Context-Aware Data Analytics for Activity Recognition

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***Abstract*— Remote Health Monitoring Systems are gaining an important role in healthcare by collecting and transmitting patient information and providing data analytics techniques to analyze the collected data and extract knowledge. Physical activity recognition and indoor localization are two of the most important concepts in assistive healthcare, where tracking the positions, motions and reactions of a patient or elderly is required for medical observation or accident prevention. In this paper, we propose a novel context-aware data analytics framework to classify and recognize the physical activity based on the signals received from a worn SmartWatch, the location information of the human subject, and advanced machine learning algorithms. In this approach, we take into account the physical location of the human subject as contextual information to improve the accuracy of the activity classification. The hypothesis is that the location information can get involved in classifier decision making as a prior probability distribution to help improve the accuracy of activity recognition. The results demonstrate improvements in accuracy and performance of the activity classification when applying the proposed method compared to conventional classifications.**

Keywords-Activity Recognition; Indoor Localization.

I. INTRODUCTION AND BACKGROUND

As the number of elderly people grows rather quickly over the past few decades and continues to do so [1], it is essential to seek alternative and innovative ways to provide affordable healthcare to the aging population [2]. A compelling solution is to enable pervasive healthcare for the elderly or patients with chronic disease at their own homes, while reducing the use and dependency of healthcare facilities. New technologies, such as Body Sensor Networks (BSN) and Remote Health Monitoring Systems (RHMS) allow for collecting continuous data and monitoring the patients in their home environment. There have been a number of studies on end-to-end remote health monitoring and medical data analytics using wearable or environmental sensors known as Smart Environment or Smart Home [3]-[7]. RHMS has shown substantial potential in reducing healthcare costs and improving quality of care [3]-[10]. Rapid advances in many technological domains including electronics, wireless communications, Internet, and sensor design has led to the development of effective RHMS that can collect varying physiological information, vital signs, and physical activity from patients [3]-[7].

Although RHMS have shown promise in reducing healthcare costs and improving quality of care, effective analysis of the data collected by these systems and the potential benefits of utilizing such analysis is by large an open problem. One of the key demands in such an assistive environment is to promptly and accurately determine the state and activities of an inhabitant subject. The physical activity recognition and indoor localization provide effective means in tracking the positions, motions, and reactions of a patient, the elderly or any person with special needs for medical observation or accident prevention [11][12].

Physical activity recognition using wearable sensors or smartphones has been a long-standing problem. There have been a number of studies on utilizing machine learning algorithms to monitor the activities of daily living [24][25]. However, in this paper, we propose a novel context-aware data analytics framework to classify the physical activity based on the signals received from a wearable sensor (e.g., SmartWatch [28]), the position information of the human subject, and advanced machine learning algorithms. The location of a patient can provide important prior information that can be used to better classify the physical activity. We hypothesize that the location information of the human subject can get involved in classifier decision making as a prior probability distribution to improve the accuracy of activity recognition. In other word, we take into account the location of the subject as contextual information to improve the accuracy of the activity classification. The results demonstrate improvements in accuracy and performance of the classifier when applying the proposed method compared to typical classifications.

The rest of the paper is organized as follows: Section II describes the systems architecture and main modules for the proposed context-aware data analytics framework, Section III provides a brief overview of the indoor localization technique that we use to come up with the contextual information. This localization technique is a novel approach developed by the authors. However, since the focus of this paper is on data analytics, we just briefly review this technique, and use the results as contextual information in

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our analytics framework. Section IV describes the details of the proposed context-aware analytics framework for activity recognition, including feature extraction, feature selection algorithms, classification, training/testing stages, and the context-awareness characteristics of the system. Finally, Section V describes the results and conclusion.

