Energy-Aware Cross-Layer Optimization for EEG-based Wireless Monitoring Applications

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***Abstract*—Body Area Sensor Networks (BASNs) for healthcare applications have gained significant research interests recently due to the growing number of patients with chronic diseases requiring constant monitoring. Because of the limited power source and small form factors, BASNs have distinguished design and operational challenges, particularly focusing on energy optimization. In this paper, an Energy-Delay-Distortion cross-layer design that aims at minimizing the total energy consumption subject to data delay deadline and distortion threshold constraints is proposed. The optimal encoding and transmission energy are computed to minimize the total energy consumption in a delay constrained wireless body area sensor network. This cross-layer framework is proposed, across Application-MAC-Physical layers, under a constraint that all successfully received packets must have their delay smaller than their corresponding delay deadline and with maximum distortion less than the application distortion threshold. Due to the complexity of the optimal-proposed solution, sub-optimal solutions are also proposed. These solutions have close-to-optimal performance with lower complexity. In this context, there is complexity/energy-consumption trade-off, as shown in the simulation results.**

***Index Terms*—Wireless healthcare applications, EEG signals, BASNs, Convex optimization, Cross-layer optimization.**

I. Introduction

The rapid increase in the number of people living for years with chronic conditions, that require ongoing clinical management, has increased the importance of electrocardiogram (ECG) and electroencephalogram (EEG) diagnosis systems. Advances in wireless sensing and wearable sensors have made body area sensor networks technology a promising solution, to meet this growing demand, and surpassing opportunity for ubiquitous real-time healthcare monitoring without constraining the activities of the patient [1]. Wireless body area sensor networks consist of tiny nodes in, on, or around a human body to monitor vital signs such as body temperature, activity or heart-rate. These sensor nodes periodically send sensed information to a coordinator node. To reduce energy consumption, it is assumed that all these sensor nodes are in standby or sleep mode until the centrally assigned time slot. There is no possibility of collision within the network, as all communication is initiated by the central node and is addressed uniquely to each node. The conventional wireless sensor network technologies are typically bulky, power hungry and based on MAC protocols such as Bluetooth and Zigbee/IEEE 802.15.4, which are inefficient for such BASNs applications [2]. They also ignore the cross-layer design which optimizes the performance by jointly considering multiple protocol layers. In the past few years, much of the research in the area of BASNs has focused on issues related to wireless sensor designs, sensor miniaturization, signal compression techniques and low-power hardware design [3][4][5][6]. A good review of state-of-the-art hardware, technologies, and standards for BASN was presented in [7].

To the best of our knowledge, the cross-layer design of energy minimization to address distortion constraints for delay sensitive transmission of EEG traffic in BASNs has not been studied before. For example, the authors in [8] investigate the properties of compressed ECG data for energy saving using a selective encryption mechanism and a two-rate unequal error protection scheme. Other researches focus on reducing power consumption at MAC layer by avoiding idle listening and collision [9], or by presenting latency-energy optimization [10]. The authors in [11] developed a MAC model for BASNs to fulfill the desired reliability and latency of data transmissions, while simultaneously maximizing battery lifetime of individual body sensors. For that purpose, a cross-layer fuzzy-rule scheduling algorithm was introduced. However, they ignored the encoding energy and source coding distortion in their model. Security of BASNs also becomes one of the attractive research points [12], due to medical data regulations.

In our model, the sensor nodes transmit the sensed information with dynamic power adaptation technique to their coordinator. This is because the wireless link quality can change rapidly in body area networks, and a fixed transmit power results in either wasted energy (when the channel state is good) or low reliability (when the channel state is bad) [13]. This model is distinct from [14], which assumes that the sensor nodes transmit their information at a constant power to their coordinator. Furthermore, the authors in [14] did not take the source coding distortion nor the encoding energy into consideration.

In this paper, to anatomize, control, and optimize the behavior of the wireless EEG monitoring system under the

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energy constraint, we develop an Energy-Rate-Distortion (E-R-D) analysis framework. This framework extends the traditional distortion analysis by including the energy consumption dimension [4][15]. Using this framework, an Energy-Delay-Distortion cross-layer design that aims at minimizing the total energy consumption subject to data delay deadline and distortion threshold constraints is proposed. This paper proposes cross-layer algorithms that optimize and adapt the transmission energy in physical layer and the encoding energy in application layer, with constraints on the delay, Bit error rate (BER) and application layer distortion. The goal of this paper is to minimize the total energy consumption for healthcare applications in a wireless body-area sensor network. To achieve this goal, different control parameters are optimized across the protocol layers (application, MAC and physical layers). An optimum algorithm to determine the optimal parameters, under a predetermined application distortion threshold and delay deadline for each packet, is first proposed. A less complex, sub-optimal algorithms are also proposed. Based on these algorithms, the optimization problem complexity is reduced by decreasing the number of optimization variables and the number of iterations to solve the optimization problem.

