Fog-centric Localization for Ambient Assisted Living

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***Abstract*—Ambient Assisted Living (AAL) is a novel discipline that aims at improving the quality of life for all generations, especially the elderly, with the help of information and communication technologies. Behavioral tracking AAL systems necessitate the monitoring and understanding of daily activities and preferences of the user for design of customized, context-aware services and detection of behavior anomalies. Localization of the user is, therefore, key to facilitate real-time activity monitoring in AAL applications. Although several localization techniques have been proposed to date, majority of them incur a high operational cost owing to dependency on dense sensor deployments for ambient intelligence or use of expensive hardware such as GPS receivers. In this paper, we propose a low-cost Wireless Sensor Networks (WSN) system, comprising of a single wearable device and a cloud gateway, for outdoor localization in the context of AAL. With the inception of the Fog Computing paradigm, we consider the implementation of a light-weight data mining technique, Iterative Edge Mining (IEM), on the wearable device for on-board activity recognition. IEM is based on the classification of signal distributions to enable real-time mobility tracking as the user moves around an environment. Given the topology information and the activity sequence generated by the algorithm, we estimate the user location by associating the distance covered over time with the orientation values. Alerts are signaled locally upon detection of behavior anomalies and transmitted to the gateway node using a delay-tolerant communication framework. As such, IEM runs autonomously on the sensor node without interaction with external objects, thereby, improving the responsiveness as well as the operational cost of our system. We evaluate the performance of IEM in terms of localization accuracy in an outdoor environment.**

Keywords—ambient assisted living; localization; fog computing; edge mining; wireless sensor network

I. Introduction

With advancing age, the elderly often experience physical disabilities and require support with mobility and the activities of daily living. Moreover, they may develop some form of Dementia, a chronic syndrome that causes deterioration in the cognitive function beyond what might be otherwise expected with ageing. This, in turn, leads to challenging behavioral and psychological changes such as repetition, aggression, agitation and psychosis. Alzheimer's is the most prevailing form of Dementia that affects the short-term memory, orientation and intellectual capacity of an individual [1]. It may result in loss of identity, thereby, increasing distress for the patient as well as the caregivers. Wandering is a common symptom for Alzheimer patients that poses serious threat to their safety and may lead to traumatic experiences. Personalized monitoring and care of the elderly is, therefore, important to assist them with daily activities and ensure their well-being. Ambient Assisted Living (AAL) is a recent trend that combines Information and Communication Technologies (ICT) with the social environment with a view to improve the quality of life for all generations, primarily the ageing population with cognitive disabilities [2]. An important aspect of AAL is localization of the user to enable activity monitoring for safe and independent living and minimize the risk of wandering [3]. AAL solutions have the potential to not only allow patients to restore their usual routine but also to reduce the burden on caregivers. Although a few activity tracking systems have been proposed for AAL, their implementation is constrained due to the high operational cost incurred by use of expensive hardware such as GPS modules or dense sensor deployments and cloud infrastructure required for ambient sensing, communication and data analysis.

Meanwhile, owing to the growth in ICT, there has been a tremendous improvement in the design and computational capabilities of small devices that constitute edge of the network in the Internet of Things (IoT). A new networking paradigm, Fog Computing, proposes a partial migration of intelligence away from the cloud towards the network edges [4]. That is, Fog Computing aims at facilitating localized data processing and event detection at the end-user terminals. The concept has gained importance owing to its ability to efficiently utilize the in-network resources while minimizing dependency on the cloud infrastructure. It not only reduces the operational cost but also improves the responsiveness of the system for alert generation. Over the past few years, numerous interpretations of fog nodes within IoT have been discussed. While some approaches propose the use of computational resources at edge devices such as network switches [5], others suggest the use of free computation slots on user mobile phones [6]. Recent studies have further brought down the concept of Fog Computing to wireless, battery-operated sensor devices that sit at the edge of Wireless Sensor Networks (WSN). Edge Mining is a novel approach that suggests the implementation of light-weight data mining tasks on the sensor devices [7]. While resource-intensive network learning is performed on the cloud, minor computations carried out at the sensor nodes enable real-time event detection. Furthermore, Edge Mining algorithms improve the energy efficiency of WSN by reducing packet transmissions to the cloud gateway via localized data reduction and, in turn, increase operational time of the system.

