International Journal of Advanced Technology in Engineering and Science
Vol. No.5, Issue No. 01, January 2017
www.ijates.com
ijates
ISSN 2348 - 7550

POWER AWARE DATA PROCESSING TECHNIQUE FOR SMART DEVICE DOMAIN

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ABSTRACT

Data processing techniques are ways to process about the given material. This paper focuses on importance of Data Processing for power aware systems like mobile . Some Data processing algorithms and strategies are described here. A place and roll of data processing techniques is described.

Index Terms:* *Classification, ,Data energy consumption, Data processing ,KNN.

I. INTRODUCTION

The 21th century could be termed as "Technological Yuga", because of phenomenal growth in technologies. One of the examples is the embedded technology, which includes variety of applications like mobiles, video cameras, data modems, wireless devices and smart portable biomedical devices. Most of the embedded applications suggest portability and energy consumption is a big issue in embedded systems. The main reason of concern is that the portable devices perform differently, in terms of power dissipation, for different applications. Embedded devices must be energy efficient in their performance and longevity.

Energy consumption of a system could be improved by optimization of Hardware or Software. One of the software aspects for optimization is data. The efficiency and performance of power management depends upon the data size, data type and data processing instructions of the system host processor. The purpose of this paper is to find a way to save energy by comparing different data processing techniques. Existing solutions for minimizing energy consumption are multifaceted. The faster algorithm having high performance and minimum power consumption is common thinking [3]. This work focuses on study of the different data processing techniques and tools of data mining.

The tools like WEKA, Data preparatory tools are commonly used against the different smart device datasets. These tools will be compared for battery consumption related factors, such as processing time/CPU cycles required for search. Because the processor performance is affected by energy efficiency [3][4]. Careful selection of data processing techniques, for improving energy efficiency, can increase performance by parallel computations without disturbing the power budget [5].

II. SIGNIFICANCE OF THE TOPIC

The research will focus on evaluation of data processing algorithms used in different tools as per the energy consumption factors like time. Data processing techniques used to process data in smart devices is an important issue because it's directly affected to power management. The energy consumption is directly affects to efficiency and performance of device.

III. PROBLEM STATEMENT

To study and carry out comparative analysis of data processing techniques according to energy consumption factors inbuilt in different data processing tools.

IV. LITERATURE REVIEW

There are number of different tools and methods used for data processing. Energy consumption is an important issue in the growing number of data mining and machine learning applications for battery-powered embedded and mobile devices. It plays a critical role in performance of device[1].Energy efficiency is an important design consideration in development of data mining algorithms for mobile and distributed environments[2].Managing data on mobile devices is always characterized by handling limited resources like memory, CPU performance, or energy supply. Mobile information systems should be able to adapt themselves in order to meet the users requirements. If a maximal uptime of the device is required, the user would (perhaps) agree to slow down the system or to avoid network communications, even if some data gets outdated. However, in order to realize such a resource substitution one needs to have a deep understanding of the interdependencies between the resources and how they are used[3][4].

In computer science and mathematics, sorting algorithms are used to arrange elements in a specific order (e.g., numerical or lexicographical order). Efficient sorting is important to optimize the use of search and merge algorithms that require sorted lists. Furthermore, many data(base) management algorithms that implement join (e.g., Sort-Merge-Join) or duplicate eliminating set operations implicitly use sorting algorithms[5].

Due to the orientation towards mobile- and embedded based systems, several research efforts have investigated into the topic of energy consumption. Optimizing energy consumption is one of the fundamental factors for an efficient battery-powered system. Jain et al. [14] classified these research efforts into four levels of abstraction; the logic design level, the processor level, the operating system level and the compiler level. However, we have classified the research in energy consumption into the two main categories software and hardware. The research, which belongs to the hardware category, attempts to optimize the energy consumption by investigating the hardware usage and innovating new hardware devices and techniques, such as [6].

