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Priority-based adaptive transmission algorithm for medical devices in wireless body area networks (WBANs)

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Abstract: A wireless body area network offers cost-effective solutions for healthcare infrastructure. An adaptive transmission algorithm is designed to handle channel efficiency, which adjusts packet size according to the difference in feature-point values that indicate biomedical signal characteristics. Furthermore, we propose a priority-adjustment method that enhances quality of service while guaranteeing signal integrity. A large number of simulations were carried out for performance evaluation. We use electrocardiogram and electromyogram signals as reference biomedical signals for performance verification. From the simulation results, we find that the average packet latency of proposed scheme is enhanced by 30% compared to conventional method. The simulation results also demonstrate that the proposed algorithm achieves significant performance improvement in terms of drop rates of high-priority packets around 0.3%−0.9 %.

Key words: wireless body area network; channel efficiency; quality of service

1 Introduction

Recent advances in wireless communications technology and low power consumption devices make novel healthcare applications come true. The applications aim to monitor the condition of the body, and furthermore, diagnose disease that may occur. There are a few networks that can be applied to such applications, but a wireless body area network (WBAN) is the most ideal solution for wireless communications in portable, wearable, or implantable sensors that monitor biomedical signals [1]. A WBAN provides preferential delivery for multiple devices that require quality of service (QoS) guarantees by ensuring sufficient bandwidth, latency and jitter, and reducing data loss.

Because WBAN devices are located around the human body, a star-shaped topology with a centered data-gathering master device and multiple biomedical signal sensing slave devices is commonly used [2−3]. A biomedical signal sensing device periodically senses and transmits sensed data to the data-gathering device. For example, an electrocardiogram (ECG) sensing device periodically (typically at 200 Hz) senses the heartbeat and transmits to the data-gathering device. A lot of WBAN healthcare systems continuously monitor ECGs, electroencephalograms (EEGs), and electromyograms (EMGs) because they can be the key to prevention and early detection of disease. But the problem is, monitoring those signals can place a heavy load on the entire WBAN network because the sensing operations for those signals are carried out at a high sampling rate, which is over 200 Hz.

In this work, we propose an adaptive transmission algorithm that utilizes the characteristics of the periodic biomedical signal, or biomedical signals with certain patterns, such as the ECG and the EMG. The goal of the algorithm is to minimize the loss of important information and to maximize utilization of the entire WBAN network. The proposed algorithm dynamically adjusts packet size and transmission priority according to a value obtained from the characteristics of the biomedical signal. Performance evaluation was carried out using the Massachusetts Institute of Technology–Beth Israel Hospital (MIT-BIH) arrhythmia database [4] and the EMGlab N2001 database [5], with a WBAN network that has 10 nodes, including ECG and EMG monitoring devices, and forms a star topology.

2 Related works

2.1 Wireless body area network

A WBAN is a wireless network of wearable, body attachable, or body implantable computing devices, defined in the IEEE 802.15.6 standard [6]. The main characteristics of a WBAN are low power consumption, QoS support, high scalability, and continuous data transfer. All of these characteristics come from the

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operational environment of WBAN devices—a series of sensors or mobile devices that operate outside of, on, or in the human body. Currently, a WBAN utilizes the 2360−2400 MHz band with various data transfer rates up to 10 Mb/s. Under the 802.15.6 standard, a WBAN offers four access modes, as shown Fig. 1. The superframe consists of the exclusive access phase (EAP), the random access phase (RAP), the managed access phase (MAP) and the contention access phase (CAP). In EAP, RAP and CAP, nodes contend for channel access using either carrier sense multiple access with collision avoidance or a slotted ALOHA access procedure. The EAP is used for the highest priority traffic, such as reporting emergency events. The RAP and CAP are used for regular traffic only. In particular, the CAP is used for additional traffic, announcing via B2. In the MAP, scheduled access method and polling access method are used for resource allocation.