The rest of the paper is organized as follows. Section II describes the system model. Section III introduces the proposed cross-layer design. Section IV introduces the proposed optimization problem and explains the proposed optimum cross-layer algorithm. Section V describes the proposed sub-optimal algorithms. Section VI presents the simulation environment and results. Finally, Section VII concludes the paper.

II. System Model

In this paper, wireless EEG monitoring system, as shown in Figure 1, is considered. We are mainly focusing on the data gathering process from the low-power sensor nodes to the coordinator. Each sensor node is miniature, battery powered and needs to run ideally for days using very low capacity batteries. It is assumed that there are N sensor nodes communicate with a coordinator by using a single-transmit and a single-receive antenna. Although the proposed framework utilizes encoding model for EEG signals, it can be extended to a range of vital signs which are typically at a low data rate e.g., temperature, pressure or heart-rate reading, or at higher data rate such as streaming of electrocardiogram (ECG) signals. We use Time Division Multiple Access (TDMA), which eliminates interference, as a multiple access scheme. At the MAC layer, the coordinator determines the scheduled sensor node and the assigned slots length, according to the requirements of the applications and the channel state, to minimize the total energy consumption.

The general structure of the typical-used EEG encoder is illustrated in Figure 1. The main modules considered are amplifier and sampling, Discrete Wavelet Transform (DWT), quantization and encoding of the quantized DWT coefficients.

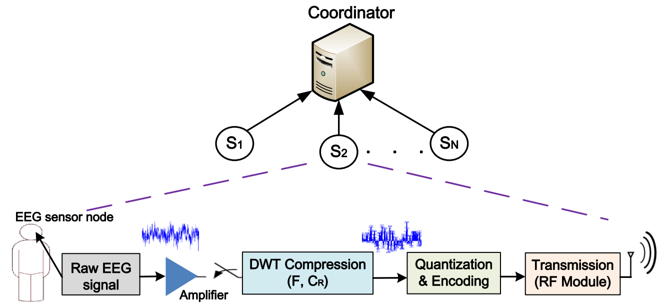

Fig. 1. System Model.

III. Cross-Layer Design

As the wireless sensor nodes are resource constrained (i.e. they have low processing power and limited memory), the gathered data by these nodes is forwarded to a central master node (coordinator) for processing. This central node is significantly less resource and power constrained relative to the wireless sensor nodes. In the proposed cross-layer architecture, different parameters are captured from different layers and passed to the coordinator to find the optimal system parameters for each node, as shown in Figure 2.

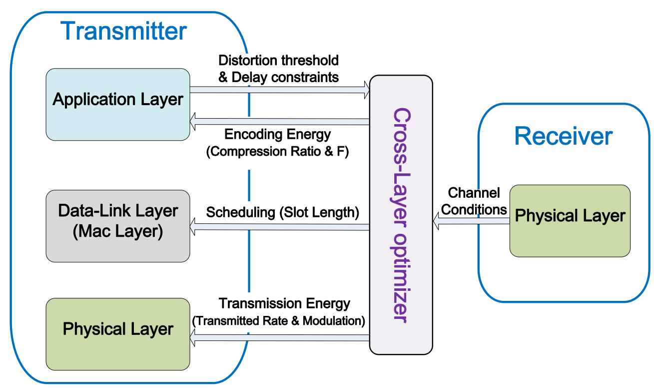

Fig. 2. Cross-layer architecture.

A. Physical Layer

At the physical layer, the coordinator receives, from each transmitter, the application layer constraints (distortion threshold and delay deadline). At the same time, it receives the channel conditions from the receivers. After that, for each scheduled sensor node, it determines the optimal transmitted rate, modulation and transmitted energy. To optimally allocate resources and maintain certain BER, whatever the channel conditions were, adaptive modulation is used where each node can change its transmission power and modulation scheme according to the channel conditions.

It is assumed that the wireless link between the sensor nodes and the coordinator is characterized by a flat fading channel, where $|h_i|$ is the fading channel magnitude for link i. The channel state remains unchanged during each frame period, but varies from frame period to another. The channel state can be characterized by the received signal to noise ratio (SNR), denoted by γ, which defined as

$$\gamma = \frac{P_r}{N_0 \cdot w} \tag{1}$$

where N_0 is the noise spectral density, w is the bandwidth and P_r is the received power. It is assumed that each sensor node and the coordinator are separated by a distance d, and connected by a direct link. A deterministic path loss model is used [16], where

$$P_r = P_t \, \frac{g_t \cdot g_r \cdot \lambda^2}{(4\pi d)^2} = P_t \cdot \alpha \tag{2}$$

