Context aware power management for motion-sensing body area network nodes

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***Abstract*—Body Area Networks (BANs) are widely used mainly for healthcare and fitness purposes. In both cases, the lifetime of sensor nodes included in the BAN is a key aspect that may affect the functionality of the whole system. Typical approaches to power management are based on a trade-off between the data rate and the monitoring time. Our work introduces a power management layer capable to opportunistically use data sampled by sensors to detect contextual information such as user activity and adapt the node operating point accordingly. The use of this layer has been demonstrated on a commercial sensor node, increasing its battery lifetime up to a factor of 5.**

Keywords—body area networks, power management, context-awareness, healthcare applications

I. Introduction

The rapid growth of interest in physiological sensors, low-power integrated circuits, and wireless communication has enabled a new generation of wireless sensor networks, called Wireless Body Area Networks (BANs) [1][2]. A BAN consists in a number of intelligent physiological sensors that can be integrated into a wearable system, which can be used for computer-assisted rehabilitation or early detection of medical conditions. BANs rely on the deployment of small biosensors on the human body that are comfortable and that do not impair normal activities. One key aspect to achieve more comfortable sensors is to use smaller batteries and thus reduce sensor node's power consumption. Unfortunately, advances in microelectronics lead to significant miniaturization of sensors, but battery technology has not grown at the same rate [19].

The wearable sensors collect various physiological characteristics in order to monitor the patient's health status no matter what their location is. The information can be treated in different ways: wirelessly transmitted to an external unit; stored on the node; locally processed to return an immediate feedback to the patient. BAN sensors thus continuously collect a variety of data from human body; this information can be used not only for the designed application (e.g. rehabilitation) but can also be exploited to improve BAN performance (for example in terms of battery duration).

BANs share some common challenges with Wireless Sensor Networks (WSNs), but also differ in some key aspects [1]: (i) BAN are often used in medical contexts where data transmission must be characterized by high reliability and low latency; (ii) the nodes of the BAN are often heterogeneous (e.g. some sensor nodes, a gateway, smart garments…) and may require different resources in terms of data rates or power consumption; (iii) All devices are equally important and cannot be substituted by other nodes in the network since redundancy is not permissible (multiplying the number of worn device will lower user comfort). For such and other reasons power saving techniques typically used for WSNs [2] cannot be always applied for BANs.

The contribution of this paper is the adaptation of well-known principle used in WSNs to the specific requirement of the field of BANs: Context Aware Power Management (CAPM) [20]. The paradigm underling CAPM is the ability of the sensor to detect current activity of the user/patient and autonomously adjust the power saving policy. This has been obtained through the integration of a new software layer that does not interfere with normal node operation and consumes a negligible quantity of energy. Such layer comprises a classifier that opportunistically collects data from sensors and identifies user's activity. This information can be used for power management policy selection. As a consequence sensors can be worn during the whole day, remaining in a dormant state if the current activity is not targeted for monitoring; whereas only the strictly necessary sensors can be activated during a specific activity.

The paper in section II provides a short overview of the background and state of the art works in the field of power management and activity detection. Section III describes the activity recognition process; in section IV we propose a policy power management approach based on the user's activity. Section V demonstrates the CAPM implementation in a commercial sensor node; measurements and results are presented in section VI. We expose our conclusions in section VII.

II. Related Work

Power management can be addressed at several levels, from hardware to firmware [7], optimizing single components and subsystems, up to application of distributed power optimization strategies of systems such as wireless sensor networks.

In typical BAN applications, healthcare in particular, the number of nodes is limited and there is often no possibility of placing redundant nodes, due to the need of enhancing wearability and usability. Furthermore, once the sensor node has been assembled or in case of commercial nodes use, the choice of the radio protocol is obliged and therefore there is no possibility to count on protocol optimization, but only to play with existing protocol configuration options. Given these

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considerations, power management of the BAN mainly overlaps with node-level power management.