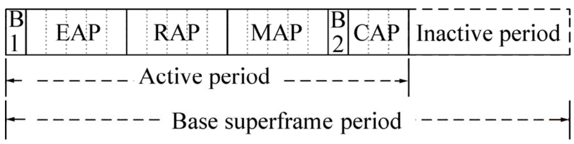

Fig. 1 A superframe structure of WBAN standard

A WBAN has a variety of applications: healthcare, sports, personal entertainment, etc. Among those, healthcare applications attract the most attention owing to growing concerns about health. Figure 2 shows an example of a WBAN healthcare application. The goal of the WBAN healthcare application is to prevent or diagnose disease. To achieve the goal, the WBAN healthcare application monitors the condition of the human body with various sensors: an ECG monitoring sensor, an EEG monitoring sensor, an EMG monitoring sensor, a body temperature monitoring sensor, etc. The main challenges for the WBAN healthcare application are the support for QoS and extremely low power consumption, and various researchers are working on them [7−8].

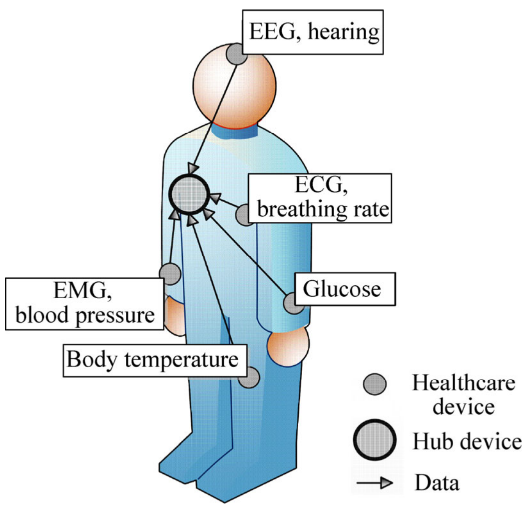

Fig. 2 An example of WBAN healthcare application

2.2 Periodic, or patterned, biomedical signals

Some of the biomedical signals are periodic or have certain patterns. Typical examples are the ECG, the EMG, and the EEG.

The ECG is an uninterrupted electrical recording of the activity of the heart. The ECG is mostly used to measure the heart's condition for early detection of heart-related disorders, such as cardiac arrest. The ECG signal consists of multiple cardiac cycle pulses. Since the heart beats periodically, the cardiac cycle pulses in an ECG are periodic. A cardiac cycle pulse consists of the P-Q-R-S-T waves, and those P, Q, R, S, T points are called feature points. The interval or period of the points, and the presence or absence of points, are main concerns of ECG analysis. Among them, the QRS complex, the RR interval, and the QT interval are the most important, giving valuable information.

The EMG is a recording of electrical activity produced by skeletal muscles. The electrical activity comes from the electrical potential generated by muscle cells when they are electrically or neurologically activated. The EMG is used to diagnose neuromuscular diseases or disorders in motor control, etc. The EMG signal consists of an F wave, an H wave (reflex), and an M wave. Movement in the muscles produces a specific combination of waves—a pattern. And the pattern repeatedly occurs with the movement of the muscles [9].

The EEG is an uninterrupted electrical recording of brain activity via the scalp. The EEG is mostly used to diagnose epilepsy, sleep disorders, coma, etc. The EEG signal has certain wave patterns (alpha, beta, gamma, delta, mu, and theta waves), which symbolize brain activity. The appearance of a particular EEG activity has periodicity, even though it has more or less regular intervals [10].

2.3 Feature extraction of biomedical signals

Automated feature extraction of a biomedical signal or a patterned signal is essential for wireless body area network devices, because the devices have to monitor and report the status or the activities of the human body. There are various examples in the literature of automated feature extraction algorithms.

