Wireless Pers Commun (2013) 72:2605–2631
DOI 10.1007/s11277-013-1169-x

A Prioritization Based Congestion Control Protocol for Healthcare Monitoring Application in Wireless Sensor Networks

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Published online: 16 April 2013

Abstract Recent developments in biosensor and wireless technology have led to a rapid progress in wearable real time health monitoring. Unlike wired networks, wireless networks are subject to more packet loss and congestion. In this paper, we propose a congestion control and service prioritization protocol for real time monitoring of patients' vital signs using wireless biomedical sensor networks. The proposed system is able to discriminate between physiological signals and assign them different priorities. Thus, it would be possible to provide a better quality of service for transmitting highly important vital signs. Congestion control is performed by considering both the congestion situation in the parent node and the priority of the child nodes in assigning network bandwidth to signals from different patients. Given the dynamic nature of patients' health conditions, the proposed system can detect an anomaly in the received vital signs from a patient and hence assign more priority to patients in need. Simulation results confirm the superior performance of the proposed protocol. To our knowledge, this is the first attempt at a special-purpose congestion control protocol specifically designed for wireless biosensor networks.

Keywords Wireless biomedical sensor networks · Wearable healthcare monitoring · Priority-based congestion control · Learning automata

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1 Introduction

Rapid advances in wireless sensor networks and wearable sensor technologies are having a significant impact on continuous and ambulatory health monitoring. Wireless Biomedical Sensor Networks (WBSNs) [1] involve a convergence of biosensors, wireless communication and networks technologies. A WBSN consists of a collection of wireless networked low-power biosensor devices, integrated with an embedded microprocessor, radio and a limited amount of storage.

Typically, these sensors are placed on the human body hidden in a user's clothes, thus allowing the monitoring of various parameters in their native environment. Wireless sensors can be used to monitor patients' physical conditions and transfer real time vital signs to the hospital, emergency center or individual doctors. WBSN can be deployed in various medical realms such as inside a hospital for monitoring patients, hospital staff and doctors, home monitoring and long-term assistive living to help the elderly or disabled in their daily activities. WBANs can be useful whenever there is the need to monitor patients in nursing institutes. This has enabled remote patient monitoring. Using remote patient monitoring systems, it is possible to monitor changes in a patient's physiological signals and vital signs, and thus provide feedback to help maintain an optimal health monitoring. This capability can be attributed to recent developments in biosensors and in wireless communication systems. WBSN, unlike wired monitoring system, can be used for long-term and continuous monitoring even when people move [2].

High performance and fault tolerant wireless devices can now be employed to eliminate medical errors, to reduce workload and increase the efficiency of hospital staff, and to improve the comfort of patients. Thus, there has been an increased interest among research groups in developing methods for real-time wireless recording and monitoring for physiological signals and vital signs such as Electrocardiograms (ECGs), Blood Pressure (BP), Heart Rate (HR) and Skin Temperature (ST), electromyograms (EMGs), electro-encephalograms (EEGs), glucose level, oxygen saturation, etc from a patient.

Although various efforts have been made to address different problems in wireless biomedical sensor networks, some key challenges still remain. A key issue is communication within the WBSN and between WBSNs in a general monitoring environment, or in emergency response applications. Lorincz et al. [3,4] and Milenković et al. [5] identified some general communication challenges for sensor networks in emergency response applications. Among the key problems identified are discovery naming (establishing communication between sensors and receivers), robust routing for potentially multiple receivers, tracking device locations, reliable communications, interoperability, and prioritization of critical data given the limited bandwidth of low-power communication devices used in WBSNs, such as those based on the ZigBee and IEEE 802.15.4 standards. Further communication problems are posed by the challenge of transmitting on or near the human body, mobility of sensor locations (on the human body), and the dynamic nature of the monitoring or care environment. There are also the traditional problems of energy efficiency and low network latencies given the potentially critical nature of the vital signs or physiological signals being transmitted.

Most of the current efforts on these problems have focused on work on the lower layers of the OSI network model, especially the physical layer (on sensors and devices [6]), and the medium access layer [7]. In particular, there has been a significant attention on the problems of mobility, transmission through and/or around the human body, and their safety implications. See for example [6,8–10]. Yet, given the special nature of the vital signs and physiological signals involved in a WBSN, improvements in performance could be achieved by designing specialized protocols at the upper layers of the network hierarchy, for instance for congestion control at the network or transport layers.

Some recent efforts on related problems at higher levels of the OSI model include the work of Latre et al. [11] and Zhou et al's BodyQoS [7]. In addition to the virtual medium access protocol proposed in [7], they also considered problems of quality of service, especially admission control algorithms suitable for wireless body sensor networks. Latre et al. [11] proposed a low-delay protocol for multihop wireless body area networks. They focused on providing multihop support between sensors within the BAN, since direct communication between them and the sink node (say a PDA) may be difficult in some cases. Thus, they used a tree topology for connecting the sensors, with the sink serving as the root of the spanning tree [12]. In a related work [13], they proposed methods for improved reliability in multi_hop body sensor networks, by modeling the probabilistic connectivity between nodes in the network, assuming a log-normal radio model [14].

At the heart of communication problems in wireless biomedical sensor networks is the problem of congestion control. A high level of congestion in a wireless sensor network often leads to many retransmissions, with a direct consequence on overall energy consumption, latencies, and data loss probability. This is becoming a critical problem, especially given the increasingly high data rates involved in modern wireless biomedical sensor networks, for instance, those that carry EKG signals [15]. To the best of our knowledge, none of the existing health care monitoring systems have paid any particular attention on congestion control problems in wireless biomedical sensor networks. The existing congestion control protocols for WSNs described earlier can not be directly applied to WBSN, since these do not consider the special nature of the signals carried in a WBSN. In this work, we propose a congestion control and prioritization protocol for monitoring and transmission of vital signs and physiological signals in a wireless biomedical sensor network. Our approach is motivated by our recent work on queue-based congestion control protocol with priority support [16] for wireless multimedia sensor networks.

Congestion control is usually performed in three steps: congestion detection, congestion notification, and rate adjustment. After detecting congestion, to prevent the negative aspects of congestion in the network, the transport protocol needs to propagate congestion information from the congested node to the upstream sensor nodes or the source nodes that contribute to congestion. This can be done explicitly by sending a special control message to the other sensors, or implicitly using piggybacking techniques. When a node receives a congestion notification message, it should adjust its transmission rate using a rate control technique.

Our proposed protocol provides a mechanism to support monitoring of vital signs and physiological signals under the following three scenarios:

1. Given the different physiological signals and vital signs, some of them are more critical and more important than the others. Using service prioritization, the physiological signals and vital signs are grouped into different service classes. The more important classes get a higher quality of service than the others.
2. The central computer of the monitoring system periodically receives physiological data from each patient, and has the capability to analyze these data on the fly. Whenever it detects any anomaly in the received physiological data, it sends a special message to the wireless device of the patient involved, and assigns a high priority to data transmitted from the patient. Thus, information from the patient will be received more quickly at the central computer, facilitating tracking of the patient, and a closer monitor of his/her health condition.

3. Given that different patents would have different medical records in the system, if a patient is known to have a special need, it should be possible to assign more priority to data transmitted from such a patient. Generally we consider three different health conditions for each patient in the monitoring system, namely, NORMAL, URGENT, and CRITICAL. Patients who are in URGENT or CRITICAL conditions get more network bandwidth than the NORMAL patients.

The reminder of this paper is organized as follows. Section 2 presents a brief review of prior related works on congestion control protocols. In Sect. 3, we present our proposed congestion control and bandwidth allocation protocol for WBSNs. Section 4 evaluates the performance of the proposed model. Final discussion and conclusions are presented in Sect. 5.

2 Related Work

Various congestion control methods have been studied for wireless sensor networks [17–23]. In particular, CODA [21], CCF [18] and PCCP [17] are three popular approaches for congestion control in traditional wireless sensor networks. *CODA* (COngestion Detection and Avoidance) is an energy-efficient congestion control scheme and comprises of three basic mechanisms: (i) receiver-based congestion detection; (ii) open-loop hop-by-hop backpressure; and (iii) closed-loop multi-source regulation. CODA detects congestion based on queue length as well as the channel load at intermediate nodes. It uses explicit congestion notification and an AIMD (Additive Increase, Multiplicative Decrease) rate adjustment technique. Congestion Control and Fairness (CCF) was proposed in [18] as a distributed and scalable algorithm that eliminates congestion within a sensor network and ensures the fair delivery of packets to a sink node. CCF exists in the transport layer and is designed to work with any MAC protocol in the data-link layer. In the CCF algorithm, each node measures the average rate r at which packets can be sent from the node, divide the rate r among the number of children nodes, adjust the rate if queues are overflowing or about to overflow and propagate the rate downstream. CCF uses packet service time to deduce the available service rate. Congestion information is implicitly reported. It controls congestion in a hop-by-hop manner and each node uses exact rate adjustment based on its available service rate and child node number. CCF, however, has two major problems. The rate adjustment in CCF relies only on packet service time which could lead to low utilization when some sensor nodes do not have enough traffic or there is a significant packet error rate. Furthermore, CCF cannot effectively allocate the remaining capacity. Since it uses a work-conservation scheduling algorithm, it has a low throughput in when some nodes do not have any packet to send.