where P_t is the transmitted power, g_t is the transmit antenna gain, g_r is the receive antenna gain, λ is the wavelength and α is the overall path loss. For a single link i with bandwidth w, the data rate that can be transmitted is

$$r_i = w \log_2(1 + k\gamma) \tag{3}$$

where $k = -1.5/(\log(5\text{BER}))$ as in [17]. By Substituting from (1) in (3), we can get the received power, as in [18]

$$P_r = \frac{N_0 \cdot w}{k}(2^{r_i/w} - 1). \tag{4}$$

The channel gain x_i is defined as in [18], where

$$x_i = \frac{k \cdot \alpha}{N_0 \cdot w} \, |h_i|^2. \tag{5}$$

From (2), (4) and (5), the required transmission energy to send a data of length l_t with rate r_i is

$$E_t = \frac{P_t \cdot l_t}{r_i} = \frac{l_t}{r_i \cdot x_i}(2^{r_i/w} - 1) \tag{6}$$

B. MAC Layer

It is assumed that each sensor node i generates data with length l_i bits, and the delay deadline for all sensor nodes is the same and equal to D_l. Variable-length TDMA scheme is used [19], where the slots' lengths are optimally assigned to the sensor nodes according to its application requirements and channel state, while minimizing the total energy consumption across the network. In our model, it is assumed that there is only one active link at a time, for a period of time $t_i = l_i/r_i$, to transmit the data of sensor node i.

It is assumed that the network is static or changing very slowly, thus, the optimization can be done in a central node. The optimal slots assignment and scheduling information is then broadcasted to the network. To make it easily implemented in a TDMA scheme, the optimal slot lengths are quantized according to a reference slot length Δ , as in [20]. The whole TDMA frame is slotted into T/Δ slots, and then the number of slots for each sensor node i is assigned by rounding t_i/Δ. As long as the reference slot length Δ is sufficiently small, the performance deviation due to rounding is negligible [21]. Accordingly, in this paper, the requirements of the MAC layer is to get the optimal t_i's for all sensor nodes. The length of the assigned slots is adaptive to the requirements of the application and the channel state to minimize the total energy consumption. Because of using TDMA scheduling, the delay deadline constraint D_l can be satisfied if $\sum_{i=1}^{N} t_i \leq D_l$. There are no queues in the network.

C. Application Layer

There is a distortion/energy consumption trade-off because of using EEG compression techniques. When the EEG compression ratio increases, the amount of data to be transmitted decreases significantly. This will lead to less transmission energy, at the cost of increasing source coding distortion. Therefore, to find the best trade-off solution, we need to develop an analytic framework to model the Energy-Rate-Distortion (E-R-D) behavior of the EEG monitoring system.

1) Encoder Energy Consumption: According to the structure of the typical EEG encoder in Figure 1, the main encoding modules are the Discrete Wavelet Transform (DWT), quantization and encoding of the quantized DWT coefficients. Consequently, the encoding energy consumption is evaluated as

$$E_p = E_{DWT} + E_Q \tag{7}$$

where E_{DWT} is the energy consumed in DWT and E_Q is the quantization-encoding energy consumption.

Regarding the thresholding-based DWT compression, it is applied using one of the wavelet families, categories and decomposition levels as in [22]. For N-dimensional EEG signal x

$$x = \Psi \alpha_w \tag{8}$$

where Ψ is the wavelet family basis, and α_w is the wavelet domain coefficients. The wavelet series expansion $f(x)$ is obtained as

$$f(x) = \sum_k c_{j_0}(k)\varphi_{j_0,k}(x) + \sum_{j=j_0}^{\infty}\sum_k d_j(k)\Psi_{j,k}(x) \tag{9}$$

where $c_{j_0}(k)$ is the approximation coefficients, $d_j(k)$ is the details coefficients, $f(x) \in L^2(R)$ and $L^2(R)$ is relative to the wavelet family $\Psi(x)$ and the scaling function $\varphi(x)$ [23]. The approximation coefficients c_{j_0} are obtained as

$$c_{j_0}(k) = \langle f(x), \varphi_{j_0,k}(x) \rangle \tag{10}$$

These coefficients use scaling function $\varphi(x)$ to provide an approximation of $f(x)$ at scale j_0, where j_0 is an arbitrary starting scale. To add more details to the approximation of $f(x)$, the details coefficients $d_j(k)$ is used. These coefficients use the wavelet function $\Psi(x)$ to provide details of $f(x)$ and are obtained as

$$d_j(k) = \langle f(x), \Psi_{j,k}(x) \rangle. \tag{11}$$

Using thresholding-based DWT, the coefficients that are below the predefined threshold can be zeroed without much signal quality loss. According to this threshold, we can control in the number of output samples generated from DWT and thus the compression ratio of the DWT, where the compression ratio is evaluated as

$$C_R = 1 - \frac{M}{N_s} \tag{12}$$

where N_s is the length of the original signal and M is the number of output samples generated after DWT.

