Patient-Centric On-Body Sensor Localization in Smart Health Systems

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***Abstract*—A major obstacle in widespread adoption of current wearable monitoring systems is that sensors must be worn on predefined locations on the body. In order to continuously detect sensor locations, we propose a localization algorithm that allows patients to wear the sensors on different body locations without having to adhere to a specific installation protocol. Our approach achieves localization accuracy of 90.8% even when the sensor nodes are mis-oriented. Integration of the resulting location information as a feature in an activity recognition classifier significantly increased the recognition accuracy from 23.5% to 99.5%.**

I. Introduction

The rapid advancement of sensors, electronics and wireless communication technology has given rise to the utilization of body-wearable sensor networks for remote health and activity monitoring. As such, body-worn sensor networks enable a personalized approach to health and wellness. Such network provide promising applications in health-care to enhance individual's quality of life, to facilitate independent living, and even to save the lives of people bearing the risk of sudden attacks. Continuous monitoring of the human body is becoming pervasive with the advent of wearable devices capable of processing and storing large amounts of health data.

As a special monitoring system, there are a variety of devices that are continuously used to monitor activities of daily living, exercise and energy expenditure [1]–[5], as well as gait [6], [7] and risk of falls [8]. The proliferation of these devices results in higher diversity of their usage. In addition, being non-intrusive in daily activities requires these devices to be adaptable to individuals' habits.

Motion sensors are the most common sensors in continuous activity monitoring. These sensors are attached to different locations on the body depending on physiological/application requirements, or comfort of the user. Unfortunately, the problem of misplaced/displaced sensors has not been given enough consideration in the pervasive computing society. Since we either assume predefined location for sensors or the location of the sensor is not inherently required, the effects of displacement/misplacement are merely investigated. Nevertheless, the effectiveness of health monitoring devices, and in particular motion sensors, is heavily contingent on the correctness of sensor installation/placement. As such, more work is needed to overcome several limiting challenges for optimal validity of the data captured through these systems. Ignoring these issues will result in faulty interfaces, responsible for unfair energy expenditure reports or false physical activity recording.

Our special focus in this paper is on studying impact of on-body sensor node localization on performance of activity recognition applications. There exist several recent studies that develop on-body localization techniques based on machine learning algorithms [9]–[18]. There remain, however, gaps in our knowledge on how to adopt these algorithms for use in real-world settings. In particular, efficient ways for integrating output of a node localization algorithm within the activity recognition engine is unknown. Furthermore, research needs to be done to discover the extent to which performance of a node localization algorithm is impacted by other unreliability situations such as sensor mis-orientation. Our first contribution in this paper is a machine learning approach to integrate sensor location information, determined by a node localization algorithm, within activity recognition algorithm. We also study the impact of sensor mis-orientation on the performance of the node localization algorithm.

II. Motivation

There exist many technologies that enable movements capturing; among them, accelerometer and gyroscope sensors are mostly quoted by researchers, since they are already present in several devices, have a reasonable price, and yield excellent performance [19]–[23]. The operation of motion monitoring systems heavily relies on the placement and orientation of accelerometer and gyroscope sensors. The functionality of pedometers is an example of the relation between the accuracy and the device placement. The step counting accuracy changes if the pedometer is attached to anywhere other than the waist, because the user's movements will be projected differently on the sensors. In an observation, we attached 6 pedometers to different regions (waist, shin, thigh, forearm, upper arm, and chest) on a subject body and asked him to take 220 steps. We

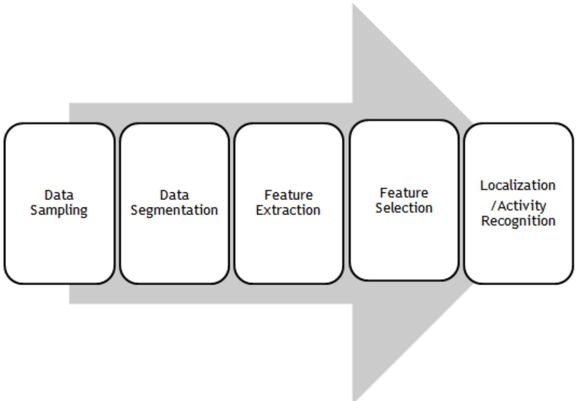

Fig. 1. High level data processing flow to develop node localization and activity recognition algorithms

