Information-Based Sensor Tasking Wireless Body Area Networks in U-Health Systems

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***Abstract*—In this paper, we focus on the problem of constructing an information gain model for stroke prevention in Ubiquitous Healthcare (U-Health) Wireless Body Area Networks (WBANs). We have constructed an information-based probabilistic relation model among the key indicators and sequenced their data gathering priority and precedence in the WBAN. Then, we constructed a cost function over the energy expenditure involved in their data gathering, and expressed the relationship between utility gain and energy loss as a constrained optimization problem. We also designed an algorithm to carry out the proposed approach. Through simulation study, we demonstrated the validity of some aspects of the approach.**

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

I. Introduction

The population of elderly over the age of 65 has increased significantly in the last few decades and their number is expected to double by 2025 [1]. With this current trend in population age demographics, Ubiquitous Healthcare (U-Health) for elderly has been a rapidly growing research area in recent years [2], [3]. The advancement in low-power electronics and sensor technologies have led to the development of small-sized biomedical sensors that are capable of monitoring a human's health. These biomedical sensors are equipped with communication abilities and form networks called Wireless Body Area Networks (WBANs) [4]. Since the first implementation of WBANs [5], the technology has continued to evolve over the years and have revolutionized medical practice in various ways, including allowing doctors to gather more first-hand information from their patients, clinicians to monitor and recognize the disease processes, and the patients to take a more comfortable physical check-up anytime. A WBAN is a collection of advanced wireless nano- and micro-sensors that are placed around the body, by attaching directly to the skin, as part of special clothing or implanted into the body.

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The primary motivation of WBAN research is to provide long-term continuous sensing without activity restriction or behavior modification. The provision of "steady", "timely", "comfortable" and "proper" monitoring of physical, physiological, and biochemical parameters without activity restriction and behavior modification is the ultimate goal of WBANs. From a system's perspective, the concept of WBANs moves beyond sensor connectivity, with specific focuses on ultra-low-power processing/communication, power scavenging, autonomic sensing, data mining, distributed inferencing, intelligent on-node processing, and integrated wireless sensor microsystems [6]. In this paper, we focus on the discussion of the information-based feature selection in the WBANs.

Wireless sensor networks (WSNs) usually operate in wide areas where the range of scale is from meters to kilometers. To cover such wide areas, a great number of nodes must be deployed. The types of nodes are also varied to perform different dedicated tasks. In particular, the small size of nodes is preferable in WSNs, but not a main constraint in many cases. Unlike the case of WSNs, WBANs operate on/in the human body and its communication range is about upto 2 meters. This restricted communication range enables the star-like transmission topology between the coordinator and the sensors, removing routing as a major source of energy expenditure [7]. However, the proximity of the body sensors and the low transmission power require better coordination among the sensors in order to achieve low latency and low collision numbers. Furthermore, because medical sensors are attached on/in the body, the sensor should consider human comforts. This makes having a reduced sensor size more important. Smaller sensors imply smaller resources such as smaller battery and storage. Energy efficiency and miniaturization are key characteristics of these sensors towards the goal of steady, timely, comfortable and proper monitoring of the health of the elderly person. Depending on the types of sensors that organize the WBAN, the characteristics of network traffic could change accordingly. Some sensors are sensitive to the latency. These kinds of sensors require minimum delay to accurately operate and continuously acquire data about vital signs of the patient. Concerning energy saving schemes, the periodical gathering of information about conventional health parameters, such as temperature and pulse, are preferable for other sensors [8].

To efficiently and optimally utilize scarce resources in a WBAN, such as limited on-board battery power supply and limited communication bandwidth, the nodes in a WBAN must be carefully tasked and controlled to carry out the required set of tasks while consuming only a modest amount of resources. It should be noted that to achieve scalability and autonomy, sensors tasking and control have to be carried out in a distributed or centralized fashion, largely using only local information available to each sensor, or global information available to the coordinator. Due to the small-scale size and specific coordinator, scheduling in a centralized way is preferable to the distributed way in WBAN.

As more nodes participate in the sensing of the body and more measurements are collected, the total utility of the data, processed as the mutual information of the data, increases and allows for a medical diagnosis to be made. However, doing so with all the nodes turned on may consume precious battery power that cannot be easily replenished or replaced, and may also reduce the effective communication bandwidth due to congestion in the wireless medium. Furthermore, as more nodes are added, the benefit often becomes less significant, which is called diminishing marginal returns in economics. To deal with the problem of diminishing marginal returns and address the balance between utility and resource costs, this paper introduces the utility approach of WBAN management.

