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Information-based Energy Efficient Sensor Selection in Wireless Body Area Networks

Hui Wang*, Hyeok-soo Choi†, Nazim Agoulmine*‡, M. Jamal Deen*§, James Won-Ki Hong*†
*ITCE, POSTECH, Pohang, South Korea
email:{polorobert,jwkhong}@postech.ac.kr
†Computer Science & Engineering, POSTECH, Pohang, South Korea
‡LRSM/IBISC, University of Evry Val d'Essonne, France
email:nazim.agoulmine@iup.univ-evry.fr
§Department of Electrical & Computer Engineering, McMaster University, Canada
email:jamal@mcmaster.ca

***Abstract*—Wireless Body Area Networks (WBANs) are mainly characterized by deployment of biomedical sensors around human body which transmit vital signs measurements about healthy status to the coordinator. Depending on the relevance between symptoms and diseases, it may not be necessary for every sensors to transmit its measurements for diagnoses. This paper shows how the relevance can be exploited on the Medium Access Control (MAC) layer by utilizing the mutual information. A theoretical framework is developed for sensor scheduling under an operation cost constraint. It is shown that the compact subset of sensors can be found to provide necessary information for timely and correct diagnoses. Based on the theoretical framework, an algorithm combining sensor selection and information gain is then designed. Simulation results show that the algorithm achieves high performance in terms of energy, latency and collision rate.**

***Index Terms*—U-Health, information utility, energy-saving.**

I. Introduction

Ubiquitous Healthcare (U-Health) smart home for elderly has been identified by governments and medical institutions, as an important part of the economical, technological and socially acceptable solution to maintain the system viable, as shown in Fig. 1. The aim of the U-Health smart home is to help elderly to continue to leave in their own home helping them to live a more independent life as long as possible, while being monitored and assisted in an unobtrusive manner for the sake of their safety and health.

Existing approaches use what we call a communication-based schema. This means that the sensors are configured according to the communication needs, i.e., sampling frequency; and are agnostic of how the collected data are used or processed by applications. In this schema all biomedical sensors are continuously activated sending data to the coordinator.

In this work, we propose a different approach called information-based schema, that aims at selecting the appropriate sensors to activate based on some knowledge about the diseases to detect. This schema takes both energy efficiency and maximum information gain into consideration. According to the theory of Pattern Recognition, a system that aims to detect diseases using WBAN is in nature a pattern classification system that covers all stages of techniques from data collection to vital signs measurement discrimination and classification, assessment of results and diagnosis. In pattern recognition applications, identifying the most characterizing features of the observed measurements, i.e., feature selection, is critical to minimize the classification error. We propose to use the same approach to select the minimum set of sensors to activate by identifying the "best" features of these sensors. In the WBANs, the features are the important physiological signs specified by the investigator (e.g., doctors) and thought to be important for classification [2]. Since each sensor in the WBAN can detect only a specific feature (or vital signs measurement), feature selection is equivalent to the sensor tasking.

Gathering vital signs has a cost in terms of energy consumption. Therefore, we have to find the optimal tradeoff between information gain and the overall cost. To summarize, the research questions we want to address in this paper are:

- What is minimum compact set of features that are the mostly relevant to detect a set of diseases?
- What relations among measurements are the most critical to whatever high-level information we need to know?
- What is the decision-making process to develop in order to identify the possible diseases based on the collected information?
- Does this information-based schema perform better than the communication-based schema and what is the tradeoff?

A. Our Contribution

Our main contribution in this paper is to jointly take into consideration the biomedical sensors task scheduling at the medium access control (MAC) layer and information gain at the application layer to design a novel medical wireless sensors selection schema for health anomaly detection (i.e., diseases). We aim to use the theories of feature selection and utility as foundations for this work. The main contributions of our proposed solution are the following:

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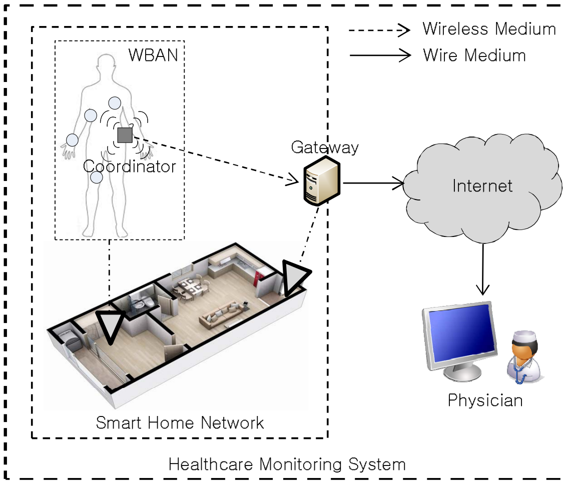

