Using QoC for Improving Energy-Efficient Context Management in U-Health Systems

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***Abstract*—Context Management Framework (CMF) for Ubiquitous Health (U-Health) Systems should be able to continuously gather raw data from observed entities to characterize their current situation (context). However, the death of battery-dependent sensors reduce their ability for detecting the context, which directly affects the availability of context-aware u-health services. This paper proposes the use of Quality of Context (QoC) integrated with a data reduction approach to minimize the amount of sensed raw data sent to CMF, reducing the energy consumption and maximizing the lifetime of sensor-based CMF. The proposed approach rebuilds the gathered raw data taking into account QoC requirements, avoiding the loss of precision (QoC Indicator precision) and timeliness (QoC Indicator up-to-dateness), which has been integrated into our Context Management Framework (CxtMF). Experimental results demonstrate the effectiveness of our approach by reducing the amount of packets sent over network to 3% for the ECG monitoring service.**

***Index Terms*—U-Health systems, Data Reduction, Context Management, Context-awareness, Quality of Context.**

I. Introduction

Context Management Framework (CMF) in U-Health Systems is in charge of gathering, processing, and providing context information [16], [15] for adapting context-aware applications, such as health [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, sensor-rich biological monitoring systems can be equipped with eletrocardiogram (ECG) sensor for continuously tracking CardioVascular Diseases (CVD). Usually, ECG gathered data is locally stored on the ubiquitous monitoring platform for later analysis, or it is continuously sent for server-side analyzer application built on a CMF. In fact, there is a huge demand for continuous ECG monitoring systems, requiring real-time response, high availability and reliability.

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 u-health 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 during the compression of gathered data, such as precision and up-to-dateness (QoC indicators).

The focus of this work is enhancing the lifetime of sensor-rich CMF by saving communication data energy, taking into account QoC requirements. We propose the use of QoC Indicator for improving a predictive data reduction mechanism (Adaptive Simple Linear Regression - ASLR) to extend the lifetime of sensor-rich CMF, preserving the quality of gathered context data. The proposed ASLR approach compresses data gathered from monitoring platform before sending it to a CMF. The monitoring infrastructure used by our U-health systems is based on the Arduino Platform[2], which was integrated with our Context Management Framework (CxtMF) for constructing context-aware u-health services, such as continuous ECG monitoring services (for more information about the CxtMF, please refers to [16], [15]).

The quality-aware ASLR uses a prediction mechanism based on the history of raw data gathered by sensors. By using the proposed ASLR approach, the monitoring systems should produce coefficients (parameters) that models the readings set from the samples window. Thus, instead of send all gathered samples, the monitoring system send to the CxtMF only the coefficients that represents the line, i.e., the set that represents the reading [18]. The production of the coefficients is controlled by the error between the real and estimated value, as well as the max size of reading window, i.e., respecting both QoC threshold: precision and up-to-dateness. The proposed data reduction approach can adjust the samples window used on the model, respecting the max size defined by the up-to-dateness threshold. Based on the received coefficients (models), the CxtMF is able to reconstruct the sample set of gathered data. The quality of gathered data is enhanced by using Pearson's Coefficient (correlation rate) in the proposed ASLR approach.

The reminder of the paper is organized as follows: Section 2

[1]Quality of Context
[2]http://www.libelium.com/130220224710/

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addresses related work about data reduction mechanisms. Section 3 gives an overview on the case study of our experiments (continuous ECG monitoring services) and section 4 presents the proposed data reduction approach. Section 5 describes the experimental results and, finally, section 6 addresses the discussion and conclusion of this work.

II. Related Work

Data Reduction for Energy Saving (DRES) is widely used in Wireless Sensor Networks (WSN) for decreasing the transmission rate of sensors on the network. The sensor node avoids the sending of gathered readings as it can be recovered at the sink node by means the raw data history. The scientific community has proposed mechanisms that seek to reduce the data transmission of sensors [22], [24], [23], [25], [26], [27], [24], [28], as well as few survey [11], [10] describes the characteristics of such data reduction mechanism.

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], [27], [28], [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, Carvalho *et al.* [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 can be a simple prediction technique based on statistical, or a more complex technique, based on time series. Although the statistical mechanisms are less robust in terms of accuracy, they can get good results and may be applied to DRES.