At a very general level, several approaches can be exploited alone or combined to reduce power consumption at node-level. Two main approaches are duty cycling and data driven techniques [13].
Duty cycling is often based on sleep/wakeup scheduling algorithms and protocols. Dynamic power management (DPM) is a duty cycling based technique that decreases the energy consumption by selectively placing idle components into lower power states. The device needs to stay in the low-power state for long enough (i.e. the *break even time*) to recover the cost of transitioning in and out of the state [14].
While duty cycling techniques are not aware of data content, data-driven approaches can be a complementary way to save energy in a smart node [21]. Data sensing can impact on energy consumption (i) because the sensing subsystem is power hungry [21], (ii) because sampled data have strong correlation (spatial or temporal [22]), so that there is no need to communicate redundant information.
CAPM combines a data driven approach through an analysis of sensor's data and DPM approach through duty-cycling of unnecessary device components during the detected activity. Context awareness has been extensively studied; authors in [18] tailor the information such as location, time, season, temperature and so forth into several aspects of user's context. Due to the variety of available sensors, and the possibility to interact with different devices, mobile phones are very suitable devices for context recognition [3]. In some occasions sensors present on mobile phones have also been used to monitor user's activity [4] [5]. The possibility to detect device's usage context also lead to algorithms capable to lever on such information to preserve energy on mobile phones [6]. Even if smartphones are more and more powerful in processing and rich in sensing and actuation, they cannot always substitute a network of sensing nodes, particularly when the position from where to capture a physiological parameters and the number of sources of information make the difference. E.g. in motor monitoring and rehabilitation of gait it is often a requirement to place at least two sensors one per leg in position such as ankle or foot dorsum. Moreover due to physical size constraints, BAN sensors have usually limited computational resources and many of the proposed algorithms for smartphones cannot be implemented on a resource-limited sensor node.
The work in [7] proposes an opportunistic classifier to optimize power consumption in a wearable movement monitoring system. In this case authors had the possibility to exploit features computed for the needs of the application. A novel system architecture has been proposed in [8] for monitoring neuro-motor activity of Parkinson's disease patients, and for detecting epileptic seizures. Such system implements power optimization policies based on sensors computed features. However, the computational cost of the chosen approach is not clear. Our work proposes node level optimization capable to extend battery life of BAN nodes. We propose a power optimization policy that relies on the possibility to switch off board components with no loss of relevant information from sensors. Since context detection always comes with a cost; in this paper we analyze trade-off between the usage of accurate classifiers and the need to minimize the energy cost of the classifier itself.

III. Activity recognition Process

In literature, many different methods have been proposed for retrieving activity information from raw sensor data. The main steps can be summarized as preprocessing, segmentation, feature extraction, dimensionality reduction and classification [9] (Figure 1). In this section we present the most widely used algorithms and methods for each of these steps.

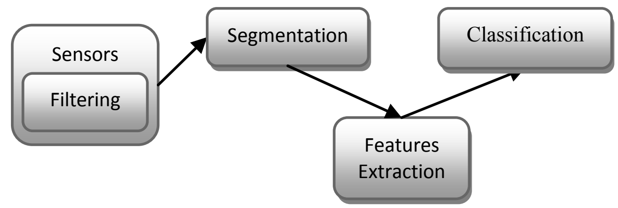

Figure 1 Classification process

A. Filtering

Due to the nature of inertial sensors, the acquired sensor data should first pass a pre-processing phase. Almost always, high frequency noise in acceleration and gyroscope data needs to be removed. Therefore, non-linear, low-pass filters should be employed for removal of high-frequency noise [10]. Nowadays digital sensors integrate this type of filtering [11].

B. Segmentation

Retrieving important and useful information from continuous stream of sensor data is a difficult issue for continuous activity and motion recognition. Several segmentation methods for time series data have been proposed.
We choose to apply a sliding window since it is simple and on-line algorithm. A sliding window algorithm starts with a small subsequence of time series and adds new data points until the number of data in the window is greater than the threshold, which is defined by the user. This kind of algorithms work with a complexity of O(nL), where L is the average length of a window; the value of L also greatly influences the following phase, which is features extraction.