In order to calculate E_{DWT}, the computational complexity that is defined as the number of computations needed in the compression process, for N-dimensional EEG signal x, is calculated as

$$C_{DWT} = F \cdot N_s \sum_{l=0}^{l=L} \frac{1}{2^l} \tag{13}$$

where L is the number of decomposition levels and F is the wavelet filter length of the utilized wavelet family that is obtained as $F = 2\kappa$, where κ is the wavelet family order. Therefore, using this computational complexity, the energy consumed in the DWT-based encoding can be evaluated as

$$E_{DWT} = C_{DWT}(F, N, L) \cdot E_{comp} \tag{14}$$

where E_{comp} is the energy consumed per computation, which heavily depends on the particular hardware in use [24].

For the sampling, quantization and encoding, the energy consumption depends on the number of conversion steps (to convert the input samples into bits), which in turn depends on the number of input samples to the quantization and encoding modules. Therefore, the total energy consumption in the sampling, quantization and encoding can be obtained as follows,

$$E_Q = N_s(1 - C_R) \cdot E_{CS} \tag{15}$$

where E_{CS} is the energy consumption at each conversion step, which can be obtained as in [25].

Consequently, from (14) and (15), the encoding energy consumption is evaluated as

$$E_p = F \cdot N_s \left(\sum_{l=0}^{l=L} \frac{1}{2^l} \right) \cdot E_{comp} + N_s \left(1 - C_R\right) \cdot E_{CS}. \tag{16}$$

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

$$D_p = \frac{\|x - x_r\|}{\|x\|} * 100, \tag{17}$$

where x is the original signal and x_r is the reconstructed signal. As shown in Figure 3, the main parameters that affect the encoding distortion are the compression ratio (C_R) and the wavelet filter length (F) [23]. The simulation results suggest the following relation between the encoding distortion D_p, C_R and F

$$D_p = c_1 e^{-c_2 \cdot C_R} + c_3 e^{c_4 \cdot C_R} - c_5 e^{c_6 \cdot F} - 2 \tag{18}$$

where the model parameters c_1, c_2, c_3, c_4, c_5 and c_6 are estimated by the statistics of the typical EEG encoder used. According to the healthcare application requirement, we have a constraint that $D_p \leq D_{th}(i), \quad \forall i \in N$. This constraint ensures that the encoding distortion, for each sensor node i, is below certain distortion threshold $D_{th}(i)$.

IV. Energy-Aware Optimum Algorithm

A. Optimization Problem

Our goal is to minimize the overall energy consumed by all sensor nodes that cooperate to transfer a known number of packets from these nodes to their coordinator. Therefore, the proposed cross-layer optimization problem can be formulated as an Energy-Delay-Distortion optimization problem, where the design objective is to minimize the total energy consumption under given delay and distortion constraints. In general, the total energy dissipation at node i ($i \in N$) consists of the encoding and the transmission energy consumptions. It is given by

$$E_i = E_t + E_p \tag{19}$$

The objective of the optimization problem is to minimize the total energy consumption at the system $\left(\sum_{i=1}^{i=N} E_i \right)$ under a constraint that the transmitted data must be received at the coordinator before its delay exceeds the delay deadline D_l and with maximum distortion less than the application distortion threshold D_{th}. Therefore, the problem of minimizing the total energy consumption can be written as

$$\min_{C_{Ri}, F_i, r_i} \left(\sum_{i=1}^{i=N} \frac{l_i \left(1 - C_{Ri}\right)}{r_i \cdot x_i} \left(2^{r_i/w} - 1\right) + E_p \right)$$

such that

$$c_1 e^{-c_2 \cdot C_{Ri}} + c_3 e^{c_4 \cdot C_{Ri}} - c_5 e^{c_6 \cdot F_i} - 2 \leq D_{th}(i), \quad \forall i \in N$$

$$\sum_{i=1}^{i=N} \frac{l_i \left(1 - C_{Ri}\right)}{r_i} \leq D_l. \tag{20}$$

This optimization problem is a function of the channel gain x_i, link bandwidth w, compression ratio C_{Ri}, wavelet filter length F_i, data length l_i, application layer distortion threshold D_{th} and delay deadline D_l. The last three variables are imposed by the application layer. Consequently, the unknowns in this problem are the transmission rates r_i, compression ratios C_{Ri} and wavelet filter lengths F_i. By knowing the transmission rates, the required transmission energy from different nodes can then be obtained from (6). Similarly, by knowing the compression ratios and wavelet filter lengths, the required encoding energy can then be obtained from (16).