Fig. 1. Healthcare Monitoring System

- *Information-based medical diagnosis*. Our information-based approach is capable of finding compact subset of features at very low cost. This greatly supports the information-based medical diagnosis like identifying strongly related features (or symptoms) and classifying a pattern to the class (or diagnosis).
- *Energy Efficient Sensor Selection*. Our information-based approach schedule activity of sensing and transmitting tasks in such a way that the information gain is kept at maximum level. The expected output are maximum information gain, efficient energy utilization, low latency and low packet collision rate in the WBANs.

II. Problem Formulation

We follow in our solution design a top-down approach that couple disease detection application requirements in terms of symptoms to monitor and the WBAN medical sensors to activate that will be able to gather the right data.

A. Notation

We use the following notation in our formulation of the information-based sensor tasking problem in a WBAN:

- Superscript t denotes time. We consider discrete times t that are nonnegative integers.
- Subscript $i \in \{1, \ldots, m\}$ denotes the sensor index; m is the total number of sensors in a WBAN. As a specific type of network topology, WBAN is deployed around the human body on a small scale. The position of each node on the body remains static. We assume that each sensor is identified by the particular index.
- Subscript $j \in \{1, \ldots, n\}$ denotes the medical diagnosis index; n is the total number of diagnoses being evaluated. Here, we also assume that each exact diagnosis is identified.
- The diagnosis state vector at time t represented by $D^{(t)} \in R^{|n|}$. For a multi-diagnosis decision problem, this is a concatenation of several diagnosis states $d_j^{(t)}$. Each state denotes a potential disease in the human body.
- The measurement of sensor i at time t, i.e., the symptom, is denoted as $e_i^{(t)}$. Also, $E^{(t)} \in R^{|m|}$ will be used to denote the corresponding vectors for time t.
- The measurement history up to time t is denoted as $\overline{E^{(t)}}$, that is, $\overline{E^{(t)}} = \{e^{(0)}, e^{(1)}, \ldots, e^{(t)}\}$. The measurements may originate from a single sensor or a set of sensors.
- The collection of all sensor measurements at time t are denoted as $\underline{E^{(t)}}$, that is, $\underline{E^{(t)}} = \{e_1^{(t)}, e_2^{(t)}, \ldots, e_m^{(t)}\}$.
- The characteristics about sensor i at time t is denoted as $\epsilon_i^{(t)}$. Typical characteristics include sensing modality (which refers to the type of sensor, such as heartbeat sensor, blood pressure sensor, temperature sensor, etc..), sensor position (which refers to the task), and other parameters, such as the noise model applied to the sensor and its power capacity. Typically, the sensor characteristics are relatively stable condition.

B. Information-Based Utility Function for Sensor Selection

We define the information utility function as a relation between utility and each data reading of a sensing node; that is

$$U : \mathcal{I} \times \mathcal{T} \rightarrow \mathcal{R}$$

where $\mathcal{I} = \{1, \ldots, K\}$ are sensor indices and $\mathcal{T}$ is the time domain. Each sensor operation is also assigned a cost. Thus, the information-based sensor tasking problem is to maximize the value of collected information. It is expressed as follows:

$$max \sum_t \sum_{i \in V_s(t)} U(i,t) \quad (1)$$

subject to

$$\sum_t \sum_{i \in V_s(t)} C_s + \sum_t \sum_{i \in V_t(t)} C_t + \sum_t \sum_{i \in V_r(t)} C_r \leq C$$

where C_s is the cost of a sensing operation, C_t is transmission cost, C_r is reception and aggregation cost and C is the total resources in a WBAN. We assume that each time a sensor do a measurement, it encapsulates the measurement data in a packet and transmits over wireless and therefore all costs are expressed in unit costs per packet. In the above formulation, we also further denote the set of nodes performing a sensing operation at time t as $V_s(t)$, transmitting nodes as $V_t(t)$, and receiving nodes as $V_r(t)$. It can be easily shown that the above problem is a constrained optimization problem to maximize the utility over a period of time by determining the sets of sensors V_s, V_t, and V_r. In the field of pattern recognition, this problem is similar to finding the compact subset of superior features at very low cost.