II. RELATED WORK

Physical activity monitoring and indoor localization are important problems in the areas of wireless health and assistive healthcare that have raised increasing attention recently [12]-[37][28][36]. Monitoring the activities of daily living with smartphones and devices with these phones have been well-studied [4][24]-[37]. In particular, Alshurafa, et al. [4] presents a comprehensive activity recognition process and particularly, looks at activity tracking for a clinical environment, and how to guarantee that patients are performing the desired activity. Gupta, et al. [37] presents an activity recognition system using a single waist-mounted accelerometer to classify gait events into six daily living activities. SmartWatches have also been used to provide activity tracking applications to date [28][35]. Mortazavi, et al. [28] provides visual feedback and interface for activity repetition counting using SmartWatch. Park, et al. [35] develops a watch sensor to track fall, walking, handrelated shocks, and general activity. Using a feature extraction and selection technique, results are presented in a 10-fold cross validation to determine the ability to track elderly patients. Park, et al. [35] uses a forward selection technique for feature selection and a support vector machine, to obtain accuracy results and recall results. In this study, we propose a new context-aware activity recognition system that utilizes the SmartWatch accelerometer and gyroscope signals, and takes into account the location of the subject as contextual information to improve the accuracy of the activity classification. The results demonstrate improvements in accuracy and performance of the classifier when applying the proposed method compared to typical classifications.

III. SYSTEM ARCHITECTURE

The proposed framework includes two main modules: a) Indoor Localization/Tracking Module and b) Context-Aware Activity Recognition Module. Indoor Localization and Tracking Module is responsible for estimating and tracking the position of a patient. We use a novel approach for localization based on spatial sparsity of target in x-y-z space and the Received-Signal-Strength (RSS) between a SmartWatch and RF beacons mounted in the building.

Context-Aware Activity Recognition Module is responsible for classifying and recognizing patients' physical activities using data analytics techniques based on the wearable embedded accelerometer and gyroscope signals. This module includes feature extraction, feature selection and dimensionality reduction, and context-aware classification submodules. In the proposed approach, we exploit the location information of the subject (received form patient tracking module) to achieve more accurate results for activity recognition. Details of these modules are described in next sections.

IV. INDOOR LOCALIZATION AND TRACKING

As mentioned before, the main focus of this paper is not on indoor localization; instead it is on context-aware data analytics for activity recognition knowing the indoor location of the individual. In other word, we take into account the position of the human subject as contextual information to improve the accuracy of the analytics engine for activity recognition. Thus, in this paper, we only provide a brief overview of the novel indoor localization techniques that we have developed in our other studies, and then apply these techniques to estimate individual's location that will be later used in our analytics framework. For more details about our developed localization techniques please refer to [11]-[17].

Indoor localization has been a long-standing and important problem in the areas of signal processing and sensor networks that has raised increasing attention recently [11]-[23]. One of the key demands in assistive environment is to promptly and accurately determine the state and activities of an inhabitant subject. Indoor localization provides an effective means in tracking the positions, motions, and reactions of a patient, the elderly or any person with special needs for medical observation or accident prevention.

The classic approach for localization is to first estimate one or more location-dependent signal parameters, such as Time-Of-Arrival (TOA), Angle-Of-Arrival (AOA) or RSS. Then in a second step, the collection of estimated parameters is used to determine an estimate of the subject's location. The TOA-based methods are usually more accurate than RSS or AOA techniques. However, the accuracy of the classic TOA based methods often suffer from massive multipath conditions for indoor localization, which is caused by the reflection and diffraction of the RF signals from objects (e.g., interior walls, doors or furniture) in the environment [23]. Moreover, it usually necessitates using synchronized emitters/sensors to be able to estimate accurate time-of arrival or time-difference-of-arrival.

In [11]-[15], we introduced a novel accurate localization method based on the spatial sparsity in the x-y-z space. In this approach, we directly estimate the location of the emitter without going through the intermediate stage of TOA or RSS estimation. To this end, we utilize the spatial sparsity of the target (SmartWatch worn by a human subject) in the X-Y-Z space, and use the convex optimization theory to estimate the location of the subject. Assume that we divide the X-Y-Z space into fine enough grids. By assigning a positive number to each grid that contains the target and zeros to all the rest of grid cells, we will have a very sparse 3-dimensional grid matrix that can be reformed as a *sparse vector*. Since each element of this

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grid vector corresponds to one grid point in the X-Y-Z space, we can estimate the location of emitters by extracting the position of non-zero element (or non-zero elements when we have more than one subject to be determined) in the sparse vector. To this end, we have to estimate the sparsest vector that minimizes the cost between the predicted received signal and the actual observed signal with respect to the signal model and distance between the transmitted signals and the received signals (for details and problem formulation please refer to [11]-[15]).

