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MINIMIZING OVERHEAD AND IMPROVING ENERGY FOR SMART MOBILE DEVICES

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Abstract: **Mobile computing has morphed into a principal form of human communication, business, and social interaction. Unfortunately, the energy demands of newer ambient intelligence and collaborative technologies on mobile devices have greatly overwhelmed modern energy storage abilities. This paper proposes several novel techniques that exploit spatiotemporal and device context to predict device wireless data and location interface configurations that can optimize energy consumption in mobile devices. These techniques, which include variants of linear discriminate analysis, linear logistic regression, non-linear logistic regression with neural networks, k-nearest neighbor, and support vector machines are explored and compared on synthetic and user traces from real-world usage studies. The experimental results show that up to 90% success s full prediction is possible with neural networks and k-nearest neighbor algorithms, improving upon prediction strategies in prior work by approximately 50%. Further, an average improvement of 24% energy savings is achieved compared to state-of-the -art prior work on energy-efficient location sensing.**

Keywords: **Mobile, PDA's, Sensor, 3D Gaming, Wi-Fi, GPS**

1. INTRODUCTION

Mobile phones and other portable devices (tablets, PDA's, and e-readers) are fundamental everyday tools used in business, communication, and social interactions. As newer technologies (e.g. 4G networking, multicore/GPUs) and applications (e.g. 3D gaming, Apple's Face Time™) gain popularity, the gap between device usage capabilities and battery lifetime continues to increase, much to the annoyance of users who are now becoming more and more reliant on their mobile devices. The growing disparity between functionality and mobile energy storage has been a strong catalyst in recent years to develop software-centric algorithms and strategies for energy optimization. Software techniques work in tandem with well-known energy optimizations implemented in hardware including CPU DVFS, power/clock gating, and low power mode configurations for device interfaces and chipsets. The notion of "smart" mobile devices has recently spawned a number of research efforts on developing "smart" energy optimization strategies. Some of these efforts employ strategies that are context-aware including utilization of device, user, spatial, temporal, and application awareness that attempt to dynamically modify or learn optimal device configurations to maximize energy savings with little or negligible impact on user perception and quality of service (QoS).

Resulting predictions manage the network interface states allowing for dynamic adaptation to optimal energy configurations, while simultaneously maintaining an acceptable level of user satisfaction. This idea is further motivated by considering the power distributions of the Google Nexus One Android smart phone illustrated in Fig. Even when 3G, Wi-Fi, and GPS interfaces are all enabled and idle, they account for more than 25% of total system power dissipation.

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A substantial amount of research has been dedicated to utilizing machine learning algorithms for the purpose of mobile user context determination. Batyuk et al. extend a traditional self-organizing map to provide a means of handling missing values and then use it to predict mobile phone settings such as screen lock pattern and Wi-Fi enable/disable. Other works attempt to predict the location of mobile users using machine learning algorithms.

The authors propose a model that predicts spatial context through supervised learning, and the authors in take advantage of signal strength and signal quality history data and model user locations using an extreme learning machine algorithm. Wireless sensor networks, nodes have limited energy resources and, consequently, protocols designed for sensor networks should be energy-efficient.

One recent technology that allows energy saving is cooperative transmission. In cooperative transmission, multiple nodes simultaneously receive, decode, and retransmit data packets. In this paper, as opposed to previous works, we use a cooperative communication model with multiple nodes on both ends of a hop and with each data packet being transmitted only once per hop. In our model of cooperative transmission, every node on the path from the source node to the destination node becomes a cluster head, with the task of recruiting other nodes in its neighborhood and coordinating their transmissions.

2. SENDER NODE

Sender node is the initiate module for the data transfer between the nodes in network communication. A sender node is the data source node which will transmit that data to desired destination /receiver node. Before the data initiated, here the sender should choose its path to transmit the data without any channel failure occurs. Once it sends the data it will receive the acknowledgement for the data from corresponding destination node. The acknowledge will receive through the GPS Clustering path.

3. RECEIVER NODE

This is the destination node where the sender data have to reach. Receiver nodes are generally aware of its neighbor nodes to get the data from sender. Like the sender node this also aware the partners of the communication with sender. After it received the data exactly receiver node should send acknowledgement to the sender for intimate that the data was received successfully through the GPS Clustering path.