In fact, sensor devices have certain peculiarities when are embedded in monitoring platforms. They should have a long lifetime, spending a minimum of energy from the batteries. Therefore, sensors should be in sleep mode when they are not gathering data. Moreover, the processing time of the applied data reduction technique should be minimized, as well as the activity of sensor device and monitoring platform. Thus, the data reduction approach can not store too much data for a long time, which will require longer time of activity of monitoring platform, expending more energy.

From this discussion, we can conclude that our data reduction approach meets the requirements of such limited embedded systems. The time taken by our approach in real experiments have been less than the QoC parameter lifeTime for ECG monitoring. In fact, the QoCP lifeTime of each information is smaller than the cycle time of one sensor reading, i.e., the sum of sensor activation time, the processing time and sending time of the data model, until the sensor enter in the sleep mode again. Therefore, more complex approaches may not meet those requirements. Moreover, any of the existing work takes into account quality requirements of context-aware services while reducing data (i.e., QoC precision and up-to-dateness).

The proposed quality-aware data reduction approach focuses on statistical mechanisms. Results obtained from experiments indicate that we can apply the adjustment mechanism for dynamically change the window size, making the proposal adaptive to the correlation of the readings, with low loss of quality for discrete (e.g., temperature) and waveform (e.g., ECG) data.

III. Case Study

In order to perform our experiments, we developed a case study for u-health systems: continuous ECG monitoring service for people with CardioVascular Diseases (CVD). 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).

In order to implement QoC control, CxtMF performs the following operations: 1) QoC gathering: sensing/profiling QoC parameters from the environment for evaluating QoC indicator (QoCI), such as QoCI precision and up-to-dateness; 2) QoC Classifying: representing QoC parameters and QoC indicators in an format understandable by ubiquitous systems; 3) QoC Evaluating: assessment of QoC indicators by using QoC measuring methods applied on QoC parameters; 4) QoC verifying: verifying the values of QoC indicators associated with context used by context-dependent decisions. We can note that QoC should be linked to context data delivered to ubiquitous systems consuming that information. Thus, it should be included in context models and handled by context management frameworks.

CxtMF was defined to support context-aware u-health services, such as ECG monitoring services [16], [15]. The main idea behind the CxtMF is the quality-aware management of context information to be used by context-dependent services and applications (e.g., remote monitoring systems, self monitoring, emergency services). This means, taking into account the quality of context information in all steps of context management operations.

The main entities of CxtMF are Context Providers (CP) and Context Information Service (CIS) [15]. 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).

In the CxtMF, context information, QoC, and QoC requirements are represented by OWL-DL ontologies. We have

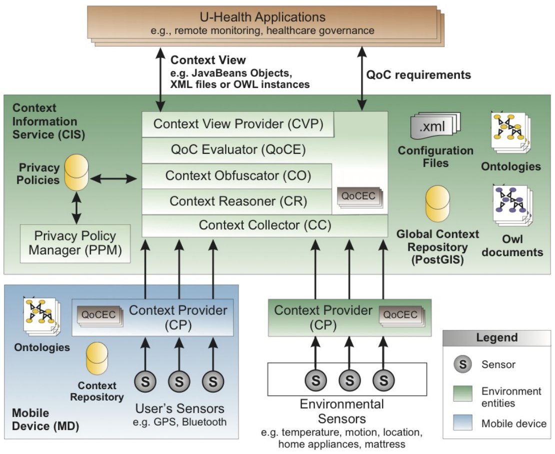

Fig. 1. Context Management Framework (CxtMF)[16], [15].

defined three ontologies to model Context, QoC, QoC requirements, which provides the semantic interoperability between all management layers in the CxtFM. For more details about this architecture, see the work described in [16], [15].

The value of each QoC indicators (e.g., QoCI up-to-dateness and precision) are defined within the range between 0 and 1, which means that the closer is the value to 1, more the verified context information is in accordance with the quality requirement. QoCI up-to-dateness describes how current the context information is for an entity at a given time, for making context-based decisions. QoCI precision describes how exactly the provided context information mirrors the reality.