PAN and TOMPKINS [11] presented an automated real-time QRS complex detection and RR interval calculation method, which is one of the most commonly used ECG feature extraction methods. First, the ECG signal passes through a digital bandpass filter, which consists of cascaded high-pass and low-pass filters. Second, the filtered signal is differentiated to provide QRS complex slope information. The authors used a five-point derivative method. Then, the signal is squared, point by point, to intensify the slope and restrict false positives caused by T waves. Next, the wave form feature information and the slope of the R wave are obtained thorough the moving window integrator. Finally, the QRS complex is determined from the rising edge of the window, and the RR interval is calculated with the consecutive R points, which are the peaks of two consecutive QRS complexes. In addition, the authors used two sets of thresholds to improve reliability of detection, which thresholds the filtered ECG signal produced by the moving window integration. These threshold values are dynamically and automatically adjusted.

XU and LIN [12] presented an ECG feature point extraction and RR interval calculation method based on a slope vector waveform. The algorithm consists of two parts; a variable stage differentiation and a non-linear amplification. The variable stage differentiation obtains the desired slope vector of the ECG signal for feature point extraction, and the non-linear amplification improves signal-to-noise ratio (SNR) to increase QRS complex detection performance, even if the ECG signal is contaminated with noise. After extracting the ECG feature points, an interval between two consecutive R points in each QRS complex is calculated.

CHU et al [13] presented an EMG pattern recognition and feature detection method based on a wavelet transform. The algorithm uses a wavelet packet transform to extract a feature vector from the EMG signal. Then, the dimension of the wavelet packet feature is reduced by an algorithm called principal component analysis. To recognize the pattern from the signal, and to separate the class of the pattern, the algorithm builds clusters of feature sets. Finally, a cluster of feature sets becomes a pattern, which symbolizes a movement.

NAZIMOV et al [14] presented an EEG pattern recognition method based on a wavelet transform. First, the algorithm applies a continuous wavelet transform (CWT) to the EEG signal. Then, the algorithm filters the signal with the proposed Phi filter. Third, the algorithm uses two threshold values to increase the performance of pattern identification. Finally, the algorithm optimizes the parameters of the CWT with values obtained through the filtering process to improve pattern recognition accuracy of the oscillating EEG signals.

3 Proposed algorithm

To extract the feature points of a biomedical signal, most of the schemes reviewed thus far focus on signal compression or pattern recognition. In this work, we propose a new adaptive transmission algorithm that enhances QoS by adjusting packet priority according to a value obtained from the characteristics of the biomedical signal.

3.1 Extracting feature points of periodic biomedical signals

As shown in Fig. 3, biomedical signal traces are periodic waveforms that consist of some waves that have particular characteristics. In this subsection, we derive the fundamental period of a periodic biomedical signal and extract feature points that represent the peculiar quality of a wave within the fundamental period. The local extrema (maxima and minima) of each wave are selected as feature points.

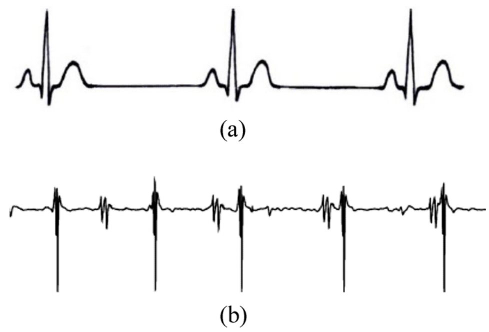

Fig. 3 An example of biomedical signal tracing: (a) ECG; (b) EMG

The periodic function is strictly defined as a function that repeats itself after a fundamental period. Depending on the biomedical signal, the signal repeats a geometric pattern instead of an exact signal value, and a periodic biomedical signal repeats the curvature value after a fundamental period. Curvature refers to the deviation rate of a curve or the curved surface from a straight line or a plane surface tangent to it. A function that represents a biomedical signal trace based on time variable t is represented as

$$Y(t) = (s(t),\ a(t)) \tag{1}$$

where $s(t)$ is a sample index at t, and $a(t)$ is a signal amplitude.