4. GPS CLUSTERING

This is the first phase of the proposed method, where the path will be chooses by the GPS method based on the shortest and efficient path. In the every node of the selected path called as header for the purpose of making group around it to transfer the data from source to destination nodes. The source node send the query in the network for the transmission once the destination connected to source node then next phase works will starts.

5. RECRUITING AND TRANSMITTING

Recruiting phase makes the cluster around the header. The header node is also called as cluster header; this will send the query to the nearest node to transfers the data from sender to receiver. If the neighbor nodes are ready to transfer the data then it will reply for the user requests. Once the cluster header gets the responses from the nodes, then it makes a group to transfer the data. Transmitting phase is the next step where the clustered nodes transmitting the data from the source, first the source sends the data to first cluster nodes, all nodes then forward to the next cluster, so at last destination get the whole data by the help of multiple paths. The following figure1 represents the transmission of data from source node to destination node.

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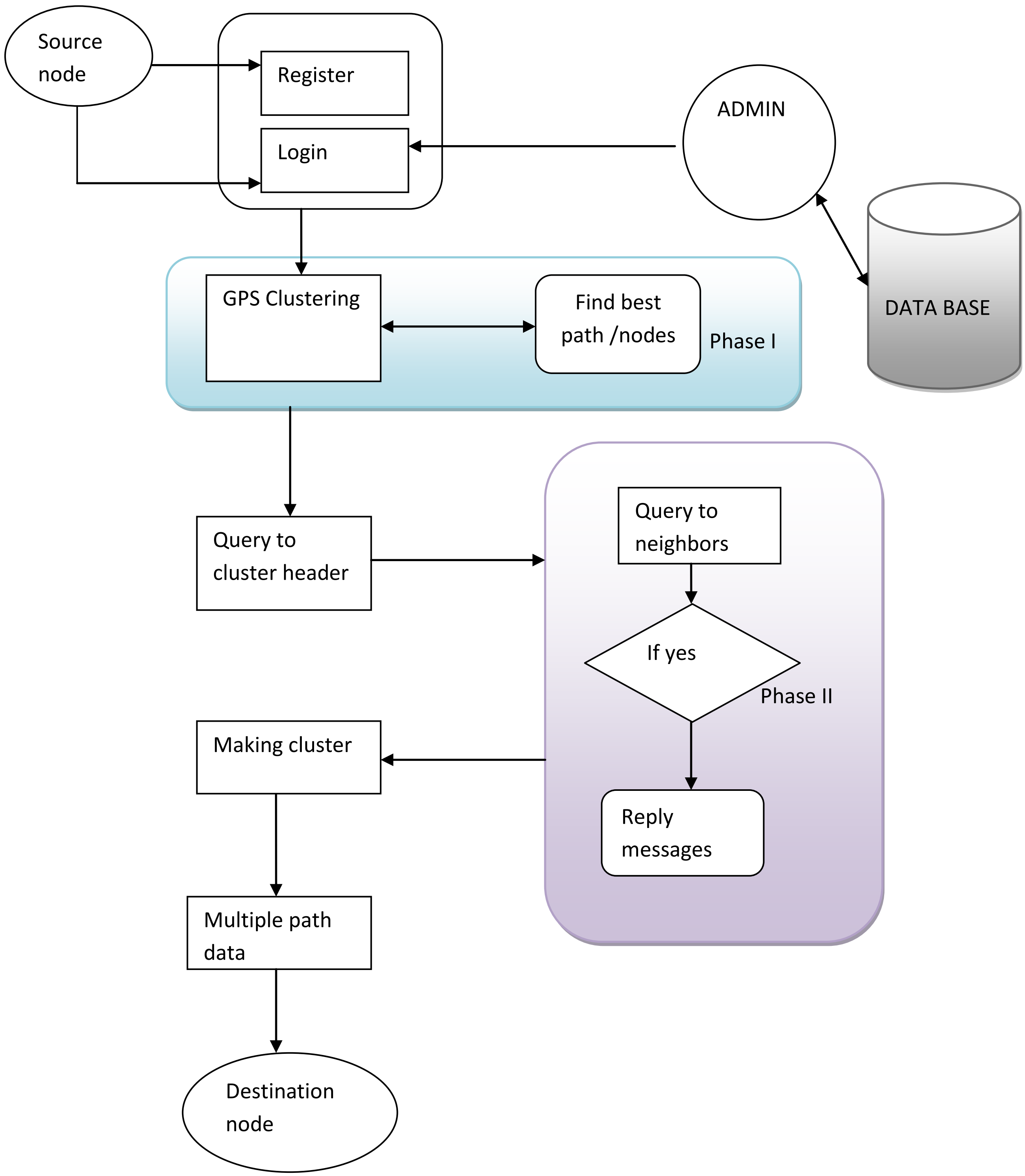