The clinical signs and symptoms of disease gathered in specific sensors have been used to identify the disease, especially in acute disease. Symptom is defined as a sign of the existence of something or evidence of a disease. In U-Health, a symptom could be labeled as a diagnostic indicator of a condition, such as fever and arrhythmia. When the relevant obvious variables defining the health status are available, the essential task is to answer the queries about the health status using some decision making algorithms. The probabilities of coupling between diagnosis and symptoms are estimated with the algorithm depending on the specific symptom [9]. Thus a new mathematical theory of algorithm design is appealing, which involves the cost of accessing the manifest variables of the problem, or determining useful intrinsic relationships among them. The implementation difficulty is that these costs cannot be precisely evaluated in advance or even only be estimated. Fortunately, there may be costs and relations that have been independently determined by the WBAN (for example, while processing other diagnoses, or according to the medical expert system), which can be made available to develop the algorithm at a relatively low cost of communication.

To design such an information gain description model in the WBAN, several key questions have to be answered.

- What parameters of manifest symptoms are most relevant to a specific disease?
- What relations among these symptoms are critical to whatever high-level information we need to know?
- Which is the best body sensor to acquire a particular parameter?
- How many sensing and communication operations will be needed to accomplish the diagnosis mission?
- How cooperative do the diagnosis models of the different body sensors need to be?

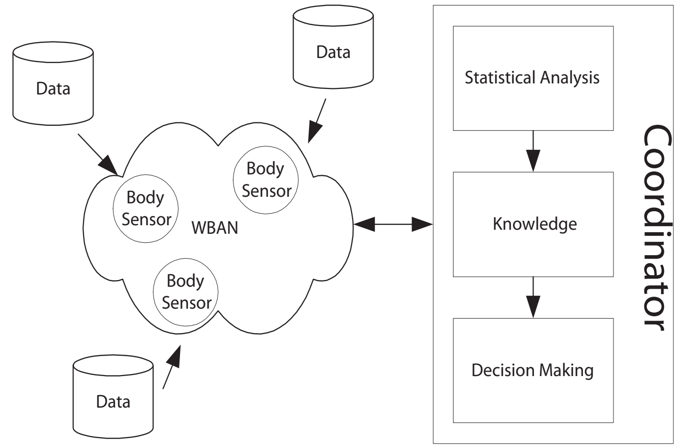

Fig. 1. WBAN system architecture

In this paper, we focus on the aforementioned five challenges. We seek answers to these challenges under the U-Health case study of stroke prevention. A number of key symptoms, such as heartbeat abnormality and breath irregularity, are all potential indicators to the onset of stroke, but with different precedence relations and conditional probabilities.

In the field of WBAN, diagnostic decision-making should rely on the analysis of input data that is very likely based on previous experience. The recommendations generated automatically at the coordinator, in response to a subscriber's or an expert's query, can be very helpful to change the communication scheme, for example, choosing the specific body sensors or modifying the priority of traffic. The coordinator regularly distributes the inquiry to the body sensors for newly arrived data, processes the received data, and stores the results as the knowledge. As soon as query from a subscriber arrives at the coordinator, the latter carries out the statistical analysis of the retrieved data, collects knowledge, and displays the decision to the subscriber, as shown in Fig. 1.

II. An Example: Stroke Prevention

Every year, approximately $500,000$ persons in the United States have a stroke and $150,000$ persons die as a result. Strokes are the third leading cause of death in the United States and are the leading cause of serious disability. Because strokes predominantly affect elderly persons, WBAN's importance in stroke prevention can be expected to grow as the number of elderly persons continues to increase. Fig. 2 represents an example of WBAN where the vital signs data of a patient being monitored (wearing different on-body sensors) are transmitted

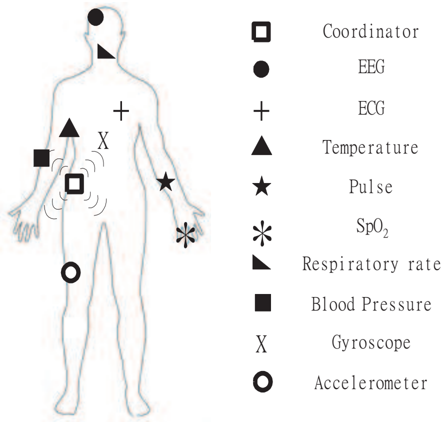

Fig. 2. A WBAN example

to a coordinator for control. In the WBAN, a centralized architecture is appropriate as the WBAN coordinator is superior to the rest of the body sensors (e.g. ECGs, EEGs, Respiratory-rate, Blood Pressure, Oxygen Saturation (SpO_2), Gyroscope, Accelerometer, Body Temperature, Pulse) in terms of memory processing and power resources.

