A Wavelet-Based Data Reduction Approach for Sensor-Rich Ubiquitous Systems

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Abstract. *Sensor-rich ubiquitous systems require continuous monitoring platforms for instantaneously providing context-aware services. These sensor-based monitoring platforms generate a large amount of discrete and waveform data, resulting in a high energy expenditure while transmitting data. In this scenario, data reduction mechanisms can be applied for saving transmission energy of sensor devices by reducing discrete and waveform data, maximizing the availability and reliability of sensor-rich ubiquitous systems. Adaptive Simple Linear Regression (ASLR) is well suited for reducing discrete data, however, it is required a more efficient data reduction approach for reducing waveform data, such as ECG signal. This paper proposes and evaluates a wavelet-based data reduction approach for reducing waveform data, which was integrated with our context management framework.*

1. Introduction

Sensor-Rich Context Management Frameworks (CMF) are in charge of gathering, processing, and providing context information [16, 15] for adapting context-aware applications, such as health monitoring services [12, 13, 14, 16]. Ubiquitous health monitoring services are sensor-based platforms able to check vital signal of people, at anytime and anywhere [12, 13, 14, 15]. For example, those mobile sensor-rich biological monitoring systems can be equipped with eletrocardiogram (ECG) sensor for continuously tracking heart disease. Usually, ECG gathered data are locally stored on the ubiquitous monitoring platform for later analysis, or it are continuously sent for server-side analyzer application constructed on CMF. In fact, there is a huge demand for continuous ECG monitoring systems, requiring real-time response, high availability and reliability.

However, these resource-constrained real-time monitoring platform of CMF usually generate a large amount of data, expending energy of sensors powered by batteries [18]. Sensors have severe physical constraints, such as memory capacity, computational power, and energy autonomy [19]. The energy consumption of sensor-rich CMF is mainly associated with three operations: i) sensing functions, ii) data processing, and iii) communication [20]. The energy spent by sensing operation varies according to the sensor type and application nature. For instance, the sporadic sensing (e.g., honey quality or blood sugar monitoring) consumes less energy than the constant event monitoring, such as bee swarming or heart disease tracking. Although there are several proposals of CMF [5, 6, 4, 9, 8, 7, 16], they do not take into account the need of maximizing the availability of the sensor-rich monitoring platform in order to reduce the probability of unavailability of context-aware services. In this scenario, it is a promising idea to integrate data reduction approaches [11] with CMF for saving energy. However, these approaches should take into account quality requirements (QoC[1]) [16, 17, 15] associated with context information generated after compression.

The focus of this work is enhancing the lifetime of sensor-rich CMF by saving communication data energy. We propose two data reduction approaches for reducing discrete and waveform data, respectively: i) a predictive data reduction mechanism (Adaptive Simple Linear Regression - ASLR) to extend the lifetime of sensor-rich CMF; ii) a wavelet-based data reduction solution for reducting waveform data, such as ECG signal data. The proposed approaches compress data gathered from monitoring platform before sending it to CMF. The monitoring infrastructure used by our ubiquitous systems is based on the Arduino Platform[2], which was integrated with our Context Management Framework (CxtMF) for constructing context-aware applications, such as ECG monitoring services (for more information about the CxtMF, please refers to [16, 15]). The reminder of the paper is organized as follows: Section 2 presents related work and Section 3 gives an overview on the ECG monitoring service built on the CxtMF. Section 4 presents the proposed data reduction approaches and Section 5 analyses the results of the experiment. Finally, we conclude the paper and discuss future work in Section 6.

2. Related Work

Data Reduction for Energy Saving (DRES) is widely used in Wireless Sensor Networks (WSN), decreasing the transmission of sensor readings on the network. The sensor node avoids sending gathered readings as it can be recovered at the sink node by means the raw data history. In literature, there are several works on WSN data reduction, such as [22, 24, 23, 26, 27, 28, 24, 29]. Also, there are few survey [11, 10] which describe the characteristics of certain mechanisms. Prediction of sensor data is often applied to DRES, since it allows that only the data model is sent to the sink node to be carried out later data recovery [24, 28, 29, 18]. The location where the generation of the data model is made depends on each approach.

