Cost-Sensitive Feature Selection for On-Body Sensor Localization

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Abstract

Activity recognition systems have demonstrated potential in a broad range of applications. A crucial aspect of creating large scale human activity sensing corpus is to develop algorithms that perform activity recognition in a way that users are not limited to wear sensors on predefined locations on the body. Therefore, effective on-body sensor localization algorithms are needed to detect the location of wearable sensors automatically and in real-time. However, power optimization is a major concern in the design of these systems. Frequent need to charge multiple sensor nodes imposes much burden on the end-users. In this paper, we propose a novel signal processing approach that leverages feature selection algorithms to minimize power consumption of node localization. With the real data collected using wearable motion sensors, we demonstrate that the proposed approach achieves an energy saving that ranges from 88% to 99.59% while obtaining an accuracy performance between 73.15% and 99.85%.

Author Keywords

On-body Sensor Localization; Low Power Design; Body Sensor Networks (BSNs); Machine Learning; Classification

ACM Classification Keywords
C.3 [Computer Systems Organization]: Special Purpose and Application-Based Systems—Real-time and embedded systems; J.3 [Computer Applications]: Life and Medical Science—Health; H.1.2 [Information Systems]: Models and Principles—User/Machine Systems Human information processing; Human factors.

Introduction
Current approaches for activity recognition constrain the user to a set of predefined sensor locations; this imposes much inconvenience for users as they are not allowed to use sensors on their own desired body locations [1-3]. For example, while some users may prefer to have a smartphone in their pocket, others may prefer to carry the smartphone in a backpack or purse. Failure to adhere to the predefined protocols (i.e., using sensors on pre-specified body locations) results in a drastic reduction of the accuracy of physical activity monitoring applications. Therefore, new algorithms and signal processing techniques are needed to detect the location of the wearable sensors automatically and in real-time, as they are being used in activity recognition systems.

On the other hand, power optimization is an inevitable criterion in wearable systems design. Frequent need to charge multiple nodes will decrease the desire of continuously using the system. To address this issue, power optimization should be considered in different levels of design. Many previous studies show that system level optimization techniques offer significant performance improvements [3].

An important aspect of the low-power system level design and optimization in wearable sensors is to develop efficient signal processing and data reduction algorithms that reduce computation load of the processing units, allowing low-cost processors to be embedded with the wearable device. Theoretically, this concept can be generalized to optimize signal processing algorithms for different types of costs such as costs associated with energy consumption, data collection, and user preferences. Our goal in this paper is to propose signal processing algorithms for on-body localization, while introducing a compromise between accuracy and power consumption of node localization. In particular, we aim to minimize sensing and computation power, while retaining a given localization accuracy.

The remainder of this paper is organized as follows. We first discuss the related work on localization and power optimization in activity recognition systems. Next, motivation for automatic node localization is presented. We then present our approach towards low power on-body localization. Finally our result section discusses experimental setup and simulation results followed by a discussion of conclusions and future work.

Related Work
Activity recognition has been addressed using different types of sensors, but accelerometers and gyroscopes are the most common sensors; in particular when detecting complex movements is the goal of activity recognition [2,5,6]. Therefore, a signal processing algorithm which uses these sensors is a desirable choice for on-body localization.

Despite the tremendous amount of research on activity recognition, there has been less effort in detecting the location of wearable nodes. Major deficiencies of current on-body sensor localization algorithms include either lack of sufficient accuracy or need for a priori knowledge about the activity being performed by the user.

Authors in [7] presented an algorithm for detecting on-body position of wearable sensors. This paper used a C4.5 classifier to perform localization for four different locations (wrist, breast pocket, trousers pocket, and right eye). The main problem with this approach is that the user must repeat a walking pattern for node localization. In [8], authors presented another method to perform localization based on daily activity routines. While this method is not limited to a predefined activity, a small set of sensors are used in this study. Also, users need to perform daily activities for a long period of time for localization.

A recent study in [9] used an unsupervised technique to discover walking activities. Once walking patterns are detected, motion signals are analyzed by a SVM classifier for node localization. This approach also needs the users to perform a predefined activity pattern.

The approach presented in [10] assumes that the activity type is known. In real world applications, however, we often face situations that knowledge about human movements does not exist beforehand. In fact, activity recognition usually is a main goal of utilizing mobile wearable motion sensors. The study in [11] introduced a method to examine if two portable devices are carried by the same person.

Power optimization is often a main concern in designing wearable embedded systems. Although, there are different approaches for energy efficient design of activity recognition systems, there is no energy efficient design for on-body localization.

Ghasemzadeh et. al. proposed an energy efficient sensor coverage for physical movement monitoring. The proposed solution is capable of eliminating redundant sensor nodes, while maintaining the activity recognition accuracy [12].