C. Features extraction

The purpose of feature extraction is to find the main characteristics of a data segment that accurately represents the original data. In other words, the transformation of large input data into a reduced representation set of features greatly simplifies classification work, giving advantages in terms of processing time. The feature vector includes important cues for distinguishing various activities and features are then used as inputs to classification algorithms [12]. Features can be grouped in the following types:

- Time-Domain: they are directly derived from a data segment. Most widely used features are: Mean, Variance, Std. Dev, RMS, Zero or mean crossing rate, Derivate, Peak counter and Amplitude, data range etc... This class of features has a computational complexity in the order of O(n)

- Frequency domain: Frequency-domain features focus on the periodic structure of the signal and often require the computation of Fourier Transform. Among them [14]: Discrete FFT Coefficients, Spectral Energy, Spectral Entropy Frequency, Power Range; the computation of frequency domain features has a complexity of at least $O(n \cdot log\ n)$
- Time-frequency domain: these features are used to investigate both time and frequency characteristics of signals and they generally employ wavelet techniques.

D. Classification

The features selected to create a feature set are used as inputs for the classification and recognition methods. In literature, it is possible to find a variety of classifiers [15], among them we choose to compare the most common [12] to find the one that better responds to our requirements, such as minimizing the trade-off between computational cost, power consumption and recognition performance

- Nearest Neighbor: algorithms used for classification of activities based on the closest training examples in the feature space. These algorithms have a complexity of $O(m \cdot n \cdot log\ n)$ where m is the number of neighbor.
- Support Vector Machines (SVM): SVM are supervised learning methods used for classification. Complexity depends on the specific implementation and Kernel characteristic; it can vary between $O(n^2)$ and $O(n^3)$
- Naïve Bayes: it is a simple probabilistic classifier based on Bayes' theorem. (complexity O(n))
- Linear Discriminant: it finds a linear combination of features which best separates two or more classes of objects or events. (complexity O(n))
- Decision Tree: it uses a tree-like graph of decisions. Each branch represents one outcome of test, while each leaf represents a class label. Complexity is in the order of O(n)

IV. Power Management Policies

The system on which we applied power management policies is an inertial sensor module developed to assist Parkinson's disease patient in motor rehabilitation. Our purpose is to extend battery life of the nodes from a few hours to a whole day, guaranteeing same performance during rehabilitation exercises.

We now briefly describe the main hardware components and software tasks in the BAN sensor node for this class of applications; this will give an overview of the main sources of power consumption.

Microcontroller (MCU): it is the brain of the sensor node, it interacts and communicates with other components. Most of the modern MCUs architectures (from 8 bit AVR to the more powerful Cortex M4) enable some of the internal components to be turned off when the system is in idle.

Radio Interface: the communication system can use different protocols (Zigbee, Bluetooth, ANT); each of them features one or more power saving policy (e.g. Sniff mode for Bluetooth).

Sensors: they can provide digital or analog data; digital sensors usually have an in-built low power mode that can be activated.

Operations performed by a typical BAN node are sensor sampling, data processing and data transmission. An advanced functionality can be power management. Our work focuses on the implementation of a Power Manager (PM) based on the detection of user's activity and the selection of the power saving policy accordingly. In designing it, we considered the energy spent to swap among low power states.

Transition between sleep states of sensor node's components comes with a cost in terms of energy and delay. For simplicity we will now analyze the cost due to the transition from *off* to on *state:* if we call t_{off} the time that the hardware component spend in a dormant state and P_{off} the power consumption in such state. The transition time $t_{off\text{->}on}$ from the dormant to the active state will thus have a power consumption of $P_{off\text{->}on}$, whereas during "on" state power consumption is P_{on}. Transition to dormant state will be convenient only if the following condition is satisfied:

$$P_{on} \cdot (t_{off} + t_{off \to on}) \geq P_{off} \cdot t_{off} + P_{off \to on} \cdot t_{off \to on}$$

In other words the transition to the dormant state is energetically convenient if the energy spent in the active state is greater than the energy spent in sleep state plus the energy spent to wake-up the component.

It is thus identifiable a minimum sleep time under which it is not convenient to switch state:

$$t_{off} \geq \left(\frac{\left(P_{on} - P_{off->on}\right) \cdot t_{off->on}}{P_{off} - P_{on}} \right)$$

If the future execution steps of the system are known a priori, as in a deterministic model, it would be possible to define a DPM strategy capable to maximize energy efficiency carefully managing transitions between low power states of the system components.