In this paper, we implement fog-enabled mobility tracking within WSN for user localization in the context of AAL. Our WSN system consists of a low-cost wearable activity tracker and a cloud-gateway, and assumes prior knowledge of the application environment and user-specific information. The wearable device consists of an Inertial Motion Unit (IMU) that gathers accelerometer and gyroscope data as the user moves around the application environment. Real-time analysis of the data is carried out on the device itself using a Fog Computing approach called Iterative Edge Mining (IEM), proposed by the authors in [8]. IEM is based on the Edge Mining algorithms and performs activity state recognition using a decision-tree classifier on signal distributions. Given the topology information of the environment, the mobility pattern produced by IEM is used along with the gyroscope data to determine user location. Alerts are generated locally at the occurrence of unexpected events and transmitted to a cloud gateway using delay-tolerant communication. While our device performs localization autonomously, the resource-intensive network learning for IEM is performed on the cloud to modify the parameters for on-board analytics, if necessary, and tune the results according to changes in application environment and requirements. Results of the learning are sent back to sensor device, in a delay-tolerant manner, to adjust the analytic model. The performance of our system has been evaluated for outdoor localization using analysis in R.

The remainder of the paper is organized as follows. In section II, we discuss the related work. The application scenario proposed solution is presented in section III. The evaluation of our system is discussed in section IV followed by the conclusions in section V.

II. Related Work

In this section, we present an overview of some of the localization techniques and AAL solutions, proposed to date. We also discuss the state-of-the-art in sensor analytics with emphasis on the Edge Mining approach that forms the basis of IEM.

A. Localization Techniques

So far, numerous approaches have been proposed for localization in both outdoor and indoor applications. The use of Global Positioning Systems (GPS) based systems is well-known for outdoor positioning owing to the high availability of GPS modules in current IoT devices and the positioning accuracy. However, GPS units are expensive as well as energy exhaustive, thereby, affecting the lifetime of a system. Additionally, their performance deteriorates significantly in crowded and indoor areas due to the absence of line of sight to GPS satellites. Consequently, cooperative techniques have been proposed that use hybrid positioning systems to improve the performance of GPS systems [9]. Alternatively, radio frequency based solutions have been proposed for localization in indoor environments such as smart buildings as discussed in [10]. The role of WSN for node localization has also been explored. The techniques proposed are either anchor-based where fixed nodes with known GPS coordinates are used to estimate the coordinates of mobile nodes using different ranging techniques [11] or anchorless that aim at determining only the relative distance between two nodes. Majority of the solutions, however, rely on dense sensor networks for accurate sensing and communication making the network installation a tedious task. In recent years, Pedestrian Dead Reckoning (PDR) systems, comprising of wearable inertial sensors for self-tracking, have been designed to calculate user position based on the past estimates and displacement over short intervals of time. Personalized monitoring with PDR systems allows better understanding of the user behavior and mobility patterns for customization of services. A 3D localization technique using multiple wearable sensors has been presented in [12]. The system monitors the spatial location of users based on the orientation of body segments and lower limb movements. Although, the experimental results show an accuracy of up to 99%, the suitability of the approach is arguable due to use of multiple sensors that may cause discomfort. Moreover, standalone PDR systems often accumulate error over time due to sensor drift. Their use is, therefore, combined with contextual information or low-cost beacons that facilitate recalibration as shown in [13].

B. Ambient Assisted Living

With improvements in the average life-expectancy of people worldwide, there has been a simultaneous increase in the number of people suffering from cognitive disabilities, such as Dementia, that appear with age. Dementia is a progressive disorder that deteriorates the memory, comprehension and behavior of an individual. The most common cause of Dementia is the Alzheimer's disease that occurs owing to the death of nerve cells and loss of brain tissue. It has a severe impact on the short-term memory, orientation and mobility of the patient, increasing the risks associated with wandering [14]. This urges the development of smart solutions to monitor the health and activities of the patients, and provide timely care. AAL proposes the use of ICT to assist people, especially the elderly, with daily activities and mobility to allow independent living and ensure their well-being. An activity recognition and assessment technique using the smart home technology has been discussed in [15]. The system proposes dense sensor deployment inside the apartment to monitor user interaction with objects of interest. Machine learning is performed on the sequence of sensor events to classify the daily activities such as cooking, cleaning, eating and telephone use. Furthermore, the authors propose a method to develop generalized models corresponding to each activity that abstract over different application scenarios and residents [16]. More recently, activity trackers have replaced the use of static sensors to personalize care and improve behavior analysis for the individuals. In [17], wearable devices consisting of environmental and inertial sensors have been designed to continuously monitor health status and mobility of the elderly. The system combines GPS and BLE technologies to assist in outdoor and indoor mobility respectively. An outdoor navigation system that facilitates independent visits to the exhibition for the cognitively impaired has been discussed in [18]. The approach aims at social inclusion of the individuals under the umbrella of AAL. Although, the solutions perform reasonably well, their implementation is challenging due to the high operational costs. To ensure validity and usability of AAL solutions, five evaluation metrics including accuracy, availability, installation complexity and user acceptance have been outlined in [19].