Since a typical biomedical signal trace contains noise, a noise removal process is needed for accurate feature point extraction. We use a Gaussian low-pass filter, which provides a smoothed biomedical signal trace to eliminate noise. The smoothed biomedical signal trace is given by

$$y(t,\sigma) = (S(t,\sigma),\ A(t,\sigma)) \tag{2}$$

where $S(t, \sigma)$ and $A(t, \sigma)$ are expressed by the following equations.

$$S(t,\sigma) = s(t) \otimes g(t,\sigma) = \int_{-\infty}^{\infty} s(\tau)\frac{1}{\sqrt{2\pi}\sigma}\exp\left(\frac{-(t-\sigma)^2}{2\sigma^2}\right)\mathrm{d}\tau \tag{3}$$

$$\begin{cases} A(t,\sigma)=a(t)\otimes g(t,\sigma) \\ \quad =\int_{-\infty}^{\infty} a(\tau)\dfrac{1}{\sqrt{2\pi}\sigma}\exp\left(\dfrac{-(t-\sigma)^2}{2\sigma^2}\right)\mathrm{d}\tau \\ g(t,\sigma)=\dfrac{1}{\sqrt{2\pi}\sigma}\exp\left(\dfrac{-t^2}{2\sigma^2}\right) \end{cases} \tag{4}$$

where $g(t, \sigma)$ is a Gaussian function for smoothing with a standard deviation σ.

After noise removal, we get the curvature, which represents the bending degree of each wave:

$$k(t,\sigma)=\frac{S''(t,\sigma)A'(t,\sigma)-S'(t,\sigma)A''(t,\sigma)}{(S'(t,\sigma)^2+A'(t,\sigma)^2)^{3/2}} \tag{5}$$

where $S'(t, \sigma)$, $S''(t, \sigma)$, $A'(t, \sigma)$, and $A''(t, \sigma)$ are given by

$$\begin{cases} S'(t,\sigma)=s(t)\otimes\dfrac{\partial}{\partial t}g(t,\sigma) \\ S''(t,\sigma)=s(t)\otimes\dfrac{\partial^2}{\partial t^2}g(t,\sigma) \\ A'(t,\sigma)=a(t)\otimes\dfrac{\partial}{\partial t}g(t,\sigma) \\ A''(t,\sigma)=a(t)\otimes\dfrac{\partial^2}{\partial t^2}g(t,\sigma) \end{cases} \tag{6}$$

For fundamental period estimation, we group sets of similar values (95% boundary) in calculated values of curvatures and calculate the average difference of the sample index in each set. These values are possible fundamental periods. In order to get a precise fundamental period, we apply the average magnitude difference function (AMDF) to the curvature value [15]. ADMF is an efficient tool for estimating the period of a 1-D periodic signal and a variation on autocorrelation, but it is faster to implement in integer arithmetic as there are no multiples. The AMDF formula is defined as

$$D(\tau)=\frac{1}{N-\tau-1}\sum_{n=0}^{N-\tau-1}\left|y[n]-y[n+\tau]\right| \tag{7}$$

where $y[n]$ is a biomedical signal sequence that is a function over a domain of the sample index, τ is a lag, and N is the size of the sequence. The range for τ is between 0 and N−1, and the constant term outside summation is for normalization.

In general, an estimation of a fundamental period is derived by

$$T=\operatorname*{Min}_{\tau} D(\tau) \tag{8}$$

where τ corresponds to possible fundamental periods.

After the fundamental period T calculation, we select local minima and maxima, which have larger curvature values than the threshold of feature points in each period.