Priority-based Congestion Control Protocol (PCCP) introduced in [17] is an upstream congestion control protocol for WSNs. It measures the congestion degree as the ratio of packet inter-arrival time to the packet service time. Based on the introduced congestion degree and node priority index, PCCP utilizes a cross-layer optimization and imposes a hop-by-hop approach to control congestion. PCCP achieves efficient congestion control and flexible weighted fairness for both single-path and multipath routing. These are general congestion control mechanisms for wireless sensor networks, and none of them made any special considerations for communication of biomedical signals.

WBSNs are classified into the same category as WSNs [1]. However, WBANs are different from usual WSN in many ways. One important requirement of applications in WBSNs is low delay bounds. Furthermore, some applications of WBSNs need relative resilience to losses. The typical application scenarios of WBSN are various. For example, Smart home health monitoring [24], used WSBN to help the patients or older people with chronic disorders. The ‘smart ward’ in the hospital allows emergency situation to be handled immediately and reduce the time of routine check-up and its real-time monitoring, too. Moreover, to reduce the possibility of infection in a contagion ward, personal contacts can be avoided for the nurses.

WBSNs can support different types of traffic classes. Similar to WSNs, applications of WBSNs share different characteristics such as: scarcity of node energy, resource constraints, unbalanced mixture traffic, data redundancy and dynamic network topology. Thus the Quality-of-Service (QoS) in WBSNs is an important task. Furthermore, physiological signals are different in data generation rate and loss - and delay-tolerances. Some of them have low data rate which are time-critical and must be delivered at the base station within a guaranteed end-to-end delay deadline; and also may require high reliability. In contrast, some others have high data rate that may allow a certain percentage of packet losses. Thus some of signs are more critical and more important than the others. Therefore, a multi objective QoS mechanism is greatly required for WBSNs.

Over the past few years different systems for vital signs monitoring have also been proposed. Gao et al. [15] described the design of an electronic triage system using lightweight, embedded systems with limited computational capabilities. The system was built on top of CodeBlue earlier described in [3,4,25], a wireless body sensor network that uses noninvasive, biomedical sensors to continuously monitor patient vital signs and to deliver pertinent information to first responders. The real-time collection of data through a mesh network in a mass casualty drill was shown to approximately triple the number of times patients that were triaged compared with the traditional paper triage system. Jovanov et al. [26–28] described a body area network for ambulatory monitoring of physical activities and physical health, with applications in computer-aided patient rehabilitation.

BodyQoS, a quality of service (QoS) system demonstrated on an emulated body sensor network was proposed in [7]. BodyQoS adopts an asymmetric architecture, in which most processing is done on a resource rich sink node, minimizing the load on sensor nodes with limited resources. Prioritized data stream service, asymmetric QoS framework, radio agnostic QoS, adaptive bandwidth scheduling and testbed implementation are the main contributions of the BodyQoS system. In [29], CustoMed, a platform for health monitoring using wireless sensor networks was proposed. CustoMed reduces the customization and reconfiguration time for medical systems that use reconfigurable embedded systems. Chen et al. [30] proposed a wireless body sensor network that enables continuous cuff-less blood pressure measurements. To enable unobtrusiveness and comfort, the network operates wirelessly on the basis of the low-power short-range IEEE 802.15.4 standard. Yuce et al. [31] describe a heterogeneous sensor network system with the capability of monitoring physiological parameters from multiple patients using different communication standards. The remote central control unit is able to communicate with the Internet or a mobile network for long distance data transfer. Thus, it is possible to obtain a patient’s physiological data on demand basis via the Internet. Patel et al. [32] described a wireless sensor platform for monitoring persons with Parkinson’s disease. The sensor data collected is then analyzed using wired wearable sensors.

Pan et al. [33] described three different forms of healthcare monitoring systems, namely in-home, global, and in-community healthcare monitoring systems. These were further categorized based on their wireless communication networks from the viewpoints of mobility, cost, and ease of deployment, scalability, and self organization. They then analyzed the architecture of a novel in-community monitoring healthcare system while comparing it with in-home and global healthcare monitoring systems. A multimodality sensor system was proposed in [34] for monitoring sleeps quality.

In [35] a simple congestion control protocol for vital signs monitoring in wireless biomedical sensor networks is proposed. To minimize congestion in each intermediate sensor node, a simple multi- threshold mechanism is used. Based on the current congestion degree and the priority of its child nodes, the parent node dynamically computes and allocates the transmission rate for each of its children. In [36] proposed a method to joint throughput and time delay performance assurance in a radio agnostic manner for heterogeneous BSNs. The approach supports different data streams and is based on a group-polling scheme that is essential for radio-agnostic BSN design. Both theoretical analysis and practical system development are used. The method, called BodyT2 presents the algorithms for admission control and time resource scheduling.

LACAS [37] is an automata base congestion control protocol for healthcare application in WSN. In LACAS there is an automaton in every intermediate node which regulates the node's incoming rate for controlling congestion locally in that node. For the input to the automaton at time, t = 0, the automaton has five actions which are based on the rate with which an intermediate sensor node receives the packets from the source node. The learning parameter is drop packets. The most optimal action, at any time instant, among the set actions in a node, is decided by the number of packets dropped. To be precise, the rate of flow of data into a node for which there is the least number of packets dropped is considered to be the most optimal action.

In [38] a mobile environment, that intermediate nodes and destination nodes (doctors) can be mobile, is considered and a modification of LACAS for mobile environment is presented. A dynamic QoS approach for U healthcare in Wireless multimedia sensor and actor networks is presented in [39]. The authors consider multiple QoS constraints to optimize the network utilization. Multiple classes of health information are considered. Each class has bandwidth level. In order to adjust the transmission rate, when available bandwidth is less than required bandwidth, a node decides which packet classes should be dropped.

Hu et al. [40] proposed accurate feature extraction method to compress the healthcare signals to reduced congestion. Compression data can reduce data rate. For this purpose a method based on multi-scale wavelet analysis is presented.

In a prior work, we proposed LACCP [41], a congestion control protocol based on learning automaton in WBSNs. LACCP can adjust intermediate node arrival rate and source sending rate using learning automata. The proposed protocol is aimed at satisfying all the requirements of different types of traffic. To do so, two different traffic classes were considered. *Critical* Class and *Normal* Class. In order to control congestion, a mechanism based on the learning automaton has been placed in the sink. At intermediate nodes that gather the patient's physiological data the sensed data are grouped into different classes. Using weighted scheduling mechanisms, higher priority classes are given a better quality of service and more bandwidth than the lower priority classes. The proposed protocol is quite different from LACCP and the way in which the automaton is used is too. The automaton in the proposed protocol is aimed to control the drop probability of each queue in intermediate nodes. The total actions and the reward/punishment mechanisms are fully different. A class based congestion control protocol with service differentiation is proposed in [42] to reduce queuing delay and provide reliable data transmission for them. HOCA [43] is a data centric congestion management protocol using AQM is proposed for healthcare applications. HOCA avoids congestion in the routing phase using multipath and QoS aware routing. And in cases where congestion cannot be avoided, it will be mitigated via an optimized congestion control algorithm. In [44] Queue management based congestion control in wireless body sensor network is presented. The proposed protocol focuses on efficient management of queue to provide reliability and reduce packet loss.

3 The Proposed Model

Unlike most existing healthcare monitoring systems which consider a single hop wireless communication system, in the proposed system we consider multi-hop communication between the end sensor nodes (patients) and the central computer (medic). Although multi-hop communications within the body sensor networks has been studied here we focus in on multi-hop communication between the sink node for each individual patient's body area network and the central computer.

Problem How to design the congestion protocol that can allocate bandwidth and define the drop probability of each node according to both patient priority and traffic priority?

- The proposed congestion control and service differentiation protocols are placed in all sensor nodes in the system which is designed for remote monitoring of patient's physiological signals.
- Our approach is motivated by the apparent limitations of existing priority based congestion control schemes designed for WSNs, such as the PCCP, and CCF.
- In the proposed protocol, the bandwidth allocation of each end sensor node is tuned depending on its congestion condition and its priority index. This means that nodes with high priority and low congestion get more network bandwidth than the others.

Definition 1 The proposed congestion control and service differentiation protocols are placed in all sensor nodes in the system which is designed for remote monitoring of patient vital signs and *physiological* signals (Fig. 1).