C. Sensor Analytics

With advances in the IoT, there has been an immense improvement in the design and computational capability of sensor devices that constitute WSN. Traditionally constrained to sense and send, the tasks assigned to these devices nowadays incorporate an analytic component. WSN-based localization, for instance, is a form of sensor analytics that has been implemented to improve the context of sensor data. Other approaches such as Data Fusion [20] and Edge Mining [7] utilize the on-board sensor resources for reducing data redundancy within the network with an aim to improve the quality of data exchange. Reduced packet transmissions to the cloud gateway, in turn, improves the energy profile of the network. Furthermore, mapping of Artificial Neural Networks (ANN) on top of the existing WSN hardware has been proposed to facilitate classification and prediction tasks within the network [21]. We base our localization approach on the Edge Mining algorithms that inherent a certain degree of intelligence and allow real-time event detection on the sensor devices as discussed below.

1) Edge Mining

The aim of Edge Mining is to improve the energy efficiency of WSN by reducing data communication to the cloud gateway or sink node. Accordingly, it suggests the implementation of light-weight data mining tasks on the sensor devices for localized data reduction. Edge Mining has been realized using the Spanish Inquisition Protocol (SIP), described in [22]. SIP proposes the use of a shared approximation model between the sensor devices and sink node to locally predict the expected application state at sink based on the past estimates. A packet containing the new state value is transmitted only if the new state differs from the estimated value by more than a threshold. Three instantiations of general-SIP have been used for the design of Edge Mining algorithms, namely Linear-SIP (L-SIP), ClassAct and Bare Necessities (BN), as presented in [7]. The algorithms differ based on the representation of application states. L-SIP encodes the state as a point-in-time value and rate of change. The state value is calculated at the sensor node per sensing cycle and compared to the estimated value at sink node. An event is generated if the difference between the two exceeds a user-specified threshold. ClassAct is a decision tree-based activity classifier that models the state value as a smoothed probability distribution over a given set of activities [23]. The state is simplified to the index of the most probable activity and transmitted to the sink node if it varies from the previous estimate. The state recognition, however, relies on a fixed set of probabilistic moments and may not distinguish signals with different distributions but same feature values. The BN approach is primarily designed for applications that only require the summary of data over time [24]. It represents the state as a distribution across non-overlapping bins, where each bin corresponds to a range of value the variable can take, and generates events based on changes in the bin distributions. The ClassAct and BN algorithms discard majority of the raw data and significantly reduce packet transmissions to sink. The two approaches are, therefore, preferred over L-SIP for applications that do not require the reconstruction of the original signal.

III. Proposed Solution

In this work, we consider the challenge of mobility monitoring and outdoor positioning for the elderly suffering from Alzheimer's to detect behavioral anomalies and alleviate the risk of wandering. Although numerous solutions have addressed the issue of outdoor localization in the past, the technologies proposed present several implementation challenges. For instance, use of expensive GPS modules for each user is impractical due to significant operational costs. Alternatively, installation of distributed systems for pervasive computing is cumbersome and labor intensive. Considering the evaluation metrics discussed in [19], we propose a low-cost WSN-based solution for mobility tracking and user localization. Our system comprises of only two nodes - a wearable device and cloud gateway, and relies on self-measurements rather than the range-based techniques, thereby, ensuring ease of deployment. The wearable device is designed to gather IMU data and performs on-board data processing using IEM for real-time activity recognition as the user moves around the environment. Given the topology information, the user location is estimated using the mobility model generated by the algorithm after short intervals of time. The above analysis is performed autonomously on the sensor device without interaction with external objects. Alerts are signaled at the occurrence of unexpected events such as detection of mobility patterns corresponding to wandering behavior. Furthermore, a delay-tolerant communication framework is used to transmit results of the analysis to the cloud gateway. Cloud-based analysis facilitates the implementation of complex learning techniques to modify input parameters, performance metrics and user information for on-board analysis, if necessary, to tune the performance according to the application requirements. For instance, while some applications may only require coarser information such as user presence in specific zones, others may require a more precise location as in case of fall detection to facilitate immediate care. The updated model is, in turn, transmitted to the user device in a delay-tolerant manner, thereby, eliminating the need for continuous Internet connectivity.