A typical scenario where the execution flow is deterministic is for example a routine that periodically samples a set of sensors. In this case the PM defines a power management policy capable to obtain optimal power consumption [23]. When the future execution flow of the system is not known a priori but depends on external events, the PM can adopt different strategies [17]. We choose to use a context aware strategy, in which the PM detects user's activity and chooses the appropriate policy.

V. System Design

The context in which we are working is motor rehabilitation of patients, thus we use inertial and magnetic sensors to detect limbs movements. Such data can be processed on the sensor node, logged in to internal memory, or transmitted through a radio device, according to clinical needs.

Among inertial sensors, accelerometer is the least power hungry and the most used in literature for motor rehabilitation [15]. We thus designed a classifier capable to detect user's activity, using only accelerometer data. This classifier has been integrated in the PM. Moreover, the PM itself brings an overhead in terms of power consumption: while accelerometer data comes with no cost (they are needed for the main application), features extraction and classification increases the energy spent during the processing phase.

The system on which we tested our PM is a sensor node, constituted by the following hardware components: STM32 Cortex M3 Microcontroller; Bluetooth 2.0 radio module, tri-axial accelerometer, gyroscope and magnetometer; 1GB NAND FLASH memory; battery and circuitry needed to power and connect different components.

Table 1 shows the clock cycles required per each feature, computed on a 500 elements array.

Table 1 MCU clock cycles per feature

Feature	Clock cycles
Mean	6636
Offset	12515
Variance	16166
RMS	10682
Max	10939
Min	10939
Mean Crossing Rate	Mean + 15986
FFT	226773
Spectral Energy	FFT+ 10940
ABS	26964

From results in Table 1, it is evident that frequency domain features require much more energy (the computation time is one order of magnitude greater w.r.t. time domain features), for this reason we choose to find a classifier capable to discriminate the activities using only time domain features.

A. Classifiers comparison

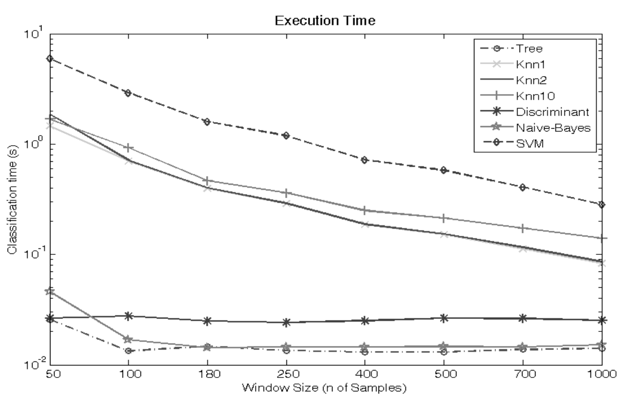

Figure 2 Time spent to classify an array of 1000 instances

In section III.D we have enumerated some of the most common classifiers; each of them has different complexity and accuracy; both these characteristics of the classifier can influence PM efficiency. A very complex classifier may require heavy resources in terms of memory utilization and computational capabilities, which might not be available in a low power embedded platform. Classification time, as well as features extraction time is affected by window size. We have compared different classifiers execution time with different window sizes.

Results of Figure 2 refer to time spent by the classifier to classify the same amount of features vectors; the window size is instead referred to the training phase.

Classifiers trained with smaller window sizes may result in a more complex classifier structure (i.e. a higher number of Support Vectors for SVM classifier) resulting in a higher classification time. It is also evident from Figure 2 that our SVM classifier is not appropriate for our purposes, since it requires computation time not compatible with our real-time application, thus it will not be further analyzed.

B. Classifier accuracy

As described in section IV, our PM uses the classifier to choose the correct power management policy; each policy differs from the other in terms of energy consumption, sampling rate frequency and the use of the radio device. A misclassification will thus result in the adoption of an incorrect policy; this will result in higher power consumption or in a loss of significant data for a given activity.

