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Energy Aware Computing in Sensor Networks

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Abstract: **Wearable sensors that measure limb movements posture, and physiological conditions can yield high resolution quantitative data .It can be used to better understand the disease and develop more effective treatments. In existing, classification algorithm is used to extract the feature from sensor, so these feature selection may lead to rapid battery depletion due to the absence of computing complexity. The notion of power aware feature selection is proposed which aims at minimizing energy consumption also it considers the energy cost of individual features that are calculated in real time. A graph model is introduced to represent correlation and computing complexity of the features. The problem is formulated using integer programming and a greedy approximation is presented to select the features in a power efficient manner. Experimental results on thirty channels of activity data collected from real subjects demonstrate that an approach can significantly reduce energy consumption of the computing module, resulting in more than 30 percent energy savings while achieving 96.7 percent classification accuracy.**

Keywords: **wearable sensor, feature selection, action recognition, energy consumption, healthcare.**

1. INTRODUCTION

Being able to identify a person activity provides a high level of information about the state of the person, which can be exploited when constructing a context aware system. Our model for a context-aware system is the E-watch, a multi sensor platform developed at CMU Body-worn accelerometers have been used to recognize different activities .However, the power resources of mobile platforms are limited, making the demands of continuous, on-line classification untenable.

Recent technology advances have led to the development of different sensing, computing, and communication artifacts that are becoming an essential part of our daily lives forming pervasive and mobile sensory platforms. These ubiquitous systems have proved to be effective in a number of domains ranging from medical and well being to military and smart vehicles . A special class of these platforms is wearable sensor networks whose computational elements are tightly coupled with the human body. These networks are known as enabling technologies for many applications such as remote patient monitoring and personalized healthcare, gaming and sports , maintenance, production and process support.

There are a number of challenges that must be overcome to fully implement wearable sensor networks including high costs, package size and weight limitations, power efficiency and battery lifetime, memory storage, connectivity, ease of use, reliability, application level accuracy, security, and privacy issues . Since wearable sensor networks are battery-operated and may have critical and life-saving purposes, power efficiency is considered the most challenging design consideration in their real life deployment.

Wearable Health-Monitoring Systems (WHMS) have drawn a lot of attention from the research community and the industry during the last decade as it is pointed out by the numerous and yearly increasing corresponding research and development efforts As healthcare costs are increasing and the world population is ageing , there has been a need to monitor a patient’s health status while he is out of the hospital in his personal environment.

To address this demand, a variety of system prototypes and commercial products have been produced in the course of recent years, which aim at providing real-time feedback information about one’s health condition, either to the user himself or to a medical center or straight to a supervising professional physician, while being able to alert the individual in case of possible imminent health threatening conditions. In addition to that, WHMS constitute a new means to address the issues of managing and monitoring chronic diseases, elderly people, postoperative rehabilitation patients, and persons with special abilities.

Wearable systems for health monitoring may comprise various types of miniature sensors, wearable or even implantable. These biosensors are capable of measuring significant physiological parameters like heart rate, blood pressure, body and skin temperature, oxygen saturation, respiration rate, electrocardiogram, etc. The obtained measurements are communicated either via a wireless or a wired link to a central node, for example, a Personal Digital Assistant (PDA) or a microcontroller board, which may then in turn display the according information on a user interface or transmit the aggregated vital signs to a medical center. The previous illustrates the fact that a wearable medical system may encompass a wide variety of components: sensors, wearable materials, smart textiles, actuators, power supplies, wireless communication modules and links, control and processing units, interface for the user, software, and advanced algorithms for data extracting and decision making.

2. EXISTING SYSTEM

Existing studies do not address the battery lifetime issue directly, since the length of related pilot studies is relatively short and they are carried out in controlled or semi-naturalistic environments. Tasks performed constantly such as sensing, processing (e.g., classification), and wireless transmissions incur significant energy expenditure in wearable nodes. As such, battery energy, if not properly managed, can be completely used up within hours and recharging is often impractical when the nodes are in- use. In medical applications, wearable units are mainly used for remote and continuous patient monitoring, and therefore, their power consumption needs to be minimized to guarantee their long term operation and infrequent battery charge or replacement.