found that each pedometer recorded a different number and that the pedometer attached to the chest missed majority of the steps. It is clear that in a location-aware pedometer, a simple dynamic threshold control technique can dramatically enhance the accuracy of the step counting. Energy expenditure estimation via motion sensing [24] is another application where the outcome accuracy highly depends on the accurate classification of the type of the activity performed (e.g., walking, jogging, running, jumping, etc.) and the placement of the accelerometer on the body [25]. If the user wears an accelerometer on his/her foot instead of the waist, the accuracy of the activity detection degrades dramatically [17], [18]. This is because the activity detection models implemented in the device are tuned for waist motions. As a result of wrong activity detection, the system will overestimate or underestimate the user's caloric expenditure. One of the most critical applications of motion sensors is fall detection where misclassification may cause severe injuries and often irreversible impairment. Authors in [26] proposed a fall detection application for smartphones, which uses machine learning classifiers to not only detect falls, but also to classify the particular type of fall, i.e., backward slip, forward trip, left lateral, and right lateral. They reported an accuracy of 98.7%, however, the smartphone was always attached to the backside of a special belt used by the subjects in their experiments. Recently, authors in [27] further examined the fall detection application by collecting training data from arbitrary on-body locations for the four types of falls. They found that the overall fall detection accuracy significantly decreased to 72.2%, which can be inadequate for use in real-life scenarios.

In general, the accuracy of any context-aware application is likely to improve if the knowledge of wearable sensor location is available. These variations introduced by the normal use of the wearable sensors correspond to sensor position changes or displacements on the user's body. Furthermore, displacement can be static when sensors are initially misplaced and the location is not corrected throughout the use.

III. General Framework

This paper studies efficient approaches for on body sensor localization. We use real data collected using wearable motion sensors to demonstrate the effectiveness of the proposed algorithms. Our node localization technique automatically discovers the on-body location of medical monitoring devices using acceleration and angular velocity data. Accelerometers are one of the most widely used types of motion sensors, which have been used for a variety of applications such as device orientation detection, game controlling, shock protection, and activity discovery. Our developed techniques allow both on-line and off-line discovery of the device location on the body.

TABLE I. Locations of the sensor nodes for data collection

Node ID	Locations (Section IV)	Locations (Section V)
1	L-side Pocket	Waist
2	R-side Pocket	R-wrist
3	L-front Pocket	L-wrist
4	R-back Pocket	R-arm
5	Waist	L-thigh
6	Hold-in-hand	R-ankle
7	——	L-ankle

On-body sensor localization is a hard problem mainly due to the large number of potential body locations to which a wearable sensor can be attached. Prior research in this area is based on several assumptions: 1) perform node localization assuming that the activity type is known a priori; 2) equal number of nodes and body locations in the network; and 3) fixed orientation of the nodes during operation.

To eliminate these limitations, we study the problem of on-body sensor localization in the context of machine learning and signal processing and offer several contributions: 1) we study impact of sensor mis-orientations on performance of our node localization algorithm; 2) we propose to integrate the output of node localization algorithm within activity recognition algorithms by adding location information as new features in the activity recognition process.

In the first step, sensor data is collected for a sequence of daily activities. After data segmentation, an exhaustive set of statistical and morphological features are extracted from each data segment. A set of different classifiers are then developed for the purpose of node localization followed by activity recognition. A high level diagram illustrating the data processing for both localization and activity recognition is shown in Fig. 1.

IV. Impact of Mis-orientation on Node Localization

In this section, we study the impact of sensor mis-orientation on performance of our node localization algorithm [17].

A. Data Collection and Processing

The data used for this analysis contains accelerometer signals collected using smartphones placed on various locations on the body. The second column in Table I shows the smartphone locations used for data collection. We used Samsung Galaxy S4 smartphones placed on 6 different locations and programmed to sample accelerometer sensor at 100Hz. We collected data for a sequence of daily activities in a natural setting. The duration of each trial was approximately 4 minutes. The activities include walking, turning left, turning right, turning clockwise 180 degrees, stairs ascent, stairs descent, standing up from an armchair, bending and grasping from the ground using left/right hand, sit to stand, and stand to sit. We also considered 4 different orientations of the smartphone on each body location. Two subjects performed the activity sequence for each specific sensor location and orientation three times. The obtained dataset was then used to develop node localization algorithms.

Before feature extraction, the collected data were segmented into windows of 350 samples. We then extracted a number of representative features from each data segment. For node localization purposes, it is largely unknown what features are most effective. In recent studies [17], [18], we used statistical features that provided promising results. Thus, we used the same set of features as a basis for node localization in this paper. The statistical features are listed in Table II. In addition to these features, we also extracted 10 morphological features from each signal segment. The morphological features aim to capture structural properties of the signal. Thus, our morphological features are signal samples evenly spaced in time over the entire signal segment associated with a particular segment of the acceleration data.