We consider the following simple health case to present the obvious advantages of energy-saving and traffic-reducing in the information-based tasking approach, compared to communication-based schemes. In the case of stroke, it is possible to notice its symptom using body sensors. For example, sudden numbness of the monitored patient's arm or leg, especially on one side of body, results in walking difficulties. For communication-based scheme, no matter which symptom the body sensor detects, the rest of sensors will transmit data to the coordinator periodically. This independent operation can cause the emergency and vital data, which are closely related to the pathogen of stroke, to be postponed or even discarded, resulting in the failure to prevent stroke in time and hence higher consumption of the precious power resources. Alternately, for an information-based scheme, we can select the next "best" sensor based on the so-called utility function measure, which captures the best correlation between the a-priori and a-posteriori knowledge. The knowledge about strokes and other diseases are a-prior knowledge stored by the coordinator to calculate its information gain. Thus, information-based sensor tasking favors sensors which can provide more information gain. In this particular case, the symptom of numbness of one side of the body is monitored by Accelerometer sensor attached on the leg and Gyroscope sensor attached on the back. Thus, the coordinator will select the related sensors, such as EEG (monitoring if the brain wave curve is abnormal), ECG (monitoring if the heartbeat frequency is abnormal) and Respiratory-rate to ensure that the patient is diagnosed with the stroke. And simultaneously, the other sensors will be forced to enter the idle state so that the energy consumption is reduced and the channel contention is reduced without degrading the quality of service.

III. Information-Based Tasking Problem

WBANs can couple body sensors directly to diagnoses and provide information that is precisely monitored as a symptom, such as hypertension and numbness, and localized in time and tissues. Therefore, such advantages enable the new and exciting approaches to ensure the provision of service, such as information representations and calculations, diagnosis decision algorithms and protocols.

With such technological advances, sensors in WBANs may play different roles, including source (i.e., transmission task) and idle nodes (i.e., do nothing but wake up periodically). In particular, each sensor can take a specific role depending on the task requirement such as a query about heart beat frequency, the sensor characteristic such as the type of sensor, and resource availability such as node remaining energy levels. For the specific task in WBANs, sensor assignment provides an opportunity for reducing the traffic in the network and prolonging the sensor lifetime by activating a limited number of sensors that are necessary for monitoring a diagnosis.

A. Notation

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

- Superscript t denotes time. We consider discrete times t that are nonnegative integers.
- Subscript $i \in \{1, \ldots, K\}$ denotes the sensor index; K 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 diagnosis index; N is the total number of diagnoses being evaluated. Here, we also assume that each exact diagnosis is identified.
- The diagnosis state at time t is denoted as $D^{(t)}$. For a multi-diagnosis decision problem, this is a concatenation of individual diagnosis states $D_j^{(t)}$, which is a theoretically described diagnosis with symptom values formed on the basis of real clinical cases.
- The measurement of sensor i at time t, i.e., the symptom, is denoted as $E_i^{(t)}$. In the context of this work, we will use the terms state and parameter interchangeably. The symptoms can be classified by the type of values they take. We will distinguish two types of symptoms: (1) Continuous symptoms, for example, high blood pressure (fluctuating around reference value); (2) Discrete symptoms, for example, low heart beat frequency.
- 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, $\underline{E^{(t)}} = \{E_1^{(t)}, E_2^{(t)}, \ldots, E_K^{(t)}\}$.
- 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 of sensor and its power reserve. Typically, the sensor characteristics are on relatively stable condition.

B. Information-Based Utility Function for Sensor Tasking

A utility function is defined 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 tasking problem is to maximize the value of collected information. It is expressed as follows:

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

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 cost of resources in a WBAN. We assume that each operation on sensors is encapsulated by packet and therefore all of the 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 the 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.

C. Information Utility Measure

From the clinical perspective, several related examinations will be performed on the patient when one of the observed health status parameters is in an abnormal range. The main idea behind such an examination schedule can be introduced to our approach. Additionally, based on analysis of clinical numerical results, the clinical monitoring data usually belong to multimodal and non-Gaussian distributions. Thus, a mutual information measure provides a better characterization of the usefulness of sensor data and characterizes the performance of data classification and compression.

Given two random variables x and y, their mutual information is defined in terms of their probabilistic density functions $p(x)$, $p(y)$, and $p(x, y)$ [5]:

$$\begin{aligned} I(x; y) &= \int\int p(x, y) \log \frac{p(x, y)}{p(x)p(y)}\, dxdy \\ &= D(p(x|y) \parallel p(x)) \end{aligned} \tag{2}$$

where $D(\cdot \parallel \cdot)$ is the Kullback-Leibler divergence between two distributions.