3. PROPOSED SYSTEM

In wearable sensor networks, where raw data is simply streamed to the gateway, the largest energy consumer is the radio subsystem (e.g., wearable ECG monitors), with the processing unit only required for formatting the data according to the utilized communications protocol. On the other hand, for wearable systems with on-node processing (e.g., movement monitoring and wearable EEG monitors), the processing subsystem is the most energy consuming subsystem. In such systems, a signal with a lower bit rate will be transmitted to the gateway after processing. This necessitates further optimization of the computing units' power consumption in order to prolong the lifetime of the entire system. This second group of wearable systems often employ embedded signal processing and machine learning blocks that use sensor data (e.g., acceleration of body segments) to extract relevant information (e.g., types of movements) about their subjects. Signal processing and machine learning methods are defined by the application and vary in complexity. Current techniques for wearable systems especially those concerning activity recognition aim at using a reduced feature set to characterize the monitored signals in a real-time fashion while meeting wearable systems' memory and processing constraints.

4. SYSTEM OVERVIEW

A wearable sensor network, also called body sensor network, is composed of several body worn sensor nodes, a gateway, and a back-end server .Each sensor node is attached to the body to sample and process physiological signals and transmit partial results to the gateway. A sensor node usually has several sensors for capturing different user's states (e.g., body acceleration), an embedded processor to perform limited signal processing and information extraction, and a radio for data transmissions. The gateway is a more powerful unit such as a cell phone or a PDA that performs data fusion and makes conclusions about current state of the user (e.g., 'walking', 'running', and 'sitting').

The results are further transmitted, through the Internet, to a back-end server for storage, further processing, and clinical decision support. This processing chain can be closed by a feedback loop from the back-end server to the user. For example, a feedback can suggest changes in patient's medication dosage due to lack of sufficient physical activity or if a Parkinson's patient is experiencing increased tremor.

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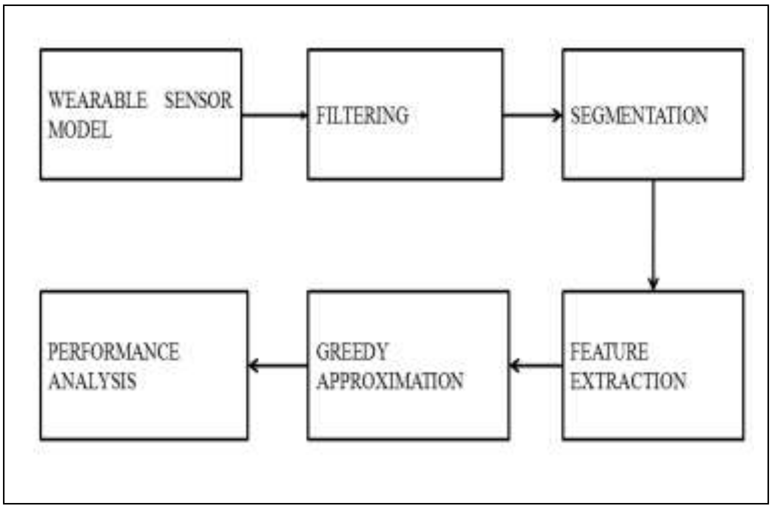

Figure 4.1 System Architecture

5. MODULE DESCRIPTION

There are four modules

5.1. Wearable sensor network model:

Wearable sensors invade many remote spots and scenarios. Essentially, wearable wireless sensor networks can be carried anywhere, but operation conditions may make effective operation hard. The concept of on body wearable sensors is gaining more and more attention in research. They can be networked in a Wireless Body Area Network (WBAN). At present, mood and emotion recognition is an active topic of research. Recognizing emotions and expressions may help to track aggression, violence, suspect behavior but also illness, boredom, weakness, unconsciousness, death, in tele-surveillance approaches. Technological challenges are the positioning of the sensors in a controlled affix position, without hindering body movements. Further technological challenges are posed by body fluids such as sweat, and shocks.