C. Sensor Selection Criterion: Mutual Information

In the real clinical routine visit, the doctor always examine patient to observe the most important physiological signs in the body. If these signs are normal no further investigation is performed and the patient can leave. However, if any of these signs is abnormal, the doctor will perform deeper investigations. We inspire from this approach to specify our sensors scheduling solution. The definition of "optimal characterization", which often means the minimal classification error (or best diagnosis), is essential for sensor selection. Given this condition, sensor selection is equivalent to finding the best subspace of superior features. One of the major approaches to implement max-dependency is to consider maximum relevance feature selection: selecting the features with the highest relevance to the target class, usually expressed in terms of mutual information.

Given two random variables x and y, their mutual information is defined in terms of their probabilistic density functions $p(x)$, $p(y)$, and $p(x, y)$ [3]:

$$\begin{aligned} I(x;y) &= \int\int p(x,y)\log\frac{p(x,y)}{p(x)p(y)}\; dxdy \\ &= D(p(x|y) \parallel p(x)) \end{aligned}$$

where $D(\cdot \parallel \cdot)$ is the Kullback-Leibler divergence between two distributions. Thus, the goal of sensor selection is to find the "best" feature set E among m features $\{e_i\}$, which jointly gives the largest dependency on the target class D. As a result, the compact subset of sensors are used jointly to make the best diagnosis. For this case, we have the following form:

$$\max F(E,D), \quad F = I(\{e_i, i = 1,\dots,m\}; D)$$

Given m features, since the number of sensors in WBAN should be limited to ensure a comfortable monitoring environment, incremental search scheme is a simple and effective way to find compact subset of features by adding one feature at one time. Assume that there is the set, E_{i-1}, with $i-1$ features. The ith feature can be obtained by selecting the one that contributes to the largest increase of $I(E; D)$, i.e.,

$$\begin{aligned} I(E_i;D) &= \int\int p(E_i,D)\log\frac{p(E_i;D)}{p(E_i)p(D)}dE_i dD \\ &= \int\int p(E_{i-1},e_i,D)\log\frac{p(E_{i-1},e_i,D)}{p(E_{i-1},e_i)p(D)} \\ &\quad dE_{i-1}de_i dD \\ &= \int\dots\int p(e_1,\dots,e_i,D)\log\frac{p(e_1,\dots,e_i,D)}{p(e_1,\dots,e_i)p(D)} \\ &\quad de_1\dots,de_i dD \end{aligned}$$

The information contribution of sensor j with measurement $e_j^{(t+1)}$ can be given by the sequential Bayesian estimation:

$$U(p_D) = I(D^{(t+1)}; e_j^{(t+1)}|\overline{E^{(t)}} = \overline{e^{(t)}})$$

where $e^{(t)}$ is the support of $E^{(t)}$. It indicates how much information $e_j^{(t+1)}$, gathered from sensor j, is conveyed about the diagnosis $D^{(t+1)}$, given the current knowledge. It can be interpreted as the Kullback-Leibler divergence between $p(D^{(t+1)}|\overline{e_j^{(t+1)}})$ and $p(D^{(t+1)}|\overline{e^{(t)}})$. Therefore, the mutual information reflects the expected amount of change in the posterior knowledge brought by sensor j.

D. Operation Cost Measure

The low-rate wireless personal area network (LR-WPAN) standard, called $IEEE802.15.4$, provides ultra-low complexity and power for low-data-rate wireless connectivity among inexpensive fixed, portable, and moving devices. It is nowadays commercially used for WBAN devices. We consider also this standard for our work operating in a beacon mode (this standard can also work in a non-beacon mode).

Consider two different cases for packet transmission, including successful packet transmission and unsuccessful packet transmission. Thus, the total energy consumption of a sensor, derived from [4], can be expressed as

$$E(\cdot) = E_s(\cdot) + E_u(\cdot)N_u(\cdot) \tag{2}$$

where E_s and E_u denote the energy consumption for successful packet transmission and unsuccessful packet transmission, respectively. $N_u(\cdot)$ are the expected number of packet failures.

1) Successful Transmission: The biomedical sensor "wakes up" at regular time to process the beacon frame sent by the coordinator (the sensor is in a sleep mode all the rest of the time). If it finds its address in the beacon frame, it performs a measurement and sends it in a packet to the coordinator and then go back to sleep mode. If there is no transmission errors, the packet will be received by the coordinator, otherwise the coordinator will need to reactivate the sensor at the next beacon cycle.

