Energy Efficient Data Transmission using PID based Data Prediction System

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ABSTRACT

In the recent years of medical science, we have to see that the wireless body sensors are used everywhere. These technologies have made our life secure and comfortable. These sensors are widely used because of its weight is very light and size is very small. To design body sensor networks we have to face the main issue of energy efficient data transmission. The continuous data transmission is an important part of the network due to need of continuous attention. To reduce the heavy traffic on the network, prediction-based data transmission approach may be use for transmission. This technique combines a dual prediction flowchart and a low-complexity prediction algorithm that takes advantage of PID (Proportional Integral Derivative) control. The energy gain and RMSE are use as performance parameters.

Keywords

WBSN,PID,RMSE,WSN

1. INTRODUCTION

In recent years wireless sensor networks are used in many different-different areas like wide area monitoring, military application, commercial application and also in biomedical history. It is used in wide areas because of it is low power microscopic sensors with wireless communication capability. These sensors are in a small physical size so it can be embedded in the physical environment [1, 2]. With an increasing number of wireless sensors becoming commercially available, WSNs have been enabling abroad range of novel applications, among which human health monitoring is a typical example. Continuous health monitoring is a key technology for realizing the transition of current healthcare systems to more proactive and affordable healthcare, especially for the elderly. Wireless communications, especially the personal area networking standards such as IEEE 802.15.1 (Bluetooth), 802.15.4 (Zigbee), and 802.15.6 (the work-in-progress body area network protocol), many physiological sensors have transformed into wireless sensors in possession of sensing, computing, and (wireless) communication capabilities [2].

Wireless body sensors are getting to be prominent in health awareness applications. Since they are either worn or embedded into human body, these sensors must be little in size and light in weight. A typical body sensor network with wireless communication is shown in the figure 1.

2. BODY SENSOR NETWORKS

Body sensor networks constitute an exceptional class of Wireless sensor networks. Like ordinary remote sensors, body sensors are regularly involved four principle segments, a sensing unit, a processing unit, a communication unit (i.e. transceiver), and a power supply unit[3, 4].

Fig.1. Wireless Body Area network scheme [9]

A BSN comprise of various wireless body sensor nodes, which measure assorted physiological phenomena of a human body, for example blood oxygen, electrocardiography (ECG), electroencephalography (EEG), electromyogram (EMG), central venous pressure (CVP), respiratory impedance, pulmonary arterial pressure (PAP), and temperature. For the most part, there is an extra base station (also called sink) perhaps worked by a cell telephone or a PDA (Personal Digital Assistant), etc. Healthcare systems based upon BSNs can possibly change how people's health is monitored, and how the damages of acute events are minimized. For instance, health data collection is traditionally conducted intermittently [8]. A BSN often contains a certain number of body sensor nodes and a base station. Each sensor node, either wearable or implanted into the human body, monitors a certain physiological parameter. It transmits (via a wireless link) sampled data to the base station, which is responsible for collecting the data from all sensor nodes and in some cases forwarding them to a remote data center on the Internet through a WLAN (wireless local area network) or cellular network [7, 8].

3. PID BASED DATA PREDICTION FOR TRANSMISSION

After The term PID (proportional-integral-derivative) refers to a popular control algorithm that was invented one hundred years ago. It is well known in the automatic control community that PID control is very powerful and is capable of solving a wide range of control problems [10]. More than 95% of all real world industrial control problems are addressed by utilizing PID control. It has been implemented in various systems of different scales and degrees of complexity, from small and simple devices to huge factories equipped with thousands of controllers. This popularity of PID control mainly benefits from its simplicity, clear functionality, wide applicability, and ease of use [5, 6].

The basic role of the controller is to adjust the manipulated variable u with respect to the control error e such that the system output (i.e. controlled variable) y will approach the setpoints. The control error is the difference between the setpoint and the actual system output, i.e., $e = r - y$.

PID control architecture.

Fig. 2. PID based data communication

As the name implies, a PID controller is comprised of three components: proportional, integral and derivative control. The input/output relation for an ideal PID controller can be written mathematically as:

$$u = K_P e + K_I \int_0^t e(\tau) d\tau + K_D \frac{de}{dt}$$

Where K_P is the proportional gain, K_I the integral gain, K_D the derivative gain and, t is the point of time, with the first three coefficient called controller parameters. From a functionality perspective, the proportional component produces a control action proportional to the control error; the integral component mitigates steady-state errors through low-frequency compensation by an integrator; the derivative component improves transient response through providing the controller with an anticipative ability.