3.2 Priority adjusting and data compression method for transmission

In Section 3.1, we derive the feature point extraction method for biomedical signals. The extracted feature points are represented with index i as

$$f_n[i]=(s_n[i],\ a_n[i]) \tag{9}$$

where $s_n[i]$ is a sample index of feature point i in cycle n, and $v_n[i]$ is a signal amplitude. The proposed algorithm adjusts packet size and priority based on the similarity between two neighboring cycles. The similarity can be calculated with the percentage of root mean square difference (PRD) [16]. Let $f_n[i]$ and $f_{n-1}[i]$ be the current and the previous feature points, respectively. The PRD formula is expressed with the following equation.

$$P=\sqrt{\frac{\sum_{i=1}^{N}(f_n[i]-f_{n-1}[i])^2}{\sum_{i=1}^{N}(f_n[i])^2}}\times 100 \tag{10}$$

If the PRD value does not exceed the threshold, there is no significant change in two adjacent cycles. Therefore, a signal compression process is carried out to reduce packet size. The signal compression process is divided into three phases:

1) Calculate signal difference from the previous cycle.

2) Perform 1-D discrete wavelet transform (DWT).

3) Eliminate the high frequency component using a window filter based on the PRD value.

On the other hand, if the PRD value between two neighboring cycles is greater than the threshold, it can be assumed that there is a significant change in the biomedical signal. In this case, only the DWT is carried out among the three phases of the signal compression process in order to prevent the loss of data.

In a WBAN, transmission delay or collisions may take place even in the case of emergency data transmission in RAP, which uses a random access mechanism for resource allocation. To handle this situation, IEEE 802.15.6 defines a user priority for data types and EAP. In EAP, transmission of the highest priority packet is allowed for erroneous emergency transmissions or medical implant event-report traffic. Table 1 shows user priority according to designations of the traffic.

The proposed scheme adjusts user priority when there is a significant change in a biomedical signal, reflecting a degree of emergency. Therefore, in order to guarantee QoS, the priorities of the compressed packet and the non-compressed packet above, are determined as medical data (priority level 5) and emergency or medical implant event report (priority level 7), respectively.

Table 1 User priority mapping

User priority	Traffic designation
0	Background (BK)
1	Best effort (BE)
2	Excellent effort (EE)
3	Video (VI)
4	Voice (VO)
5	Medical data or network control
6	High-priority medical data or network control
7	Emergency or medical implant event report

After per cycle processing, signal assembling and Huffman coding are performed to generate a data packet [17]. Figure 4 shows the complete process of the proposed algorithm.

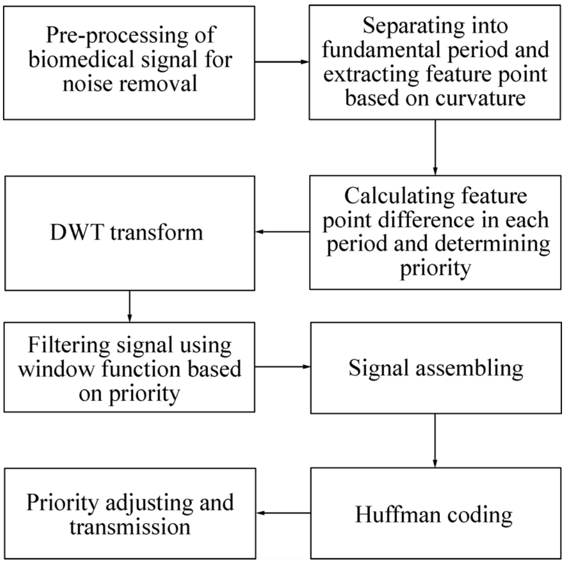

Fig. 4 Diagram of proposed algorithm

4 Simulations and analyses

To evaluate the performance of the proposed scheme, we set up a simulation environment using NS-2. The simulations were carried out under the assumption that a WBAN network has a star topology with a centered hub as a central controller. Table 2 shows the values of the simulation parameters. The sampling frequency of the MIT-BIH arrhythmia database and the N2001 database are 360 Hz and 20 kHz, respectively. In our simulation, the WBAN network includes two ECG devices, two EMG monitoring devices, and six nodes that generate backlog traffic. It is assumed that the offered backlog load suddenly and randomly changes within the limit of an average value. The threshold PRD value is set to be 7, and the window size for post-DWT filtering is determined as follows:

$$s = 100 - P \times 10 \quad (11)$$

Table 2 Simulation parameter

Parameter	Value
Number of ECG nodes	2
Number of EMG nodes	2
Number of backlog nodes	6
ECG database (MIT-BIH arrhythmia)	112 ML II 116 ML II
EMG database (EMGlab N2001)	ALS (biceps brachii) Myopathy (tensor fasciae latae)
Signal acquisition time/s	1800
PRD threshold	7

The window size determines the integrity of the compressed data using elimination of high-frequency signals and is expressed as a percentage of the original data size.