Definition 2 we suppose there are 4 different biosensors attached to each patient which collect different vital and *physiological* signs, namely: Electrocardiogram (ECG), Blood Pressure (BP), Heart Rate (HR) and Skin Temperature (ST). The gathered information is sent to a local PDA which is allocated to each patient. The monitored vital signs are transmitted to the PDA using the 402–405 MHz frequency band. The Federal Communications Commission (FCC) has designated the 402–405 MHz frequency band as the Medical Implant Communication Systems (MICS) band which is unlicensed in the air. The merged signals at the PDA are then transmitted toward the central computer using intermediate motes in a multi-hop communication manner (Fig. 1).

Definition 3 The vital signs from each patient are recorded and processed by the central computer. When the central computer detects any unusual changes which may indicate that at least one patient is in URGENT or CRITICAL situation, it sends a special message to that particular sensor node and assigns it a high priority. Thus, the proposed protocol is able to provide more network bandwidth for transmission of data packets related to the vital signs from patients in urgent need.

Figure 1 shows the overall system view of the current study.

In practice, some *physiological* signals such as ECG and BP are more important than the others. Thus, we propose a service prioritization unit needed to support differentiated services in the local PDAs. The proposed service prioritization can be tuned to support any number of *physiological* signals defined in the monitoring system. Without loss of generality, we consider only the four *physiological* signals (HR, BP, ECG, and ST) as shown in Fig. 1. The ECG signal is assigned to the high priority class. In general, the proposed system assigns higher throughput and lower delay to high traffic classes. Let TH_n and D_n denote the respective throughput and delay of traffic class n ($n = 1, 2, 3, 4$). The high priority traffic class

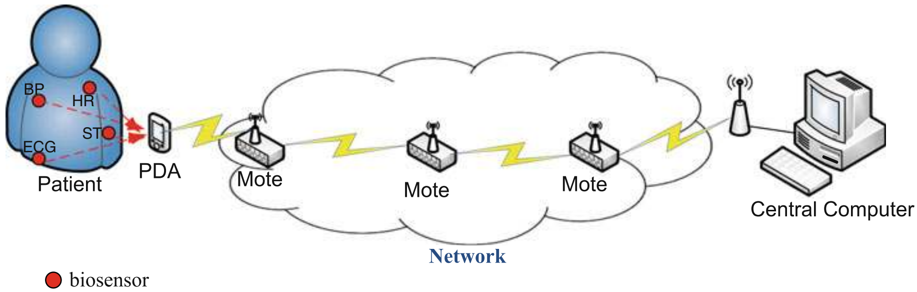

Fig. 1 The system overview

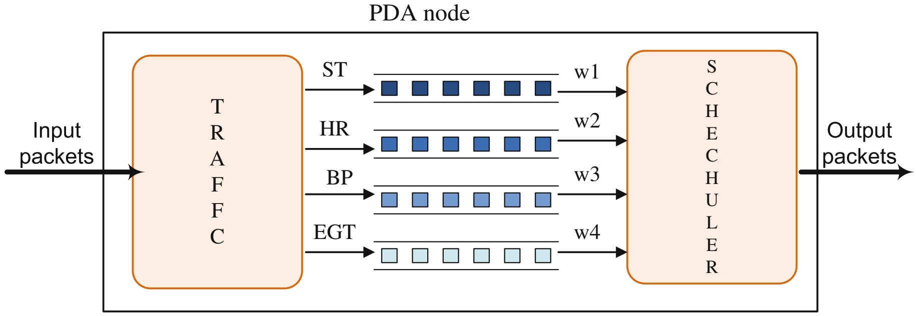

Fig. 2 Queuing model of each PDA

(class 4) needs to have high throughput and low delay bound. The constraints on throughput and delay for the *traffic classes* are given as follows:

$$TH_4 \geq TH_3 \geq TH_2 \geq TH_1$$
$$D_4 \leq D_3 \leq D_2 \leq D_1 \tag{1}$$

In the service prioritization unit, the ECG, BP, HR and ST signals are assigned to traffic class 4, 3, 2 and 1, respectively. Notice that this assignment could be varied on patient-by-patient basis. At the PDA node, separate queues are allocated for each type of traffic class. The queuing model of each PDA node is shown in Fig. 2. To discriminate traffic classes from each other, the PDA adds a traffic class identifier to the incoming data packets and puts them in the proper queue. This identifier represents the traffic class of each packet. As shown in Fig. 2 at the, in each PDA, each arriving packet is sent to a different queue depending on its traffic class. A weighted fair queue (WFQ) scheduler is used to schedule the incoming packets. To provide better quality of service for high priority traffic classes, the assigned weights used in the WFQ scheduler follows the constraint: $w_4 \geq w_3 \geq w_2 \geq w_1$.

We assume that at the central computer, there is a pre-hospital patient care software with algorithms to continuously monitor patients' vital signs and alert first responders of critical changes. This software receives real-time patient data and processes them to detect anomalies. Whenever the central computer detects any anomaly in the received vital signs of a particular patient, it sends a special message to the patient's wireless device (PDA) and assigns a high priority to that particular patient. Since the proposed congestion control and service differentiation unit are priority based, all sensor nodes along the path between the patient and the central computer will allocate more network bandwidth to data packets from the patient. In this way more information from a patient in need is received at the central

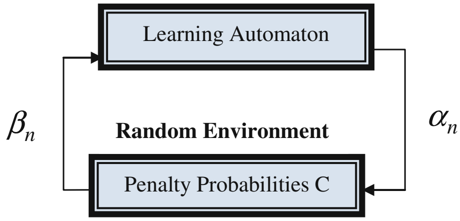

Fig. 3 Automaton operating in the environment

computer, thus it is possible to track and monitor the health condition of the patient. If the patient has a previously entered medical record, such information could be used by the alert detection algorithm.

In this section we describe our proposed congestion control model for wireless body sensor networks. The proposed model consists of two different parts:

(1) Learning Automata based AQM Mechanism in Intermediate Nodes and
(2) Bandwidth Allocation Mechanism

In the following subsections, we describe these two parts in details.

3.1 Learning Automata Based AQM Mechanism in Intermediate Nodes

3.1.1 Learning Automata

Here we give a brief overview of learning automata [45]. A learning automaton is a mechanism that can be applied to learn the characteristics of a system's environment. Figure 3 illustrates the relationship between the random environment and the learning automaton. An environment represented by a triple $E = \{\alpha, \beta, c\}$, where $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_r\}$ is represents all the possible actions of the automaton and r is the total number of actions. $\beta = \{\beta_1, \beta_2, \ldots, \beta_m\}$ denotes the response received by the automata.

The goal is to find an optimal action among a set of actions, such that the average penalty received by the environment is minimized. The automaton uses a vector $P(n) = \{P_1(n), P_2(n), \ldots, P_r(n)\}$ which represents the probability distribution for choosing one of the actions at cycle n. In each cycle n, an action α_i is selected with probability P_i and the environment provides a penalty or reward c_i, which is used by the automaton to update the probabilities in $P(n)$. Action probabilities are updated using Eq. (2):

$$P_i(n+1) = P_i(n) + (1-\beta(n)) \sum_{j,i} g_j\left(P(n)\right) - \beta(n) \sum_{j,i} h_j\left(P(n)\right); \quad \text{if } \alpha(n) = \alpha_i$$
$$P_i(n+1) = P_i(n) + (1-\beta(n))\, g_i\left(P(n)\right) + \beta(n) h_i\left(P(n)\right); \quad \text{if } \alpha(n) \neq \alpha_i \tag{2}$$

where $\beta(n)$ is normalized in [0,1]. The lower the value of $\beta(n)$, the more favorable the response. g_i and h_i (i $= 1, 2, \ldots,$ r) are continuous, nonnegative functions and associated with reward and penalty functions for action respectively. Depending on the functions g_i and h_i, several linear and non-linear reinforcement (updating) schemes can be obtained. Linear schemes are simplest and commonly used. In general linear reinforcement schemes, the reward and penalty functions can be expressed as follows:

$$g_k\left(P(n)\right) = a P_k(n), \quad h_k\left(P(n)\right) = \frac{b}{r-1} - b P_k(n) \tag{3}$$

With $0 < a, b < 1$ where a is associated with reward response, and b with penalty response [45].

3.1.2 Proposed Algorithm

Here, we propose the use of learning automata with an active queue management (AQM) approach at the intermediate nodes. It is clear that when the packet arrival rate is more than the departure rate, the node's queue will be filled. This, in turn, causes increased packet loss and delays. In a healthcare application, different patients would have different medical records in the system. If a patient is known to have a special need, it should be possible to assign more priority to data transmitted from such a patient. In the proposed AQM protocol, a packet is entered into the node's queue, based on its traffic class (HR, BP, ECG, or ST).