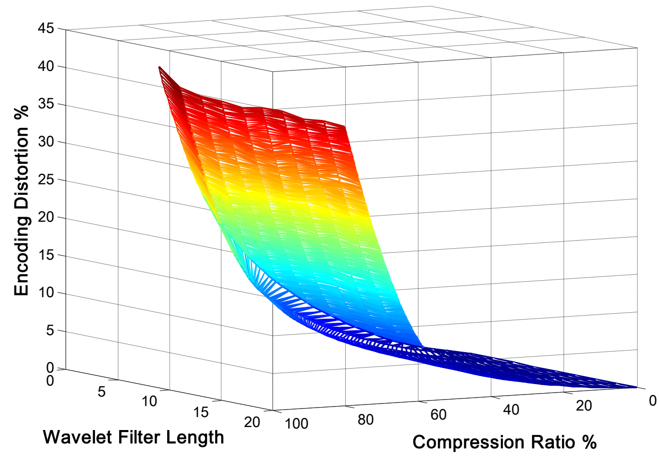

Fig. 3. The relation between the encoding distortion, the compression ratio and the wavelet filter length.

B. Joint Cross-Layer Optimum Algorithm (JCLO)

To solve the optimization problem in (20), the objective of the optimization problem is divided into two parts. The first part is related to the transmission energy and the second part is related to the encoding energy. Regarding the first part, for higher-order modulation, the (-1) term can be neglected with respect to $2^{r_i/w}$ to have a convex problem, as in [18]. Regarding the second part, the relation between encoding energy and wavelet filter length F_i is concave. In addition to that, due to practical constraints the wavelet filter length must be an even number [23]. Therefore, we will solve the optimization problem in (20) iteratively for all possible values of wavelet filter length N_{WFL} (e.g. 2, 4, 6 ... 20). Accordingly, for each value of the wavelet filter length, the convex optimization problem will be solved, using the interior-point methods [26], as shown in Algorithm 1.

Algorithm 1 is considered optimum because we take into consideration all possible values for all variables and choose the optimal values that give the minimum energy and satisfy the distortion and delay constraints.

Algorithm 1 Joint Cross-Layer Optimum algorithm (JCLO)

1: Calculate channel gain x_i using (5).
2: **for** $j = 1 \rightarrow N_{WFL}$ **do**
3: Solve the optimization problem in (20), get C_{Ri}'s and r_i's.
4: Calculate $\sum_{i=1}^{i=N} E_i(j)$.
5: **end for**
6: Choose the optimum F_i's that give min $\left(\sum_{i=1}^{i=N} E_i\right)$ and the corresponding C_{Ri}'s and r_i's.
7: End

The main step of this algorithm involves the solution of the convex optimization problem in (20) multiple times, equal to the number of wavelet filter length values N_{WFL}. This step makes the optimum algorithm complex to implement.

V. Energy-Aware Sub-optimal Algorithms

A. Disjoint Cross-Layer Algorithm (DCL)

To decrease the complexity of the joint cross-layer optimum algorithm (JCLO), a disjoint cross-layer algorithm is proposed. In this algorithm, the complex optimization problem in (20) is divided into two less-complex disjoint optimization problems. The first one is the application layer optimization. The objective of this problem is to minimize the encoding energy under certain distortion threshold constraint D_{th}. It can be written as

$$\min_{C_{Ri},F_i} \left(\sum_{i=1}^{i=N} E_p\right), \text{ S.t. } D_p \leq D_{th}(i), \quad \forall i \in N \qquad (21)$$

The optimization variables in (21) are the compression ratios C_{Ri} and the wavelet filter lengths F_i. It can be solved iteratively for all possible values of wavelet filter length. By knowing the compression ratios and wavelet filter lengths, the required encoding energy at different nodes can then be obtained from (16). The second optimization problem is the joint MAC-Physical optimization. The objective of this optimization problem is to minimize the transmission energy under certain delay deadline constraint D_l. It can be written as

$$\begin{aligned} &\min_{r_i} \left(\sum_{i=1}^{i=N} \frac{l_i\left(1-C_{Ri}\right)}{r_i \cdot x_i} 2^{r_i/w}\right) \\ &\text{S.t.} \\ &\sum_{i=1}^{i=N} \frac{l_i\left(1-C_{Ri}\right)}{r_i} \leq D_l. \end{aligned} \qquad (22)$$

The optimization variables in (22) are the transmission rates r_i. It can be solved using the conventional convex optimization methods [26]. According to the optimization problem in (21), we get the optimum application layer parameters that minimize the encoding energy only not the total energy consumption. Therefore, there is a degradation in the performance of this algorithm compared to the JCLO algorithm's performance, as shown in the simulation results.