Even if it is common belief that faster algorithms need less energy – and knowledge of their run time therefore is sufficient – the simulations and calculations based on the model to be introduced will be used to analyze the expected energy consumption of several algorithms from searching and sorting. As a surprise the results show that there are pairs of algorithms where the faster one consumes more energy[7]. Hannah Bayer and Markus Nebel says that in binary searches it can be stated for the sorting algorithms illustrated that the fastest algorithms is not the one with the lowest energy consumption. Regarding the run time ”List Insertion Sort” is the worst algorithm but regarding the power consumption on the DSP it is the best and ”Straight Selection Sort” is the worst regarding the power consumption of both DSP and ARM7TDMI but has definitely not the longest run time. Again the shown plots pictures the average case but in difference to the binary search algorithms the average case is unlike the worst case but nonetheless in the worst case the order of the algorithms changes as well from run time to energy consumption[8],[20].

Power management is addressed in the context of embedded systems from energy-aware design to energy-efficient implementation. A set of mechanisms specifically conceived for this scenario is proposed, including a power management API defined at the level of user-visible system components, the infrastructure necessary to implement that API (namely, battery monitoring, accounting, auto suspend, and auto resume), an energy-event propagation mechanism based on *Petri nets* and implemented with *aspect-oriented programming* techniques, and an autonomous power manager build upon the proposed API and infrastructure by[9].Given the rising importance of mobile and small embedded devices, energy consumption becomes increasingly important. Currents estimates by EUROSTATS predict that in 2020 10-35 percent (depending on which devices are taken into account) of the global energy consumption is consumed by computers and that this value will likely rise (Bunse & H¨opfner 2008). Therefore, means have to be found to reduce the energy consumption of such devices is stated by[10].

Narseo Vallina-Rodriguez and Jon Crowcroft, *Fellow, IEEE* describes the different energy management techniques for different models[11].To address the problem of technique integration for power-aware embedded systems, we propose a new design tool framework called IMPACCT and the associated design methodology. The system modeling methodology includes application model for capturing timing/power constraints and their mode dependency at the system level. The tool performs power-aware scheduling and mode selection to ensure that all timing/power constraints are satisfied and that all overhead is taken into account. IMPACCT then synthesizes the implementation targeting a symmetric multiprocessor platform[12].

In paper [13], they highlight the need of power management in embedded systems and survey several research works which are aimed at improving energy efficiency of embedded systems. To provide insights into the working of these techniques, they classify them on the basis of their key research idea. We believe that this survey will help the researchers and designers in understanding the state-of-the-art in power management of embedded systems and also motivate them to further improve the energy efficiency of embedded systems. The purpose of thesis by [8][15] is to find a way, to save energy without accepting significant inconveniences to the consumer. Therefore, it uses the data from the key electrical appliances recorded by an existing smart home automation system, to analyze the behavior in the household.

Objectives of the Study:

- To study different data processing algorithms.
- To provide comparative analysis of data processing algorithms for energy efficiency.

V. HYPOTHESIS

The process of data processing is basic of any smart device. This is very difficult and time consuming according to device used. The proposed research work will study techniques of the processing of data in different tools and how it affects the datasets as per energy consumption factors are considered.

High performance systems consume more energy and to the contrary energy efficient devices may not perform faster. Many hardware techniques are being developed to improve energy efficiency without affecting performance. Some of the recent additions are parallel architectures and nano scale fabrication. In fact hardware solutions will not perform without software enhancements. Few groups of researchers have suggested software architectural enhancements such as RISC and perfecting. But with increasing data size these hardware/software approaches may fail, without proper selection of data sets and data processing/mining strategies as well as tools.

VI. RESEARCH METHODOLOGY

a) <u>**Research Method:**</u>

In this research paper focus on Different data processing techniques as follows:

I] Data processes techniques used by different data processing tools on dataset such as,

1. Data Classification methods

2.Data Searching methods

II] Effect of methods on energy consumption factors

III] Effect of changes in dataset proportion on data process.

Data processing is a complex process, which also depends on environmental conditions, the types of sensor, the capabilities of the mobile device used and the types of data collected. The type of application also influences the use of data processing methods. Data processing may be executed locally, using the capabilities of the mobile device, or at the server side, sending the collected data to a remote server, where the data processing methods are executed [22,23]. For server-side processing, the mobile device is only required to acquire the sensors data and to present the results to the user. As frequent sensor sampling operations and further data processing can significantly reduce the battery lifetime and the capacities of the mobile device [24,25], several methods may be used to process different types of data. For example, while for audio processing, the time-scale modification (TSM) algorithm and, for medical imaging, remote processing methods are highly recommended, for other sensors, data can be processed locally in the mobile device without significant consumption of local resources [26–28].