When the central computer detects any anomaly in the received data from a given patient, it realizes that there is an urgent situation for a particular patient. In this case it assigns a high priority to that patient so that it would be possible for the system to get more information about the vital signs of that particular patient. To achieve this goal, the upstream node dynamically considers the priority of each of its child nodes as well as its congestion degree to calculate the transmission rate of the child nodes. Based on the current congestion index and the current node priority, the new transmission rate of each child node is calculated. The new rate is then sent to all the child nodes. To decrease energy consumption, the proposed protocol uses an implicit notification by adding the new rate of each child node to the sending data of each sensor node. When a node receives a new rate assignment message from its upstream node, the node is expected to adjust its traffic rate accordingly.

To minimize congestion in each intermediate sensor node, a separate queue is allocated to each child node to store its input packets. The sent traffic from each child node is buffered in a separate queue. Furthermore, as each sensor node may have some local source traffic to be sent to the sink node, an additional queue is also reserved for local traffic of the sensor node. So, if an intermediate node i has N_i child nodes, then it needs $N_i + 1$ queues to store packets. When a packet reaches an intermediate sensor node, at first it is delivered to the classifier. Classifier delivers packets to its corresponding traffic queue based on their profile. After recognizing the traffic class of each packet, intermediate node delivers packet to P_i unit. P_i unit makes decides either to drop the packet or to put it along the queue. The decision is based on learning automata. Figure 4 shows the network model used in each sensor node.

Note that in the intermediate sensor nodes all packets are placed in the same buffer. To discriminate between different traffic classes at each intermediate node, we use learning automata in order to adjust the drop probability of the queue.

At each intermediate node, there is a variable automaton denoted by {A, B, P, T}, where: A is a set of four actions on drop probability described as follows: A = {$DPIL$, $DPIH$,

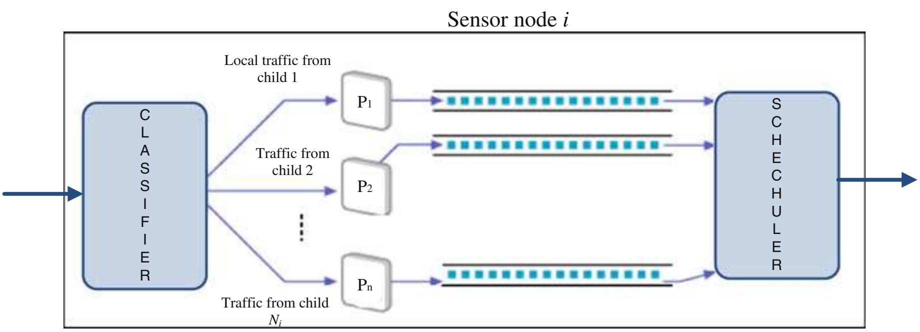

Fig. 4 Per child queuing in intermediate sensor node i

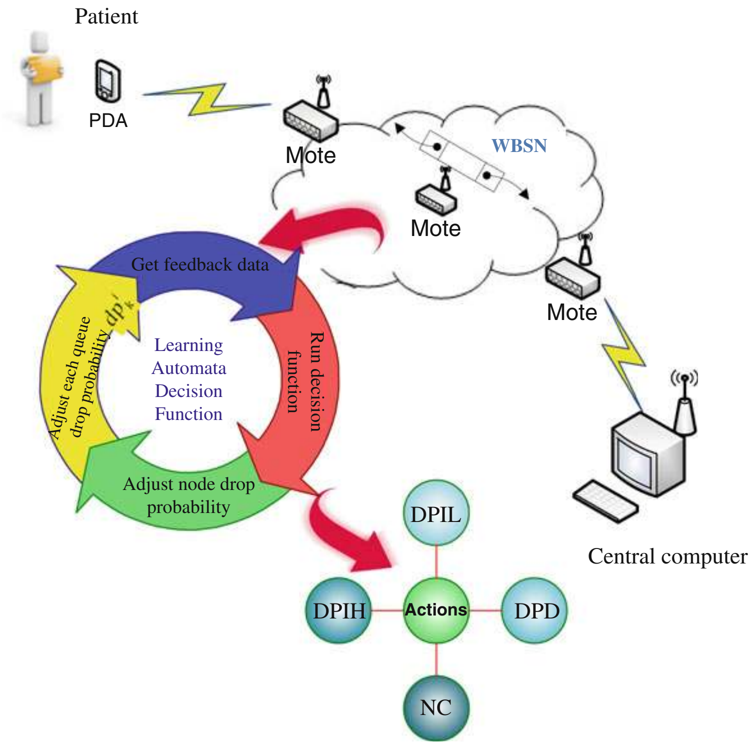

Fig. 5 Automaton structure of intermediate nodes

NC, $DPD\}$. B includes the set of inputs and P is the probability vector of the four automata actions, and T$[A(n), B(n), P(n)]$ is the learning automata, where n is the step index. Figure 5 shows learning automata structure of intermediate nodes.

Table 1 gives a summarized definition of the four automata actions. Every automaton after selecting proper action receives feedback from the environment (i.e. the network in this paper). Based on the action, the acceptance rate could be increased or decreased. The learning automaton at the intermediate nodes adjusts the transmission rate based on:

1. The number of packets in the queue and
2. The ratio of packet inter arrival rate to packet service time.

These two parameters provide a good assessment of the automata performance.

In the proposed AQM protocol, based on traffic class, the current queue length, and ratio of packet inter arrival rate to packet service time, the congestion index of each queue is calculated as shown in Eq. 4. The packet inter arrival rate efficiently provides the status of the network in terms of traffic load to the node. By combining this parameter with the queue length we can come up with a fair estimate of the probability of congestion in the network. Consider the ith sensor node at time t. Let $q^i_{kj}(t)$ denote the queue length for the jth class of the kth queue of node i at time t. is the total queue size of kth queue. We use two parameter $\lambda_{kj}(t)$ (packet inter arrival time of jth class of kth queue) and $\mu_k(t)$(packet service time of kth queue) to compute the congestion index. The congestion index, $I^i_k(t)$, is calculated as follows:

Table 1 Automaton actions at the intermediate nodes

Action	Definition	Description
DPIL	Increase the packet Drop probability with lower rate	Packet Drop probability is Increase slowly in order to prevent congestion and queue overflow.
DPIH	Increase the packet Drop probability with higher rate	Packet a Drop probability is increased quickly in order to control congestion avoid queue overflow.
NC	There is no need to change the drop probability	The network has reached stability.
DPD	Drop probability decrease	Node can decrease Drop probability in order to improve network throughput

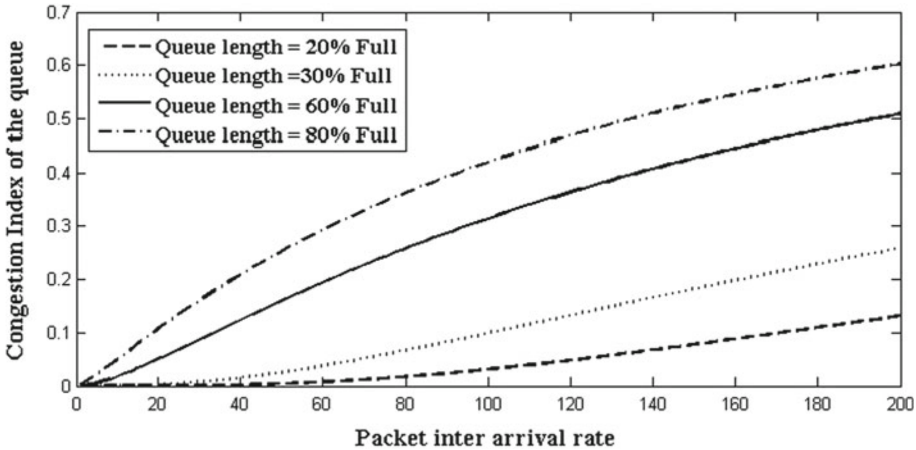

Fig. 6 Behavior of the congestion index function

$$I_k^i(t) = \sum_{j \in T} \left[\left(\frac{\lambda_{kj}(t)}{\lambda_{kj}(t) + \mu_k(t)} \right)^{\frac{N_k}{q_{kj}^i(t)}} *CP(j) \right] \tag{4}$$

where T is the traffic classes (HP, BP, ECG, ST) and *CP(j)* is the priority of the jth class. Using the above definition for the congestion index, we will always have $0 \leq I_k^i(t) \leq 1$.

Figure 6 illustrates the congestion index function at different queue lengths and ratio of packet arrival rate to packet service time (R). As illustrated in this figure, the shorter the queue length, the more softly and slowly the congestion index grows with the increase in R. As the queue length increases, the congestion index grows increasingly with the increase in R value. It can be seen that by using these parameters, the congestion can be detected efficiently.