As described above, the original PID algorithm is devised for feedback control. In order to apply it to data prediction, some modifications must be made. The prediction algorithm used in this work is given by:

$$\hat{x}_k = f(y_{k-1}, y_{k-2}, \dots, y_{k-M})$$

$$\hat{x}_k = K_P y_{k-1} + K_I \sum_{i=k-M}^{k-1} \frac{y_i}{M} + K_D (y_{k-1} - y_{k-2})$$

Like the PID controller, the above prediction algorithm consists of three components:

- The ‘proportional’ term $K_P y_{k-1}$ attempts to track the changes in the sampled values quickly by assuming that the current value will remain close, to some extent, to the last record. The dependency between the predicted value and the last record is determined by the proportional gain K_P .
- The ‘integral’ term $K_I \sum_{i=k-M}^{k-1} \frac{y_i}{M}$ considers a longer history of the records than the proportional term. It is based on the point of view that the current value will be close to the mean of the previous M consecutive samples. This term contributes to mitigate the impact of measurement noise but makes the predictor to response more slowly to changes.

The ‘derivative’ term $K_D (y_{k-1} - y_{k-2})$ assumes that the rate of change (in the values of the physiological parameter) is likely to remain the same as in the last interval. This term represents a prediction of the change in value.

We record the root mean squared error (RMSE), which is calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{5000} e_i^2}{5000}}$$

4. SYSTEM DESCRIPTION

The data predication based transmission is shown in figure 3. The data sources are medical data. The M length queue has been used for initial data. Up to length M no prediction on the data [5, 6].

Fig. 3 Data transmission scheme of system

5. RESULT

There are 3 biological data has been used in this paper. The data type is given below

5.1 ECG DATA (electrocardiography)

ECG signal has four data features P, Q, R, S.

Fig.4 Signal (P-feature)

Fig. 5 Signal (Q-feature)

Fig. 6 Signal (R-feature)

Fig. 9 Signal (Delta-feature)

Fig. 7 Signal (S-feature)

Fig. 10 Signal (Theta-feature)

Fig. 8 Error Signal

Fig. 11 Signal (Alpha-feature)

Table 1: Values of P, Q, R, S Feature for ECG Signal

	P	Q	R	S
Error Rate	0.618261	1.846441	1.318843	0.758710
Mean Absolute Error	0.382246	3.409343	1.739347	0.575641
Energy of the Transmission	259.898022	259.898022	259.898022	259.898022
Energy of Prediction based Transmission	189.783861	275.713210	248.411362	165.216024
Energy Gain	70.114161	15.815189	11.486660	94.681997
Percentage Gain in Energy	26.977566	6.085152	4.419680	36.430442

Fig. 12 Signal (Beta-feature)

Fig. 13 Signal (Gamma-feature)

5.2 EEG DATA (electroencephalography)

EEG data has six data features Delta, Theta, Alpha, Beta, Gamma, Mu (μ).

Fig. 14 Signal (Mu (μ)-feature)

Fig. 17 Signal (Diastolic-feature)

Fig. 15 Error Signal

Fig. 18 Error Signal

Table 2: Values of Delta, Theta, Alpha, Beta, Gamma, Mu (μ)

	Delta	Theta	Alpha	Beta	Gamma	Mu(μ)
Error Rate	0.7684	0.8862	1.0850	0.8360	0.7285	0.8774
Mean Absolute Error	0.5905	0.7855	1.1772	0.6990	0.5307	0.7699
Energy of the Transmission	178.684	178.684	178.684	178.684	178.684	178.684
Energy of Prediction based Transmission	92.959	103.50	62.965	99.993	98.630	87.342
Energy Gain	85.725	75.180	115.71	78.691	80.054	91.342
Percentage Gain in Energy	47.975	42.074	64.761	44.039	44.802	51.119

➤ GUI (Graphical User Interface)

Fig. 19 GUI for Evaluating Signal

5.3 PAP (pulmonary arterial pressure)

PAP has Two Features Systolic and Diastolic.

Fig. 16 Signal (Systolic-feature)

Table 3: Value for Systolic and Diastolic feature for PAP

	Systolic	Diastolic
Error Rate	6.847459	7.289190
Mean Absolute Error	46.887697	53.132290
Energy of the Transmission	10319.797651	10319.797651
Energy of Prediction based Transmission	4341.117433	4483.771023
Energy Gain	5978.680218	5836.026628
Percentage Gain in Energy	57.934084	56.551754

6. CONCLUSION

The simulation on the ECG, EEG, and PAP signals has been carried out. These signals are more common healthcare signals which need to monitor continuously in the ill condition of critical patient. The 4, 6 and 2 features are used for ECG, EEG and PAP signal respectively. The 30 % gain has been achieved with the

prediction based method. There is possibility to optimize the PID coefficient further to reduce the error and enhance the energy gain.

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8. REFERENCES

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