Authors in [13] proposed a genetic programming-based feature selection algorithm for activity recognition systems. The goal is to find a set of discriminative and variation tolerant features that may reduce the energy requirements of the wearable sensor system and to enhance the robustness of the activity recognition solution.

Zappi et. al. [14] presented a gesture recognition system that minimizes power consumption while maintaining a run-time application defined performance target through dynamic sensor selection. By this technique, network lifetime is extended 4 times while the accuracy remains approximately the same.

Motivation

Accurate activity recognition requires a global view of the entire wearable sensor network. The ability of a node to recognize an activity varies depending on the type of the activity and the location of the sensors. For example, consider two locations ‘ankle’ and ‘arm’. The node mounted on the arm could distinguish a ‘sit to stand’ movement, whereas the ankle sensor might not provide useful information to recognize this movement. Therefore, the location of the on-body sensors provides useful contextual information useful for activity recognition. Furthermore, automatically detecting the location of the node is important in realization of real-world applications of wearable sensors. This is primarily due to two reasons: 1) it simplifies the installation of body sensor networks and provides a seamless data gathering and deployment platform; 2) it improves robustness of the system against potential sensor displacements, a major problem in obtaining high levels of accuracy performance in harsh and uncontrolled environments.

In a recent work [15], we showed that a wearable sensor network without automatic sensor localization may achieve an activity recognition accuracy as low as 33.6%. The node localization algorithm, however, can increase the accuracy of activity recognition to 98.8%.

Furthermore, an important goal in designing wearable sensors is to optimize power consumption while preserving an acceptable accuracy performance.

On-body sensor localization without prior knowledge about the type of activity that is being performed is a hard problem mainly due to the large number of potential body locations that can accommodate a wearable sensor and the large amount of activities that can be performed. Prior research either assumes that the type of activity is known a priori or uses computationally expensive processing algorithms for node localization. Furthermore, research in the area of on-body sensor localization is very new and has not explored what algorithms are most effective in detecting sensor locations and what factors affect the performance of such algorithms. Motivated by these needs, our goal in this paper is to identify signal processing algorithms that are promising for on-body sensor localization while attempting to optimize the amount of power consumption of the system by examining power consumption of sensing and processing components.

To the best of our knowledge, finding power-efficient features for node localization has not been investigated previously.

Energy-Aware Sensor Localization

Potentially, there are many different features that can be extracted from human activity signals coming from a variety of sensors (e.g. accelerometers, and gyroscopes). Statistical features have shown effectiveness in human activity recognition based on previous studies [4]. For node localization purposes, however, it is largely unknown which features are most effective. Thus, our goal in this paper is to explore features that are most effective and power-efficient for node localization. For this purpose, we extracted an exhaustive set of features that may be useful for on-body localization.

In our feature selection procedure, we consider power consumption as a criterion while localization accuracy is retained at a minimum level of accuracy. Each sensor node in our network consists of a 3-axis accelerometer and a 2-axis gyroscope. For each sensor axis, as mentioned before, a set of exhaustive features is extracted. Therefore, the total number of features is relatively high for real-time execution on wearable sensor nodes with limited processing power and energy sources. Our feature selection algorithm is designed to 1) reduce the number of features to a discriminative set which results in a system robust to sensor displacements; 2) significantly decrease sensing and computation power dissipation.

Feature	Energy(nJ)	Description
AMP	16386	Signal Amp(Max - Mean)
Med	405159	Median of signal segment
Mean	8126	Mean value of signal segment
Max	8103	Max amplitude of signal segment
Min	8108	Min amplitude of signal segment
P2P	16291	Peak to peak amplitude
VAR	38846	Variance of signal segment
STD	40431	Standard deviation
RMS	29705	Root mean square power
S2E	83	Start to end value
MORPH	45	Morphological features

Table 1. Per-feature energy consumption

To achieve our goal, we try to turn off unnecessary sensors in each node to decrease the sensing power, and also use the minimum number of features for each sensor to decrease the computation power. In the rest of this section, a set of terms are defined that are the basis for our problem formulation.

Our approach in using the motion sensor data for on-body localization is motivated by applications of these sensors in activity recognition procedures. In this approach, on-body sensor localization is considered as a classification problem, where sensor locations determine class labels. After collecting data with various movement types, we extract an exhaustive set of features from the collected acceleration and angular velocity signals. We then select the most prominent features in terms of power consumption from the large set of feature pool, while retaining the localization accuracy at a minimum level. In the rest of this section, a set of terms is defined. This is the basis for the problem formulation.