Table 2 Energy policy for each user's activity

Activity	Sampling Frequency	Sensors	Send / Log	Node Average Power Consumption (mA)
Run	200	Acc + Gyr + Mag	Send	28.19
Walk	100	Acc + Gyr + Mag	Send	20.45
Stair Up	200	Acc + Gyr + Mag	Log	16.74
Stair Down	200	Acc + Gyr + Mag	Log	16.74
Bicycling	50	Acc + Gyr	Log	11.37
Sit	50	Acc	Log	3.10
Lie	30	Acc	Log	2.80

Choices made for policy implementation are dictated by the type of application for which the sensor is used: in our case study, it is a system used for gait rehabilitation and patient monitoring. During rehabilitation sessions; data must be transmitted wirelessly to another device for further real-time analysis, whereas during other activities data can be stored onboard and analyzed off-line by clinicians. This explains why radio is active only during "run" and "walk" activities, as the activity becomes less dynamic or clinically relevant, the sampling rate, or the set of active sensors, is reduced accordingly.

Sampling frequency of the sensor has been kept above 30Hz to correctly detect gait [10] and to avoid an increase in classification error.

To evaluate the cost of a misclassification we have given a penalty score proportional to the difference of power consumption between correct and misclassified activity (e.g. if the classifier does not recognize the activity "run" correctly and interpret it as "walk", a penalty proportional to 28.19mA – 20.45mA will be assigned). Using this criterion we have evaluated penalty for the loss of data or higher power consumption due to an incorrect classification.

It can be seen from Figure 3 that the tree classifier works well with smaller window size w.r.t. other classifiers. This result, together with measurements presented in Figure 2 lead our choice to the classification tree as best classifier for context-aware power management in our application scenario.

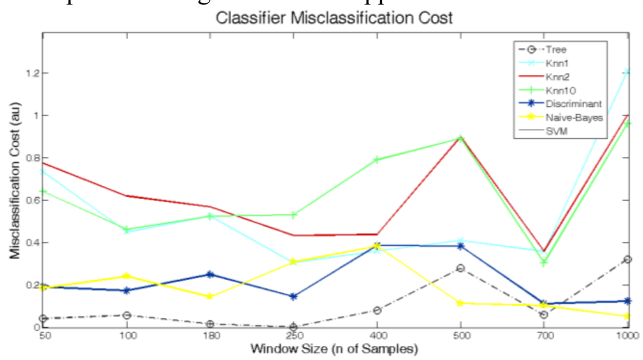

Figure 3 Misclassification costs for different classifiers expressed in penalty point

C. *Classifier characteristics*

The classification tree is applied to the responses feature vector. To assign a response, the tree is followed from the root (beginning) node down to a leaf node. The leaf node contains the response. Each step in a classification involves checking the value of one variable. The implementation in an embedded system can be very simple: once features have been computed, a series of nested if-then-else instructions checks for the value of some features, until a leaf is reached. The structure of the tree and the value of each feature used to select a branch are determined during the training phase.

In our case, the number of nodes (decision points) in the tree was dependent on the window size: a smaller window on which the features are computed resulted in a more complex tree structure.

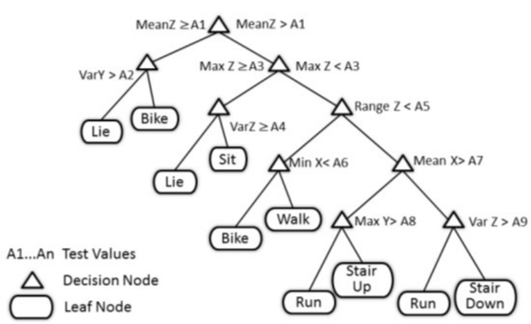

Figure 4 example of a classification tree used for activity recognition

A nice feature provided by the tree classifier is that even if in the training phase all features are used for the purpose, during the classification phase, not necessarily all features are used . Once the model has been built it is thus possible to instruct the PM to compute only a subset of features.

Another advantage of using classification tree is that it is possible to prune it by removing branches of leafs with lower importance. It is in fact possible to evaluate the error due to pruning of certain branches and eventually accept an error to reduce classifier complexity. In the specific case study we present, this was not necessary since time spent by the classifier resulted to be negligible. However, this characteristic can be beneficial in other cases.