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

$$U(p_D) = I(D^{(t+1)}; E_j^{(t+1)} | \overline{E^{(t)}} = \overline{e^{(t)}}) \tag{3}$$

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.

Given K features $E = \{E_i,\ i = 1, \ldots, K\}$, and the target diagnosis variable $D = \{D_j,\ j = 1, \ldots, N\}$, the feature selection problem is to find from the K-dimensional observation space, R^K, a subspace of k features, R^k, that "optimally" characterizes D. Here, the optimal characterization condition means the maximal statistical dependency of the target class D on the data distribution in the subspace R^k, called as maximal dependency or maximal relevance feature selection.

D. Operation Cost Measure

In WBANs, it is shown that the TDMA scheme is more suitable for such centralized, small-scale and non-dynamic types of networks. Therefore, we employ a TDMA-based MAC protocol, in which time is divided into MAC frames with period M and each MAC frame is composed of multiple time slots m_l, $l \in \{1, \ldots, L\}$. Each sensor node periodically sends its acquired data λ_l to the coordinator through a different channel l in such a way that no collision occurs.

In the physical layer, $G \in \mathbf{R}^{|L| \times |L|}$ is the link gain matrix associated with the graph $\mathcal{G}$. Depending upon the path loss from the transmitter of link k to the receiver of link l, G_{lk} denotes the power gain from the transmitter of link k to the receiver of link l, for $l \neq k$. In TDMA-based WBANs, all of them vanish and there exist only the diagonal entries G_{ll}, representing the gain over each link l. We assume a deterministic path loss model where the power falls off as d^m for distance d, with $m = 4$. Thus $G_{ll} = \kappa / d^4$, where κ is a constant. The channel over each link is assumed to be an additive white Gaussian noise (AWGN) channel with noise power spectral density N_0. Let $r_l^{m_l}$ denotes rate per unit bandwidth over link l during slot m_l, where $r_l^{m_l} = \lambda_l / m_l$.

It is known that communicating 1 bit over the wireless medium at short ranges consumes far more energy than processing that bit. For each link, only the transmission energy consumption is considered. However, the solutions to the formulated information-based tasking problem can be easily extended to the ones without this simplification. C denotes the total amount of initial energy in the WBAN. Thus, the operation cost function is

$$\sum_{i \in V_t(t)} \sum_{l \in \mathcal{O}(n)} \beta_l \delta(e^{\frac{\lambda_l}{m_l}} - 1) \leq C \tag{4}$$

where $\beta_l = \frac{N_0(1+\alpha)}{G_{ll}}$. $\mathcal{O}(n)$ is defined as the set of outgoing links at node n. In the WBAN, the cardinality of $|\mathcal{O}(n)|$ of a set $\mathcal{O}(n)$ is one, since body sensors only transmit data to the coordinator. δ is denoted to the duty cycle of sensor.

IV. Information-Driven Tasking Service

In WBANs, the sensors need to transmit data, such as temperature, ECG, EEG, EMG and gait monitoring, at relatively wide range of data ranges from $1kbit/s$ to $1Mbit/s$. Therefore, we must balance the information contribution of individual sensors against the cost of communicating them. Consider the coordinator choosing 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 $B \subset \{1, \ldots, K\}$ is the subset of sensors whose symptom has already been gathered and incorporated. The information-based tasking scheme (1) is to choose which sensor, reflecting the largest dependency on the target class D, to query among the remaining unincorporated set $A = \{1, \ldots, K\} - B$. To illustrate the idea, we consider the problem of chronic disease diagnosis with time-invariant sensor characteristics.

In order to obtain the optimal 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:

$$\begin{aligned} F & \quad (p(D|\{E_i\}_{i \in B} \cup \{E_j\})) \\ = & \quad \alpha \cdot \xi(p(D|\{E_i\}_{i \in B} \cup \{E_j\})) - (1-\alpha) \cdot \rho(E_j) \\ = & \quad \alpha \cdot D(p(u|v) \parallel p(u)) - (1-\alpha) \cdot \rho(E_j) \end{aligned} \tag{5}$$

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 has the following form

$$\begin{aligned} Find\ \hat{v} &= arg \max_{j \in A} F(p(D|\{E_i\}_{i \in B} \cup \{E_j\})), \\ where \quad F &: R^K \mapsto R \end{aligned} \tag{6}$$

Unfortunately, the measurement value E_j is unknown until it is transmitted to the coordinator s. However, in this case, we just want to choose the most likely best sensor, which is based on the current knowledge state $p(D|\{E_i\}_{i \in B})$ as well as the newly arrived knowledge and the sensor characteristics. Here the cost function ρ may be approximated as the distance between sensor j and s raised to the power of 4 to show the rough transmission cost. For more complicated cases, we may calculate an estimate of the cost, $\hat{\rho}$, from the sensor characteristics, i.e., ϵ_j and ϵ_s. In particular, 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. The approximations $\hat{\xi}$ and $\hat{\rho}$ are usually necessary in the tough situation where real ξ and real ρ are too difficult to obtain.