For example, if the value of QoCI precision associated with a context information is 1, it means that context information has the highest level of precision that the sensing platform is able to provide it. In the case of the QoCI up-to-dateness, the value 1 means that the context information is extremely current and valid for use by a context-sensitive service. It is important to note that for measuring the QoC indicator we need to define the QoC parameter lifeTime. LifeTime is the period of time after which context information becomes obsolete and it is necessary to take its value again. Each context information has a lifeTime, which is related with each tuple (sensor, application/service). For more information about how to measure the QoC indicator precision and up-to-dateness, please refer to [16], [15].

We are using these two QoC indicator to improve our ALSR algorithm. In the following, we describe the characteristics of each monitoring service to further present experiment results.

A. 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.

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

Fig. 2. Normal electrocardiographic wave.

It is responsability of surgeons, general practitioners and emergency care physicians, the interpretation of ECG signals. The heart activity produces currents that radiate through the surrounding tissue to the skin. ECG electrodes are attached to the skin to capture that heart's electrical activity (electrical currents). The equipment converts that current into waves which represents the heart depolarization and repolarization cycle.

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.

P wave is the first component of a normal ECG (Figure 2) and represents the atrial depolarization. A normal P wave has the following characteristics:

- Location: Precedes the QRS complex;
- Width: 2 to 3 mm in height;
- Duration: 0.06 to 0.12 seconds;
- Configuration: Generally rounded up.

PR interval is from the beginning of the P wave to the beginning of the QRS complex and takes between 0.12 to 0.20 seconds. QRS complex comes shortly after the P wave and represents the depolarization of the ventricles. A normal QRS complex has the following configuration:

- Location: After the PR interval;
- Width: 5 to 30 mm in height;
- Duration: 0.06 to 0.10 seconds or half the PR interval;
- Configuration: Q waves (deflection below the baseline), R (first positive deflection following the Q wave) and S (first negative deflection after the R wave).

ST segment, also known as J point represents the end of ventricular depolarization and the beginning of ventricular repolarization. This segment under normal has the following characteristics:

- Location: extends from the S wave to the beginning of the P wave follows;
- Deflection: Generally isoelectric (neither positive nor negative);
- Amplitude: Can range from -0.5 to 1 mm.

T wave represents ventricular repolarization. It has the following characteristics:

- Location: Follows the S wave;
- Width: 0.5 to 10 mm;
- Setup: Typically rounded and smooth;
- Deflection: Generally up, but may appear reversed in some derivations.

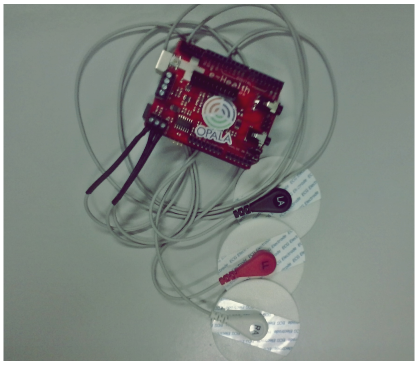

Fig. 3. ECG monitoring service built on the Arduino platform.

QT interval is from the beginning of the QRS complex to the end of T wave. This range varies with age, sex and heart rate. Usually takes from 0.36 to 0.44 seconds. From this value, we define the QoC parameter lifeTime for ECG data as 0.45s. Heart rate is the number of times that the complete cycle (the start of a P wave to the beginning of another wave P) occurs per minute. The reference values for adults is 60-100 bpm (beats per minute) and the heart rate is the distance between R wave peaks from two successive QRS complexes. If all those distances are in the same size range, the rhythm is normal. Furthermore, the electrocardiographic wave is diagnosed as normal if it meets the following five characteristics:

- Regular rhythm;
- Normal frequency;
- A P wave for every QRS complex and all the P waves and QRS complexes similar in size and shape;
- PR and QT intervals normal;
- T waves up and rounded.

Figure 3 illustrates the Arduino platform used for sensing ECG signal. Our data reduction mechanism implemented on the CxtMF (Context Collector - CC) receives the 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.

IV. Using QoC for Improving Energy-Eficient Monitoring Approach

This section outlines the proposed approach of DRES based on Adaptive Simple Linear Regression (ASLR), which minimizes the error generated by Pearson's Coefficient (correlation rate). Instead of calculate the data model with sample size with a fixed size, the ASLR approximates the predicted values to the actual values by adjusting the window samples guided by the Pearson's Coefficient.