The results demonstrate that the proposed method has very good performance even with small number of sensors. The results also indicate that, in contrary to the classic methods, the proposed approach is a very effective and robust tool to overcome multipath issues, which is a very serious problem in indoor localization. Furthermore, the system works well in noisy environments with low SNRs. It implies that, even with low transmitted power (to keep the devices small with long battery life), we can still achieve a high localization accuracy.

Figure 1 shows some of the results for patient localization and tracking in a sample building using only 4 RF sensors mounted at the corners of a building. Figure 1-(a) shows the actual trajectory (blue line) of the patient walking around in the room, and the estimated path (red line) by the proposed system. Figure 1-(b) shows the error defined as the root-mean-square (RMS) errors for positioning in the X, Y and Z dimensions.

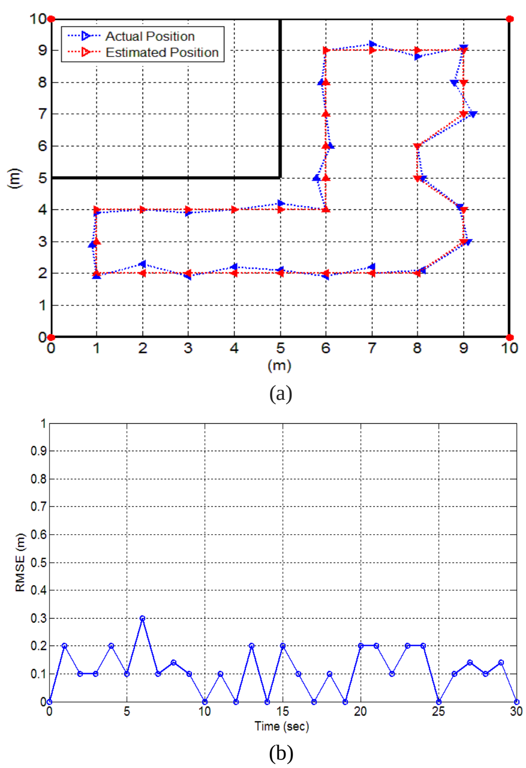

Figure 1. (a) True position of the patient (in blue) and the estimated position (in red), (b) Error in positioning for each location in part (a).

V. Context-Aware Analytics Framework for Activity Recognition

Context-Aware Activity Recognition Module is responsible for recognizing the physical activities based on the accelerometer and gyroscope signals. This work will investigate the ability of the SmartWatch to recognize and track the necessary activities of human subjects in order to better assess their health status. In particular, by identifying the transitions between sitting, standing, and lying, this work approaches the classification of patient status. Monitoring the Activities of Daily Living (ADL) through wearable body sensors has attracted extensive attention recently [24]-[28]. In this study, we propose a context-aware activity recognition system based on the signals received from embedded accelerometer and gyroscope of a SmartWatch, a real-time machine learning based analytics engine, and the position information received from the indoor localization module.

Our preliminary results [28] show that the watch can provide accurate activity tracking results similar to custom sensing environment. However, in this work, we propose a context-aware technique by taking into account the indoor position of the individual as prior contextual information that can modify the classifier model, and consequently provide more accurate results for activity recognition. The activity recognition module includes feature extraction, feature selection, and context-aware classification submodules as described in the following.

