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Context-aware Sensing of Physiological Signals

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Abstract— **Recent advancement in microsensor technology permits miniaturization of conventional physiological sensors. Combined with low-power, energy-aware embedded systems and low power wireless interfaces, these sensors now enable patient monitoring in home and workplace environments in addition to the clinic. Low energy operation is critical for meeting typical long operating lifetime requirements.**

Some of these physiological sensors, such as electrocardiographs (ECG), introduce large energy demand because of the need for high sampling rate and resolution, and also introduce limitations due to reduced user wearability. In this paper, we show how context-aware sensing can provide the required monitoring capability while eliminating the need for energy-intensive continuous ECG signal acquisition. We have implemented a wearable system based on standard widely-used handheld computing hardware components. This system relies on a new software architecture and an embedded inference engine developed for these standard platforms. The performance of the system is evaluated using experimental data sets acquired for subjects wearing this system during an exercise sequence. This same approach can be used in context-aware monitoring of diverse physiological signals in a patient's daily life.

I. INTRODUCTION

Advancement in wireless sensing technology over the past decade can enable a capability of continuous and unobtrusive monitoring of patients who are at risk outside the confines of traditional clinics and for a wide range of patient conditions. Conventional physiological sensors (e.g., electrocardiographs (ECGs), pulse oximeters (SpO_2)) and motion activity sensors (e.g., accelerometers, gyros) can now be miniaturized and integrated with embedded computing platforms and wireless interfaces to produce inexpensive, lightweight sensor nodes that can be worn on the patient body [1], [2]. Although these sensor nodes offer the potential low power operation, the need to limit the battery volume to enable a compact package, and the need for supporting energy-intensive sensing systems requires an energy management method. This further must optimize the operation of sensors and other components to meet measurement demands while minimizing energy.

Energy usage of the sensor nodes may be reduced by activating and deactivating sensors according to real-time measurement demand. Indeed, as will be described, not all the physiological sensors are needed at all times in order to determine the need for each measurement. For example, an ECG signal from a patient at risk with a particular heart condition may be needed for analysis only at certain times, such as during or after an exercise [3], [4]. ECG sensors, on the other hand, introduce a large cost in terms of energy due to its high sampling rate. Also, the ECG sensor is costly in terms of patient wearability because of the uncomfortable electrode systems. Motion and activity detection sensors offer a lower cost measurement capability. Thus, an opportunity exists for the use of low cost sensor data acquisition combined with proper real time computation to determine patient context and apply this information to properly schedule use of high cost sensors, for example, ECG sensor systems.

Determination of patient context with motion sensors has been explored previously using Bayesian and other equivalent classifiers [5], [6], [7], [8]. In this paper, we also use a Bayesian classifier to classify the patient context. The result of the patient context classification is then used to determine when the ECG sensor is ultimately needed, based on the use of other low-power sensors. The decision is made in real-time by an inference engine [6] supported on a wearable testbed system based on commercially available hardware components [2]. It is important to note that this general purpose testbed, the design of the embedded inference engine, and other components are intended to support standard handheld wireless products. This introduces the potential for large scale use since these handheld devices are ubiquitously available and in global use.

This new capability is generally applicable to a wide range of applications in patient monitoring. In this paper, we describe how data from a wrist-worn pulse oximeter is used to determine the requirement for the ECG sensor use, which we define here as *immediately after* an exercise. We show that the pulse rate information is a reliable predictor in determining the start of an exercise sequence but cannot be used to determine the termination of a period of physical exertion, such as represented by continuous motion during exercise. As a result, we use accelerometers to determine the end of the exercise. In each case, determination is based on a systematic inference that exploits actual, measured patient behavior. The wearable device computes this decision to activate the ECG sensor autonomously and streams the captured ECG signals via a wireless network to a centralized server. This provides data access to medical personnel who can view this data in real-time. We illustrate the performance of this system using test subject experiments.

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II. MATERIALS AND METHODS

The testbed system proposed in [2] is supplemented with additional physiological sensors.