Further, for each queue k at each sensor node i, we also use the complement of the congestion index, CCI, denoted as $\bar{I}_k^i$ and defined as follows:

$$\bar{I}_k^i(t) = 1 - I_k^i(t) \tag{5}$$

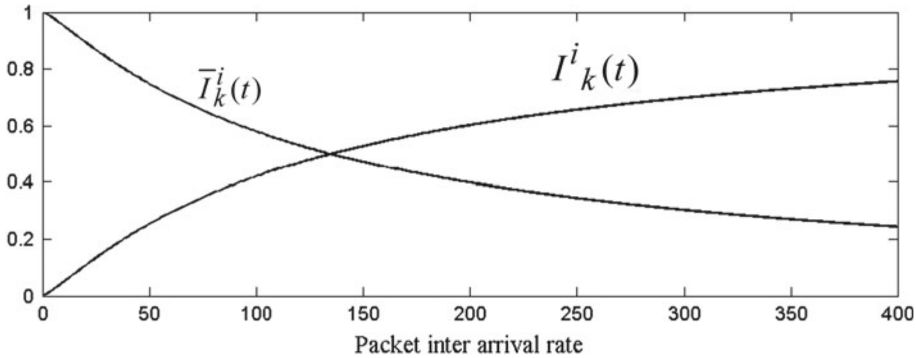

Fig. 7 Variation of congestion index, $I_k^i(t)$ and its complement $\overline{I}_k^i(t)$

Figure 7 shows a schematic diagram of the variation of congestion index $I_k^i(t)$ and its complement $\overline{I}_k^i(t)$ with queue length at 80 % full.

The loss probability function is quite simple and efficient and requires a short execution time. It can be of great value in sensor nodes which have computational and energy limitations.

Let $SP_i(t)$ denote the source priority of sensor node i at time t. We define the total priority, $TP_i(t)$, as the sum of the priorities from each node in the sub_tree rooted at node i and at time t. Let $C(i)$ be the set of child nodes belonging to node i. Then the total priority, $TP_i(t)$, is calculated as:

$$TP_i(t) = \sum_{j \in C(i)} TP_j(t) + SP_i(t) \tag{6}$$

Let $\Delta CI_i(t)$ and $CI_i(t)$ denote respectively, the variation of the congestion index and the congestion index of node i at time t. The learning automata placed at node i calculates $\Delta CI_i(t)$ as follows:

$$CI_i(t) = \sum_{k \in C(i)} \left(I_k^i(t) * \frac{TP_k(t)}{\sum_{s \in C(i)} TP_s} \right) \tag{7}$$

$$\Delta CI_i(t) = CI_i(t) - CI_i(t-1) \tag{8}$$

where $CI(t-1)$ is the congestion index rate at time $t-1$. Different values of $\Delta CI_i(t)$ have different meanings and interpretations. For example $\Delta CI_i(t) = 0$ means that the congestion index has not been changed. When $\Delta CI_i(t) < 0$ or $\Delta CI_i(t) > 0$ this means that the congestion index has been decreased or increased, respectively. After choosing an action, the automata rewards or penalizes the action based on network feedback as follows:

- If $\Delta CI_i(t) \leq \eta;\ \eta \geq 0$ the automaton is rewarded according to Eq. (9)
- If $\Delta CI_i(t) > \eta;\ \eta \geq 0$ the automaton is penalized according to Eq. (10).

$$\begin{aligned} P_i(n+1) &= P_i(n) + a\,[1 - P_i(n)] \\ P_j(n+1) &= (1-a)P_j(n), \quad \forall j\ j \neq i \end{aligned} \tag{9}$$

$$\begin{aligned} P_i(n+1) &= (1-b)P_i(n) \\ P_j(n+1) &= (b/r - 1) + (1-a)P_j(n), \quad \forall j\ j \neq i \end{aligned} \tag{10}$$

In the above equations, a is the reward and b is the punishment parameter. Unlike in the protocol used in LACAS, the values of parameters a and b in Eqs. (9) and (10) are not constant, but defined based on the congestion level. Thus different congestion levels have different effects on the automata. Although at the beginning of operation all probabilities P_i are equal, as time passes the reward and punishment mechanism explained above will change these probabilities. Thus the learning automata determine the drop probability of node i at time $t(dp^i(t))$. Each queue at a node has four different drop probabilities, namely dp_{HR}, dp_{BP}, dp_{ECG} and dp_{ST}. For each queue of node i, the following relation always holds:

$$dp_k^i = \sum_{j \in T} dp_{kj}^i, \; T = \{HR, BP, ECG, ST\} \tag{11}$$

Thus if the number of received higher priority packets increase the number of lower acceptance rate is decreased.

If a node does not have any child (such as the PDA nodes shown in Fig. 3), then at any time its total priority is equal to its source priority. The HR, BP, ECG and ST drop probability of each queue are calculated as follows:

$$TA_k^i(t) = \sum_{j \in T} [CP_j {*} TA_{kj}^i(t)], \quad 1 > CP_{HR} \geq CP_{BP} \geq CP_{ECG} \geq CP_{ST} > 0 \tag{12}$$

$$np_k^i(t) = \frac{TP_k(t)}{\sum_{m \in C_i} TP_m(t)}, 0 \leq np_k^i(t) \leq 1 \tag{13}$$

$$TA^i(t) = \sum_{k \in C_i} [TA_k^i(t) {*} np_k^i(t)] \tag{14}$$

$$Wq_k^i(t) = \frac{np_k^i(t) {*} TA_k^i(t)}{TA^i(t)} \tag{15}$$

$$dp_{kj}^i(t) = (1 - CP_j){*}\left(1 - Wq_k^i(t)\right){*}dp^i(t) \tag{16}$$

Table 2 provides a description of the parameters used.

Note that in above formula C_i denotes the set of child nodes from node i that are alive and active. Another parameter concerned in determining the congestion index is the traffic class of the incoming packet. Since the proposed method pays attention to different traffic flows with different requirements, the node behavior in accepting or rejecting the packet also depends on the packet type.

Table 2 Definition of parameters

Parameter	Definition
$TA_k^i(t)$	Total packets that arrive from kth child of node i at time t
CP_j	Priority of jth traffic
$TA_{kj}^i(t)$	Total jth class packets that arrive from kth child of node i at time t
$np_k^i(t)$	Node priority of kth child of node i
$TA^i(t)$	Total packet that arrive from node i at time t
$Wq_k^i(t)$	Queue weight of kth queue of node i *at* time t
$dp^i(t)$	Drop probability of node i at time t
$dp_k^i(t)$	Drop probability of jth class of kth queue of node i at time t
T	Set of traffic classes {HR, BP, ECG, ST}

3.2 Bandwidth Allocation Mechanism

In the proposed system, the maximum transmission rate of each sensor node depends on both the current service time and the rate allocated by the parent node. Let $T_s^i(t)$ denote the service time of the current packet in node i at time t. We define the service time as the time taken to successfully transmit a data packet over the MAC layer. It is measured starting from the time when the network layer first sends the packet to the MAC layer to the time when the MAC layer notifies the network layer that the packet has been transmitted. Using the exponential weighted sum, the average service time $\overline{T}_s^i(t)$ is calculated as follows:

$$\overline{T}_s^i(t) = (1-\omega)\overline{T}_s^i(t-1) + \omega T_s^i(t), \quad 0 \le \omega \le 1 \tag{17}$$

where ω is a constant coefficient. Suppose $r_i^p(t)$ is the assigned transmission rate by the parent $r_i(t)$, the maximum transmission rate of the sensor node i, is obtained as follows:

$$r_i^p(t) = r^p * \left(\frac{TP_i(t)}{TP_i^p(t)} \right) \tag{18}$$

$$r_i(t) = \min\left(\frac{1}{T_s^i(t)}, r_i^p(t) \right) \tag{19}$$

where $r_i^p(t)$ is rate for node i's parent and $TP_i^p(t)$ is the global priority of node i's parent. In each queue k in node i and at each time t, the scheduling weight $w_k^i(t)$ is computed as:

$$w_k^i(t) = \frac{TP_k(t)\overline{I}_k^i(t)}{\sum_{j=1}^{N_i+1} TP_j(t)\overline{I}_j^i(t)}, \quad \mathrm{k} = 1, 2, \ldots, \mathrm{N}_i + 1 \tag{20}$$

At each node i, there is a scheduler that is responsible to service each queue k based on its current weight $w_k^i(t)$. To provide fairness based on the priority of each sensor node, the scheduler should service each queue according to its weight. From Eq. (20), we expect all the weights in each node i to sum to unity, (i.e. $\sum_{k=1}^{N_i+1} w_k^i(t) = 1$). We use a WFQ scheduler which is able to service each queue based on its weight.

After obtaining $w_k^i(t)$, we then determine $r_k^i(t)$, the transmission rate of child node k which is allocated by the parent node i, as follows:

$$r_k^i(t) = w_k^i(t) * r_i(t) \tag{21}$$

Note that the rate $r_k^i(t)$ is calculated for all active sources. When a sensor node is not active, then $\overline{I}_k^i(t)$ is set to 0. In this case the allocated rate to all inactive nodes will be equal to zero. So in each sensor node i, the output rate r_i is shared only between active nodes. Equation (21) shows that the sensor nodes with low congestion and high priority get more bandwidth than the other sensor nodes. Figure 8 shows the weight function plotted against the normalized total priority and complement of congestion index (CCI), for a particular sensor node and at a given time t. As can be observed from the figure, by increasing the priority and decreasing the congestion (increasing the complement of congestion index), the assigned weight (and hence the child transmission rate) is increased.