5.2. Segmentation:

Segmentation is intended to identify'start' and 'end' points of the actions that are being classified. In fact, motion sensors sample capture human movements constantly, streaming continuous actions. Thus, it is essential to partition the signal into segments of interest. Each segment will be further processed for the purpose of action recognition, which maps the signal segment onto a specific action

5.3. Feature Extraction:

Feature extraction module is responsible for calculating statistical and morphological characteristics of the signal segment. Prominent feature are known a priori as they are defined in the learning phase. Features represent different attributes of the signal such as peak-to-peak amplitude standard deviation and mean value. Features extracted from different sensors form a feature vector that will be used for classification.

5.4. Graph analysis:

In general, feature selection aims to find an optimal set of features from an exhaustively extracted set of features. In most cases, the optimality of the solution is defined by two criteria, relevance and redundancy. While relevance criterion focuses on eliminating features that are irrelevant to the classification task, redundancy criterion uses inter-feature correlation measures to eliminate features with high correlation. By removing most irrelevant and redundant features from the data, feature selection helps to improve the analysis of high-dimensional spaces. This speeds up the learning process by highlighting the important features and under-standing how they interrelate. Feature selection methods can be categorized into wrapper, filter, and embedded methods. Filter based methods rank the features as a pre-processing step prior to the learning algorithm, and select those features with higher ranking scores. Wrapper methods score the features using the learning algorithm that will eventually be employed.

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6. EVALUATION

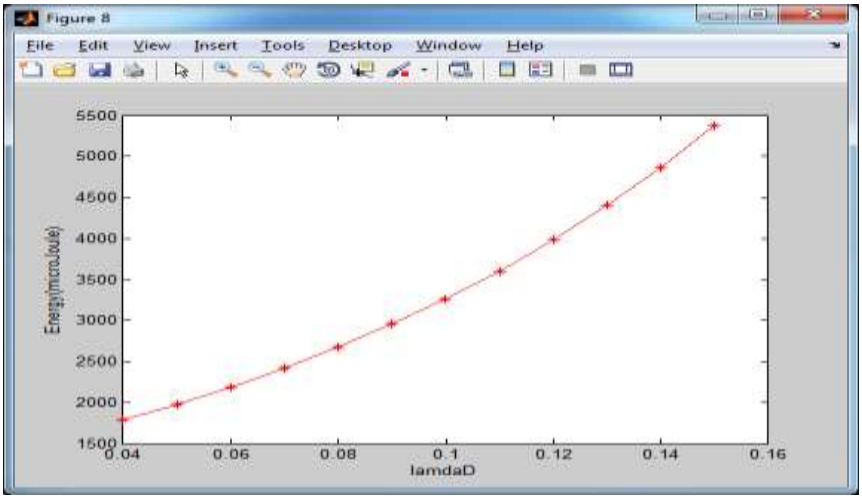

Figure 6.1 Performance Analysis

Here the graph explains the Energy consumption. The proposed system takes less energy consumption than the existing systems.

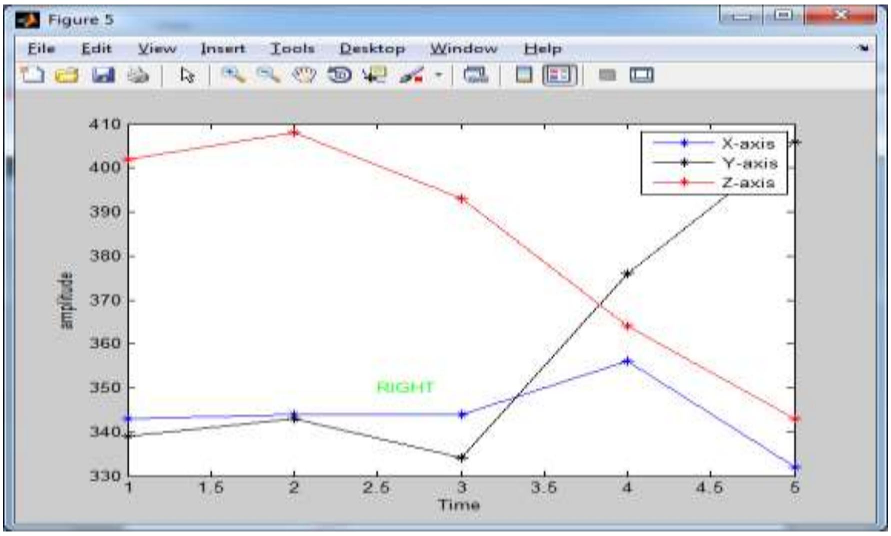

Figure 6.2 Action Recognition

The below graph explains that the action of the user with the help of this action identify the health of the patient .plot the x-axis as time and y-axis as amplitude. Demonstrate the performance of the proposed feature analysis techniques utilizing real data collected from three human subjects.