A. Hardware

The testbed includes commercially available hardware components such as a standard PDA [9], Bluetooth data acquisition modules [10], and a pulse oximeter [11]. The Bluetooth modules are integrated into a new embedded sensor node platform based on open-source designs, such as ECG systems [12] and accelerometer systems [13] (Fig. 1).

The sensors nodes (pulse oximeter, ECG, and accelerometer) form a wireless body area network (WBAN) with the PDA as the master node over the Bluetooth network. The 16-bit, 0-5 volt data (biased around 2.5 V) from the ECG and accelerometers can be acquired up to 300 samples per second (Hz) and streamed in real-time to the PDA. For our application, the ECG signal is acquired at a sample rate of 250 Hz while the three accelerometer axes are sampled at 100 Hz. Each data point from the Bluetooth module is accompanied by a tracking sequence number to verify errors in Bluetooth communication. From the pulse oximeter, one data point consisting of pulse rate and SpO_2 is received at the PDA every second.

B. Software

A multi-threaded *device server* system on the PDA (Fig. 2) acquires and forwards data from the sensor nodes to client programs such as the inference engine [6] and graphical user interface [2], enabling the client programs to process data as well as display in real-time. A *device driver* thread handles communication to each sensor node over the Bluetooth Serial Port Profile. The *device server* receives the data from the *device driver* threads asynchronously via dedicated buffers before forwarding to the client programs over TCP/IP sockets.

C. Context-aware Sensing

The context-aware sensing algorithm of an ECG signal (Fig. 3) consists of two naïve Bayes classifiers, one each for pulse and motion classifications. Each naïve Bayes classifier is preceded by a feature extraction step.

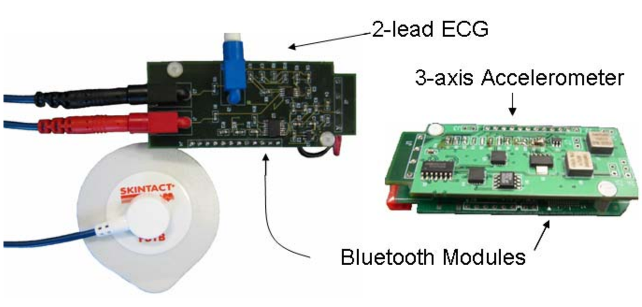

Fig. 1. 2-lead ECG and 3-axis Accelerometer sensor boards attached to commercially available Bluetooth modules

1) Feature Extraction: For pulse classification, the pulse rate and SpO_2 values are directly used as feature values (Eq. 1 and Eq. 2).

$$f_{pulse} = pulse\ rate \tag{1}$$

$$f_{SpO2} = SpO2\ value \tag{2}$$

In contrast, the accelerometer classification involves motion states with cyclical movement. Thus, features from the spectral domain are used instead of the time domain values. Note that in the general case, features in the time domain may also be vital in characterizing patent states involving non-cyclical movements [14]. Additional feature extraction procedures can be incorporated in the inference engine without changes to the other parts of the system.

Two spectral feature values from each axis of the accelerometer are extracted in the feature extraction step, on a window of every 512 data points. The classifier runs once every second, combining the 100 new data points (due to 100 Hz sampling) with 412 previous data points. After low-pass filter with a cutoff frequency at 40 Hz on the 512 data points, the peak spectral value f_{peak} and the spectral energy value f_{energy} are selected as feature values for the classifier, where $X(k) = F(x(t))$ and N is 512.

$$f_{peak} = max_k \|X(k)\| \tag{3}$$

$$f_{energy} = \sum_{k=1}^{N/2} X(k) * X(k) \tag{4}$$

The time-independent (dc) component is excluded from the spectral energy calculation in Eq. 4. The output of this step is a feature vector, $\mathbf{F} = \{F_1, \cdots, F_n\}$, extracted from the sensor data.

