shown in Table I. In particular, the results show that a significant decrease in data size can be obtained for $\delta < 0.6$. It is also worth mentioning here that the results depend on the set of data that are initially considered. For example, at the sensor or PDA level, for class Healthy or Non-active, the number of samples is less than 70 for $\delta < 0.8$, while for class Active there are 400 samples for $\delta < 0.4$. At the MHC, when we consider the collective data from three classes patients, we have less than 430 samples, per patient, when $\delta < 0.4$, as shown in Figure 6. We remark here that the proposed SS scheme obtains the transmitted data size taking into consideration the data class (it can be considered as a class-based reduction), unlike CBR and FD-FE approaches. Thus, at normal condition (i.e., class Healthy or Non-active), we can significantly reduce data size without incurring any knowledge loss, while in the case of emergency, the generated data size increases due to the rapid variations of the signal in this case.

In FD-FE, the EEG signal is segmented into multiple sub-bands, each sub-band has a certain number of frequency components. Different subsets of these sub-bands can be selected as feature vectors, in order to control the length of the transmitted data (see Table I). On the other hand, in CBR we can reduce the size of transmitted data, hence the energy consumption, by increasing the compression ratio C_r, but at the expense of an increased signal distortion. On the contrary, the greater the filter length F, the more details are maintained in the sampled signal, which leads to a smaller distortion (see Figure 7). These two conflicting trends underline that there always exists a tradeoff between energy consumption and encoding distortion.

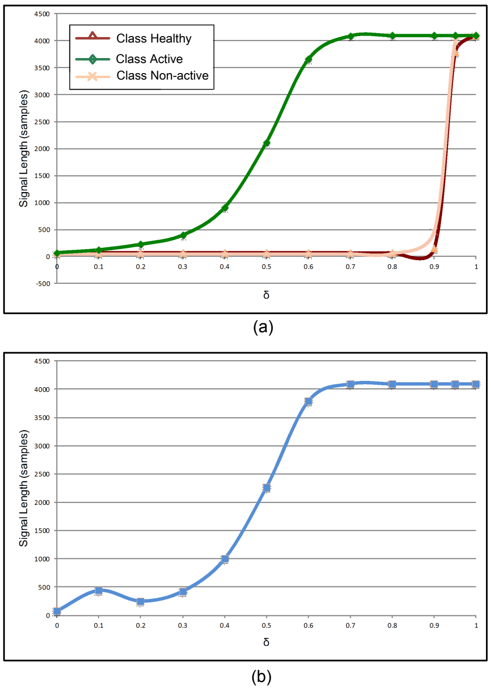

Fig. 6. Generated number of samples with varying precision level δ, (a) at sensor or PDA level, (b) at MHC level.

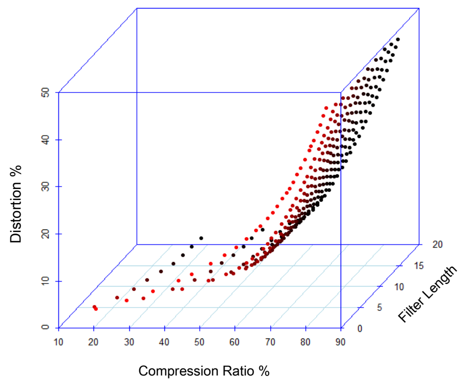

Fig. 7. CBR method: relation among encoding distortion, compression ratio and wavelet filter length.