Fig. 1 illustrates the design of our prototype devices - wearable activity tracker and cloud gateway node. The main component of the wearable is CM5000 [25] mote that consists of a MSP430 processor and CC2420 radio module. A 10 degrees of freedom IMU consisting of the MPU6050 IC [26], is connected externally to the CM5000 board to measure acceleration and orientation of the user. The components are soldered together on a PCB and placed inside a pelican casing. The device is powered up using 2 AA batteries. A light-weight TinyOS [27] program runs on the device for periodic data collection and analysis using IEM. While our system runs autonomously, it assumes prior knowledge of user-specific

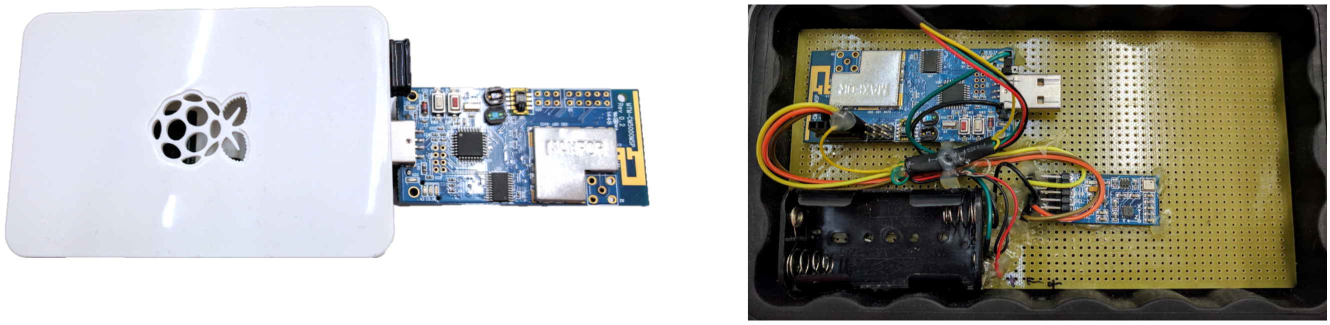

(a) (b)

Fig. 1. (a) Cloud gateway node (b) Wearable activity tracker

information, such as the average pace and normal activity levels, and topology of the application environment using initial supervised learning. The distance travelled by the person is accordingly calculated using the time series data generated by IEM and the average speed of the person. Given the topology and gyro data, user can then be localized within the environment using the displacement measure. Alerts are signaled upon identification of significant deviations from the normal behavior. The results of analysis are stored locally in the flash memory of the device as the user moves around and transmitted to the cloud gateway, hosted indoors, once the user is in its vicinity. The gateway node (fig. 1(b)) consists of a CM5000 mote connected to a Raspberry Pi 2B [28] module. The data is, in turn, uploaded on the cloud for further learning using a Wi-Fi module connected to the Pi. Once the learning is complete, the updated parameters are transmitted back to the wearable device in a similar manner. Our system design, thus, ensures the autonomy of user mobility while providing timely interventions when required.