We assume that the transceiver supports several transmission power levels and each transmission signal power level $P_t(i)$ at sensor i is given by $P_t(i) = I_t(i)V_s$, where $I_t(i)$ is the supply current for $P_t(i)$ and V_s is the supply voltage. Similarly, the power consumption for reception for all the sensor have the same expression: $P_r = I_rV_s$, where I_r denotes the supply current for reception. The time interval to transmit or receive a packet is L/R_b where L represents the length of the packet and R_b denotes the transmission rate.

The total number of bits in the packet has the following expression: $L_{pack} = 8 \times (L_{header} + L_{data})\ bits$. Thus, the total energy consumption for successful transmission is

$$E_s(i, L_{pack}) = E_{Tx}(i, L_{pack}) + E_{Rx}(L_{Beac}) \tag{3}$$

where $E_{Tx}(\cdot)$ denotes the transmission energy consumption. $E_{Rx}(\cdot)$ denotes the receiving energy consumption. We have $E_{Tx}(i, L_{pack}) = P_t(i)L_{pack}/R_b$; $E_{Rx}(L_{Beac}) = P_rL_{Beac}/R_b$. Substituting it into (3), we have

$$E(i, L_{pack}) = \frac{(L_{pack}I_t(i) + L_{Beac}I_r)V_s}{R_b}$$

2) Unsuccessful Transmission: In this case, we assume the data packet is received in error. Thus, the energy consumption for unsuccessful transmission is the following

$$E_u(i, L_{pack}) = E_{Tx}(i, L_{pack}) \doteq \frac{I_t(i)V_sL_{pack}}{R_b}$$

N_u depends on the probability of packet failure, P_{PER}. Here, we assume P_{PER} for each transmission are independent and identically distributed (i.i.d.). Retransmissions continue until the data packet is successfully received by the coordinator. Thus, the expected number of retransmissions depends on the probability that the data packet is received in error, $P_{PER}(i, d, L_{pack})$. Thus, we have

$$N_u(i, d, L_{pack}) = \frac{P_{PER}(i, d, L_{pack})}{1 - P_{PER}(i, d, L_{pack})}$$

where $P_{PER}(i, d, L) = 1-(1-P_{BER}(i, d))^L$. The LR-WPAN use O-QPSK modulation due to $f_c = 2.4GHz$ and the bit error rate is expressed by

$$P_{BER}(i, d) = Q(\sqrt{\frac{2E_b(i, d)}{N_0}})$$

where $E_b(i, d)$ denotes the energy per bit and N_0 denotes the noise spectral density. The energy per bit in mJ is given by

$$E_b(i, d) = \frac{10^{\frac{\bar{P_r}(i,d)}{10}}}{R_b}$$

where $\bar{P}_r(i, d)$ is the expected received power in dBm and the distance from the sensor and the coordinator is d. Thus, the signal to noise ratio is given by

$$\frac{E_b(i, d)}{N_0} = 7.6007 \times 10^{\frac{\bar{P_r}(i,d)+94}{10}}$$

where N_0 was derived in [5] for the LR-WPAN.

The average received power, $\bar{P}_r(i, d)$, is expressed as

$$\bar{P}_r(i, d) = P_t(i) - (\bar{P_L}(d_0) + 10\alpha \log(\frac{d}{d_0}))dBm$$

where $P_t(i)$ denotes the transmission power in dBm, $\bar{P_L}(d_0)$ represents the expected path loss in dB from the sensor to reference distance d_0 and α is a path loss exponent [6]. The reference path loss, $\bar{P_L}(d_0)$, can be evaluated empirically as

$$\bar{P_L}(d_0) = 10 \log_{10}(\frac{(4\pi d_0)^2 L}{G_T G_R \lambda^2})dB$$

where G_T and G_R denote the transmitter and receiver antenna gains, respectively. L denotes the system loss factor not related to propagation and λ denotes the wave length related to the carrier frequency f_c by $\lambda = c/f_c$. Here $G_T = G_R = L = 1$.