Some authors [24] argue that data modeling should be done by the sink node (e.g., CMF) and the data model must be forwarded to source nodes to performs data recovery. The source node checks if data model still holds, i.e., if it is within a previously established threshold. Otherwise, it alerts the sink node to recalculate a new model. However, authors as [18] recommend that data modeling should be done by source node and sent to the sink node. That approach enables the sensor node make decisions instantly, regardless of the transmission delay of the model. The mechanism adopted by these approaches

[1]Quality of Context

[2]http://www.libelium.com/130220224710/

can be a simple prediction technique based on statistical or a more complex technique, based on time series or another. Although the statistical mechanisms are less robust in terms of accuracy, they can get good results and may be applied to DRES. Our approach focuses on statistical mechanisms and the results obtained from experiments indicate that we can apply the simple adjustment mechanism, making it adaptive to correlation of the readings of discrete values, with low loss of quality data. However, for waveform data, it is most suitable to apply a wavelet-based data reduction approach for preserving quality of waveform data. In fact, by discretizing waveform signals, there is a loss of information, which directly interferes in the quality of the reconstructed waveform signal. For this reason, it is necessary to specify a specific approach to reduce waveform data, which is what this paper proposes.

3. ECG monitoring service

In order to perform our experiments, we developped a case study with a continuous ECG monitoring service for patients with heart diseases. This service was built on the CxtMF illustred in Figure 1. CxtMF fully support QoC control, including the collection (gathering), measurement, interpretation, access, and delivery of QoC-enriched context information, as well as other functionalities to efficiently handle QoC (e.g., to delivery context with a minimum QoC).

The main entities of CxtMF are Context Providers (CP) and Context Information Service (CIS) [16]. CP is an agent that sends CxtObj (an instance of a given context information) associated with some QoC parameters (QoCP) to the Context Information Service (CIS) belonging to the same domain, e.g., ECG signal. Each CP (e.g., Arduino platform) is registered in a CIS, which is composed by various modules in charge of context management functions: i) Context Collector (CC), Context Reasoner (CR), Context Obfuscator (CO), QoC Evaluator (QoCE), and Context View Provider (CVP). The separation of CxtMF into two main entities (i.e., CP and CIS) is only functional, which means that these entities may run together on a single processing unit (e.g., a server in a smart environment running a CP and CIS) or on various distributed processing units (e.g., CP running on smartphones and CIS in a server). In the CxtMF, context information, QoC, and QoC requirements are represented by OWL-DL ontologies. We have defined three ontologies to model Context, QoC, QoC requirements, which provides the semantic interoperability between all management layers in the CxtFM.

3.1. ECG monitoring overview

ECG is an exam which records electrical pulses generated during the cardiac activity and, thus, aids the diagnosis of heart and other diseases, not only related to the circulatory system [21]. Among the main diagnoses, can be highlighted diseases[3]: arrhythmias, overload, areas electrically inactive, neurological and congenital diseases.

A ECG Complex represents the electrical events occurring in the cardiac cycle and consists of five waves denominated by the letters P, Q, R, S and T. The letters Q, R and S are considered a unit, namely, the QRS Complex.

Figure 2 illustrates the Arduino platform used for sensing ECG signal. Our data reduction mechanisms implemented on the CxtMF (Context Collector - CC) receives the

[3]http://www.heart.org/

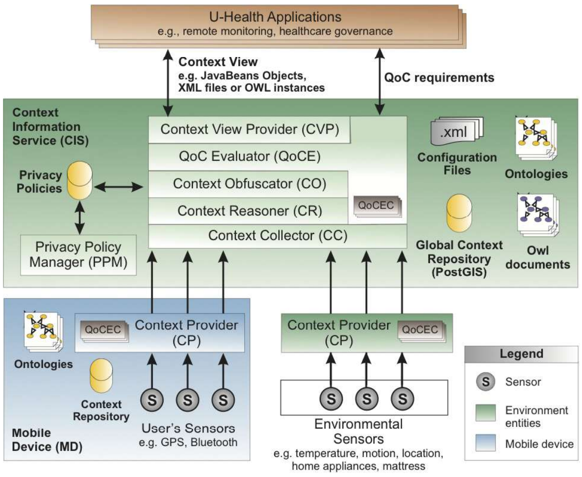

Figure 1. Context Management Framework (CxtMF)[16, 15].

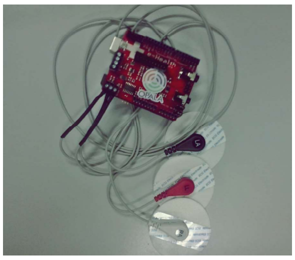

Figure 2. ECG monitoring service built using the Arduino platform.

data from the ECG signal and checks the correlation between the readings. If it does not reaches a error threshold, the parameters are computed, which represent those data (modeling), and forward to the CxtMF only the coefficients of the linear equations. Therefore, the original ECG signals are reconstructed at the CxtMF, prior to being provide for context-aware services. We note in the experiments that ALRS approach performs prediction for generating data models for recovering signals maintaining the complex characteristics of ECG signal, containing all five waves. However, the wavelet-based data reduction approach presents best results with regarding the quality of data than the ALRS approach while reducing ECG signal data.