V. Information-Based Tasking Algorithm

We assume there are K_1 body sensors in a WBAN as shown in Fig. 2, where each node is labeled by the index $\{1, \ldots, K_1\}$. Each body sensor i only stores information of its own position and the remaining energy level at the coordinator.

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. 3, which is identical for every body sensor in the WBAN. The various steps are as follows:

1) Initialization: Body sensors transmit their own characteristics $\{\epsilon_i\}_{i=1}^{K_1}$, 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 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 $\{\epsilon_i\}_{i=1}^{K_1}$ 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, $\{\epsilon_i\}_{i=1}^{K_1}$, the coordinator selects a body sensor from $A = \{1, \ldots, K_1\} - B$ 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.

Thus, the coordinator stores all the information about the knowledge of diagnosis from the body sensors by intelligently querying a subset of the nodes that provide the majority of the requested information. This illustrates the advantages of energy-saving by transmitting only the most useful information

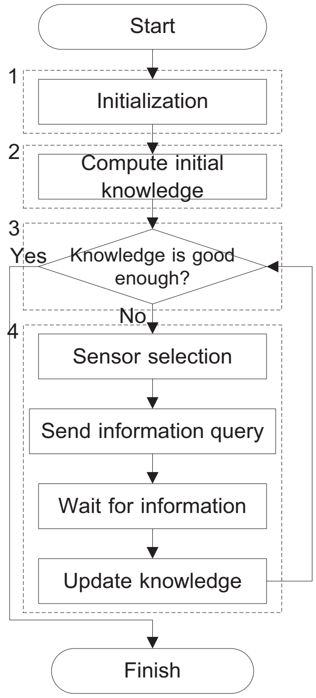

Fig. 3. Flowchart of information-based decision algorithm

TABLE I
CLINICAL SYMPTOMS STATISTICS OF STROKE ACCIDENT PATIENTS

Symptoms	Probability
Infarction	53%
Paresis	36%
Atrial Fibrillation	15%
Hemiparesis	27%

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

VI. INFORMATION-BASED TASKING IMPLEMENTATION: A STROKE CASE

In this section, we present the example we mentioned in the section II to better illustrate the above analysis. Because the clinical diagnosis of stroke may be different depending on many physiological parameters, we concentrate on the following important vital signs, such as, Paresis, ECG, and EEG. Estimating mutual information from empirical data commonly involves two steps

1) Estimating the joint distribution of symptom and stroke;
2) Calculating the mutual information based on this estimated distribution.

According to these two steps, we developed a software tool to compute the mutual information. The statistical results for cause of stroke are summarized in Table I.

Based on the computation tool, the mutual information and utility values are obtained in Table II. From the Table, we see that the vital indicators of stroke symptoms are present with high information gain and the coordinator choose exactly these key sensors to gather additional information and thus is able to obtain the correct diagnosis. In comparison with non information-based gathering approach, our approach is energy efficient and low latency owing to the strongly targeted tasking provided by the information model.

TABLE II
CLINICAL SYMPTOMS STATISTICS OF STROKE ACCIDENT PATIENTS

Symptoms	Utility Value	Sensor Selection
Infarction	0.765	EEG
Paresis	0.424	Gyroscope
Atrial Fibrillation	0.314	ECG
Hemiparesis	0.521	Accelerometer and Gyroscope

VII. CONCLUSION

In this paper, we focus on the problem of constructing a information gain model for stroke prevention in U-health WBAN. We have identified a number of key parameters such as localized paralysis, heartbeat abnormality and breath irregularity that are all potential indicators of a stroke condition but with different precedence relations and conditional probabilities. We have constructed an information-based probabilistic relation model using these key indicators and sequencing their data gathering priority and precedence in the WBAN. Then, we constructed a cost function over the energy expenditure involved in their data gathering, and expressed the relationship between utility gain and energy loss as a constrained optimization problem. We also designed an algorithm to achieve the solution approach. We find that constructing a correct and simple information model for a specific U-Health scenario is a fundamental design step. Through simulation studies, we have demonstrated some aspects of our model design and principle approach for solving the stroke prevention case problem.

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