Energy-efficient Long Term Physiological Monitoring

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ABSTRACT

Recently, several wireless body sensor-based systems have been proposed for continuous, long-term physiological monitoring. A major challenge in such systems is that a large amount of data is collected, and transmission of this data incurs significant energy consumption at the sensor. In this work, we demonstrate a data reporting method that significantly reduces energy consumption while maintaining a high diagnostic accuracy of the reported physiological signal. This is achieved by using a generative model of the physiological signal of interest at the sensor, and suppressing data transmission when sensed data matches the model. In this demonstration, we implement the proposed technique for electrocardiogram (ECG) signal and illustrate its performance in terms of energy savings and accuracy of reported data.

1. INTRODUCTION

Wearable sensor-based systems have been proposed for long-term physiological monitoring and promise to provide continuous, unobtrusive and remote monitoring at low infrastructure cost. A significant challenge in such continuous, long-term physiological monitoring applications is to minimize the energy consumption of the body-worn sensors in order to maximize their battery life. However, due to continuous sampling of physiological signals at clinically recommended sampling rates, a large amount of data is collected at the sensor and transmission of this data incurs very high energy consumption. Simply reducing the sampling rate or bit resolution could lead to loss of diagnostic accuracy of the signal reported to the physician. Current approaches to achieve efficient monitoring are based on reducing the data size, and hence transmission energy, at the sensor using known compression schemes [3, 7]. However, these schemes require periodic transmission of data, which limit their energy savings.

In this work, we take a generative model-based approach to physiological data monitoring. As shown in Figure 1, our approach uses a generative model ($\mathcal{G}$) of the physiological signal of interest at both, the server and the sensor. Initially, the model $\mathcal{G}$ is trained on the patient's physiological data. This includes deriving suitable input parameter values for $\mathcal{G}$, such that the output generated by $\mathcal{G}$ closely matches the patient's physiological signal. These parameter values are stored in the sensor as well as at the server. During normal operation, the sensor uses $\mathcal{G}$ to generate a signal, and compares this signal to the sensed data. If the signals match within specified thresholds, no data is transmitted. Otherwise, the sensor sends updates to the base station. These updates can be single model parameter values (called *feature updates*) or set of raw signal samples (called *raw signal updates*) as explained in [5]. At the server, if no data is received from the sensor, the server uses $\mathcal{G}$ to generate a waveform closely resembling the physiological signal of interest. Feature updates from the sensor are used to update the parameters of $\mathcal{G}$, thus capturing temporal variations in the patient's physiological signal. Raw signal updates are considered as the patient's real data and are used to overwrite the corresponding time intervals of the model-generated waveform. The resultant waveform is then reported to the physician for diagnosis.

This generative model-based technique is generic and can be applied to various specific physiological signals. For example, it was used to develop an ECG monitoring technique called GeM-REM in our prior work [5], where the widely accepted ECGSYN model [4] was used as the generative model $\mathcal{G}$. Evaluation with real-life ECG traces from MIT-BIH database showed significant energy savings (factor of 42) while maintaining diagnostic accuracy above 93%. In [6], we adopted a similar approach for PPG monitoring, and developed two generative models (*Tem-PPG* and *DE-PPG*) for the PPG signal. Evaluation on MIT-BIH data as well as wearable sensor-based data showed average reduction in energy consumption by a factor of 300, which significantly exceeds that of existing compression techniques. Further, we proposed methods to improve the robustness of the proposed technique to wireless channel errors such as random bit errors, burst errors and fading. These methods were observed to improve the accuracy of the reported data at a marginal cost in energy consumption.

2. DEMONSTRATION

In this section, we describe the system model and implementation of our physiological monitoring demonstration.