First, we compare the evolution of average packet transmission latency. Average packet transmission latency is defined as the time between the point that a transmitting node starts to prepare, and transmits, the data through a wireless network, and the point at which a receiving node finishes receiving and decompressing the data. Prior research into a WBAN that utilizes feature point extraction methods only focused on compressing data. In this work, we compare the proposed scheme, which compresses data and adjusts packet priority with extracted feature point characteristics, to a compression scheme that only compresses the data and a conventional scheme that does nothing to the data.

In general, the conventional scheme has lower transmission latency than the compression scheme. However, the conventional method has a lot more traffic to transmit. Therefore, collision probability and packet retransmission rate for devices using the conventional scheme are increased in accordance with the increasing amount of backlog traffic in the entire network.

Figure 5 shows the relationship between average packet transmission latency of an ECG device (112 ML

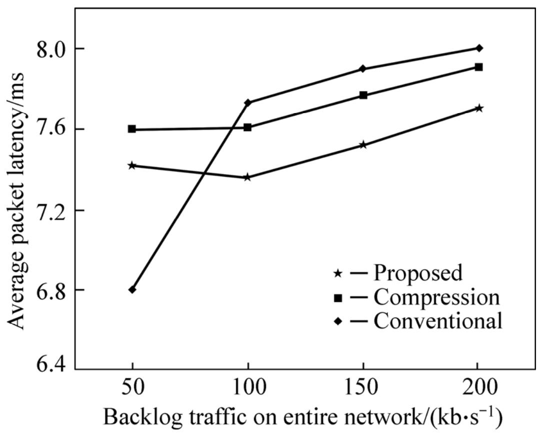

Fig. 5 Average packet latency versus backlog traffic

II) and backlog traffic. When the average transmission rate of the backlog traffic is 50 kb/s, the conventional scheme has the lowest packet transmission latency. However, as the amount of backlog traffic increases, packet transmission latency of the conventional scheme greatly increases when compared to the others.

Table 3 outlines the average packet transmission latencies of medical devices in the network (two ECG devices and two EMG devices). We can see that the proposed scheme shows better performance (up to 30%) in terms of average packet latency when compared to both the compression scheme and the conventional scheme. The proposed scheme performs lossless compression using full window size when the biomedical signal has significant changes, and raises priority to reduce packet transmission latency by cutting down decompression time. In addition, the average packet latencies of the proposed scheme are not noticeably affected by an increase in the congestion level of the network. Furthermore, the average packet transmission latency of the proposed scheme is reduced by 30% when compared to the compression scheme, since medical devices using the proposed scheme compress the data only if compression is needed to reduce decompression overhead.

Table 3 Average packet latency comparisons (ms)

Data base	Algorithm	Average transmission rate of backlog/(kb·s^{-1})		
		50	100	200
112 ML II	Conventional	6.8	7.73	8.01
	Compression	7.6	7.61	7.91
	Proposed	7.42	7.36	7.71
116 ML II	Conventional	6.98	6.78	7.40
	Compression	7.06	6.63	7.16
	Proposed	6.68	6.15	6.86
Myopathy	Conventional	3.64	3.92	4.89
	Compression	4.17	3.73	4.84
	Proposed	3.78	3.64	4.39
ALS	Conventional	6.17	7.37	10.07
	Compression	6.42	7.33	9.97
	Proposed	6.33	7.23	9.82

