Power Optimization in Wearable Biomedical Systems: A Signal Processing Perspective

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ABSTRACT

Wearable monitoring systems have caught considerable attention recently due to their potential in many domains including smart health and well-being. These new biomedical monitoring systems aim to provide continuous patient monitoring and proactive care options. Realization of this vision requires research that addresses a number of challenges, in particular, regarding limited resources that the wearable sensor networks offer. This paper presents an overview of different strategies for prolonging system lifetimes through power optimization in such systems. Particular emphasis is given to enhancing processing and communication architectures with respect to the signal processing requirements of the system.

Keywords: Embedded Systems, Healthcare, Wearable Computing, Signal Processing, Power Optimization

1. INTRODUCTION

Technology advancements have resulted in creation of novel sensing, computing and communication artifacts that are becoming essential part of our daily lives constructing wearable mobile sensory platforms that can be operated in different settings regardless of physical and geographical constraints. These systems have proved to be efficacious in a number of research fields ranging from medical and well-being[1–3] to military, smart vehicles, maintenance, production and process support.[4–7] A particular class of these systems is wearable sensor networks[8] where computation modules are coupled with the human body. As this new class of biomedical systems becomes more ubiquitous, design and development of power-efficient techniques gains more significance to allow for sustainable realization of the entire monitoring system. Power-efficient design issues are even more challenging in wearable platforms because these modules are often powered by batteries.

This paper focuses on recent advancements in design and development of power-efficient algorithms that enable effective signal processing in wearable biomedical sensor networks. The system is divided into two categories including processing and communication architectures each focusing on a particular aspect of the power efficiency. While optimization of processing architecture aims at minimizing power consumption of the processing modules where signal processing algorithms are implemented, the network architecture optimization focused on reduction of the power consumption by minimizing the number of sensor nodes participating in the signal processing and reducing the amount of inter-node data transmissions.

2. PROCESSING ARCHITECTURE

Wearable biomedical systems employ varying signal processing algorithms to extract useful information about the subject wearing the sensor nodes. Typically, signal processing includes a chain of computing tasks that are executed in a sequence and provide a limited view of the entire network. The overall operation of the system is inferred through a higher-level processing module such as a cell phone or a more powerful computing unit. This section focuses on those approaches that minimize power consumption of the individual sensor nodes. The energy-efficient techniques that examine communication aspects of the system will be discussed in Section 3.

Two approaches to optimize the power consumption of the processing modules are discussed in this section. The first approach, called screening and discussed in Section 2.1 , utilizes an ultra low-power wake-up circuitry module that is located prior to the main processor (e.g., microcontroller) and activates the main processing unit upon existence of an event which is of interest to the application of the wearable sensor network. For example,

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if the system is designed for gait analysis, the main processing unit is activated only when a walking pattern is observed by the wake-up module. The second class of processing architecture optimization algorithms examines individual processing tasks what run on the main processor and minimizes power consumption of each processing task.

2.1 Signal Screening

Often times, biomedical applications focus on a particular physiological event. For example, gait analysis[9] only is concerned with walking, fall detection with falls,[10] and sleep apnea with restless leg movements.[11] These target events happen less frequently in this class of biomedical applications. A signal screening module can be designed to reject non-target events. The significant power saving is achieved by performing a preliminary signal screening and hence, keeping the main processor off when the incoming signal is not of interest. The screening module is a classifier that looks for events of interest in the observed signal. It attempts to detect events that are not of interest as early as possible while operating in an ultra low-power regime. The module will turn on the main processor for further processing when the incoming event is likely to be of interest.

While the main processor employs classical patter recognition algorithms, the screening module benefits from computationally simple processing algorithms such as template matching. A template matching block functions as a binary classifier. An example of metrics based on which the classification tasks can be done is a cross correlation function.[12,13] The cross correlation score for an incoming signal is measured by comparing the signal with a predefined template and a signal is classified as target event if the score exceed a pre-specified threshold.

As it can be understood from the aforementioned discussion, the threshold value used for template matching provides a design parameter that defines sensitivity of the screening module for each specific target event. As the sensitivity increases, the amount of power consumed by the screening module grows. This approach has shown promising results for design and development of future processing architectures for wearable biomedical systems. The results reported in[14] show that the power consumption of the system ranges from 0.21 mW for 50% sensitivity to 1.29 mW for 100% sensitivity, resulting in an average power consumption of 0.67 nW. The power consumption numbers can be divided into three distinct areas with low (50% to 70%), moderate (75% to 90%) and high (95% to 100%) sensitivity rates. This provides the designer with the flexibility to choose higher accuracy rates at the cost of extra power consumption and less power savings. Furthermore, with the screening approach, the power saving numbers range from 57% for 100% sensitivity to 92% for the case of 50% sensitivity, with an average savings of 78%.

2.2 Task Optimization

This approach examines optimization of individual processing tasks for the purpose of minimizing energy consumption. For instance, in a classification tasks,[15,16,16–24] a set of statistical features are extracted from the signal. One task optimization mechanism is to perform feature selection while taking into account power consumption of the individual features. Examples of applications that benefit from classification algorithms include human action recognition and fall detection using accelerometer and gyroscope sensors, and arrhythmia detection from ECG signals. In the classification process, a set of representative features, such as 'signal amplitude' and 'root mean square' power, are typically extracted from the measured signal prior to performing the classification task.