A. 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 $[-1, +1]$.

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 $[0.6 - 1]$. In our proposal, the Pearson's Coefficient is equivalent to the QoCI precision, i.e., the context information will be acceptable if the value is between the range of $[0.6 - 1]$.

- 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 and the QoCI up-to-dateness is verified (considering the lifeTime of 0.45s for ECG data). If the value of the coefficient and the QoCI up-to-dateness is equal or bigger than a predefined threshold (for example, 0.6 for QoCI precision and 0.3 for QoCI up-to-dateness), 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;

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

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

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.

- Step #7: End of cycle; Go back to Step #1.

These seven steps are summarized in Algorithm presented in Figure 4. Algorithm is used for predicting ECG signals by applying DRES. The threshold is defined according to the application requirements, which reflects in the performance of the DRES. By increasing the threshold the accuracy will increase together, but the algorithm generates more coefficients α and β to be sent on the network. The challenge is to define the best configuration for this tradeoff. It should still be analyzed further, to ensure a better adjust of ASLR approach, but experiments show satisfactory results.

Algorithm 1

```
Counter = 1;
While True:
        Temp = readTemp();
        Buffer.add(Temp);
        P = calculatePearson(Buffer);
        If P < THRESHOLD:
                α, β = linearRegression(Buffer, Counter)
                Counter = 1
                sendToBaseStation(α, β, Counter)
        Else
                Counter = Counter + 1
        End-if
End-while
```

Fig. 4. Algorithm for DRES based on Quality-Aware ASLR

V. Experimental results

In order to measure performance of our solution, 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. $e_{prediction}$ computes the accuracy of prediction approach. Experiments were conducted for both monitoring services, which will discussed in the following.

We conducted experiment with 399 ECG signals, using $threshold = 0.95$ (QoCI precision) and QoCP lifeTime 0.45s (for measuring QoCI up-to-dateness). That amount of signals corresponds to a complete cycle of the heart. A conventional application of ECG gets $p_{sent} = 399$. Meanwhile, our approach obtains $p_{sent} = 13$ (3%) and $e_{prediction}$ have been 0.0009, saving about 97% of the packets. 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 399 readings.

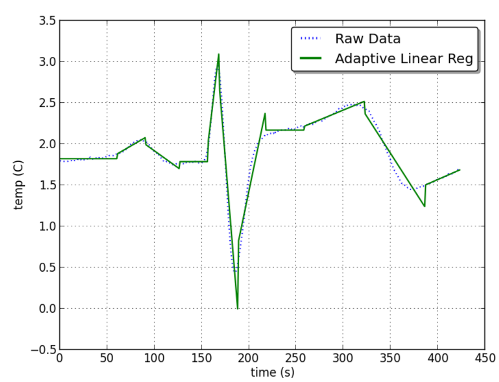

Fig. 5. The quality-aware ASLR algorithm recovers the gathered ECG signals.

Figure 5 shows prediction results from ECG monitoring service using the Quality-aware ASLR algorithm and the raw data. The recovered ECG signal by the CxtMF is well similar with the original raw signals gathered by sensors, proving that our approach is precise and effective. 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 into a threshold error.

Experimental results show that our approach reduces the amount of packets sent (p_{sent}) on the network. 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 ECG service on the experiments, we obtained the following results: 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, the energy consumption for this service was 823.25J (i.e., 13 coefficients/cycle X 0.48375 X 130,909 cycles, every 0.66s).

VI. Discussion and Conclusions

Context Management for U-Health Systems should be quality-aware and energy efficient in order to maximize the lifetime of monitoring platform and improve the availability and reliability of context-aware u-health services, such continuous ECG services. This paper proposes a quality-aware data reduction approach that was integrated with the CxtMF [16], [15], [17] in order to gather raw data and saving energy of sensors, increasing its lifetime. The quality-aware ASLR approach uses prediction of readings gathered based on SLR, which performs approximation by generating values by a straight line (linear approximation). We applied an adaptive mechanism on the window samples that takes into account the QoC indicator precision and up-to-dateness for defining the window size. With the quality-aware ASLR proposed in this work, we decreased the noise driven by the correlation coefficient. As future work, we plan to investigate an efficient data reduction solution based on wavelet [4] for reducing waveform signal, preserving the quality of data.

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