A. *Feature Extraction and Feature Selection*

The first step is to gathering the patient's activity signals from the SmartWatch embedded accelerometer and gyroscope. After receiving the signals, the next step is to data preprocessing and feature extraction. We use a moving average window as a low-complexity low-pass filter for the purpose of denoising. Then, a total number of 150 features are extracted from accelerometer and gyroscope signals. Statistical and morphological features are the most common features used for data analytics. Theses feature are extracted for each one of the three axes of the accelerometer and gyroscope. Some of the extracted features include Mean, Standard Deviation, Kurtosis, Skewness, Energy, Variance, Median, RMS, Minimum, Maximum, Sum, Average Difference, Eigenvalues of Dominant Directions, CAGH, Average Mean Intensity, Dominant Freq., Peak Diff., Peak RMS, Root Sum of Squares, First Peak, Second Peak. In this study, the Samsung Galaxy Gear SmartWatch is used for experimentation. It employs a $\pm 2g$ triaxial accelerometer and ± 300 degree per second gyroscope sensors.

Once the features are extracted, a dimensionality reduction algorithm is applied to select the most prominent features and reduce the redundancy. The conventional feature selection algorithms usually focus on specific metrics to quantify the relevance and redundancy of each feature with the goal of finding the smallest subset of features that provides the maximum amount of useful information for prediction. Thus, the main goal of feature selection algorithms is to eliminate redundant or irrelevant features in a given feature set. Applying an effective feature selection algorithm not only decreases the computational complexity of the system by reducing the dimensionality and eliminating the redundancy, but also increases the performance of the classifier by removing irrelevant features. In this paper, we tried both wrapper and filter methods; the two well-known feature selection categories. Wrapper methods usually utilize a classifier to evaluate feature subsets in an iterative manner according to their predictive power. A new feature subset is used to train a predictive model that will later be evaluated on a testing dataset to assess the relative usefulness of subsets of features [39]. Figure 2-(a) provides an illustration of the wrapper feature selection method.

Filter methods use a specific metric to score each individual feature (or a subset of features together). The most popular metrics used in filter methods include correlation coefficient, mutual information, Fisher score, chi-square parameters, entropy and consistency. Filter methods are very popular (especially for large datasets) since they are usually very fast and much less computationally intensive than wrapper methods. Figure 2-(b) illustrates the steps involved in the filter feature selection method.

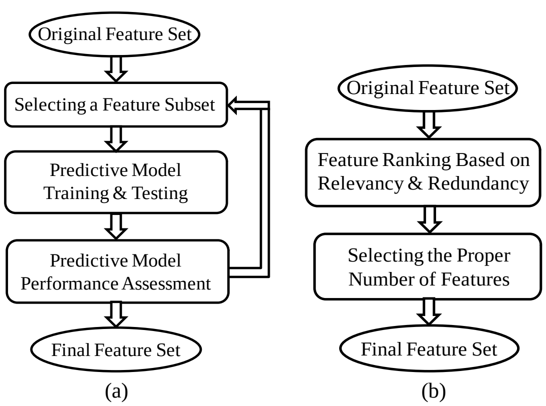

Figure 2. Feature Selection: (a) Wrapper method, (b) Filter method.

In this study, after trying several filter and wrapper methods, we finally chose only 5 features to keep the computational complexity low on the device. The selected features includes: minimum of acceleration axis x (min ax), average acceleration axis z (avg az), eigenvalue acceleration axis z (eigen az), correlation between acceleration axis x and y (cor axy), sum gyro axis z (sum gz).

B. *Classification: Training and Testing*

Once the subset of features is selected, a machine learning based classifier is applied to classify the motions. In this research, we tried various classification algorithms such as SVM, Random Forest, BayesNet, and Artificial Neural Net (ANN) as the predictor. According to our results, a Random Forest classifier with 100 trees provided fast and accurate prediction results for our dataset. Random Forest is an ensemble learning classification method comprising of a collection of decision tree predictors operating based on i.i.d random vectors. In this process, each tree casts a unit vote for the most popular class [40]. The classifier was supplied with training data labeled with 6 labels being the six transition movements (sit_to_lie, sit_to_stand, stand_to_sit, stand_to_lie, lie_to_sit, lie_to_stand). The recognition algorithm must then be validated to ensure the proper development of a system to accurately track the state of subjects. Figure 3 indicates the Training and Testing stages. The next section describes the context-awareness approach and how we take into account the location information to improve the classifier accuracy.