2) Naïve Bayes classifier: The inference engine uses a naïve Bayes classifier model to infer patient state probabilities given the feature vector, $\mathbf{F}$. The classifier is implemented with a naïve Bayes network [15], which is based on a conditional probability $p(C|\mathbf{F})$ (i.e., the probability

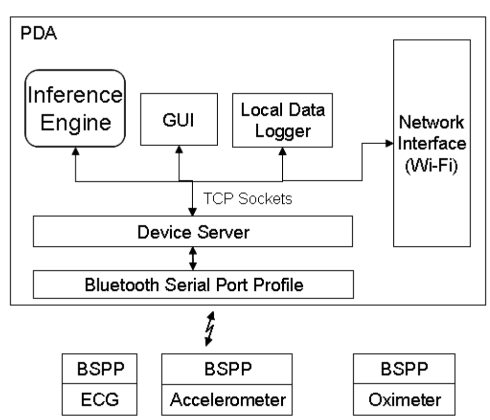

Fig. 2. Software Architecture

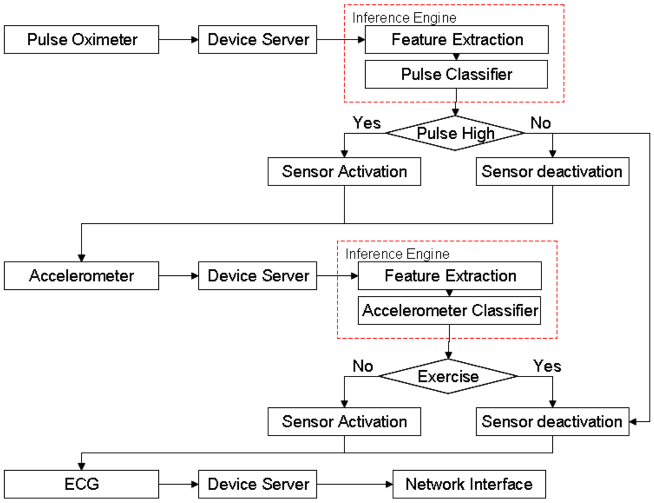

Fig. 3. Context-aware sensing algorithm of an ECG signal

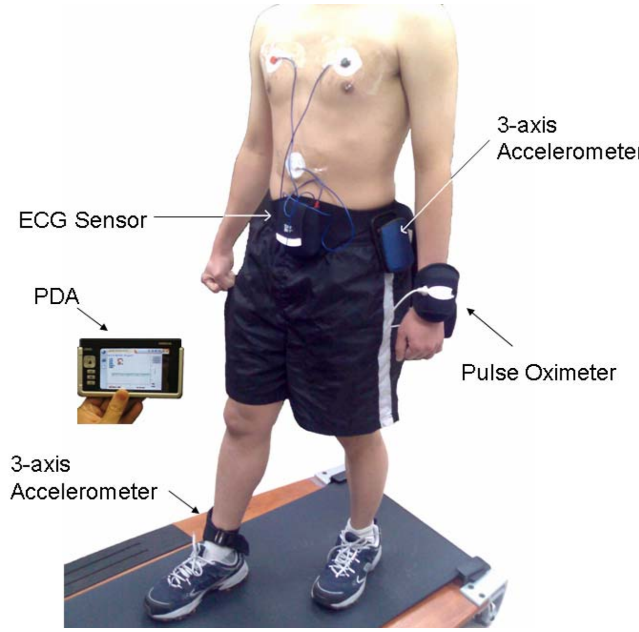

Fig. 4. Experiment setup

of a class variable C with a small number of outcomes or classes, conditioned on a vector of feature variables $\mathbf{F} = \{F_1, \cdots, F_n\}$). Note that $\mathbf{F}$ is a vector consisting of the sensor features (Eqs. 1 – 4) and C consists of the patient states of interest. Now, using Bayes's theorem and applying the "naïve" assumption that if the class C is known, each feature F_i is conditionally independent of every other feature F_j for j≠i. Hence, $p(\mathbf{F}|C) = \prod_{i=1}^{n} p(F_i|C)$ and $p(\mathbf{F}) = \prod_{i=1}^{n} p(F_i)$. The conditional distribution over the class variable can be expressed as shown below.

$$p(C|\mathbf{F}) = \frac{p(C)\prod_{i=1}^{n} p(F_i|C)}{\prod_{i=1}^{n} p(F_i)} \tag{5}$$