3) Operation Cost Function: Finally, from (2), the operation cost function can be expressed by

$$\sum_{i \in V_t(t)} [E_s(i) + E_u(i)N_u(i)] \leq C$$

III. INFORMATION-DRIVEN SENSOR TASKING SERVICE

In WBANs, medical sensors need to transmit measurements (e.g., temperature, ECG, EEG, EMG and gait monitoring), at relatively wide range of data rates from $1kbit/s$ to $1Mbit/s$. Therefore, we must balance the information contribution of individual sensors against the cost of communicating with them. Consider that the coordinator has identified the best feature e_i to have the largest mutual information $I(e_i; D)$ with the target class D. The current knowledge can be interpreted as $p(D|e_{i \in B})$, where $B \subset \{1, \ldots, i\}$ is the subset of sensors whose symptom has already been gathered and incorporated. The information-based tasking scheme (1) aims at selecting the sensor to query among the remaining unincorporated set of sensors $A = \{1, \ldots, m\} - B$ that provides the highest dependency (i.e., information) with the target class of disease D. To illustrate the idea, we consider the problem of chronic disease diagnosis with time-invariant sensor characteristics.

In order to obtain the best solution, the optimization problem of information-based tasking service is reformulated as an unconstrained optimization problem by utilizing the Lagrangian duality method. Thus, the objective function is augmented with a weighted cost functions as follows:

$$\begin{aligned} F & \quad (p(D|\{e_i\}_{i \in B} \cup \{e_j\})) \qquad (4) \\ & = \alpha \cdot \xi(p(D|\{e_i\}_{i \in B} \cup \{e_j\})) - (1-\alpha) \cdot \rho(e_j) \\ & = \alpha \cdot D(p(D|e_j) \parallel p(D)) - (1-\alpha) \cdot \rho(e_j) \end{aligned}$$

where ξ denotes the information utility of including the symptom e_j from sensor $j \in A$, ρ denotes the communication cost as well as other resources associated with the getting of e_j, and α is the relative weight between the utility and cost. In particular, we could exploit the flexibility to obtain ξ by calculating either the total information gain of the knowledge state after including the new symptom or just the increase in the information gain. Based on the above objective function, the criterion for choosing the sensor to activate has the following form

$$\begin{aligned} Find\ \hat{v} & = arg \max_{j \in A} F(p(D|\{e_i\}_{i \in B} \cup \{e_j\})), \qquad (5) \\ where\ F & : R^m \mapsto R \end{aligned}$$

The utility function ξ cannot be calculated without the knowledge e_j. To deal with this case, we can compute an estimate of the utility, $\hat{\xi}$, by giving the particular value of e_j. Finally, given any value of e_j for sensor j, we obtain a particular value for ξ performing on the new knowledge state $p(D|\{e_i\}_{i \in B} \cup \{e_j\})$. Thus, for each sensor j, the set of all values of ξ for different choices of e_j are calculated and stored at the coordinator. Estimation for summarizing the set of values of ξ by a single quantity may involve considering the average, the worst, or the best case.

IV. INFORMATION-BASED SENSOR TASKING ALGORITHM

We assume there are m_1 body sensors in a WBAN as shown in Fig. 1, where each node is labeled by the index $\{1, \ldots, m_1\}$. Based on information utility for sensor selection and Bayesian filtering for data fusion, we propose a new algorithm in the context of diagnosis. The proposed algorithm to compute information-based tasking strategy is summarized in Fig. 2, which is identical for every body sensor in the WBAN. The various steps are as follows:

1) Initialization: Body sensors transmit their own characteristics $\{\epsilon_i\}_{i=1}^{m_1}$, including the attached position and power level, to the coordinator s.
2) Knowledge State Update: The coordinator s computes a representation of the knowledge state with its own