A. Iterative Edge Mining

A key component of our device based analytics is activity state recognition that is performed by the IEM [8] algorithm. IEM is a fog-centric, sensor analytics approach that is implemented by superimposing two Edge Mining algorithms - BN and ClassAct, on a single node. IEM reads the raw acceleration values from the IMU and converts it into a smooth signal distribution using BN, per sensing cycle. An intermediate event is detected if the change in any bin distribution is significant. The sequence of BN events is fed as input to the ClassAct algorithm that determines the user activity state. The interaction between the two algorithms is controlled by the value of three input parameters - decay factor (γ), error threshold (ε) and heartbeat ($t_{heartbeat}$) that are determined using cloud-based analysis. The γ parameter ranges between 0-1 and is introduced to smooth the signal distributions on the assumption that the application state does not change abruptly. A higher value of γ, increases the weight of past estimates and reduces the fluctuations in the distribution. The resultant smoothing leads to fewer BN events and classification checks. This improves the energy efficiency and, in turn, the lifetime of the device. The reduced frequency of classification, however, also results in an increase in misclassifications and latency in detecting activity changes. The value of ε is determined based on the user-specified accuracy requirements. While the ε value does not affect the nature of signal, it sets the percentage change in bin distributions from previous estimates that is considered significant for classification. A higher value of ε ignores the small fluctuations in the bin distributions, leading to reduced BN events. Accordingly, higher values of both γ and ε are preferred to optimize the resource utilization on sensor nodes when the accuracy requirements are not rigid. A heartbeat mechanism using a parameter $t_{heartbeat}$ can be used to set the maximum time difference between two consecutive BN events and ensure periodicity of classification checks, especially in case of large decay and threshold values, if required. In [8], IEM has been proposed for activity monitoring and behavior analysis in the context of Precision Dairy Farming. The performance evaluation shows the effect of input parameters on classification accuracy and number of BN events for different mobility patterns. Once the activity state for a BN event is determined, the distance traveled since the previous event is calculated for walking activities using the average pace of the person. The user displacement is estimated with the help of gyroscope data, and the updated state and location is recorded in the flash memory of the device. Fig. 2 shows the state diagram for the on-based analytics on the wearable devices.

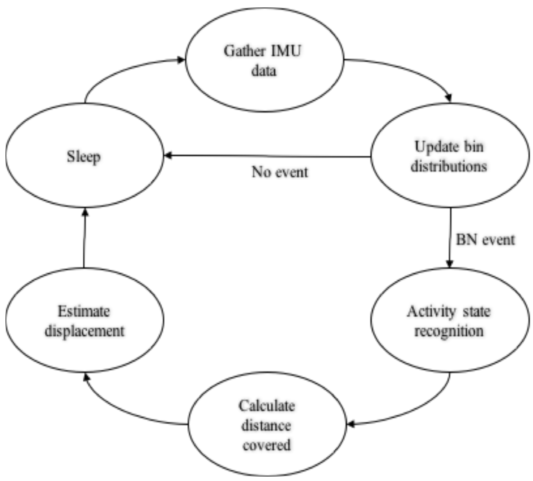


Fig. 2. State diagram for on-board analysis on wearable devices

IV. EVALUATION

We evaluate the performance of IEM in terms of accuracy of classification, cumulative error in distance calculation and reduction in classification frequency (BN events) using acceleration data collected outside our laboratory using the wearable device shown in fig 1(a). The device was hand-held in front of the body and data was collected at a frequency of 10Hz by a single user for a duration of 16 minutes by alternating between walk and stand activities every four minutes. The experiment was repeated for a total of 12 times and the distance covered in each run was 600m (300m*2). We correct the raw data collected during the experiments by removing the offset along each axis and calculate the net acceleration (square root of the sum of squares of each component) to use as input for our algorithm. Of the 12 data sets collected, we reserve 6 files for training the classifier and the other 6 files for testing the model using analysis in R. The mobility traces in training sets are used to calculate the average pace of the user through supervised learning. Moreover, the training data is used to understand the distribution of acceleration values to define bins for the BN algorithm. Fig 3. shows the density distribution of walk and stand activities for one training set. As is evident, there is a significant overlap between walk and stand data that may lead to inaccuracies in the classifier. It is, therefore, imperative to carefully define the bins such that the classification errors and latency in detecting activity state changes is minimized. Since the distribution of stand values is narrow, we use the 68-95-99.7 rule for normal curves and define three bins based on the mean and standard deviation over stand data.