As a result, one can infer the probabilities for the patient being in one of $|C|$ states given the sensor feature vector, $\mathbf{F}$. In our test case, the pulse classifier consists of three states {Low, Medium, High} and directly uses the pulse rate and SpO_2 data values as features. When the pulse classification is found to be low or medium, neither accelerometer nor ECG sensor node is activated. When the pulse is high, the accelerometers are activated for motion classification. Also, for purposes of this prototype application, the accelerometer classifier consists of four states {Rest, Walk, Jog, Run}. If the accelerometer classifier indicates that the patient is exercising (Jog or Run), the ECG sensor is not activated. Otherwise, the ECG sensor is activated; its data is acquired over the Bluetooth wireless network and streamed from the PDA to a back-end centralized server via WiFi network.

III. RESULTS

The experimental testbed system (Fig. 4) consists of a wrist-worn pulse oximeter, two sets of 3-axis accelerometers, and a 2-lead ECG sensor node. One of the accelerometers is attached to the left hip while the other is attached to the right ankle so that diverse motion signals can be captured. We acquired both classifier training and testing data from a single healthy male subject during two separate exercises on different days. The test data is shown in Fig. 5 while the training data is not shown. The subject sits on a chair when resting, and walks, jogs, and runs on a treadmill at speeds of 2, 4, and 6 miles per hour, respectively.

The pulse rate data is shown in Fig. 5 along with the ground truth patient context, the classification results, and the ECG usage decision. The test begins with the subject sitting on a chair for about 3 minutes, followed by walking on a treadmill. The pulse classification correctly detects the change of pulse rate from Low to Medium. As our context model (Fig. 3) does not require accelerometers and ECG sensors in these states, they remain deactivated and in a power-off state.

After 4 minutes of walking, the subject jogs for about 3 minutes, which is detected by the pulse classification. Because the pulse rate changes to High, the accelerometers are turned on, resulting in an accelerometer classification of Jog. As the subject is exercising (Jog or Run), the context model does not require the ECG sensor, which remains off. The subject rests for about 2 minutes after jogging, resulting in a gradual decline of the pulse rate. Because a few seconds are required for the subject to decelerate from the treadmill and walk to a chair before sitting down, the accelerometer classification reflects these states. When the accelerometers classify the subject as walking and resting, the context model triggers the use of the ECG sensor as the pulse rate is now high and the patient is not exercising. The ECG sensor is deactivated as soon as the pulse classification changes to Medium.

The subject then runs for about 4 minutes, resulting in a gradual increase of pulse rate. The pulse classifier indicates High, resulting in activation of the accelerometers. The accelerometer classification indicates the subject is running, resulting in the decision not to activate the ECG sensor. After the subject completes the running step, the ECG