Second, we compare the packet drop rate of high-priority packets, the most important metric for medical data transmission. Figure 6 shows measurements for the high-priority packet drop rate when the accompanying backlog traffic in the network increases from 50 kb/s to 200 kb/s. We use the log scale for the high-priority packet drop rate graph due to the considerable differences in the rate. From Fig. 6, we can see that the

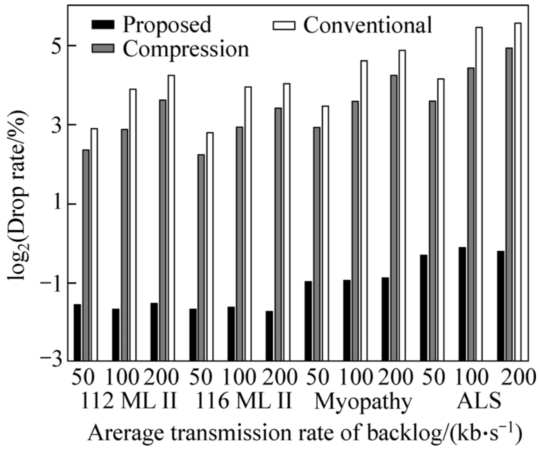

Fig. 6 Drop rates of high-priority packets

packet drop rates of the proposed algorithm are extremely low compared to the others. The packet drop rates of the compression scheme and the conventional scheme are about 5%−31% and 7%−47%, respectively, while those of the proposed scheme are about 0.3%−0.9%. In addition, it can be seen that the packet drop rates are not noticeably affected by increases in backlog traffic in the network.

And finally, we compare channel efficiency of the proposed algorithm to the others. Figure 7 shows the relationship between channel efficiency and the average transmission rate of backlog traffic. When the average transmission rate of backlog traffic is less than 50 kb/s, channel efficiency is not noticeably affected by the increase in congestion level in the network. On the other hand, when the average transmission rate of backlog traffic is higher than 100 kb/s, channel efficiency of the conventional scheme fluctuates by nearly 10%, and when the average transmission rate of backlog traffic is higher than 180 kb/s, channel efficiency of the compression scheme also decreases by around 12%. The proposed scheme achieves the best channel efficiency even in cases where the average transmission rate of backlog

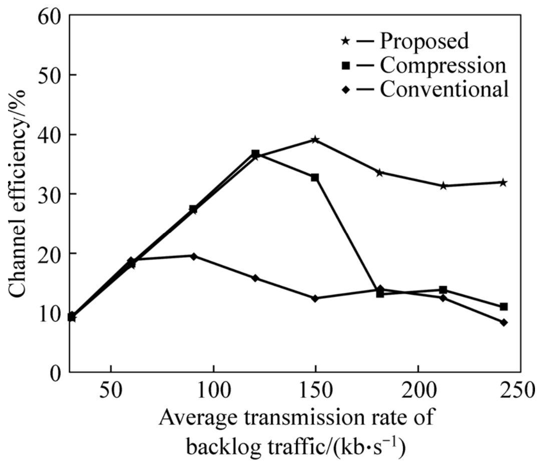

Fig. 7 Comparison of channel efficiency

traffic increases up to 250 kb/s. The proposed scheme adjusts the priority of all packets when it recognizes significant changes in a biomedical signal. The transmission of these packets is guaranteed by transmitting those packets in EAP. Thus, the proposed scheme can transmit emergency packets of medical devices even if a collision occurs during transmission between normal devices. Therefore, we can say the proposed algorithm improves QoS, because the proposed algorithm guarantees the reliability of important medical data transmission, even in a congested network.

5 Conclusions

1) We propose a novel adaptive transmission scheme to improve QoS for medical devices in a WBAN. In a WBAN, there are various devices trying to transmit medical or non-medical data. The medical devices set the packet priority to an apposite value that fits the characteristics of the biomedical signal information to guarantee QoS and maximize the channel efficiency.