Definition 1. Given a finite set of wearable nodes $N = \{n_1, n_2, \dots, n_k\}$ each with a finite set of sensors $S = \{s_1, s_2, \dots, s_l\}$, the Minimum-Cost Location Detection (MCLD) problem is finding a set of features such that the total sensing and computation energy of the features is minimized subject to achieving a given minimum accuracy of the node localization algorithm.

Definition 2. Given the finite set of sensors $S = \{s_1, s_2, \dots, s_l\}$, a set of weight $W = \{w_1, w_2, \dots, w_l\}$ is defined based on sensing power consumption. We assume that the network is homogeneous in the sense that all nodes have the same types of motion sensors. From each sensor s_i, we extract k features $\{f_{i1}, f_{i2} \dots, f_{ik}\}$. Also, we define weight p_{ij} for each feature f_{ij} based on computation power.

Definition 3. Given the set of features f_{ij} , ranking of a feature is defined as a function of its power consumption (computation and sensing) and its contribution to node localization, measured by a feature selection algorithm.

Assume that β_{ij} is a given binary parameter that encodes the existence of feature f_{ij} in classification, and α_i is a given binary that encodes the existence of sensor s_i in data collection:

$$\beta_{ij} = \begin{cases} 1, & if\ f_{ij}\ is\ chosen \\ 0, & otherwise \end{cases} \qquad (1)$$

$$\alpha_i = \begin{cases} 1 & if \sum_{j=1}^{l} \beta_{ij} > 0 \\ 0 & otherwise \end{cases} \qquad (2)$$

Our objective is to minimize function Z given by:

$$Z = \sum_{i=1}^{l} \alpha_i w_i + \sum_{i=1}^{l} \sum_{j=1}^{k} \beta_{ij} p_{ij} \qquad (3)$$

Subject to:

$$\lambda_{\text{FSA}} \geq \Lambda \qquad (4)$$

Which λ_{FSA} is the localization accuracy, and Λ is the minimum acceptable accuracy for on-body sensor localization.

A greedy approach is proposed to solve the MCLD problem. A brief description of the algorithm is as follows: at each stage, the algorithm selects the feature with the highest rank; features are ranked based on the product of computation and the rank of feature using the ranker algorithm implemented in Weka [16]. Then, the number associated with each feature is normalized. In each step, the feature with the smallest number is selected which is the best choice in terms of power consumption, and importance.

Algorithm 1: Greedy Approach to Find Power Optimized Set of Features

INPUT: Activity Data Segments
OUPUT: Power Optimized Set of Features Ω
$\Omega = \phi$
1: Generate Exhaustive Set of Statistical Features f_{ij} According to Table 1.
2: Rank remained features based on power consumption and importance in localization.
3: Add the next highest rank feature to Ω
4: Perform localization using the selected features and kNN classifier.
5: if $\lambda_{\text{FSA}} \geq \Lambda$ stop, else go to stage 2.

In the next step, the kNN classifier is used to classify and measure the accuracy of the currently selected feature set. Also, in each repetition, feature ranking will change; as we add a feature from a specific sensor, the cost of other features for that sensor is only based on computation power. This process continues until the given accuracy threshold is obtained. This approach is shown in the Algorithm 1.

Experimental Results

We calculated the energy consumption for each feature based on the power consumption of the MSP430 microcontroller, which is available on the TelosB motes used in our experiments. The power consumption of the gyroscope used in our experiments is 31.35 mW, whereas the accelerometer consumes 2.64 mW in active mode.

Node ID	Node Location
1	Waist
2	Right Wrist (R-Wrist)
3	Left Wrist (L-Wrist)
4	Right Arm (R-Arm)
5	Left Thigh (L-Thigh)
6	Right Ankle (R-Ankle)
7	Left Ankle (L-Ankle)

Figure 1. Data collection setting: sensor node and body locations

We assumed that for each sensor (e.g. the accelerometer), the power consumption is evenly distributed among different axes of the sensor. Thus, the power consumption for each axis of the accelerometer is 0.88 mW, whereas for the gyroscope this value is 15.67 mW. In our experiments, the duration of each activity was 2.5 seconds on average. Therefore, we could infer that the amount of energy dissipation to sense each data segment is 2.2 mJ and 39.17 mJ for each accelerometer and gyroscope sensor respectively. The set of features extracted from individual sensor streams and the corresponding power consumption for each feature is shown in Table 1. This list includes ten statistical features, and ten morphological features for each data segment.

We used a network of wearable motion sensors with accelerometer and gyroscope sensors that collect data through a wireless link on each node's transmission unit. We used the sensor node in [1] to collect data in this paper. Figure 1 shows the body locations on which the sensor is worn during data collection.

