POWER AWARE COMPUTING BASED ON FEATURE SELECTION

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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, notion of power aware feature selection used which aims at minimizing energy consumption, also it considers the energy cost of individual features that are calculated in real time. In high performance systems, power-aware design techniques aim to maximize performance under power dissipation and power consumption constraints such as in portable equipment. The main driving factors include cost, power consumption, and wearability, with power consumption being the center of many research efforts due to its dramatic influence on other design objectives. In this paper, we propose efficient probabilistic neural network approach which aims at minimizing energy consumption and computation time. The proposed algorithm balances node energy utilization to reduce energy consumption and increase the life of nodes thus increasing the network lifetime, reducing the routing delay and increasing the reliability of the packets reaching the destination. In addition the T test based feature selection algorithm is presented which select the most discriminative features. Experimental results show the effectiveness of our proposed approach.

Keywords: wearable sensor, feature selection, computation time, power dissipation, discriminative features.

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.

2. EXISTING 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. The drawbacks of existing system are chance to miss the feature consumes more time and energy

3. PROPOSED SYSTEM

Proposed Probabilistic neural network approach , With the activity image built from raw sensor signals as input, PNN outputs a probability distribution over Na activities. Then we take probability of Walking Downstairs (W.D.)" is overwhelmingly higher than the others, thus it is confident to determine the user's activity is walking down-stairs, although the probability of Walking Downstairs" is still the highest, it's close to Walking" and "Standing", thus the activity recognition is not confident. We train pair-wise SVM classifiers to mitigate the uncertainty. For Na = 6, 15 bi-class SVM classifiers are trained based on the statistic features . Then we compare each two activities in the descending order of their probability values., the result is determined by the activity with the highest probability, when the ratio between the highest probability and the second highest is higher than a threshold T.

Proposed T test(transposition of matrix) based feature selection algorithm

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. 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)

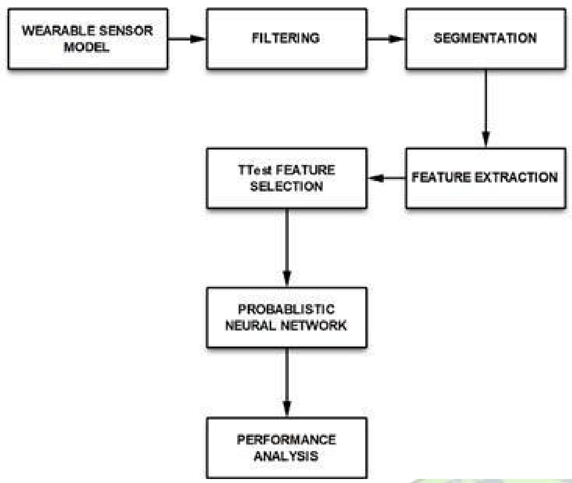

Figure 4.1 System Architecture

5. MODULE DESCRIPTION

There are four modules

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.

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

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 . Probabilistic neural network

The probabilistic neural networks are made up of processing elements called neurons which process the information by their dynamic state response to external inputs. Neural networks are organized as layers one input layer, one or more hidden layers and an output layer. Hidden layers are made up of a number of neurons. Features/patterns are given to the network via the input layer, which are connected to one or more of the hidden layers. The actual processing is done in the hidden layers through a system of weighted connections. The hidden layers are connected to the output layer. The output layer provides the outcome of the processing or classification most neural networks contain some kind of learning function, which modifies the weights of the connections according to the training pattern presented to it .

6. ALGORITHM

Probabilistic neural network algorithm:

Step 1: pre-processing of data

- Collect the data for the PNN based prediction algorithm.
- Define the set of values for the training and testing purposes. Here from the literature, the collected. And then transform it to the format of PNN.

Step 2: training of PNN

- Train the network, with the help of PNN training algorithm, input and output matrices.
- Identify the suitable value of spread constant s. The value of s cannot be selected arbitrarily. A too small s value can result in

a solution that does not generalize from the input/ target vectors used in the design. In contrast, if the spread constant is large enough, the radial basis neurons will output large values for all the inputs used to design a network.

Step 3: testing of PNN

- Define the matrix for the testing of the PNN network.
- Verify the predicted and actual values for the efficiency check of the network.

T-test algorithm:

The most common type of t-test, is often used to assess whether the means of two classes are statistically different from each other by calculating a ratio between the difference of two class means and the variability of the two classes. The t-test has been used to rank features for microarray data and for mass spectrometry data. These uses of t-test are limited to two-class problems. For multi-class problems, Tibshirani et al calculated a t-statistics value for each gene of each class by evaluating the difference between the mean of one class and the mean of all the classes, where the difference is standardized by the within-class standard deviation.

$$t_{ic} = \frac{\overline{x}_{ic} - \overline{x}_i}{M_c \cdot (S_i + S_0)}$$

$$S_i^2 = \frac{1}{N-C} \sum_{c=1}^{C} \sum_{j \in c} (x_{ij} - \overline{x}_{ic})^2$$

$$M_c = \sqrt{1/n_c + 1/N}$$

Here t_{ic} is the t-statistics value for the i-th gene (feature) of the c-th class; $\overline{x}_{ic}$ is the mean of the i-th feature in the c-th class, and $\overline{x}_i$ is the mean of the i-th feature for all classes; x_{ij} refers to the i-th feature of the j-th sample;

N is the number of all the samples in the C classes and n_c is the number of samples in class c;

S_i is the within-class standard deviation and S_0 is set to be the median value of S_i for all the features.

$$t_i = max\left\{\frac{|\overline{x}_{ic} - \overline{x}_i|}{M_c S_i}, c = 1, 2, ...C\right\}$$

Therefore, we generalize the t-score of each feature as follows:

1. Suppose the feature set is $F = \{f_1, ..., f_i, ..., f_g\}$, and feature i has m_i different nominal values represented as $f_i = \{x_i^{(1)}, x_i^{(2)}, ..., x_i^{(m_i)}\}$.

2. Transform each nominal feature value into a vector with the dimension m_i:

$$x_i^{(1)} \Rightarrow \vec{X}_i^{(1)} = (0, \ldots, 0, 1), x_i^{(2)} \Rightarrow \vec{X}_i^{(2)} = (0, \ldots, 1, 0), \ldots, x_i^{(m_i)} \Rightarrow \vec{X}_i^{(m_i)} = (1, \ldots, 0, 0).$$

3. Replace all the numerical features in Equations 1 and 2 with those vectors.

$$t_i = max\left\{\frac{\left|\overline{\vec{X}}_{ic} - \overline{\vec{X}}_i\right|}{M_c S_i}, c = 1, 2, ...C\right\}$$

$$S_i^2 = \frac{1}{N-C} \sum_{c=1}^{C} \sum_{j \in c} (\vec{X}_{ij} - \overline{\vec{X}}_{ic})(\vec{X}_{ij} - \overline{\vec{X}}_{ic})^T$$

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 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, Greedy approach is used on using the greedy approach there is a chance to miss the feature model-based design and optimization approach used ,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 so only T test feature selection algorithm is used on using the T test features consumes less time and less energy also no chance to miss the feature and probabilistic neural network approach is used. In this paper, our primary focus was to detect the activity recognition with the help of activity recognition we have to measure the health condition of the patient and consumes less energy.

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