The pseudo-code of the proposed protocol is given in Fig. 9.

The Proposed Protocol has the following Characteristics:

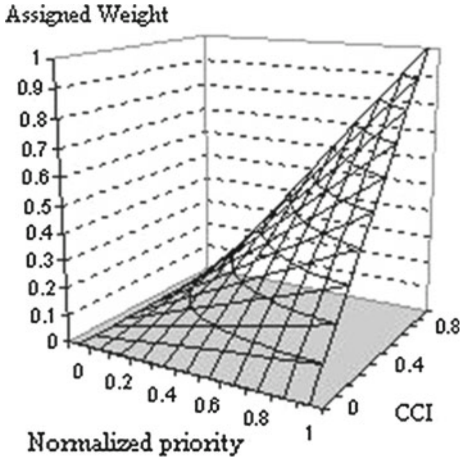

Fig. 8 The weight function versus node priority and complement of congestion index (CCI)

- The proposed protocol is a learning automata base congestion control protocol that intelligently reduces congestion. In the proposed protocol, the bandwidth allocation of each source node is tuned depending on its congestion condition and its priority index.
- Unlike the LACAS protocol [37], the reward and penalty values are variable. These values are determined based on the congestion level. So the automata can be learned with better quality and even less time consuming.
- The proposed protocol can select the appropriate source rate in order to achieve higher throughput and less packet loss.
- The proposed protocol tries to choose optimum packet service rate in the intermediate nodes, preventing queuing delay so the end to end delay would be reduced.
- In the proposed protocol, unlike the LACAS protocol, the URGENT and CRITICAL packets have higher priority and achieve higher quality of service than others.
- In the proposed protocol, unlike the LACAS protocol, patients have different priority base on their physiological conditions. Thus the proposed protocol is able to provide more network bandwidth for transmission of data packets related to the vital signs from patients in URGENT need.

4 Simulation Results

In this section, we use a simulation study to evaluate the performance of the proposed protocol under different scenarios. For this purpose, we simulated a wireless biomedical sensor network topology as shown in Fig. 10. A multi-hop WSBN consisting of 12 different motes (to transmit vital signals to the central computer) and 15 PDAs is used to monitor the vital signs of 15 patients positioned at different locations (for example in their homes or a wide area medical network). A central computer gathers information about 4 different vital signs, (namely ECG, BP, HR and ST) for each patient and records them in a database. We suppose that these different vital signs require different priorities, and thus assigned them different weights. The weights assigned to Class 4, Class 3, Class 2 and Class 1 data packets were 0.4, 0.3, 0.2 and 0.1, respectively. Each queue size was set to 400 packets, and we consider exponentially weighted service time at each sensor node. At the beginning of the simulation,

Algorithm: Learning based Congestion control and service differentiation protocols

- **Given:**
  - ✓ *Set of intermediate nodes' actions :* $\alpha^N \equiv \{\alpha_1^N, \alpha_2^N, ..., \alpha_r^N\}$
  - ✓ $\alpha^N \equiv \{\alpha_1^N, \alpha_2^N, \ldots, \alpha_r^N\}$ *Set of sinks' actions :* $\alpha^s \equiv \{\alpha_1^s, \alpha_2^s, ..., \alpha_m^s\}$.
  - ✓ *Set of intermediate nodes' probabilities:* $P^N(n) \equiv \{P_1^N(n), P_2^N(n), ..., P_r^N(n)\}$
  - ✓ *Set of sinks' probabilities:*
    $P^s(n) \equiv \{P_1^s(n), P_2^s(n), ..., P_m^s(n)\}$
  - ✓ *random environment: network*
  - ✓ *number of intermediate nodes' actions: r*
  - ✓ *penalty value :* $\{b_1, ...b_x\}$
  - ✓ *reward value :* $\{a_1, ...a_x\}$
  - ✓ *The number of packets in the queue*
  - ✓ *The ratio of packet inter arrival rate to packet service time.*
- **Algorithms :**

1: **Procedure ()**
2: Initialize the probability of selecting an action from the set of actions as follows:

$$P_i = \frac{1}{r} \quad i = 1...r$$

3: Repeat
4: Pick up action $\alpha(n) = \alpha_i(n)$ according to $P(n)$
5: Compute each queue's congestion Index (I_k^i)according to eq.(4)
6: Compute CCI of each queue ($\overline{I}_k^i$) according to eq.(5)
7: Compute the Total Priority of node i (TP_i) according to eq.(6)
8: Compute the Congestion Index of node i (CI_i) according to eq.(7)
9: Calculate the network changes as follows (eq.8)

$$\Delta CI_i(t) = CI_i(t) - CI_i(t-1)$$

10: Compute the environment response (β) according to calculated values in step 9.
11: Update the probabilities according to environment response as follows :
12: If $\Delta CI_i(t) \leq \eta;\ \eta \geq 0$ the automaton is rewarded according to eq. (9)
13: If $\Delta CI_i(t) > \eta;\ \eta \geq 0$ the automaton is penalized according to eq. (10).
14: Update the <u>*node' Drop Probability*</u> according to selected action by the automaton
15: Update the Drop probability of *j-th* class of *k-th* queue of node *i* according to eq (11) to (16)
16: Compute the average service time ($\overline{T}_s^i$) according to eq.(17)
17: Set the upper bound of node i's service rate as follows:

$$r_i(t) = \min\left(\frac{1}{T_s^i(t)}, r_i^p(t)\right)$$

18: Compute the Scheduling weight of node i (w_k^i) according to eq.(20)
19: Compute the transmission rate of child node *k* which is allocated by the parent node *i* (r_k^i) according to eq.(21)
20: end loop
21: end *Procedure*

Fig. 9 Pseudo-code of proposed protocol

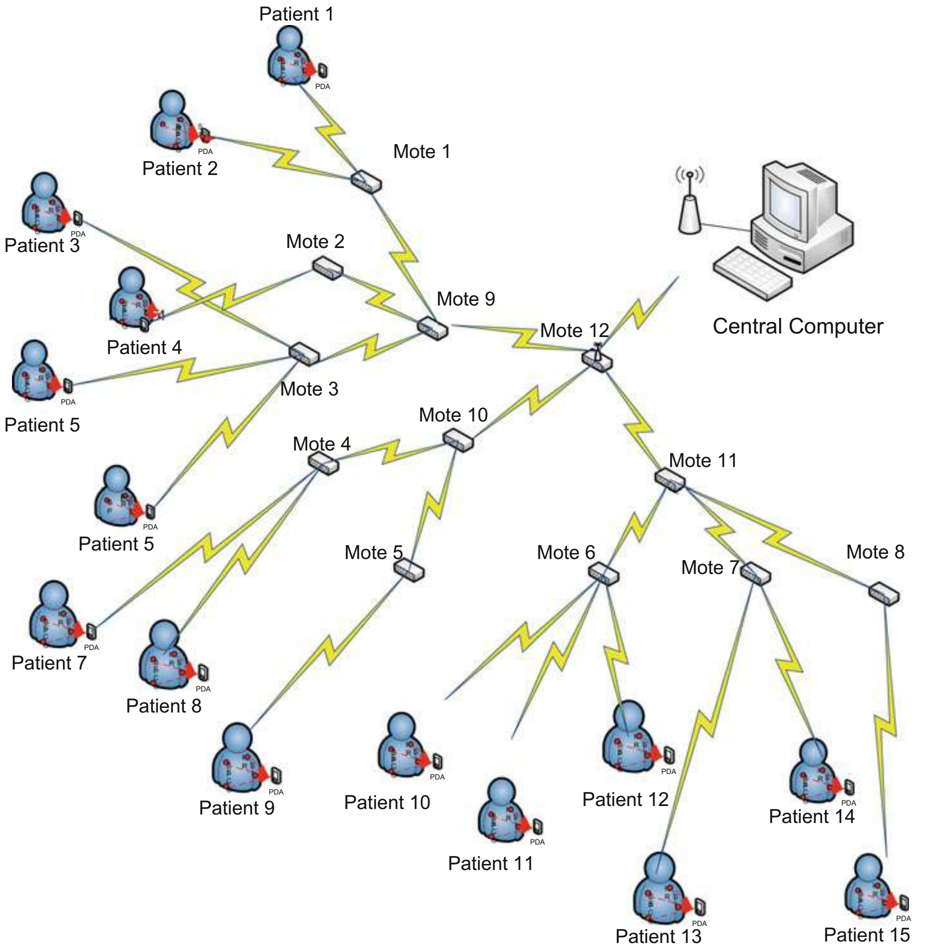

Fig. 10 The network topology used in the simulation

we assume all end sensor nodes (the patients) have the same priorities. The source priorities assigned to NORMAL, URGENT and CRITICAL patients were set to 1, 2 and 3, respectively.