No.	Movement
1	Stand to Sit
2	Sit to Stand
3	Sit to Lie
4	Lie to Sit
5	Bend to Grasp
6	Rising from Bending
7	Kneeling Right
8	Rising from Kneeling
9	Look Back
10	Return from Look back
11	Turn Clockwise
12	Step Forward
13	Step Backward
14	Jumping

Figure 2. Experimental movements

A survey study in [17] reports that the number of sensor nodes used for activity recognition may vary from a single node to 19 sensor nodes resulting in an accuracy that ranges from 79% to 98%. In this paper, we decided to use seven sensor nodes located on different body segments. Through our prior research, we have found that this setting provides reasonably high classification accuracy for activity recognition.

The data collection was performed for a variety of movements. The reason that we used different types of movements is to create a reasonable dataset to train a classifier for localization purposes. Therefore, on-body localization could be performed without knowledge about activity types in testing mode. The data collection was performed with 14 different types of transitional movements that mimic typical daily activities. The list of these transitional movements is shown in Figure 2. Unlike previous research, our localization algorithm does not need to know the activity performed by the user because the classifier is trained based on different types of movements.

The feature selection was performed on a PC. The output of the algorithm, which is a set of power-optimized features, was used for execution on the sensor node prototype. The localization is executed prior to activity recognition during the setup time on each node to determine the location of the node.

Table 2 shows the accuracy of individual node localization using various feature sets that have been selected by our feature selection algorithm.

Table 3 shows the energy consumption of various configurations. As it can be observed from this table, for accuracy thresholds of 70% to 99%, we acquire total energy savings that range from 99.95% to 88% compared to the case with the 100 features used in the classification procedure. Furthermore, we can see that the accuracy is higher compared to the case where all the features are involved in the classification. Also, we can see that adding more features for classification beyond a certain point will decrease the localization accuracy perhaps due to addition of features that are irrelevant to the classification problem. When all features (100 features per node) are used for localization, the overall accuracy of the kNN algorithm is only 75.4%. The accuracy, however, reaches an average of 99.85% resulting in 88% energy savings.

Conclusion

In this paper, we presented a signal processing approach for on-body sensor localization with applications in activity recognition and monitoring. Our approach relies on computationally simple classification algorithms that operate on a small set of low complexity features extracted from wearable sensor nodes. The algorithm not only outperforms previous techniques in terms of power, but also obtains much less computing complexity and higher accuracy.

An important observation based on the results obtained in our study is that a limited number of features extracted from a sensor node can be effectively used to detect the precise location of an on-body sensor. It is also interesting that these prominent features can be used separately from accelerometer or gyroscope sensors while obtaining a reasonable level of localization accuracy. A wearable sensor can potentially be worn on many different locations on the body. In this paper, we focused on an experimental setting with seven body locations. In the future, we plan to collect data from a larger set of wearable sensors and revise our algorithms accordingly.

#Features	Sensors	Waist	R-Wrist	L-Wrist	R-Arm	L-Thigh	R-Ankle	L-Ankle
10	Acc–Z	90%	72.9%	71.2%	77.6%	70.6%	66.2%	63.5%
13	Acc-X,Y	83.2%	85.1%	89.5%	97.1%	79.04%	82.2%	71.5%
23	Acc-X,Y,Z	96.2%	96.1%	97.6%	99.5%	91.7%	87.1%	89%
2	Gyro-X,Y	98%	99.5%	100%	99%	98%	97.5%	100%
5	Gyro-X,Y	99.5%	100%	100%	99.5%	97.6%	100%	100%
10	Gyro-X,Y	100%	100%	100%	100%	99%	100%	100%
15	Gyro-X,Y	99%	100%	100%	100%	98.2%	93.5%	100%
100	All	78.4%	67.9%	70.2%	70.2%	78.1%	75.5%	87.5%

Table 2. The accuracy of individual node localization using various feature sets

Accuracy	#Features	Selected Sensors	Computation Energy(nJ)	Sensing Energy(mJ)	Total Energy(mJ)	Energy Saving
73.15%	10	Acc –Z	450	2.2	2.65	99.59%
83.92%	13	Acc-X,Y	1190	4.4	5.590	99.14%
93.89%	23	Acc-X,Y,Z	1640	6.6	8.24	98.74%
98.85%	2	Gyro-X,Y	90	78.34	78.43	88.05%
99.51%	5	Gyro-X,Y	225	78.34	78.565	88.03%
99.85%	10	Gyro-X,Y	450	78.34	78.79	88%
98.67%	15	Gyro-X,Y	675	78.34	79.015	87%
75.4%	100	All Sensors	571688	84.94	656.628	0%

Table 3. The energy consumption of various configurations

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