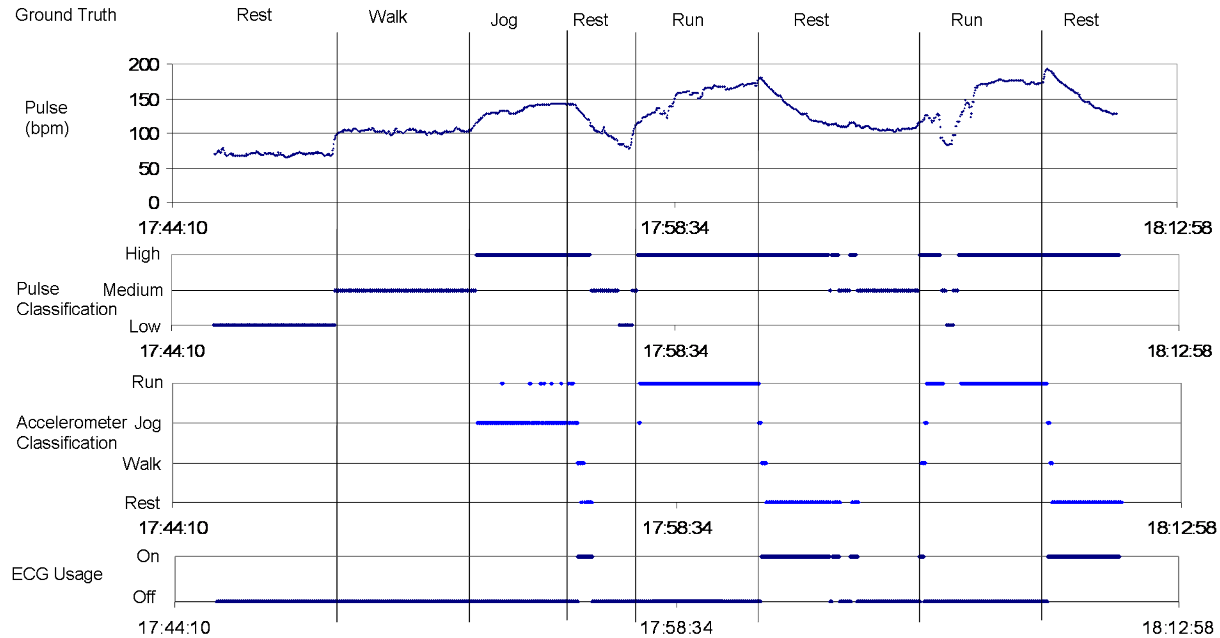

Fig. 5. Experiment test data showing the pulse rate. The pulse and accelerometer classification results along with the decision of whether to actuate the ECG sensor are also shown. The accelerometers and ECG sensor nodes are off at times when the classification or decision results are not shown. The x-axis indicates the local time of the PDA's system clock.

sensor is activated because the patient has stopped exercising and the pulse rate remains high. When the decline of the pulse rate oscillates near the threshold between Medium and High states, the erratic activation and deactivation of the accelerometers and ECG sensor can be observed.

Errors in sensor operation appear and can be identified. For example, we show an example where the patient runs again for the second time and errors in the pulse rate values can be observed. These errors are not due to the Bluetooth communication, but rather because of the failure of the pulse oximeter measurement resulting from intense hand movement. As soon as the subject is asked to steady his hand, the pulse rate values return to normal and the classification results become similar to the previous run. Activation of the ECG sensor following the run is similar to that of the first run. A few accelerometer classification errors between Jog and Run states can also be observed when the subject was jogging. We believe this can be improved by including more features relevant to Jog and Run in the classification and several other techniques that we currently investigating. Example data points acquired from the ECG sensor node is shown in Fig. 6.

IV. CONCLUSIONS AND FUTURE WORKS

In this paper, we have presented the design, implementation, and experimental evaluation of context aware sensing enabled by an embedded inference engine and a real time decision system based on fusion of multiple sensor signals. We have also demonstrated the support of this system on conventional, standard, wireless handheld devices. We also presented experimental results for ECG measurements. With the addition of a new software architecture, the wearable system based on commercially available hardware components can be used to efficiently and effectively monitor patients in real-time. Central to this capacity is the use of a Bayesian classifier based context-aware algorithm, permitting the wearable system to intelligently adapt to the patient context. We presented the system performance using a real data set during an exercise. In general, the same approach can be used in context-aware monitoring of physiological signals in a patient's daily life.

In future work, this testbed will be deployed and applied to many patient studies for investigation of the effect of exercise-induced stress on patients with heart disease. The set of Bluetooth supported sensors is also being expanded and accompanied with an open source release of the new platform and its software systems. An important application being studied is chronic obstructive pulmonary disease (COPD), which requires the correlation of many different patient parameters and benefits directly from the methods described here. As the number of sensors increase in wireless body area networks, the context-aware algorithm described here will also expand its support, taking advantage of the successful Incremental Diagnosis Method used in gait analysis [6].