We used Opnet simulator [46]. We implemented the proposed protocol, and compared with the popular LACAS [37] protocol (LACAS is explained in detail in Sect. 2). The simulations were run using CSMA protocol as MAC layer protocol.

Although LACAS [37] is capable of adaptively learning and "intelligently" choosing "better" data rates, it has the following drawbacks:

- LACAS limited the number of rates (actions) associated with an automaton to 5. These 5 rates are defined randomly and not changed during simulation. As a result the network may have poor performance due to the selecting non-proper rates (actions). Non-proper rate allocation may result in inefficient channel utilization.
- LACAS does not require the source nodes to use feedback from the intermediate nodes to reduce its transmission. Although this action can reduce the number of forwarded messages, it may not improve the performance of the network. If the congestion condition

continues, queue lengths at the intermediate nodes will increase suddenly, so the number of packet drops increase. Therefore other mechanisms such as redirection, path change, source rate decrease, etc are required to reduce congestion.

- Although LACAS has been presented for healthcare applications, it does not consider different types of vital signs. In LACAS all traffic streams are treated in the same manner.

In order to assess the performance of the proposed AQM algorithm, the following parameters were used in the simulation.

- Packet loss ratio = total number of lost packets/total number of generated packets.
- Source rate = number of send packets/total time.
- Delivery ratio = total number of received packets by the sink/total number of generated packets.
- Throughput = total number of received packets by the sink/time
- Queue Length = number of packets in the queue
- Delay (average delay, end to end delay)

4.1 Service Differentiation and Prioritization

In the first experiment, we evaluated the impact of service differentiation and prioritization in monitoring vital signs and physiological signals in a WBSN. We assume that all patients in the system are in NORMAL condition.

Table 3 shows the average end to end delay. Obviously, shorter queue lengths will cause shorter packet queuing delay. Class 4 packets are delay intolerant so these packets have a higher priority in entering and exiting the node, so they reach their destinations faster. Table 3 also shows the packet loss rate in the intermediate nodes. In sever congestion, the increase in channel load and queue length leads to a higher probability of loss in the intermediate nodes. So the number of accepted packets in the node is decreased. From Table 3, the number of Class 4 lost packets is less than that of other classes. In LACAS only 5 rates are considered for selection by the automaton, which is not optimal. This indicates the adaptability of the proposed AQM mechanism in the intermediate nodes with the congestion control protocol. The loss performance of the proposed protocol is always better than that of LACAS protocol. This is not unexpected, especially given that the proposed protocol will incur less congestion on average, when compare to LACAS.

Figure 11a, we can observe that the proposed protocol can assign network bandwidth to each traffic class based on its weight (0.4 for Class 4, 0.3 for Class 3, 0.2 for Class 2 and 0.1 for Class 1). The Class 4 has the highest throughput while Class 1 has the lowest throughput. Therefore the Class 4 has the lowest drop ratio while Class 1 has the highest drop ratio.

Table 3 Impact of the service differentiation

	Proposed protocol					*LACAS*
	Total	Class 4 (EGT)	Class 3 (BP)	Class 2 (HR)	Class 1 (ST)	Total
Normal condition						
Average delay	0.27	0.2	0.23	0.28	0.36	0.19
Packet loss rate	1.89	1.55	1.57	2.1	2.35	33.26
Network delivery ratio (%)	98	98	98	97	96	67

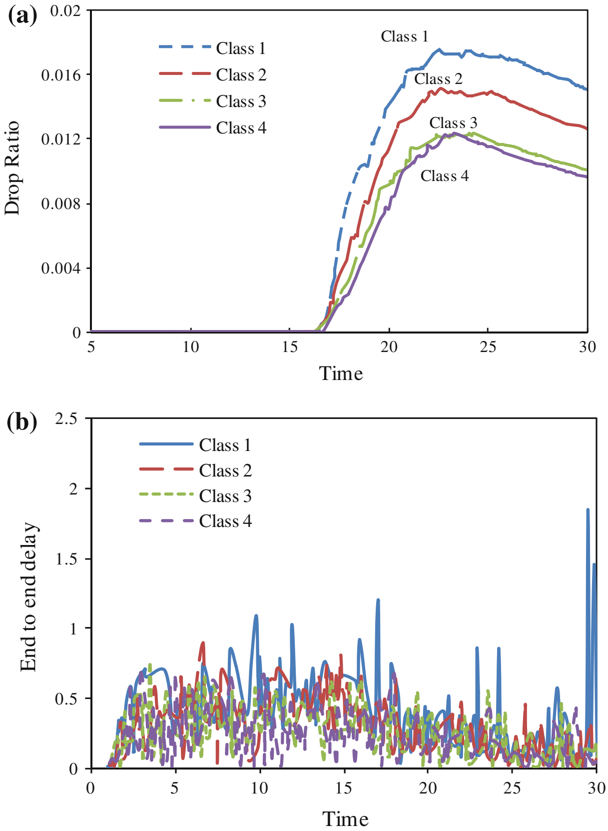

Fig. 11 Impact of service differentiation and prioritization: **a** drop ratio; **b** end to end delay (all patients are assumed to be in NORMAL condition)

Figure 11b shows that in the proposed protocol, higher traffic classes have a shorter queuing delay.

Figure 12 shows the variation in queue length for Mote 12 in the topology used for evaluation (see Fig. 10). Since Mote 12 has 3 different child nodes, under the proposed protocol, Mote 12 uses 3 separate queues, one for each child node. As shown in Fig. 12, the proposed protocol results in a shorter queue length. This confirms the low delay of the proposed protocol shown in Fig. 11b.

4.2 Responding to Dynamic Changes in Patient Conditions

In the next experiment, we considered the effect of dynamic changes in a patient's condition, for instance, when a patient requires immediate attention. Suppose that at time $t = 6$ s. the central computer detects an anomaly in the received physiological signals from Patient 4. In this case it transmits a message to Patient 4's PDA and changes the patient's condition from NORMAL to URGENT. Given the change in the source priority of Patient 4, all sensor nodes along the path between Patient 4 and the destination (sink node) allocate more network bandwidth to data from Patient 4. Suppose at time $t = 14$ s. Patient 4 goes back to NORMAL condition. Figure 12 shows the response of the proposed congestion control protocol (and also of LACAS) to the changing patient conditions described above.

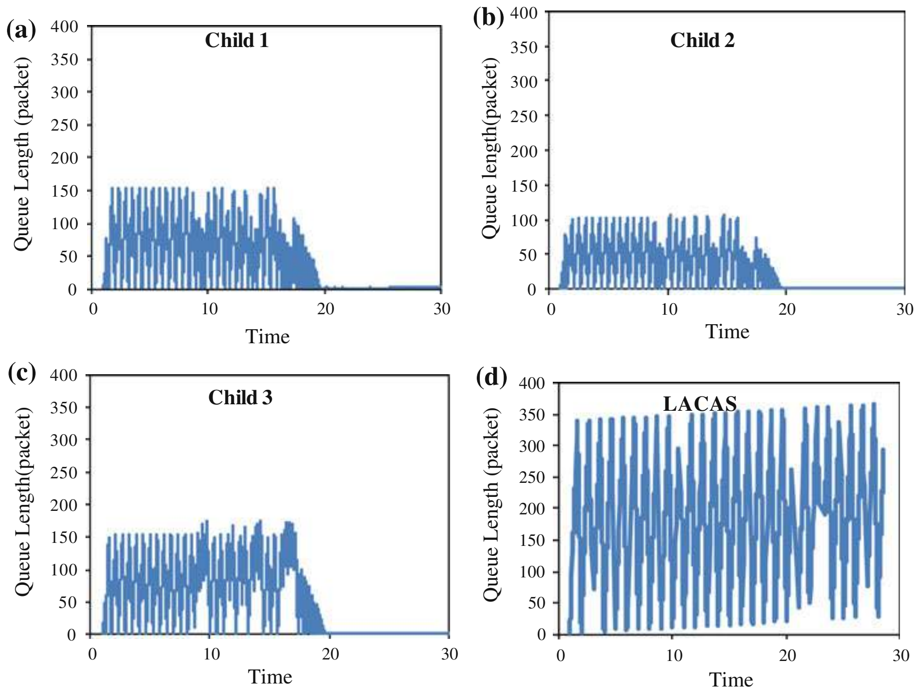

Fig. 12 Queue length at Mote 12: **a** child 1 under the proposed protocol; **b** child 2 under the proposed protocol; **c** child 3 under the proposed protocol; **d** LACAS protocol

As shown in Fig. 13a, for the proposed protocol, when all patients are in NORMAL condition (that is, before time $t = 6$ s. and after time $t = 14$ s), the network throughput is shared equally between the patients. When Patient 4 went to URGENT condition (during time interval [6 s, 14 s]), the system assigned more bandwidth to Patient 4. Therefore Patient 4's rate is increased. During this time interval there is a decrease in bandwidth assignment to the other patients. Unlike the proposed protocol, the LACAS protocol (see Fig. 13b) is not able to detect this change in patient condition, and hence could not adjust its bandwidth allocation to the patient in need.