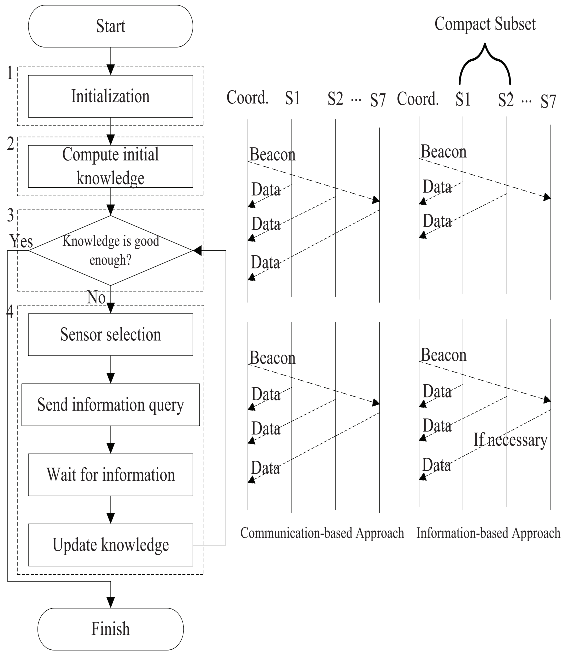

Fig. 2. Flowchart of information-based decision algorithm

measurement, $p(D|e_s)$, and records which body sensor measurements have been incorporated into the knowledge state from the set B. Notice that it is assumed that the coordinator has knowledge of the characteristics $\{\epsilon_i\}_{i=1}^{m_1}$ of all the body sensors in the WBAN.

3) Knowledge Quality Evaluation: Based on the measure of diagnosis, $p(D|\{e_i\}_{i\in B})$, if the knowledge is good enough to support the diagnosis, the coordinator stop processing. Otherwise, it moves to the next step.
4) Sensor Selection: Based on the knowledge state, $p(D|\{e_i\}_{i\in B})$ and sensor characteristics, $\{\epsilon_i\}_{i=1}^{m_1}$, the coordinator selects a body sensor from $A = \{1,\ldots,m_1\} - B$ that maximizes the information utility ξ. For example, if node j is chosen, then the coordinator will send a request to sensor j to require a measurement. After the coordinator receives the requested information, it will update the knowledge state with e_j to get a representation of

$$p(D|\{e_i\}_{i\in B} \cup e_j),$$

and add j to the set of sensors whose measurements have already been incorporated, i.e.,

$$U := U \cup \{j\}.$$

Now, loop back to step 3 until the knowledge state is good enough to support the correct diagnosis.

The knowledge stored by the coordinator can then be distributed for processing at higher levels.

V. Experimental Results

In order to gain a deeper understanding of the information-based model of sensor selection in WBANs, we have performed a wide range of simulations and case-studies. We present several interesting results and discuss their implications.

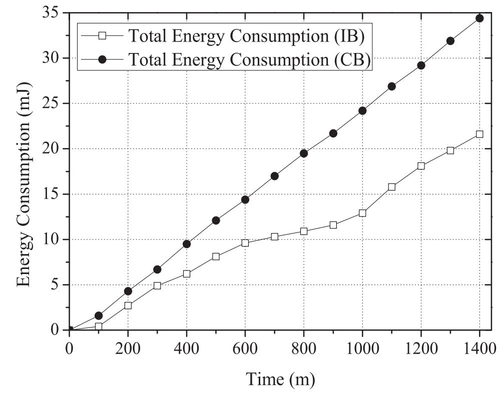

Fig. 3. Total Energy Consumption

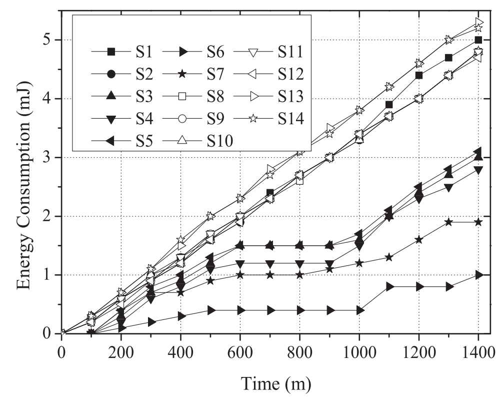

Fig. 4. Energy Consumptions at Sensors

A. Simulation Platform

We have used the NS2 simulator version 2.31 to develop our testbed. Network Simulator 2 (NS2) 2.31 full version is used to verify the proposed models. We have used the IEEE802.15.4 package to simulate a WBAN composed of one coordinator sensor and seven medical sensors organized in a star topology, which coverage is up to 2 meters. Fig. 2 shows data flow and packet exchange scheme between the coordinator and sensors in the WBAN. We have used as previously specified the beacon mode and the contention access period (CAP).