Algorithm 2 Disjoint Cross-Layer Algorithm (DCL)

1: Calculate channel gain x_i using (5).
2: Solve the optimization problem in (21), get C_{Ri} and F_i.
3: Solve the optimization problem in (22), get r_i.
4: Calculate the total energy consumption from (19).
5: End

B. Joint Cross-Layer With Arbitrary Filter Length Algorithm (JCL-AFL)

The main step that increases the complexity of the other algorithms is solving the convex optimization problem in (20) multiple times, equal to the number of wavelet filter length values N_{WFL}. Accordingly, to decrease number of solving this optimization problem, we will find a relation between distortion threshold constraint D_{th} and wavelet filter length. From (18), it is noted that $F_i \propto \frac{1}{D_p}$. Consequently, we define a relationship between the distortion threshold constraint D_{th} and the corresponding wavelet filter length F_i. As a result, instead of solving the convex optimization problem multiple times to get the wavelet filter lengths, we will use this relation to calculate them. Then, solve the optimization problem (20) only once to get C_{Ri} and r_i, as shown in Algorithm 3. Therefore, the complexity will decrease. On the contrary, there is a degradation in the performance compared to the JCLO algorithm's performance, as will be shown in the simulation results. Because the calculated F_i, using the defined relation, is not equal to the optimum F_i that is found by JCLO algorithm. Algorithm 3 summarizes the main steps of this algorithm.

C. Joint Cross-Layer With Equal Slot Length Algorithm (JCL-ESL)

The main idea of this algorithm is solving a less complex optimization problem than the optimization problem in (20). To achieve that, a distributed cross-layer algorithm is

Algorithm 3 Joint Cross-Layer With Arbitrary Filter Length Algorithm (JCL-AFL)

1: From the required application distortion threshold, calculate wavelet filter length as
$$F_i = \frac{F_{max}}{D_{th}(i)} \tag{23}$$
where F_{max} is the maximum wavelet filter length.
2: Calculate C_{Ri} from distortion threshold constraint (18).
3: Calculate channel gain x_i using (5).
4: Solve the optimization problem in (20), get r_i
5: End

proposed. In this algorithm, each sensor node will solve its own optimization problem to get its parameters. Therefore, we will distribute the total delay deadline equally between sensor nodes. As we use TDMA scheduling, each sensor node will send its data on time D_l/N, where N is the number of sensor nodes. The main steps of this algorithm are the same as JCLO algorithm except step 3. In this step, instead of solving the optimization problem in (20), we will solve the following simple optimization problem

$$\min_{C_{Ri},F_i,r_i} \left(\sum_{i=1}^{i=N} \frac{l_i\,(1-C_{Ri})}{r_i \cdot x_i} 2^{r_i/w} + E_p \right)$$
such that
$$c_1 e^{-c_2 \cdot C_R} + c_3 e^{c_4 \cdot C_R} - c_5 e^{c_6 \cdot F} - 2 \leq D_{th}(i), \quad \forall i \in N$$
$$\frac{l_i\,(1-C_{Ri})}{r_i} \leq \frac{D_l}{N}, \quad \forall i \in N. \tag{24}$$

It should be noted that, with increasing the number of sensor nodes, there is a complexity/energy-consumption tradeoff. Because as the number of sensor nodes increases, the complexity of this algorithm decreases compared to the JCLO algorithm. On the other hand, the assigned slot length for each sensor node will decrease, as the total delay is distributed equally between sensor nodes. In this case, the sensor nodes who have bad channel conditions should increase their transmitted energy significantly to maintain the required constraints (delay deadline and distortion threshold). Therefore, the total energy consumption will increase compared to the JCLO algorithm.

VI. Simulation Results

In this section, the performance and the complexity are compared for the different proposed algorithms. The simulation results were generated using the network topology shown in Figure 1. In the BASNs network considered, all the connected nodes are assumed to be separated by the same distance d. It is assumed that all sensor nodes' data have the same length l and the distortion threshold constraint is the same for all sensor nodes. To model small scale channel variations, flat Rayleigh fading is used, with Doppler frequency 0.1 Hz and sampling time 0.1 sec. The simulation parameters used are given in Table I.

TABLE I
Simulation Parameters

Parameter	Value	Parameter	Value
N_0	-174 dBm	λ	0.12 m
w	5 kHz	d	5 m
l	6 kbyte	BER	10^{-4}
L	2	N_s	4029
E_{comp}	96 nJ	E_{CS}	168 nJ/step
c_1	4.01	c_2	0.01
c_3	0.353	c_4	0.06
c_5	1.17	c_6	0.03