As discussed in section III, while the error threshold ε only regulates the interaction between BN and ClassAct, the decay factor γ also influences the nature of signal distribution. Fig 4. illustrates the smoothing phenomenon, for the same training set as above, across different values of γ. Although the parameter value depends on decay half-life [24], we have chosen three random values to show the change in distributions for a wider range of γ. As expected, the effect of the previous distributions on the current estimate is negligible for very small value of γ (fig. 4(a)), resulting into coarse bin distributions. The smoothness of the distributions increases for higher γ values (fig. 4(b) and 4(c)) due to small changes in bin distributions per sensing cycle. The extent of smoothing affects the frequency of BN events and, in turn, the localization accuracy. We consider the performance of IEM for different γ and ε pairs. We build C5.0 decision-tree classifiers using all data instances from the 6 training files (i.e. ε=0) for five different values of γ. The performance of each classifier is tested with the remaining 6 files using the respective γ values paired with three different ε values. The mean classification accuracy of IEM for walk and stand activities across all test files, for different parameter values, is presented in table I. IEM achieves high accuracy for all γ and ε pairs. The values illustrate the expected drop in accuracy with increased smoothing in the signal distributions. Moreover, while the accuracy is same across all ε values for small γ, it decreases slightly with increase in ε for higher values of γ. This is because the frequency of classification for the former is primarily governed by γ as even the slightest changes in the bin distributions are detected as BN events. An increase in γ value, however, increases the smoothness of the curve and relies on the ε value to capture the significant changes. The effect of γ and ε on the accuracy of distance calculation and classification frequency is shown in fig 5. Instead of calculating the distance travelled for short intervals of walk, we estimate the total distance covered over 8 minutes (4+4mins) using the average pace. The cumulative error over a stretch 600m is shown in fig. 5(a). Our approach performs reasonably well for all different parameter values with the error ranging from 0.4-1%. The error in estimate increases with increase in ε due to latency in detecting state changes and reduced periodicity of distance calculation. Although, the classification accuracy decreases with increasing γ value, a consequent increase in the cumulative error is not recorded. This is because the error is calculated based on the relative time spent in each state which may be identical to the raw data despite the misclassifications. Fig. 5(b) displays the reduction in BN events across different γ and ε values. While the reduction is insignificant for small parameter values, it increases considerably for higher values of both γ and ε as expected. A reduction of 95% is achieved for a γ and ε value of (0.95, 0.7). The values of input parameters can, thus, be chosen to balance the trade-off between accuracy and energy utilization on the sensor nodes according to the user-specified requirements. A heartbeat mechanism can be implemented to ensure periodicity of updates at large γ and ε values, if required.

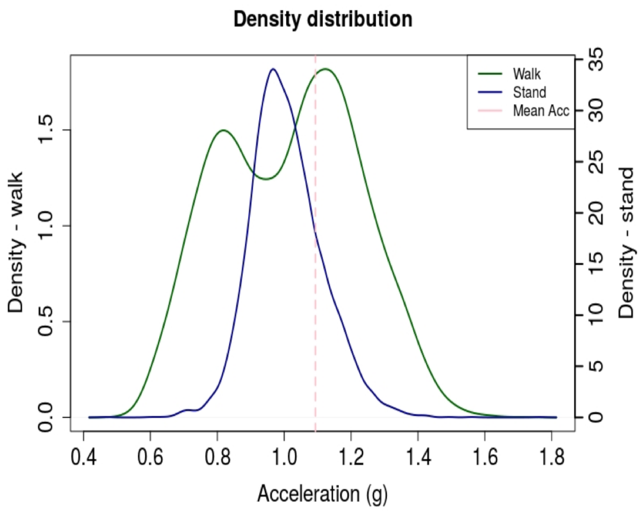
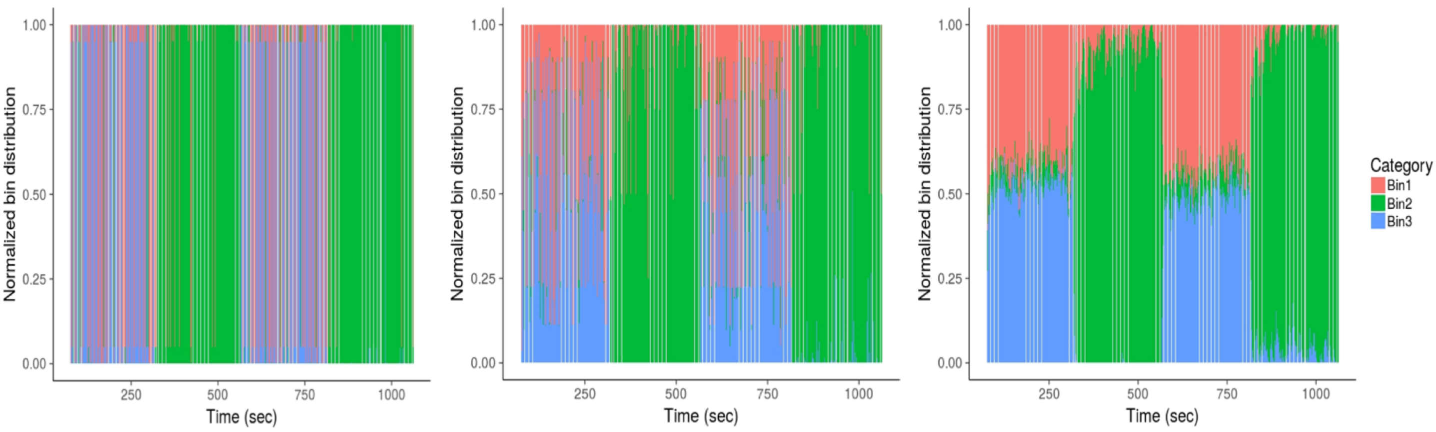