To evaluate our approach, we have considered five distinct diseases and randomly generated these diseases in a period of 24 hours. We have defined for each received measurement from the medical sensor a validity time, during which the coordinator consider the information as valid and do not require to refresh it again. We have fixed this validity time to 10 minutes but it is a configurable parameter of our simulation. To highlight different situations of the patient, we have defined three parts in our scenario: Part 1 (from 0 minute to 540 minutes) and Part 3 (from 960 minutes to 1440 minutes) are active periods where the patient experiments diseases and Part 2 is a quiet period. We have implemented the proposed

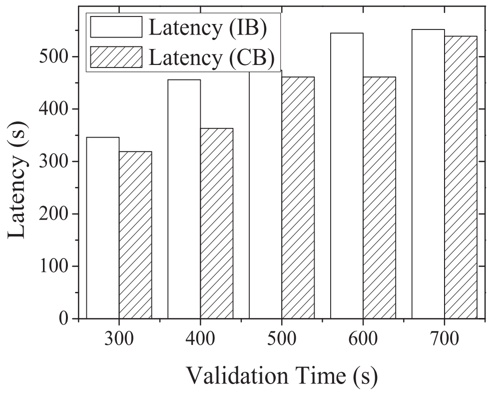

Fig. 5. Latency of Information-based and Communication-based Approaches

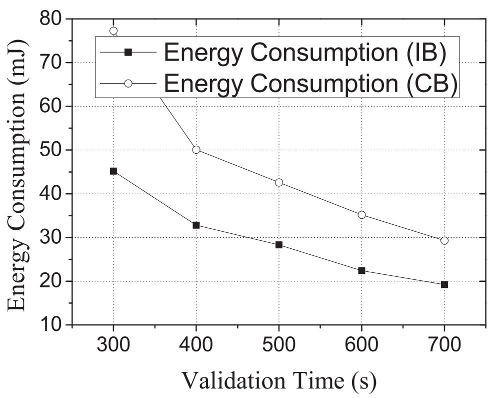

Fig. 6. Energy Consumptions at Different Validation Time

information-based schema (IBS) in the coordinator and the sensors as well as the communication-based schema (CBS) for comparison. We have performed a number of simulation to evaluate our solution.

B. Energy Consumption

We have measured during the simulation the consumption of energy for both schemas. The results presented on Fig. 3 show total energy consumption for IBS and CBS. This figure shows that our proposed IBS consume about 30% less energy than CBS during a day simulation. During Part 2 of the simulation, our solution outperforms specially CBS because only sensors parts of the compact set are active. During the other periods of time, not all the sensors are active in IBS and the coordinator activate them as more information about diseases is required. For instance, in Part 1, the coordinator only activates sensor 1 and 2. In contrary, in CBS, all sensors are activated during the whole simulation time.

The energy consumption of each sensor in IBS (S1-S7) and CBS (S8-S14) is depicted in Fig. 4. Sensor S8-S14 have a linear consumption because they are activate by the CBS coordinator at the beginning of the simulation. Sensor 1 and 2 have also the same behavior because the coordinator has detected them as part of the compact subset. Other sensors such as S3 to S7 are only activated when the coordinator detects a new symptom. For example, in the second period of the simulation, sensors S3-S4, S6-S7 are activated because they are part of the new compact subset of sensors that provide the maximum information to identify the suspected diseases.

C. Validity Time

In the next simulation, we aim to identify the impact of the validity time on the energy consumption and latency in detecting diseases. Fig. 5 shows the positive correlation between latency and validity time. This means that if we choose a high validity time, the time before detecting diseases increases (in both schema). This may suggest that we need to set a small validity time. However, as depicted in Fig. 6, smaller validity time implies more energy consumption. This is mainly due to the fact that sensors information are overdue more quickly and the coordinator needs to request them more frequently. Consume therefore more energy in communications. This suggests that there is a trade-off between the latency time and the energy consumption. If doctors want to detect as soon as possible specific diseases, then the validity time should be short but the sensors lifetime may be shorten. Otherwise, the validity time can be increased and therefore extend the WBAN lifetime.

VI. CONCLUSION

We have addressed in this paper the problem of energy efficiency in medical WBAN. We have shown that existing approaches are not efficient as they focus mainly on the communication schema. We have proposed a top-down cross-layer approach that aims at scheduling medical sensors based on the information gain they provided at a certain time to detect suspected diseases. We have used both theory of feature selection and theory of utility to find compact subset of symptoms to monitor to support disease identification at lower cost of energy consumption. Our information-based approach schedules medical sensors activity of sensing to maximize the information gain. The performed simulations have shown that our solution outperforms the communication based solution at a very small price that is the latency in detecting the diseases. We have shown also that the energy consumption and the validity time of medical measurement are positively correlated and our solution should be carefully configured with the help of doctors.

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