Next, we assess the performance of FD-FE and CBR techniques compared to that of the proposed SS algorithm. Results are shown in Figure 8 and Table II in terms of

TABLE I
GENERATED NUMBER OF SAMPLES USING FD-FE AND SS

Frequency sub-bands γ	β	α	θ	σ	Signal length in FD (samples)	SS precision level δ	Signal length (samples)
0	0	0	0	1	133	0.0	78
0	0	0	1	0	236	0.1	442
0	0	0	1	1	369	0.2	254
0	0	1	1	1	557	0.3	427
0	1	1	1	1	1501	0.4	1001
1	0	0	0	1	2719	0.5	2269
1	0	1	0	0	2774	0.6	3793
1	1	1	1	0	3954	0.7	4096
1	1	1	1	1	4087	1.0	4096

classification accuracy and transmission energy consumption, respectively. In general, by increasing the length of the transmitted signal, classification accuracy at the MHC increases for both FD-FE and SS, while it is almost constant for CBR (see Figure 8). This happens because in SS we transmit the most representative samples to the MHC, thus with increasing δ, the transmitted data size increases, which results in a better accuracy at the MHC. The same behavior holds for FD-FE: an increased transmitted signal length facilitates the classification process at the MHC (see Figure 8). On the contrary, in CBR the transmitted data size is just a function of the compression ratio and is totally blind to the importance of the eliminated/transmitted samples. It follows that increasing the transmitted data size does not necessarily improve the classification accuracy as redundant samples may be added.

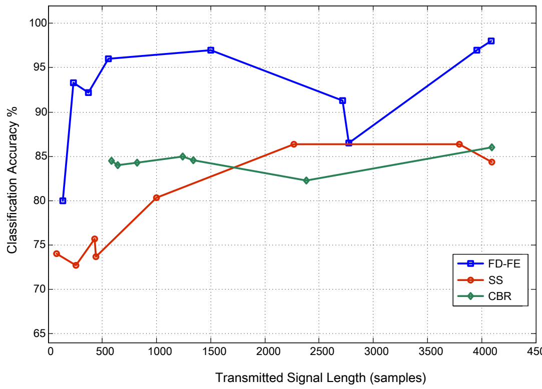

Fig. 8. Classification accuracy versus transmitted signal length.

Regarding transmission energy consumption, we leverage the energy consumption model presented in [25] and show the results in Table II. As energy consumption increases with the transmitted signal length, our study can be used to identify the best tradeoff between classification accuracy and energy consumption, based on application requirements, patient's status, and energy availability at the PDA.

In conclusion, on one hand, our SS algorithm surpasses the lossy CBR technique by achieving higher classification accuracy while maintaining same energy consumption. On the other hand, it outperforms both FD-FE and CBR techniques through:

1) Implying no loss of knowledge, as it selects and transmits the most representative samples (i.e., raw data) while neglecting the redundant samples.
2) Taking into consideration the rapid and irregular variations of the data, as well as the class of the data.

As far as FD-FE is concerned, this achieves better performance in terms of classification accuracy compared to SS and CBR. However, it is irreversible at the MHC: the original EEG signal cannot be reconstructed from its features, which may not be acceptable for many applications.

TABLE II
TRANSMISSION ENERGY CONSUMPTION VS. CLASSIFICATION ACCURACY

Transmission Energy (nJ)	CA % FD-FE	SS	CBR
2.3	95.7	77	84
4	96	81	84.5
7	95.4	83.7	83.7
9	93	86.8	82
11	87	87	83
13.3	92.5	87	84.2
15.5	97	87.2	85.4

VI. CONCLUSION

We addressed a wireless EEG monitoring system, and investigated different data reduction techniques that can be used for epileptic seizure detection. In particular, we proposed a technique, named SS, which is based on reduced fuzzy formal context. SS can be applied at sensor or PDA level in order to reduce the amount of transmitted data, or at the mobile health cloud to reduce the size of stored data. We found that, by selecting only the most representative EEG samples that are pertinent to seizure detection, our solution is very effective in reducing the amount of data while generating the same knowledge that can be extracted from the initial data set. Our results also show that the proposed SS scheme provides a level of classification accuracy and data reduction that is comparable to that of feature extraction, with the important advantage that SS allows for EEG signal reconstruction at the receiver side. When compared to compression-based reduction, given the data size, SS achieves a much higher classification accuracy.

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