7. RELATED WORK

Power efficiency in wearable platforms is usually at odds with all other design objectives such as performance and reliability. Many techniques to improve power efficiency can incur performance, power, or classification accuracy penalties. In the context of real-time computing, Zhao et al. explore the energy-reliability tradeoff. Their approach minimizes the system-level energy consumption while satisfying a certain reliability target in the task scheduler. More specifically, their approach specifies the optimal number of recoveries to deploy together with task-level processing frequencies to minimize the energy consumption while achieving the tar-get reliability and meeting the deadline constraints. Until recently, power awareness and classification accuracy have been studied independently in the context of wireless sensor networks and wearable computing. How-ever, there is an interesting tradeoff between a system's power

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efficiency and classification accuracy as both goals compete for processing resources. There exists a growing body of related research that implicitly or explicitly deals with such a tradeoff.

8. CONCLUSION

In this study, used an information theory measure (symmetric uncertainty) to quantify correlation between two features or between a feature and a class. Our model-based design and optimization approach, however, is independent of the choice of correlation measurement. One can replace the symmetric uncertainly with any other measure, build our graph model, and apply the proposed algorithms. In this paper, our primary focus was to tackle the problem of feature selection in wearable sensor networks. For this, we focused on a static feature selection approach where the optimal feature set for a particular application setting is deter-mined prior to execution of the signal processing algorithms in real-time. Although fully dynamic feature selection requires extensive research and is out of scope of this paper, the static feature selection approach presented in this paper can address a semi-dynamic feature selection as well.

REFERENCES

[1] Anliker U., Ward J. and Baer M. (2004), ‘A Wearable Multiparameter Medical Monitoring and Alert System’, IEEE Trans. Inf. Technol. Biomed, vol.8, no.4, pp.415–427.

[2] Blount V., Batra M. and Ebling M.R. (2007), ‘Remote Healthcare Monitoring using Personal care connect’, IBM syst J,vol.46, no.1, pp.95-113.

[3] Chan M., Estve J. and Campo E. (2012), ‘Smart wearable systems Current status and future challenges’, Artif Intell. Med, vol.56, no.3, pp.137-156.

[4] Ghasemzadeh H. and Jafari R. (2011), ‘Coordination analysis of human movements with body sensor networks’, IEEE Sens. J, vol.11, no.3, pp. 603-610.

[5] Karpiriski M. and Senart A. (2006), ‘Sensor networks for smart roads’, in Proc.4th Anna. IEEE Int. Conf. Pervasive Compute, pp.306-310A.

[6] Lee S.H and Lee H.S. (2009), ‘Wireless sensor network design for tactical military applications remote large-scale environments’, in Proc. IEEE Military Commun. Conf, pp.1–7.

[7] Lukowicz P. and Cheng D. (2010), ‘On-body sensing from gesture based input to activity driven interaction’, compute, vol.43, no.10, pp.92-96.

[8] Pantelopoulos A. and Bourbakis N. (2010), ‘A survey on wearable sensor-based systems for health monitoring and prognosis’, IEEE Trans Syst, Man, part C: Appl. Rev, vol.40, no.1, pp.1-12.

[9] Ward M., Lukowicz P., and Starner T. (2006), ‘Activity recognition of assembly tasks using body-worn microphones and accelerometers’, IEEE Trans. Pattern Anal. Mach. Intel, vol. 28, no.10, pp.1553-1567.

[10] Yang Y., Jafari R., Sastry S. and Bajcsy R. (2009), ‘Distributed recognition of human actions using wearable motion sensor networks’, J. Ambient Intel. Smart Environment, vol.1, no.2, pp.103-115.