4. Data reduction approaches

4.1. Adaptive Simple Linear Regression Based on Pearson's Coefficient

Simple Linear Regression (SLR) models the relationship between a scalar dependent variable Y and one explanatory or independent variable named X. SLR is based on least squares [Equations (1) and (2)].

Each sensor node calculates α and β by using as the independent variable a counter that represents the time. The monitored physical variable is the dependent variable to be predicted (temperature or ECG signals). In our adaptive scheme, the sensor node adjust the samples window based on correlation coefficient. In that case, α and β are computed from samples based on Pearson's Coefficient, according to Equation (3). That coefficient shows the level of intensity between two variables and the direction from that correlation (positive or negative). The Value of the coefficient should be in the range $[-1, +1]$.

$$\beta = \frac{\sum_{i=1}^{n}\left(x_i - \overline{X}\right)\left(y_i - \overline{Y}\right)}{\sum_{i=1}^{n}\left(x_i - \overline{X}\right)^2} \tag{1}$$

$$\alpha = \overline{Y} - \beta\overline{X} \tag{2}$$

where β represents a constant that is multiplied by the value of each independent variable. α is a constant added to the previous multiplication, resulting in the predicted value. X and Y are two one-dimensional vectors, which respectively represent samples window of the independent and dependent variables, with $X = x_1, x_2, ..., x_i$ and $Y = y_1, y_2, ..., y_i$, where $i = 1, ..., n$ and n is the number of samples. $\overline{X}$ and $\overline{Y}$ represent the average of samples of each vector.

$$r = \frac{n\sum_{i=1}^{n} x_i y_i - (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{\sqrt{\left[n\sum_{i=1}^{n} x^2 - (\sum_{i=1}^{n} x_i)^2\right]\left[n\sum_{i=1}^{n} y^2 - (\sum_{i=1}^{n} y_i)^2\right]}} \tag{3}$$

where r represents the relationship between two one-dimensional vectors X and Y, to be compared in terms of its correlation. It contains samples window of two variables, $X = x_1, x_2, ..., x_i$ and $Y = y_1, y_2, ..., y_i$, where $i = 1, ..., n$ and n is the number of samples (window size). $\overline{X}$ and $\overline{Y}$ represent the average of samples of each variable vector.

Value of coefficient can be played as follows: if value is $+1$, then there is a perfect positive correlation between the two variables; if value is -1, then there is a perfect negative correlation between two variables. If the value is 0 then there is not correlation or correlation is non-linear. In our case, the better results on performance evaluation from prediction (low error) were got when Pearson's Coefficient ranged between $[0.6 - 1]$. The same mechanism adopted for ECG monitoring was used to understand the monitoring of beehives.

- Step #1: The sensor node takes one measurement from the interested variable, for instance, the ECG signals (in this case, the dependent variable), and stores the measured value in a internal buffer;
- Step #2: The Pearson coefficient is calculated, based on the values stored in the buffer;
- Step #3: The Pearson coefficient is evaluated. If the value of the coefficient is equal or bigger than a predefined threshold (for example, 0.6), then the values in the buffer has a stronger correlation and the algorithm goes to Step #7; otherwise, it goes to Step #4;
- Step #4: The Pearson coefficient is below the predefined threshold which means that the last value measured was the responsible to the decay of the value. In this case, the algorithm calculates α and β coefficients of the linear regression based on the values stored in buffer, without the last value measured. The X variable is represented by a counter, which represents how many measurements were taken. α and β coefficients and the counter are sent to the sink node (i.e., CxtMF);
- Step #5: The buffer is cleared, and the last value measured is stored in it;
- Step #6: The α and β coefficients are transmitted to the CxtMF;
- Step #7: End of cycle; Go back to Step #1.