B. Results

As shown in Table II and discussed in Section IV-A, 20 features were extracted from each signal segment. Given that each sensor on smartphone has 3 axes, the total number of features extracted from each sensor node was 120. Using these features, Table III shows accuracy performance of our sensor node localization algorithm. As it can be observed from this table, all the nodes can be detected with a minimum accuracy of 82.9% using a kNN (k-Nearest Neighbor) classifier. On average, the system achieved 89.8%, 87.1%, 91.4%, and 90.8% accuracy using SVM (Support Vector Machines), J48 (decision tree), MLP (Multi-Layer Perceptron), and kNN respectively. Compared to previous studies [17], the localization accuracy remains approximately the same, although the dataset contains sensor variations in the form of mis-orientations. We also note that these results are based on a classification scheme that is activity-independent.

V. Integration of Node Localization with Activity Recognition

Previous research on on-body sensor localization assumes that the output of the localization algorithm is used to activate an activity recognition (AR) algorithm specifically devised for the identified sensor locations. This scenario is illustrated in Fig. 2. Assume a scenario where a localization algorithm is developed to identify the location of the sensor among L possible body locations. Furthermore, assume that during execution of the system, N sensor nodes are utilized. The approach in Fig. 2 results in training $M = C(L, N)$ classifiers for activity recognition, because the sensors can be placed in any combination of the locations. Therefore, the computation complexity, the classifier training, and resource consumption of such implementation will be extremely high. We propose to use the output of the localization algorithm as a feature vector fed into the classification algorithm reducing the number of AR classifiers to one. In this section, we demonstrate the effectiveness of such a combined node localization and activity recognition technique.

TABLE II. Extracted features from each sensor axis

Feature	Description
AMP	Amplitude of signal segment
MED	Median of signal
MNVALUE	Mean value of signal
MAX	Maximum value of signal
MIN	Minimum value of signal
P2P	Peak to peak amplitude
STD	Standard deviation
VAR	Variance
RMS	Root mean square power
S2E	Start to end value

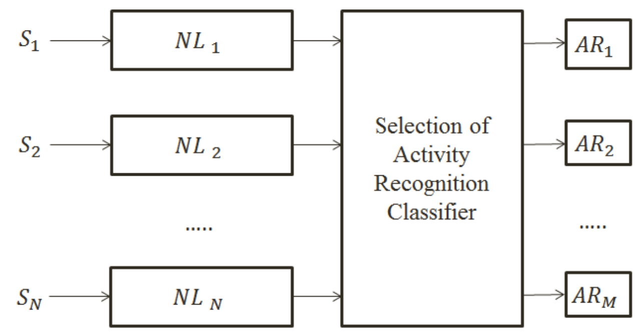

Fig. 2. Activity recognition model for lower number of nodes compare to locations

A. Data Collection and Processing

We used a wearable sensor network composed of seven motion sensor nodes with embedded accelerometer and gyroscope sensors. The data was collected for 14 transitional activities including sit to stand (1), stand to set (2), sit to lie (3), lie to sit (4), bend to grasp (5), rising from bending (6), kneeling right(7), rising from kneeling (8), look back (9), return from look back (10), turn clockwise (11), step forward (12), step backward (13), and jump (14). A total of 3 healthy subjects performed each activity 10 times. Each sensor node was programmed to transmit the data to a laptop computer where all the data was stored for off-line data processing and algorithm development. The third column in Table I shows the body locations on which the sensors were worn during the data collection.

In a recent study [28], we showed that the set of features in Table II are effective in activity recognition. In addition to these statistical features, the location of each sensor node was added to the feature space. The features were then fed into a kNN classifier to assess performance of our single-classifier activity recognition.

B. Results

Fig. 3 shows accuracy of the activity recognition with two sensor nodes and six locations based on a kNN classifier. The results are obtained using cross-validation analysis. On average, the activity recognition system achieved 99.5%, and 99.3% precision and recall respectively. The accuracy of the

TABLE III. ACCURACY (%) OF NODE LOCALIZATION IN PRESENCE OF SENSOR MIS-ORIENTATION

Classification/Node	**L-side pocket**	**R-side pocket**	**L-front pocket**	**R-back pocket**	**Waist**	**Hold-in-hand**	**Average**
SVM	90.3	91.4	91.2	82.9	92.5	90.8	89.8
J48	87	88.3	86	84	88	89.4	87.1
MLP	91.6	91.2	91.7	92	93.3	88.6	91.4
KNN	94.3	93.3	92.6	82.7	89.3	92.6	90.8