2) The proposed scheme extracts the feature points of a biomedical signal based on a curvature value, and adjusts packet size and packet priority with the extracted feature points that represent the human body information. In addition, the proposed scheme compresses non-medical data packets to reduce transmission overhead and adjusts the priority of emergency medical data (which has significant changes in signal) to guarantee QoS.

3) From the simulation results, we find that the average packet transmission latency of the proposed scheme is reduced. The simulation results also show that the average high-priority packet drop rate decreases even if the average offered load increases.

References

[1] MARTELLI F, BURATTI C, VERDONE R. On the performance of an IEEE 802.15.6 wireless body area network [C]// Proceedings of Wireless Conference 2011−Sustainable Wireless Technologies (European Wireless). Vienna, Austria, 2011: 1−6.

[2] YANG G. Body sensor networks 2nd Ed [M]. London: Springer, 2014: 4−13.

[3] KIM J, SONG I, JANG E, CHOI S. A dynamic duty cycle mac algorithm for wireless body area networks [J]. International Journal of Bio-Science and Bio-Technology, 2012, 4(2): 84−92.

[4] GOLDBERGER A L, AMARAL L, GLASS L, HAUSDORFF J M, IVANOV P C H, MARK R G, MIETUS J E, MOODY G B, PENG C K, STANLEY H E. PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals [J]. Circulation, 2000, 101(23): 215−220.

[5] NIKOLIC M. Detailed analysis of clinical electromyography signals EMG decomposition, findings and firing pattern analysis in controls and patients with myopathy and amytrophic lateral sclerosis [D]. University of Copenhagen, 2001.

[6] IEEE 802. 15. 6. Standard for local and metropolitan area networks-Part 15.6: Wireless body area networks [S]. 2012

[7] KIM J, HONG C, CHOI S. Optimal allocation of random access period for wireless body area network [J]. Journal of Central South University, 2013, 20: 2195−2201.

[8] LIU B, YAN Z, CHEN C W. MAC protocol in wireless body area networks for E-health: Challenges and a context-aware design [J]. Wireless Communications, 2013, 20(4): 64−72.

[9] LEE R G, MUSTARD B E. Relationship between EMG patterns and kinematic properties for flexion movements at the human wrist [J]. Experimental Brain Research, 1987, 66(2): 247−256

[10] NG B S W, LOGOTHETIS N K, KAYSER C. EEG phase patterns reflect the selectivity of neural firing [J]. Cerebral Cortex, 2013, 23(2): 389−398.

[11] PAN J, TOMPKINS W J. A real-time QRS detection algorithm [J]. IEEE Transactions on Biomedical Engineering, 1985, 32(3): 230−236.

[12] XU X, LIN Y. ECG QRS complex detection using slope vector waveform (SVW) algorithm [C]// Proceedings of the 26th Annual International Conference of the IEEE EMBS. San Francisco, USA, 2004: 3597−3600.

[13] CHU J, MOON I, MUN M. A real-time EMG pattern recognition system based on linear-nonlinear feature projection for a multifunction myoelectric hand [J]. IEEE Transactions on Biomedical Engineering, 2006, 53(11): 2232−2239

[14] NAZIMOV A I, PAVLOV A N, HRAMOV A E, GRUBOV V V, KORONOVSKII A A, SITNIKOVA E Y. Adaptive wavelet-based recognition of oscillatory patterns on electroencephalograms [C]// SPIE Proceedings. San Francisco, USA, 2013: 8580−8581

[15] MUHAMMAD G. Extended average magnitude difference function based pitch detection [J]. The International Arab Journal of Information Technology, 2011, 8(2): 197−203.

[16] ABHINANDINI U, ARPITHA, V, MADHURI C R, VIJAY V. Comparative study on ECG data compression methods [J]. International Journal of Innovative Research and Development, 2013, 2(11): 413−415

[17] SETIA V, KUMAR V. Coding of DWT coefficients using run-length coding and Huffman coding for the purpose of color image compression [J]. International Journal of Computer and Communication Engineering, 2012, 6: 201−204.

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