4.2. Wavelet-based Data Reduction Approach

The proposed wavelet-based approach compress ECG signals by using Discrete Wavelet Transform (DWT) [25]. For applying DWT, there are several wavelet filters that could be used for reducing waveform data, such Daubechie wavelets [25]. Daubechie wavelets is a family of orthogonal wavelets, defining a discrete wavelet transform, which is characterized by a maximal number of vanishing moments for some given support. With each wavelet type of this class, there is a scaling function (called the father wavelet) which generates an orthogonal multiresolution analysis. We are using the filter Daubechie 04 from this family for reducing electrocardiogram signals, which generates a reconstructed signal nearest to the original signal. An average, one cycle of the heart have 400 ECG signal data. We applyied 3 (three) levels while reducing data using our waveled-based approach. In the first level, the proposed approach use 400 ECG signals to be reduced by 200. In the second level are used 200 ECG signals to be reduced by 100, and in the third and final level are used 100 ECG signals to be reduced by 50. In the next, we present experimental results comparing the proposed data reduction approaches.

5. Experimental results

In order to measure the performance of proposed data reduction approaches, we define metrics such as amount of packets sent on network (p_{sent}) and the error of prediction ($e_{prediction}$). p_{sent} shows the energy saved of sensor by reducing the communication data over the network. $e_{prediction}$ computes the accuracy of prediction approach. Experiments were conducted for both data reduction approaches, which will discussed in the following.

We conducted experiment with the ASLR-based data reduction approach. We defined three test cases, applying the ASLR-based data reduction approach on 400 ECG signal data, changing the threshold: i) test case 1: $threshold = 0.9$; ii) test case 2: $threshold = 0,95$; and iii) test case 3: $threshold = 0,97$. 400 ECG signal data corresponds to a complete cycle of the heart. A conventional ECG monitoring service, without applying any data reduction approach, gets $p_{sent} = 400$ by heart cycle. Meanwhile, our ASLR-based approach obtains p_{sent} 13 (3,25%), 13 (3,25%), and 15 (3,75%) for test case 1, 2, and 3, respectively. The $e_{prediction}$ have been 0,008694, 0,005174, and 0,00374, for test case 1, 2, and 3, respectively. By applying that data reduction approach, we save about 96% of the packets, which means a reduction of energy consumption about 96%. These results are justified because ECG signals are modeled in 13 linear regression functions, which its parameters (coefficients α and β) must be sent to the CxtMF, instead of the 400 readings.

Figure 3, 4, and 5 shows prediction results from ECG monitoring service using our ASLR-based algorithm, as well as the raw data, for test case 1, 2, and 3, respectively. The recovered ECG signal by the CxtMF is well similar with the original raw signals gathered by sensors. Note that the complexity of the ECG signal is maintained even after applying the DRES, since we are using linear regression approximation. The adjustment has been done in the samples window in an adaptive way that enables the creation of multiple data models respecting a threshold error.

Figure 6 illustrate the original ECG wave data (graph on the left), which is composed by 400 ECG signal data. By applying our wavelet-based data reduction approach, 400 ECG signal data are reducted to only 50 ECG signal data. By comparing the original

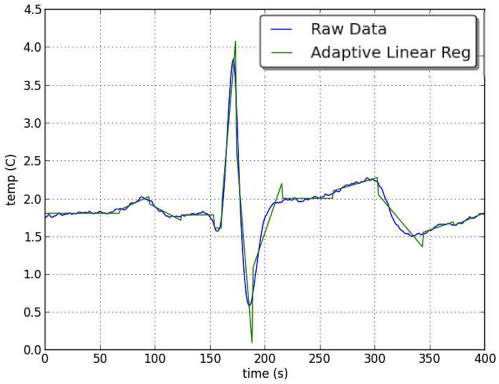

Figure 3. Prediction from ECG signals for test case 1.

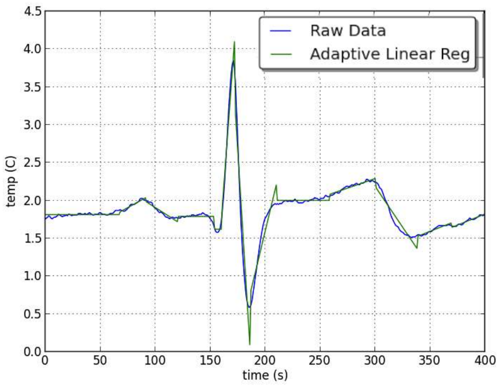

Figure 4. Prediction from ECG signals for test case 2.

ECG data with the resulting ECG waveform data (graph on the right), we can see that the wavelet-based data reduction approach generates a signal with quality similar to the original wave data. Furthermore, the noise level of the obtained wave is much lower.