At first, in order to assess the importance of optimizing both the transmission and encoding energy and to show the effect of varying the wavelet filter length, Figure 4 is presented. This figure illustrates the relation between the transmission energy and encoding energy and their effect on the total energy consumption. It was generated for different delay deadlines and distortion threshold 5%. As shown in the figure, at low delay deadline, the transmitted rate increases to satisfy the delay deadline constraint. This will lead to significant increasing in the transmitted energy. Therefore, the compression ratio must be increased to decrease the number of bits to be sent. To acheive that, the wavelet filter length will increase, to add more details to the sampled signal, to decrease the distortion and hence increases the compression ratio (as from (18) $F \propto \frac{1}{D_p}$ and $C_R \propto D_p$). Consequently, as the wavelet filter length increases, the encoding energy will increase. On the contrary, the number of bits to be transmitted will decrease. As a result, the transmission energy will decrease. With increasing the delay dealine, the transmitted rate decreases, so the wavelet filter length and the encoding energy will decrease. Therefore, in order to minimize the total energy consumption, it is important to take into consideration both the transmission and encoding energy together to get the best dominant control parameters that affect both of encoding and transmission.

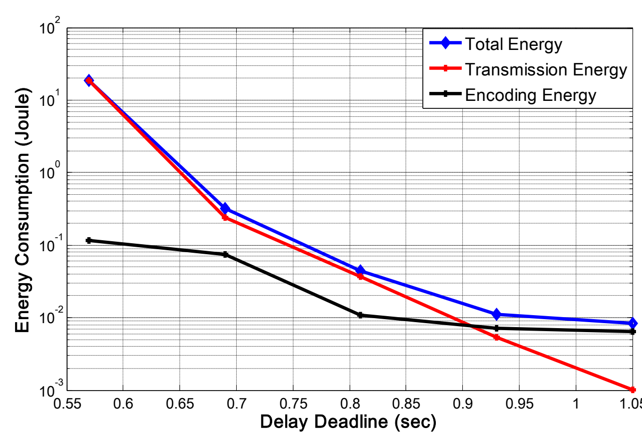

Fig. 4. The relation between the transmission energy and encoding energy and their effect on the total energy consumption.

In order to assess the performance of the proposed algorithms, comparisons with varying distortion threshold and

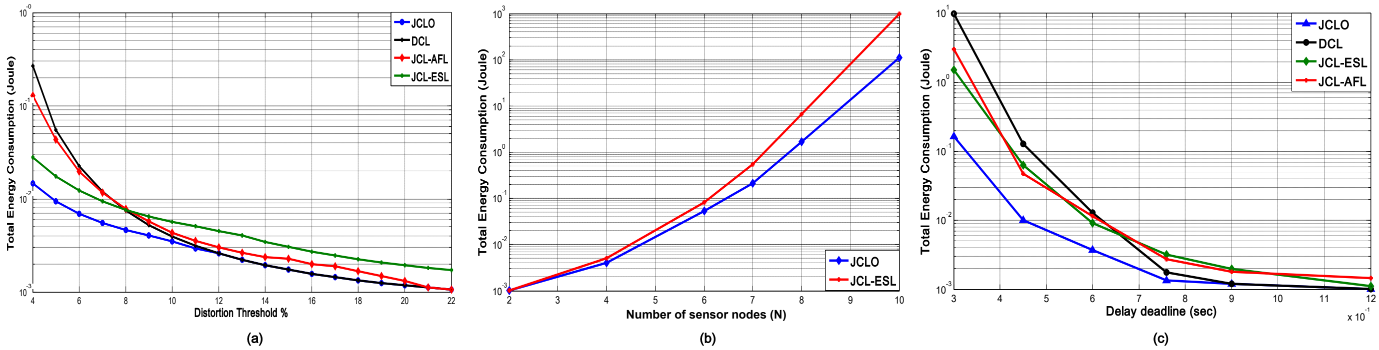

Fig. 5. A comparison between the total energy consumption using the proposed algorithms, (a) For different distortion thresholds, (b) With increasing the number of sensor nodes and (c) For different delay deadlines.

delay deadline are presented. Figure 5-(a) illustrates the performance of the proposed algorithms for different distortion thresholds and with delay deadline 0.8 sec for three sensor nodes. As shown in the figure, we can divide the figure into two regions, low distortion threshold and high distortion threshold. At low distortion threshold, the DCL algorithm consumes more energy than other algorithms, because it finds the optimum application layer parameters that minimize the encoding energy only not the total energy. Accordingly, it chooses small value for the wavelet filter length to minimize the encoding energy in (16). This will lead to low compression ratio, to maintain distortion threshold constraint, and large transmission rate, to maintain delay deadline constraint. As a result, the total energy consumption increases. Regarding the JCL-AFL algorithm, it chooses the wavelet filter length according to (23). Therefore, at low distortion threshold it gets large wavelet filter length than DCL algorithm, but not the optimum value as the JCLO algorithm. As a result, it consumes energy less than DCL algorithm. Because as the wavelet filter length increases the encoding energy increases according to (16). However, at the same time, for high F_i, the source coding distortion decreases, according to (18). Therefore the C_R will increase to maintain the distortion threshold constraint. With increasing C_R, the transmitted rate decreases and the transmitted energy decreases. Therefore, the total energy consumption decreases. In contrast, at high distortion threshold, DCL algorithm converges to the JCLO algorithm's performance faster than JCL-AFL algorithm. Because the JCL-AFL algorithm gets large F_i than DCL algorithm; and at high distortion threshold, the effect of decreasing the transmitted energy (due to large F_i) is less than the increasing in the encoding energy.