The traditional feature selection algorithms focus on specific criteria that find redundancy and relevance in a given feature set. This approach is generally acceptable in conventional pattern recognition algorithms such as image processing and text mining which run on highly powerful computers. These techniques, however, do not take into consideration computing complexity of individual features. That is, they give equal weight to features of varying complexity. In wearable biomedical systems, however, the amount of power that is required for calculation of individual features needs to be taken into consideration to achieve power-efficiency objectives of the application.

The study in[25] presents a novel learning processing to find power-efficient features for the classification applications. The proposed technique provides a model-based design methodology for feature extraction where feature redundancy analysis results in a graph model that represents not only inter-feature redundancy both also computing complexity of the individual features. It is shown that the minimum cost feature selection problem is transformed into the classical minimum cost dominating set problem, which is known to be NP-hard. A greedy approximation algorithm is presented in[25] which hold an $\ln n$ approximation ratio. The results show an average energy saving of 71.6%.

3. NETWORK ARCHITECTURE

The two broad approaches that aim at minimizing power consumption of the communication system with respect of the signal processing requirements of wearable biomedical systems include *sensor selection* and *power-aware transmission*. The former attempts to minimize the number of sensor nodes used to form a wearable sensor network while maintaining acceptable accuracy performance. The latter, which is feasible for applications that do not expect real-time responsiveness, employs buffers on individual sensor nodes to store signal processing results prior data transmissions, and therefore reduce the number of data transmissions.

3.1 Sensor Selection

In a distributed signal processing model, each sensor node performs local signal processing and decision making and may decide to propagate its local results to a next node in the network. The amount of data transmitted over the network can be reduced to only a subset of the nodes that contribute to the objectives of the application. For instance, if the system is designed to classify human movements, the only nodes that need to be active are those that are effective in classification of the movements.[19,26]

Two approaches on collaborative signal processing for the purpose of action recognition include *pseudo-dynamic node selection* and *dynamic node selection*. Pseudo-dynamic node selection introduced in[19] uses spatial primitives of the movements to construct a decision tree for classification. While a subset of the nodes is used to build the decision tree, classification takes different paths on the tree for detecting different actions. In dynamic node selection presented in,[26] active nodes are detected in real-time based on observations made by individual sensor nodes. This distributed classification model uses movement transcripts to reduce the amount of data that are being transmitted among the nodes. A more heuristic approach to dynamic node selection is presented in.[27]

Pseudo-dynamic node selection focuses on developing a computationally simple and distributed algorithm for action recognition. The distributed algorithm is developed to detect human actions according to a decision tree model.[19,28] With this approach, the set of active nodes are not completely known a priori because for each classification only a subset of the nodes from the root to a leave are activated in the decision tree. This technique involves introducing a novel representation of human actions in terms of their basic building blocks, called primitives. With this approach, each action is represented as a set of spatially distributed symbols, each associated with a primitive. The decision tree is derived directly from interpretation of action primitives and the level of contribution of each sensor node for action identification. The distributed algorithm produces a global classification decision based on a subset of results generated by individual sensor nodes. The compact representation of actions along with distributed nature of the algorithm enables the platform to lower the amount of information stored at individual nodes, and to minimize the amount of data passed in the network. Therefore, the amount of energy required by individual nodes for data transmission is reduced. Furthermore, with the dynamic selection of the nodes needed for classification the overall number of active nodes is reduced. This would lead to reducing the overall power consumption of the system and can potentially increase system lifetimes.

In the dynamic node selection, the recognition algorithm relies on motion transcripts.[29,30] Each action is divided into several segments each with a consistent physical pattern. The algorithm to create motion transcripts will maintain temporal and structural properties of the observed sensor readings. This representation of human movements is then used for local data segmentation and classification. Accuracy for such local classification depends heavily on the physical placement of a given sensor. The distributed algorithm produces a global classification decision based on a subset of results generated by individual sensor nodes. The distributed nature of the algorithm enables the system to lower the amount of information stored at individual nodes, and to minimize the amount of data passed in the network. Therefore, the amount of energy required by individual nodes for data transmission is reduced. Furthermore, with the dynamic selection of the nodes needed for classification the overall number of active nodes is reduced.

3.2 Power-Aware Transmission

The collaborative nature of signal processing for healthcare applications calls for optimizing the communication system with respect to signal processing requirements of the application. From the application point of view, communication cost depends only on the amount of data being transmitted. Because of this, energy saving techniques frequently focus on decreasing the amount of data that needs to be communicated through greater local processing.[31] Furthermore, in a collaborative model, a sensor node may not be able to process data unless it receives some intermediate results from other nodes. This model introduces dependencies among the nodes. In order to enhance communication system and reduce energy consumption, the work in[32] proposes a buffer allocation approach for transmission reduction. This transmission reduction approach limits communications to short bursts by accommodating buffers on transmission links. Intuitively, data are accumulated in buffers and will be transmitted in bursts and at a higher rate. Burst transmission is an efficient power saving approach in wireless sensor networks. It can reduce transmission energy per bit,[33] and can simplify communication by lowering packet scheduling overhead.[34] Buffers can be utilized to accumulate sensor data before burst transmission[35] and studies in[36] show that long messages can be handled by efficient MAC protocols for the purpose of communication enhancement. Another approach introduced in[37] is a data aggregation model for energy optimization in body sensor networks. This data aggregation algorithm is a data-centering routing model that minimizes communication energy by taking collaborative nature of signal processing for healthcare applications into consideration. Transmission energy for a path is determined as a compromise between the path length and the amount of data being transmitted along the path. Data produced by different nodes are aggregated to form packets of large size that consume smaller energy per bit.

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