C. *Context Awareness*

The indoor position of a patient (received from indoor localization and tracking module) can provide significant prior information about the possible physical activity. For example, when we know that the patient is in the kitchen, the probability of standing is much higher than lying, consequently, the labels are not uniformly distributed anymore. Thus, by knowing the approximate position of the patient, we will have better understanding about the possible activities that the patient can have.

We hypothesize that the location information can get involved in classifier decision making as a prior probability distribution to help improve the accuracy of activity

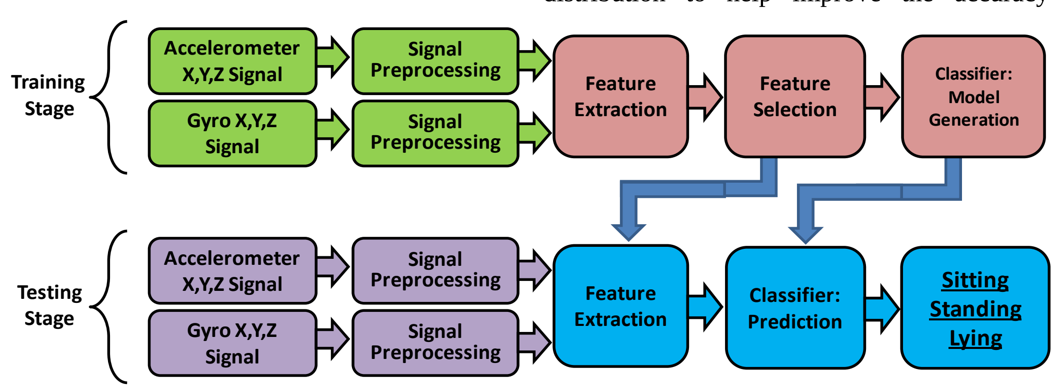

Figure 3. The regular Physical Activity Classification.

recognition module.

Assume that $F_1, \ldots, F_N$ are the classifier input features and C represents the classifier labels. Then, the classifier probability model can be expressed as a conditional probability $p\,(C \mid F_1, \ldots, F_N)$ (known as *Posterior Probability*) that can be formulated using the Bayes' Theorem as following [41]:

$$p\,(C \mid F_1, \ldots, F_N) = \frac{p\,(C, F_1, \ldots, F_N)}{p\,(F_1, \ldots, F_N)} \qquad (1)$$

The joint probability in the numerator can be reformulated as:

$$\begin{aligned} &p\,(C, F_1, \ldots, F_N) = p\,(C)\,p\,(F_1, \ldots, F_N \mid C) \\ &= p\,(C)\,p\,(F_1 \mid C)\,p\,(F_2, \ldots, F_N \mid C, F_1) \\ &= p\,(C)\,p\,(F_1 \mid C)\ p\,(F_2 \mid C, F_1)\ \ldots\ p\,(F_N \mid C, F_1, \ldots, F_{N-1}) \end{aligned} \qquad (2)$$

A "*Maximum A Posteriori*" (MAP) decision making rule can be applied as following to pick the most probable class label:

$$\begin{aligned} &calssify\,(f_1, \ldots, f_N) \\ &\quad = \arg\max_c\ p\,(C = c)\ p\,(f_1, \ldots, f_N \mid C = c) \end{aligned} \qquad (3)$$

The term $p\,(F_1, \ldots, F_N \mid C)$ (called *likelihood*) is usually determined in the training stage. For the case of simplicity (e.g., in Naive Bayes classifier [41]), the features can be assumed to be conditionally independent. In this case, the equation (3) can be simplified to:

$$\begin{aligned} &calssify\,(f_1, \ldots, f_N) \\ &\quad = \arg\max_c\ p\,(C = c) \prod_{i=1}^{N} p\,(F_i = f_i \mid C = c) \end{aligned} \qquad (4)$$