Classification accuracy varies from subject to subject and if the classifier is trained on data collected from only one subject or on multiple subjects. Using 10 fold cross validation we measured an accuracy of 98% using one subject data and an accuracy of 90% when we trained the classifier using data from 3 different subjects. However, in our case study the rehabilitation is personalized on each patient, therefore it is legitimate to have a training set for each subject. It is possible in fact to train the classifier for each subject during a preliminary session; where a doctor supervises and collects data on patient's activities.

VI. EXPERIMENTAL RESULTS

Without power management policy power consumption of the node is 28mA. Using our PM we've been able to extend battery life of a sensor node to more than a whole day in a scenario where the node is used to monitor user gait and running, during those activities sampling rate is kept high (Table 2) and data is sent to an external device to assess user performance. We have evaluated power consumption during one day of typical activity of a subject. From results shown in Table 3, we have that a battery of 160mAh would least more than one day, compared to the 5 hours when no policy is adopted and thus maximum sampling frequency must be used.

Table 3 Node power consumption and typical activity

Activity	Hrs. per day	Total Power consumption per day (mAh)
Walk	3	61.38
Run	0.5	14.10
Stair Up	0.25	4.19
Stair Down	0.25	4.19
Bicycling	0.5	5.69
Sit	11.5	35.63
Lie	8	22.33

The flexibility of the system makes it possible to use it also for different applications scenarios. An example is the use of the inertial sensors in an assistive scenario. The BAN is used to assist patients during rehabilitation exercises. This is the case of the CuPiD Project, where people with Parkinson's disease perform gait and posture rehabilitation for one hour a day. The patient is asked to perform outdoor walking session wearing inertial sensors. A smartphone connected to sensors tutors the patient through audio feedback.

In this scenario we can benefit from the possibility of the classifier to detect user's activity. This information can be in fact used to choose the appropriate power management policy and reduce power consumption during activities different than walking, which is the target activity for the rehabilitation.

Furthermore, context information derived by our CAPM can be used to trigger the execution of the exercise by the patient. Once the walking activity has been detected, a message is sent to the patient to ask whether he wants to start rehabilitation gait session. When 1 hour of exercises has been performed, no further requests will be sent. The output of the classifier thus can be used not only for power management purposes, but also for application needs. Using the proposed power management policies, it is possible to wear the sensors all day and keep them responsive. Our approach reduced power consumption to 80mAh per day, extending battery life to two days; moreover the output of the classifier can be used to suggest the patient to start exercises.

Our power management layer has been applied to a sensor node that was designed for continuous streaming at high sampling rates (100-200Hz), greatly increasing its flexibility and battery duration. The impact of our layer in terms of resources can be considered negligible: in Figure 5 it is possible to notice that for "walk" policy, power consumption of different components is balanced, with classifier accounting for only 0.6% of power consumption. Whereas when a low power policy is adopted (e.g. in case of sitting or lying) much of the power is used by the board itself (power regulators and the components that cannot be switched off) evidencing that the system is not designed to operate in ultra-low power mode.

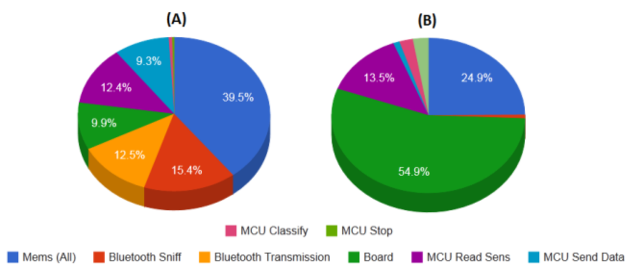

Figure 5 Node's energy breakdown (A "walking" policy, B "seated")

VII. CONCLUSIONS

In our work, we proposed a new power management layer for motor monitoring sensor nodes. The presented layer is based on opportunistic data collection from accelerometer sensor (since it is the less energy hungry MEMS) and a classifier capable to detect user's activity. We tested different classifiers in terms of accuracy and classification time, showing that a tree classifier is the best compromise among them. We were able to achieve an accuracy of 98% using the same subject for training and classification (this scenario is realistic for many medical applications). Output of classifier can be used not only to reduce power consumption of the sensor node, but also to trigger specific application needs. In a typical use case scenario with continuous monitoring and feedback exercises, we have been able to increase battery lifetime by a factor of 5, without sacrificing relevant data.

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