Now suppose there are different patients with different health records in the monitoring system. Also suppose Patients 1, 2, 5, 6, 7, 9, 10, 12, 13 and 15 are in NORMAL condition, Patients 3, 4 and 14 are in URGENT condition, and Patients 8, and 11 are in CRITICAL condition. As mentioned earlier, one of the major objectives of the proposed protocol is to detect different health situations of the patients and to share the limited network bandwidth accordingly, based on patient priorities. Figure 14 shows how the proposed scheme can adapt to the changing health condition of the patients being monitored.

As can be observed in Fig. 14a, the patients in CRITICAL condition gets the highest amount of total network bandwidth. Clearly, the system can detect the health condition of each patient and assign the proper network bandwidth based on the health condition of each patient. Figure 14b shows the variation of total network throughput over time, for both the proposed protocol and the LACAS protocol. The total throughput of the proposed protocol is close to 95 % while that of LACAS protocol is close to 85 % (total bandwidth is 1100). Thus, the proposed protocol can achieve 10 % more network throughput.

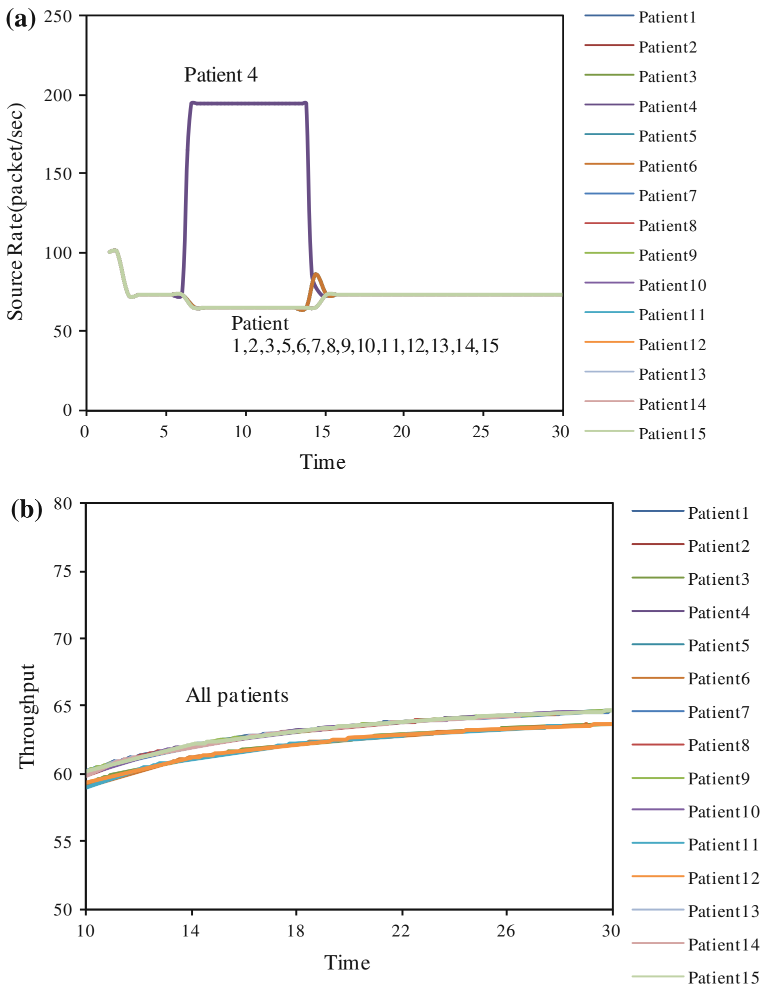

Fig. 13 Normalized throughput under dynamic changes in patient condition: **a** proposed protocol; **b** LACAS. (Patient 4 went to CRITICAL situation during time interval [6 s, 14 s])

5 Conclusion and Future Work

In sensor-based healthcare monitoring systems, some of philological signals and vital signs could be more important than the others, and thus need to be sent as quickly as possible to the central monitoring system. Furthermore, as different patients may have different medical conditions, it may be necessary to give more priority to patients in a CRITICAL condition when compared to other normal patients. In this paper, we presented a service prioritization and congestion control protocol for wireless biomedical networks involved in healthcare monitoring. At the local wireless device that gathers the patient's physiological data (the PDA in our description), the sensed vital signs and physiological signals are grouped into different classes. Using weighted scheduling mechanisms, higher priority classes are given a better quality of service and more bandwidth than the lower priority classes. Congestion is detected in advance using an automata based congestion detection strategy at each intermediate sensor

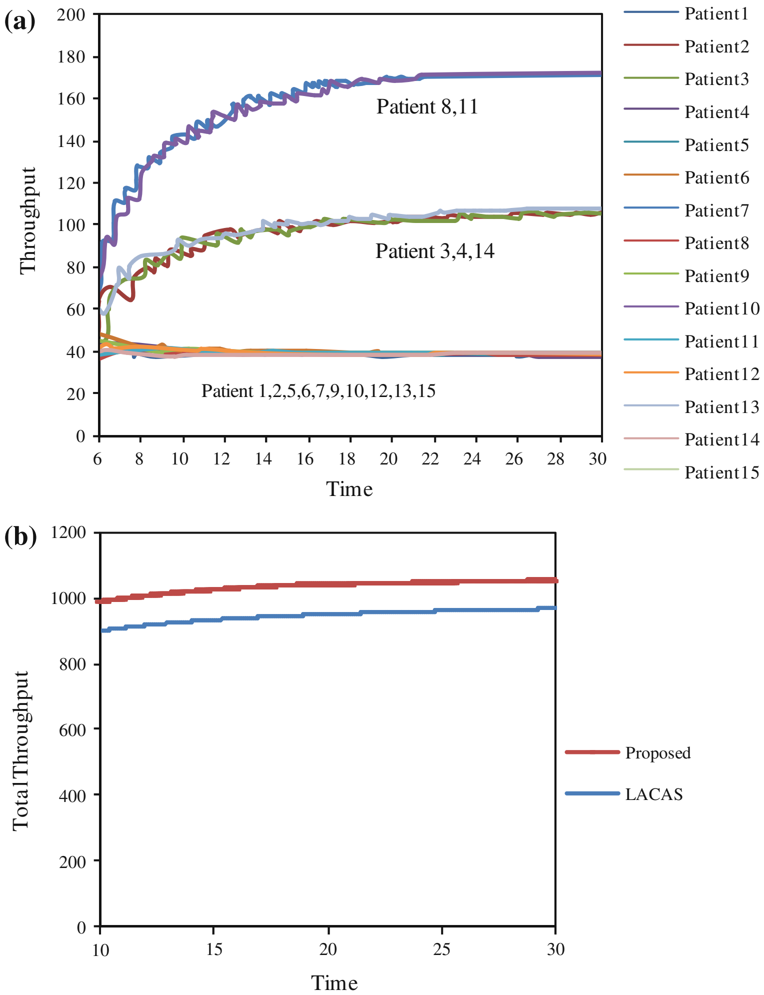

Fig. 14 Performance evaluation under different combinations of priority: **a** normalized throughput of each patient in the proposed protocol; **b** total normalized throughput of proposed protocol and LACAS protocol

node. Based on the current congestion degree and the priority of its child nodes, the parent node dynamically computes and allocates the transmission rate for each of its children. When the central computer which maintains the physiological data for each patient detects any anomaly in the received data, it sends a special message to the particular patient's sensor node and increases the patient's priority. All sensor nodes along the path detect this change in situation and allocate more network bandwidth for vital signs and physiological signals from the patient in need. Simulation results show the superior performance using the proposed congestion control protocol.

While we have presented the basic scheme using vital signs monitoring, the technique is also applicable to other situations where wireless biomedical sensor networks are being deployed, for instance, in emergency response against disasters, and for tracking and monitoring of first responders and the injured.

Even if WSNs were originally thought to have static network infrastructure, recent applications require sensing nodes to be mobile. For example, WBSN, unlike wired monitoring system, can be used for continuous monitoring even when patients move.

Thus it shows the future need for supporting mobility while monitoring vital body signs in hospital and home care. PDAs are used in WBSNs for data collection and transmit the data via wireless sensor network toward the central emergency center.

For future development, The proposed protocol will be improved in terms of supporting the patents mobility and have the ability to adapt to mobility of sensing nodes (patients) by dynamically change of route from patients to clinic via wireless sensor networks.

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