Fig. 3. Density distribution for walk and stand acceleration values

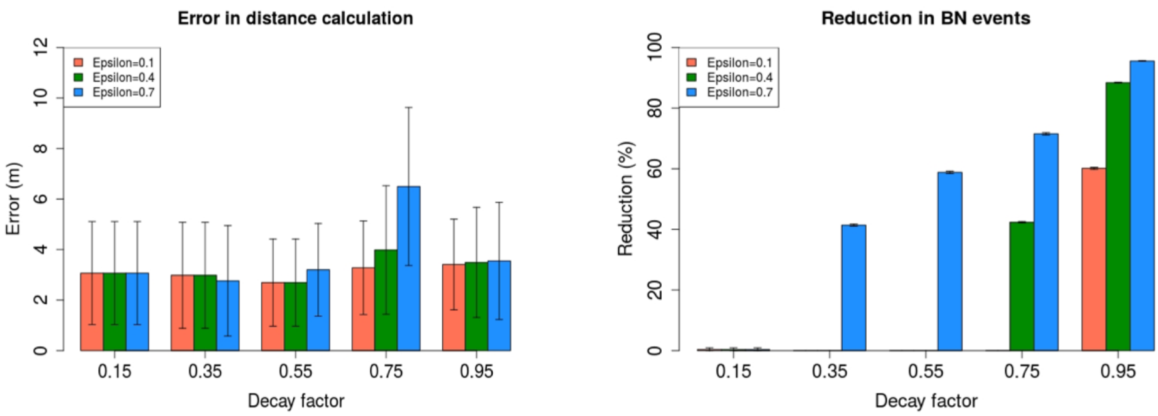
TABLE I. CLASSIFICATION ACCURACY (%)

Error Threshold (ε)	Decay Factor (γ)				
	0.15	**0.35**	**0.55**	**0.75**	**0.95**
0.1	99.36	99.31	99.17	99.12	99.01
0.4	99.36	99.31	99.17	98.77	98.75
0.7	99.36	99.19	98.75	98.59	97.95



(a) (b) (c)

Fig. 4. Smoothing effect of γ on the signal distributions (a) γ = 0.05 (b) γ = 0.50 (c) γ = 0.95



(a) (b)

Fig. 5. Variation in cumulative error and BN events with 95% confidence interval

V. Conclusions

In this paper, we present the design of our low-cost WSN system for mobility monitoring and outdoor localization of Alzheimer's patients. Our system consists of an activity tracker and gateway node, and relies on self-tracking and sensor based analytics to perform autonomous, real-time localization as the user moves around an application environment. We discuss our on-board analytics approach along with the IEM algorithm that is used for on-board activity recognition. The mobility traces generated by IEM are used to calculate the distance traveled over short intervals of time to localize the user within the given topology. Moreover, the activity sequence helps in understanding the mobility pattern of the user and enables detection of behavior anomalies to mitigate the risk of wandering. The performance of IEM has been evaluated in terms of accuracy of classification of stand and walk activities, cumulative error in distance calculations and reduction in localization frequency. The results show a classification accuracy above 97.9% and cumulative error percent between 0.4-1 across different values of the input parameters. Although the reduction in localization frequency is negligible for small values of input parameters, reduction up to 95% has been recorded. Fewer calculations can significantly improve the energy profile of sensor devices, especially for a large set of application states. In future, we plan to evaluate the performance of IEM for different mobility patterns and indoor applications. We will also look at how the alerts can be generated and transmitted to the caregivers in case the patients diverge from their normal routes or wander too far.

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