Data processing methods may include a segmentation method, which divides a larger data stream into smaller chunks appropriate for processing, and a definition of the window size [29].

According to Pejovic and Musolesi [30], the challenges of data processing in mobile devices lie in the adaptation, context-driven operation, computation, storage and communication. The adaptation and the context-driven operation have several solutions that include the adaptive sampling, the hierarchical modality switching, the harnessing domain structure and the use of cloud offloading.

Possible solutions for computation, storage and communication are hierarchical processing, cloud offloading and hardware co-processing.

Several systems and frameworks to classify and to process sensors' data have been developed during the last few years. An option is, after contexts are extracted from the collected data, to discard part of the data to reduce memory usage [31]. Methods such as support vector machines (SVM), artificial neural networks (ANN), Bayes classifiers and k-nearest neighbor (KNN) algorithms, among others, may be used for data processing. In several research studies, the analysis and processing of sensor data include complex tasks that need high processing and memory capabilities [32]. In such cases, these activities need to be performed at the server-side.

In [31], Imai et al. present a rule-based data processing engine for sensor nodes to minimize the amount of energy needed to process the tasks. The data processing may be performed on a computer located in the neighborhood of the sensor nodes, which processes the data and provides the results, obtaining a good balance between reducing the network load and advanced sensor data analysis and processing.

Yamada et al. [33] present a location-based information delivery method using Stream Spinner, which achieves efficient stream data processing based on novel multiple continuous query optimization techniques.

In [34], the Dandelion system is presented, achieving good results with sense let, a Smartphone-style, platform-agnostic programming abstraction for in-sensor data processing. Dandelion provides a unified programming model for heterogeneous systems that span diverse execution contexts, supporting data-parallel applications.

Dolui et al. [35] defined two architectures: the Device Data Processing Architecture and the Server Data Processing Architecture. The Device Data Processing Architecture is designed to acquire the data from the sensors embedded in an off-the-shelf mobile device and to process the data locally.

This architecture is useful when the processing methods require low resources, such as processing the accelerometer data, proximity sensor data and others. On the contrary, the Server Data Processing Architecture consists of the dispatch of the data collected to a remote server allowing the computation of a large amount of data, as well as computations of a complex nature. This architecture is employed for instance with data acquired with the GPS receiver and the imaging sensors.

Imai et al. [36] defined a method for data processing using the similarity of motions between observed persons. The method presented implements sensor data processing using a neighbour host, executed in two phases: a basic action phase and a changing sensor node settings phase [36]. In the basic action phase, a neighbouring host receives sensor data from the sensor nodes. Then, this host analyses and processes the data and sends the results to a different host. In the changing sensor node settings phase, when analytic results of sensor data fulfill the conditions determined in advance, the

neighbouring host instructs sensor nodes to change the settings. Next, the sensor data processing method based on similarity is defined, where the system acquires and accumulates a newly-observed person's acceleration data, while it estimates the related motions using a similar observed person's profile. When the system acquires sufficient acceleration data of a newly-observed person, the system creates a profile that is added to the knowledge base.

The ACQUA framework optimizes the data processing, using ASRS algorithms.

The ACQUA framework can also be implemented in systems with a remote processing architecture or in systems that process the tasks locally.

Reilent et al.developed an open software architecture for patient monitoring, which supports semantic data processing and (soft) real-time reasoning. Usually, in medical environments, the context awareness and decision making are performed in a remote server, which returns the results to the mobile device [22]. Another option used for processing the collected data is the use of a cloud-based server that processes the data in real time. However, it makes the mobile device and data processing dependent on a constant Internet connection [37].

In order to avoid this constraint, some tele-medicine systems have implemented data processing locally on the mobile device. For instance, Postolache et al. [38] implemented advanced data processing, data management, human computing interfacing and data communication using a smartphone running the Android operating system.