In traditional classification, a uniform distribution is used for *Prior Probability* $p\,(C)$. However, in our approach, we hypothesize that the patient's position can provide some information about the distribution of the *prior probability* $p\,(C)$. Thus, we can write $p\,(C)$ as:

$$\begin{aligned} p\,(C = c) &= \sum_i p\,(C = c, L = l_i) \\ &= \sum_i p\,(L = l_i)\,p\,(C = c \mid L = l_i) \end{aligned} \qquad (5)$$

where $p\,(C, L)$ is the joint probability distribution of location and activity label. Thus, when the location is known, the uniformly distributed *Prior Probability* $p\,(C)$ will be replaced by the conditional probability $p\,(C \mid L = l_i)$ and consequently, the equation (4) provides more accurate model for activity recognition.

VI. RESULTS AND CONCLUSION

A pilot trial has been conducted to collect the data. The dataset contains 1200 data samples collected from 20 subjects. Table I shows the F-Score results for the activity recognition using only 5 features in two different cases: a) Using conventional classification without considering the location information, b) Context-aware activity recognition knowing and taking into account the location information. As we see, for example in the kitchen, we achieve 7% improvement (using 5 features) since knowing the location of the subject provides significant information about the activity. However, in the living room, we achieve 3% improvement, and it totally makes sense, because the likelihoods of sitting, lying, and standing in the living room are almost similar, and consequently the prior probability distribution is closer to the uniform distribution which is the pre-assumption for conventional activity recognition too.

TABLE I. F-SCORE FOR REGULAR AND CONTEXT-AWARE ANALYTICS USING ONLY 5 FEATURES

Location	F-Score for conventional classification	F-Score for context-aware classification
Kitchen	0.81	0.88
Living room	0.82	0.85
Bedroom	0.80	0.84

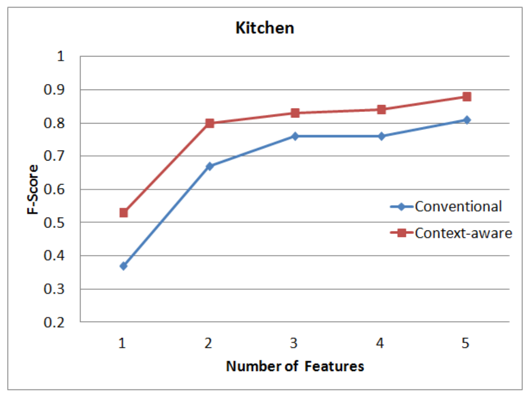

Figure 4. F-Score versus the number of selected features for conventional and context-aware activity recognition in kitchen.

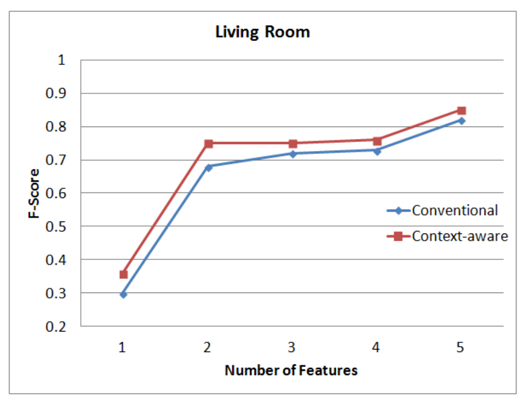

Figure 5. F-Score versus the number of selected features for conventional and context-aware activity recognition in the living room.

Figures 4 and 5 show the F-Score [41] versus the number of selected features for conventional and context-aware analytics in the kitchen and living room. F-Score is a well-known measure for classification accuracy, and it can be interpreted as the harmonic mean of precision (the fraction of retrieved instances that are relevant) and recall (the fraction of relevant instances that are retrieved). Thus, F-score is an indication of how well the system can identify the activity and how strong it is at not mis-predicting.

For example, for kitchen, we achieved 43% improvement using 1 feature and 9% improvement using 5 features in activity recognition accuracy, which is a significant improvement. Our work in [42] investigates the impact of improvement in classification accuracy on cost.

Again, as we expected, the improvement by using context-aware approach is higher in the kitchen compared to living room because the probability distribution of various activities in the living room is closer to uniform distribution.

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