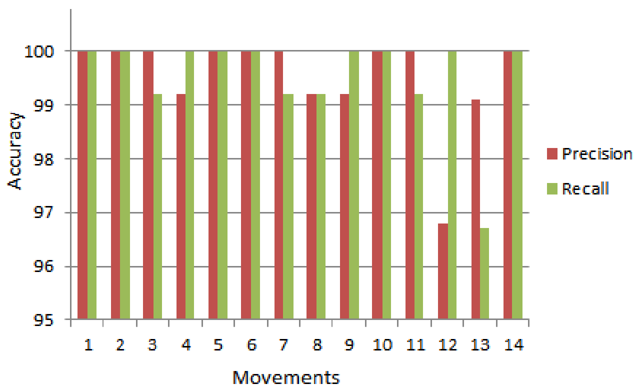

Fig. 3. Activity recognition accuracy for 14 transitional movements using 2 sensor nodes and 6 body locations

activity recognition degraded to 23.5% in absence of the node localization algorithm. This approach demonstrates the promise of directly adding location information from node localization algorithm into the activity recognition algorithm.

VI. RELATED WORK

In general, studies related to sensor placement variations can be divided into three categories: 1) sensor placement on different parts of the body (back pocket of trousers versus side pocket of jacket) [9]–[14]; 2) sensor displacement within a given coarse location (shifting from top upper arm to middle upper arm) [15], [16]; 3) change in the orientation of sensors [29], [30].

Most of the existing studies are related to the first category of sensor placement variations. The problem of localization on the human body has been addressed by a number of researchers. The most well-known studies were conducted by Kunze in [9]–[11]. While these studies address the problem of localizing devices on the body, the results of their classification is limited to four exact locations (wrist, breast pocket, trousers pocket, and right eye). As denoted by the authors, the locations that have been chosen represent typical location of appliances and accessories. In contrast, our approach is designed to discover device location on a variety of regions on the body. As a result, our approach can be applied to a larger group of applications. In another study, Vahdatpour et al. [12], [13] proposed a method based on mixed supervised and unsupervised time series analysis to identify 6 regions on the body, where an accelerometer was attached directly on the skin or on the clothing. An accuracy of 89% was achieved although the classification method for identifying left and right limbs yielded poor results [14]. A limitation of their approach is that it depends on the assumption that users are capable of walking and sensor locations are identified during walking activities.

Alanezi and Mishra [27] have recently proposed a position discovery service for smartphones. The service finds the actual position of the smartphone, such as hand-holding, watching a video, talking on the phone, pants pocket, hip pocket, jacket pocket. They showed that total accuracy increased dramatically when both accelerometer and gyroscope were used and individual users trained their own classifiers. The authors showed that the latter has a more pronounced effect on the improvement in accuracy and the former led to significantly higher energy usage by the smartphone, as a gyroscope sensor consumes more power than an accelerometer. Two downsides of this position discovery service are: 1) The length of the training period can be problematic as some users may refrain from using services that require training beforehand let alone a lengthy one; and 2) the subjects of the study had to wear similar clothing on both the training day and the day of experiment.

In the area of sensor displacement, Banos et al. [30] explored the effects of sensor displacement caused by both the intentional misplacement of sensors and self-placement by the user. Investigators in [16] considered the sensor displacement a continuous tracking problem. They also detected anomalies in the recorded data that the inference algorithm should disregard. However, in order for their algorithm to work, the initial exact location of the sensor must be known.

As for studies related to sensor orientation and rotation, Jiang and colleagues [29] calculated a transformation matrix with the Gram-Schmidt orthogonalization process to eliminate the sensor's orientation error. Another study presented a weighted sensor fusion-based model to compensate for variations caused by sensor rotation.

VII. CONCLUSION

In this paper, we presented a machine learning approach for on-body sensor localization. Our approach which relies on computationally simple classification algorithms showed promising results for on-body node localization. We specifically focused on activity recognition applications and studied the impact of sensor mis-orientations on the performance of the node localization. The results demonstrated that mis-orientations have minimal impact on node localization. We obtained an accuracy of 90.8% using a kNN (k-Nearest Neighbor) classifier even when the sensor nodes are mis-oriented during their operations. We also devised an approach to integrate outputs of node localization with activity recognition. Our activity recognition achieved 99.5% precision and 99.3% recall while sensor location information is used as a feature in activity recognition. The results of our study help in designing future activity monitoring technologies. We proposed a unified activity recognition that allows users to wear the sensor nodes on desirable locations on the body.

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