Augmented reality is also an application relevant for AAL. Paucher and Turk implemented a system for image

Architectures	**Methods**	**Achievements**
Device Data Processing Architecture	Dandelion system; SVM; ANN; Bayes classifiers; KNN algorithms; location-based information delivery method using Stream Spinner	Acquisition of the data from the sensors embedded in an off-the-shelf mobile device; process the data locally; the results are rapidly presented to the user; processing methods should require low resources; using segmentation methods, a larger data stream is divided into smaller chunks improving the methods; the correct definition of the window size is important for achieve good results.
Server Data Processing Architecture	SVM; ANN; Bayes classifiers; KNN algorithms; nearest neighbor search of descriptors using a KD-Tree structure	Dispatching of the data collected to a remote server allowing the computation of a large amount of data, as well as computations of complex nature; in some cases, the data processing may be performed on a computer located in the neighborhood of the sensor nodes; in server-side processing, the mobile device and data processing are dependent on a constant Internet connection.

processing that used a remote server. The system implements a nearest neighbor search of descriptors using a k-dimensional (KD)-Tree structure, applying it for each image. Other algorithms for image processing using the camera of a mobile device are presented in [38].

Table summarizes the different architectures for data processing, presenting the most relevant methods and achievements. It is often described in the literature that the data that can be processed locally on the mobile device include the motion or positioning sensors. However, the processing of images or videos is computationally expensive, and due to the low memory and processing capabilities of mobile devices, it is highly recommended that these tasks use external processing.

Dataset Analysis:

A total of 2268 records with 15 medical attributes (factors) were obtained from the Heart Disease database. The records were split equally into two datasets: training dataset (1857 records) and testing dataset (411 records). The attribute "Diagnosis" was identified as the predictable attribute with value "1" for patients with heart disease and value "0" for patients with no heart disease.

Predictable attribute

1. Diagnosis (value 0: < 50% diameter narrowing (no heart disease); value 1: > 5
0% diameter narrowing (has heart disease))

Key attribute

1. Patientid –Patient‟ s identification number

Input attributes

1. Sex (value 1: Male; value 0 : Female)
2. Chest Pain Type (value 1: typical type 1 angina, value2: typical type angina, value 3: non-angina pain; value 4: asymptomatic)
3. Fasting Blood Sugar (value 1: > 120 mg/dl; value 0: < 120 mg/dl)
4. Restecg –resting electrographic results (value 0: normal; value 1: 1 having ST-T wave abnormality; value2: showing probable or definite left ventricular hypertrophy)
5. Exang –exercise induced angina (value 1: yes; value 0: no)
6. Slope –the slope of the peak exercise ST segment (value1: unsloping; value 2: flat; value 3: down sloping)
7. CA –number of major vessels colored by fluoroscopy (value 0 –3)
8.Thal (value 3: normal; value 6: fixed defect; value7:reversible defect)
9. Trest Blood Pressure (mm Hg on admission to the hospital)
10. Serum Cholesterol (mg/dl)
11. Thalach-maximum heart rate achieved
12. Oldpeak –ST depression induced by exercise relative to rest
13. Age in Year.

II] Effect of methods on energy consumption factors

and

III] Effect of changes in dataset proportion on data process.

Table summarizes the different effects on energy consumption and dataset proportion changes for data processing techniques. It is often described in the literature that the data that can be processed locally on the mobile device include the motion or positioning sensors.

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ISSN 2348 - 7550

Data Processing Techniques	Time Taken to process(in secs)	Effect of methods on energy consumption factors	Effect of changes in dataset proportion on data process.
SVM	**0.19**	Low consumption of energy	Rapidly process and improve the methods
ANN	**0.11**	Low consumption of energy	Rapidly process and improve the methods
KNN	**0**	Lowest consumption of energy	Rapidly process and improve the methods
Bayes Classifier	**0.17**	Low consumption of energy	Rapidly process and improve the methods
KD-Tree structure	High consumption of energy due to the internet connection		Dataset splitting is necessary for complex and large data

The processing of data effected by complexity and type of data used. Processes are improved by splitting the dataset on server side.SVM,ANN,KNN and Bayes Classifiers are perform best on actual device data with low power consumption and KD-Tree structure and other techniques required high power at server side with continuous internet connection. KNN is best option as per CPU cycles per second are considered.

VII. CONCLUSION AND FUTURE WORK

Energy efficiency is an important issue data processing techniques for smart portable devices like mobile and other biomedical devices. The paper is experimentally quantify the performance of KNN,SVM,ANN and Bayes classifier algorithms on local daily used datasets. The processing of data effected by complexity and type of data used. Processes are improved by splitting the dataset. KNN is best option as per CPU cycles per second are considered. In future the research will be carried out for some another data processing algorithms and datasets.

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