Figure 1. Transmission of Data from Source Node to Destination Node

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6. ALGORITHMS USED IN MOBILE TECHNIQUES

6.1 K-Nearest Neighbours Algorithm

In pattern recognition, the **k-nearest neighbours algorithm (k-NN)** is a non-parametric method for classification and regression, that predicts objects "values" or class memberships based on the k closest training examples in the feature space. k-NN is a type of instance-based learning, or lazy learning where the function is only approximated locally and all computation is deferred until classification. Since KNN is non parametric, it can do estimation for arbitrary distributions. The idea is very similar to use of Parzen window . Instead of using hypercube and kernel functions, here we do the estimation as follows – For estimating the density at a point x, place a hypercube centered at x and keep increasing its size till k neighbours are captured. Now estimate the density using the formula,

P(x)= (k/n) / V

6.2 Non-Linear Logistic Regression With Neural Networks

Neural network models, also known as *Artificial Neural Networks*, are inspired by the way the human brain is believed to function. The main difference being that the human brain consists of billions of these simple parallel processing units,(neurons) which are interconnected in a massive multi-layered distributive network of synapses and neurons. The data consist of error-free independent variables (explanatory variables), x, and their associated observed dependent variables (response variables),y. Each y is modeled as a random variable with a mean given by a nonlinear function $f(x,\beta)$. Systematic error may be present but its treatment is outside the scope of regression analysis. If the independent variables are not error-free, this is an errors-in-variables model, also outside this scope.

The notion of "smart" mobile devices has recently spawned a number of research efforts on developing "smart" energy optimization strategies. Some of these efforts employ strategies that are context-aware including utilization of device, user, spatial, temporal, and application awareness that attempt to dynamically modify or learn optimal device configurations to maximize energy savings with little or negligible impact on user perception and quality of service (QoS). This idea is further motivated by considering the power distributions of the MANET devices. Even when 3G, Wi-Fi, and GPS interfaces are all enabled and idle, they account for more than 25% of total system power dissipation. Furthermore, when only one of the interfaces is active, the other two idle interfaces still consume a non-negligible amount of power. Our work exploits this fact to save energy more aggressively than the default energy management strategy used in a mobile device, by dynamically managing data and location interfaces, e.g., turning off unnecessary interfaces at runtime.We propose and demonstrate the use of five different classes of machine learning algorithms:

(i) Linear discriminant analysis,

(ii) Linear logistic regression,

(iii) K-nearest neighbor,

(iv) Non-linear logistic regression with neural networks, and

(v) Support vector machines,

These strategies are tested on both synthetic and real-world user usage patterns, which demonstrate that high and consistent prediction rates are possible. The proposed techniques are also compared with prior work on device configuration prediction using self-organizing maps and energy-aware location sensing, showing an improvement upon these state-of-the-art techniques.

7. CONCLUSION

This paper demonstrates the effectiveness of using various machine learning algorithms on user spatiotemporal and device contexts in order to dynamically predict energy-efficient device interface configurations. It demonstrated up to a 90% successful prediction using support vector machines, neural networks and k-nearest neighbor algorithms, showing improvements over the self-organizing map prediction approach proposed in by approximately 50%. In addition, approximately 85% energy savings was achieved for minimally active users with an average improvement of 15% energy savings compared to the variable rate logging algorithm (VRL) proposed in for our best approach involving support vector machines that also has high prediction accuracy and low overhead. If slightly more implementation overhead is acceptable, our approach involving non-linear logistic regression with neural networks can provide even more energy savings, with an average improvement of 24% compared to VRL. A possible extension to our work is to conduct large scale studies that recruit sample groups much larger than that considered in this work. Such large user groups could lead to the creation of user classes for which unique class-specific usage patterns could be discovered.

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