By comparing the ECG wave from Figure 5 (ASLR-based data reduction) and 6 (wavelet-based data reduction), we can see that the ECG wave resulting from the application of wavelet-based approach gets a result of better quality. With regarding the energy comsuption, experimental results show that our approach reduces the amount of packets sent (p_{sent}) on the network for both data reduction approaches. As our experiments take into account only the useful application data (payload) of packets, the energy spent for sending a packet is 0.48375 mJ, neglecting the overhead and signaling from network layer.

Considering the p_{sent} from each data reduction approach on the experiments, we obtained the following results: 1) ASLR-based data reduction aproach: the ECG monitoring service, without applying any data reduction mechanism, the energy consumption of daily usage was 25,267.56J (i.e., 399 readings/cycle X 0.48375 X 130,909 cycles, every 0.66s). After applying our data reduction approach, for the test case 1 and 2, the energy consumption for this service was 823.25J (i.e., 13 coefficients/cycle X 0.48375 X 130,909 cycles, every 0.66s), reducing approximately 97% of energy consumption with

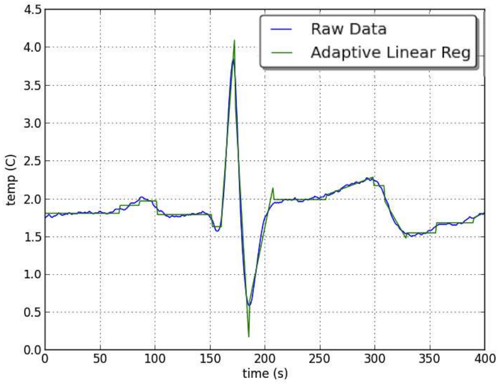

Figure 5. Prediction from ECG signals for test case 3.

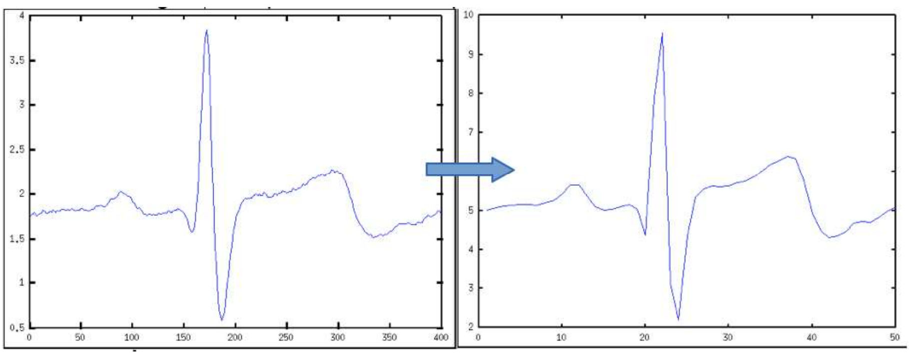

Figure 6. Wavelet-based data reduction approach applied on ECG signal data (On the left, the wave composed by 400 ECG as input. On the right, the wave rebuilt with only 50 ECG signal data.

data transmission; 2) wavelet-based data reduction aproach: after applying the data reduction approach, the energy consumption for this service was 3,166.35J (i.e., 50 ECG data/cycle X 0.48375 X 130,909 cycles, every 0.66s), reducing approximately 87,5% of energy consumption with data transmission, but preserving the data quality of the resulting wave.

6. Discussion and conclusions

This paper proposed a wavelet-based data reduction approach for ubiquitous context management framework, for improving sensor-rich monitoring platforms. The proposed data reduction approach was integrated with the CxtMF in order to gather raw discrete and waveform data and saving energy of sensors, increasing its lifetime. Our ASLR approach uses prediction of readings gathered based on SLR. Indeed, it is a simple mechanism (based on linear function) and can generate a lot of noise in the result of prediction, which adapts the size of window samples. With the Adaptative SLR (ASLR) proposed in this work, we decreased the noise making with the mechanism driven by correlation coefficient. Thus, we have a more robust solution against the basic mechanism of SLR, saving more energy that mechanism without data reduction. However, the proposed wavelet-based data reduction approach presents better quality of resultant wave for reducing waveform data, although the power consumption of data transmission is slightly higher (3,25%

and 12,5% of energy consumption, for ASLR-based and wavelet-based data-reduction approach, respectively). From these results, we can conclude that the wavelet-based data reduction approach is most suitable than the ASLR-based solution for reducing waveform data, when quality requirements has higher priority than availability requirements with regarding the sensor-rich monitoring platform. In future work, we plan to extend the experiment with others sensors that gather waveform data, in order to validate the proposed wavelet-based data reduction approach.

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