For the JCL-ESL algorithm, it finds the optimum wavelet filter length that minimizes the total energy consumption, as the JCLO algorithm. However, it does not converge to the JCLO algorithm with varying distortion threshold. Because it mainly depends on the number of sensor nodes in the system, as shown in Figure 5-(b). This figure shows the performance of JCL-ESL algorithm compared to JCLO algorithm, with increasing the number of sensor nodes in the system. It is clear from the figure that increasing the number of sensor nodes will result in increasing the performance deviation for the JCL-ESL algorithm. On the other hand the complexity decreases with respect to the JCLO algorithm. This figure was generated with delay deadline 1 sec and distortion threshold 10%.

Regarding the effect of varying the delay deadline, Figure 5-(c) illustrates the performance of the different proposed algorithms for different delay deadlines, and with distortion threshold 8%. In this case, JCL-AFL algorithm does not converge to the optimum performance with increaseing delay deadline, as it mainly depends on the distortion threshold to get the wavelet filter length, from (23). Meanwhile, with incresing delay deadline, JCL-ESL algorithm converges to the JCLO performance because the effect of equally slot length assignment becomes less effective on the energy consumption. For DCL algorithm, increasing delay deadline has the same effect as increasing distortion threshold. This algorithm always converges to the JCLO algorithm's performance at soft constraints (at high delay deadline or distortion threshold) and diverges at tough constraints (at low delay deadline or distortion threshold).

In our proposed algorithms, the main parameter that effects the complexity is the number of wavelet filter length values N_{WFL}. To illustrate the complexity analysis of the proposed algorithms, we compare between them experimentally as shown in Table II. As in the JCLO algorithm, the optimization problem in (20) is solved N_{WFL} times to get the optimal solution. Therefore, it has complexity $C_{JCLO} = N_{WFL} \cdot C_t$, where C_t is the complexity of solving the optimization problem in (20). For DCL algorithm, it solves the optimization problem in (21) N_{WFL} times to get the application layer parameters, then solves the optimization problem in (22) once to get the MAC-PHY layer parameters. Therefore, it has complexity $C_{DCL} = N_{WFL} \cdot C_p + C_{ts}$, where C_p is the complexity of solving the optimization problem in (21) and C_{ts} is the complexity of solving the optimization problem in (22). Regarding JCL-ESL algorithm, it solves the optimization problem in (24) N_{WFL} times. Therefore, it has complexity $C_{JCL-ESL} = N_{WFL} \cdot C_u$, where C_u is the complexity of solving the optimization problem in (24). For JCL-AFL algorithm, it gets the wavelet filter length from (23), then solves the optimization problem in (20) once. Therefore, it does not depend on N_{WFL}.

TABLE II
COMPARISON OF NUMBER OF ITERATIONS TO GET THE SOLUTION, FOR DIFFERENT PROPOSED ALGORITHMS EXECUTED ON THE SAME PLATFORM.

N_{WFL}	**JCLO**	**JCL-ESL**	**DCL**	**JGL-AFL**
2	12	4	7	7
6	36	12	11	7
10	60	20	15	7
14	84	28	19	7
18	108	36	23	7
20	120	40	25	7

VII. CONCLUSION

In this paper, wireless EEG monitoring system is considered. In the proposed approach, transmission energy, encoding energy, application quality of service (QoS) constraints, and scheduling are jointly integrated into a cross-layer design framework. This framework is used to dynamically perform radio resource allocation for multiple sensor nodes, and to effectively choose the optimal system parameters to adapt to the varying channel conditions. This framework jointly minimizes the total energy consumption and determines the optimal transmitted rate at physical layer, assigned slots length at MAC layer, wavelet filter length and compression ratio at application layer. The minimization is performed under the constraint that all successfully received packets must have a delay smaller than their corresponding delay deadline while maintaining the total distortion at a specific threshold dictated by the application.

As the number of sensor nodes in the system increases, the complexity of the optimum-proposed algorithm increases. Therefore, in addition to the optimum-proposed solution, sub-optimal solutions are presented to reduce the complexity significantly with minimal performance degradation. The simulation results show that the proposed sub-optimal algorithms make a trade-off between complexity and energy consumption. This work is planned to be extend for different multiple access techniques (like TDMA-FDMA and OFDMA).

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