2.1 System Model

The monitoring system, as shown in Figure 1, comprises of a wireless sensor and a server. The sensor is worn by the patient and continuously senses the physiological parameter of interest, while the server is at the physician end and provides data reports and visualization. In this demonstration, we focus on ECG as an example of physiological signals. The sensor uses the generative model-based approach described in Section 1 to reduce data transmissions, thus saving energy. For ease of demonstration, the sensor and server are directly connected via a wireless link. This design can easily be

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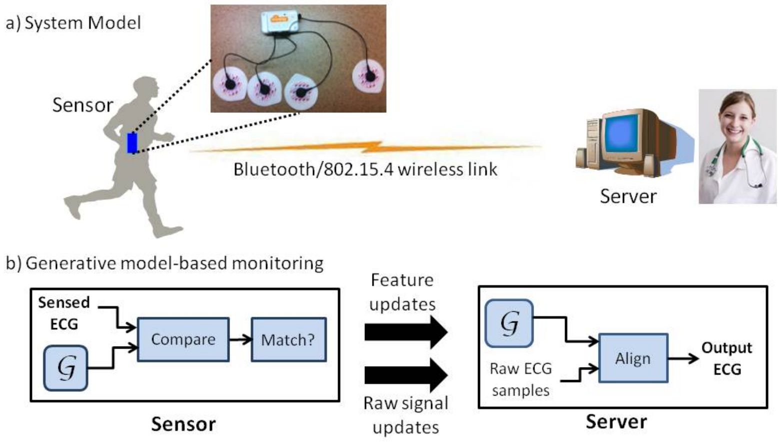

Figure 1: a) System model for the generative model-based ECG monitoring system. A SHIMMER 2R mote is used as the ECG sensor and a PC is used as the server. b) Illustration of the generative model-based monitoring scheme.

extended to use a remote server by introducing a gateway device such as a smartphone to relay the sensor data over the Internet.

2.2 Implementation

For ECG monitoring, we use SHIMMER 2R wireless ECG sensors [1] along with 3M Red-Dot Ag/AgCl electrodes to collect 3-lead ECG measurements at 125 Hz. The sensor-side algorithms of the monitoring technique are implemented in nesC for TinyOS 2.x. A PC is used as the server, and the model $\mathcal{G}$ is trained using curve fitting functions in MATLAB. Two options are available for the sensor-server link: the 802.15.4 radio of SHIMMER can be used for transmitting data to another SHIMMER node, which is connected to the PC through the USB port. Alternatively, the Bluetooth radio of SHIMMER can be used to transmit data directly to the PC. We demonstrate two data reporting methods on the sensor side: 1) Basic periodic transmission, which periodically transmits the ECG samples collected by the sensor; and 2) Proposed generative model-based monitoring technique described in Section 1. The PC runs a MATLAB script to receive sensor data updates through the serial port and generate an ECG signal using the ECGSYN model. The server GUI displays the generated ECG as well as all the packets transmitted by the sensor. This allows us to clearly show the reduction in data transmission in the proposed scheme compared to the basic periodic transmission scheme. The server GUI also allows users to dynamically modify the thresholds used by the sensor for model comparison. A video of the current version of the implementation is available at [2]. We have also developed an Android-based implementation of the server module using a Nexus one smartphone. In this case, the sensor transmits data to the server over Bluetooth. The two implementations clearly show that the proposed method is independent of the hardware platform as well as the wireless communication protocol used.

3. CONCLUSION AND FUTURE WORK

In this work, we demonstrated a generative model-based data reporting technique for long term physiological monitoring using BSNs. The proposed demonstration clearly illustrates the reduction in data transmission and subsequent energy savings provided by the generative model-based data monitoring technique. Moreover, the diagnostic content of the reported physiological signal is not compromised. The proposed ECG monitoring system implementation is currently in the testing and validation stage. Following this stage, we will collect ECG data from volunteers and measure the energy and memory savings provided by the proposed method in realistic, wearable sensor-based scenarios. We will then compare these results to those obtained for clean ECG traces reported in [5].

4. ACKNOWLEDGMENTS

We would like to thank Sunit Verma and Joseph Milazzo from IMPACT Lab at Arizona State University for their contributions to this demonstration. The work of ASU contributors is partially funded by NSF grant CT-0831544. We are also thankful to Google for donating Android phones used in this project.

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