V. ACKNOWLEDGMENTS

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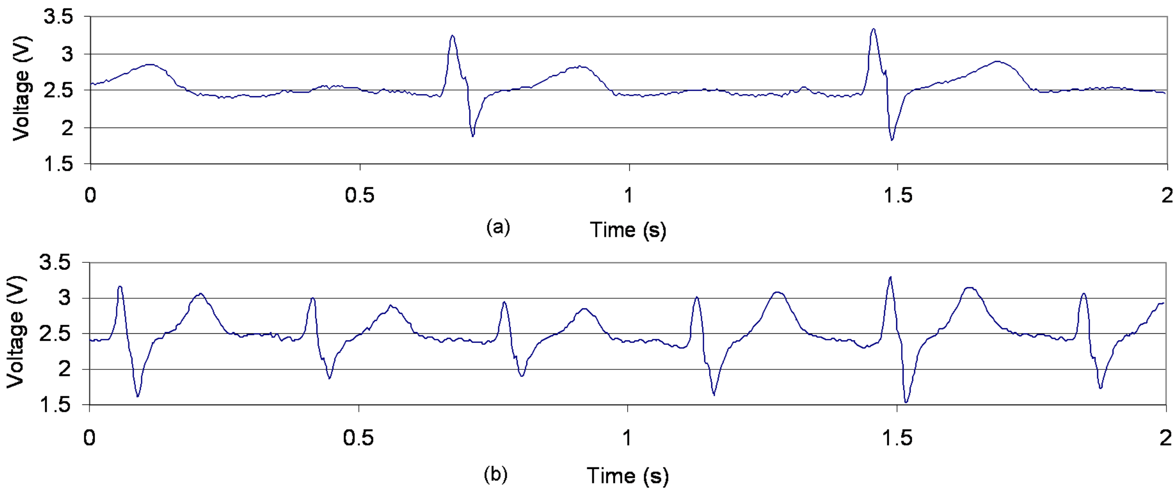

Fig. 6. Example ECG data when the subject was resting initially (above) and resting right after Run (below). The ECG signal of the subject when resting initially is not part of the experiment but included here for comparison.

REFERENCES

[1] R.S.H. Istepanian, E. Jovanov and Y.T. Zhang, Guest Editorial Introduction to the Special Section on M-Health: Beyond Seamless Mobility and Global Wireless Health-Care Connectivity, *IEEE Trans Info. Tech. in Biomed.*, vol. 8, issue 4, pp 405- 414.

[2] W.H. Wu, A.A.T. Bui, M.A. Batalin, L.K. Au, J.D. Binney and William J. Kaiser, MEDIC: Medical Embedded Device for Individualized Care, *Artificial Intelligence in Medicine*, submitted for publication, 2006.

[3] P.M. Okin and P. Kligfield, Heart rate adjustment of ST segment depression and performance of the exercise electrocardiogram: a critical evaluation, *J Am Coll Cardiol*, 25:1726-1735, 1995.

[4] J. Hill and A. Timmis, Exercise tolerance testing, *BMJ*, 324:10847, 2002.

[5] P. Korpip, M. Koskinen, J. Peltola, S.M. Mkel and T. Seppnen, Bayesian Approach to Sensor-Based Context Awareness, *Personal and Ubiquitous Comp. J*, vol 7, issue 4, pp 113-124, Feb 2003.

[6] W.H. Wu, A.A.T. Bui, M.A. Batalin, D. Liu and W.J. Kaiser, Incremental Diagnosis Method for Intelligent Wearable Sensor Systems, *IEEE Trans Info. Tech. in Biomed*, accepted for publication, 2006.

[7] L. Bao and S.S. Intille, Activity recognition from user-annotated acceleration data, *Proc. 2nd Int. Conf. on Pervasive Computing*, 2004.

[8] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola and I. Korhonen, Activity classification using realistic data from wearable sensors, *IEEE Trans Info Tech in Biomed*, vol 10, issue 1, pp 119-128 Jan. 2006.

[9] Nokia N770 Tablet PDA, http://www.nokiausa.com/770

[10] BlueSentry AD data acquisition and control module, http://www.rovingnetworks.com/bluesentry.htm.

[11] Nonin 4100 Bluetooth oximeter, http://www.nonin.com.

[12] Texas Instruments Inc. Electrocardiogram (ECG) Front End, http://focus.ti.com/docs/solution/folders/print/272.html.

[13] Analog Devices ADXL330 accelerometer data sheets, http://www.analog.com/en/prod/0,2877,ADXL330,00.html.

[14] T. Huynh and B. Schiele, Analyzing features for activity recognition, *Joint sOc-EUSAI Conf*, pp 159-64, Oct, 2005.

[15] J. Pearl, Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference, *Morgan Kaufmann Pub Co, San Francisco, CA*, 1988.