Smart Watch RSSI Localization and Refinement for Behavioral Classification using Laser-SLAM for Mapping and Fingerprinting

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Abstract— **As a first step toward building a smart home behavioral monitoring system capable of classifying a wide variety of human behavior, a wireless sensor network (WSN) system is presented for RSSI localization. The low-cost, non-intrusive system uses a smart watch worn by the user to broadcast data to the WSN, where the strength of the radio signal is evaluated at each WSN node to localize the user. A method is presented that uses simultaneous localization and mapping (SLAM) for system calibration, providing automated fingerprinting associating the radio signal strength patterns to the user's location within the living space. To improve the accuracy of localization, a novel refinement technique is introduced that takes into account typical movement patterns of people within their homes. Experimental results demonstrate that the system is capable of providing accurate localization results in a typical living space.**

I. INTRODUCTION

The year 2011 saw the beginning of the baby boomer retirement; ten thousand Americans will turn 65 every day until 2029, and by 2030, almost 20% of the U.S. population will be 65 and older [1]. Unlike other age groups, nearly 70% of these people will require some type of long-term care, including both medical services that help manage chronic illness, and non-medical services like assistance with Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs). Not only is there a drastic increase in the number of people who need long-term managed care — the life expectancy is continuing to rise at the same time. This means that many people will require long-term care for 20 or more years [2].

We can reduce the cost of long-term care by delaying its onset and improving its efficiency. Smart home health monitoring systems — which track behaviors and activities of users in their homes — can help with both of these goals, but have yet to see broad deployment because they require expensive components, provide limited data resolution, and are time-consuming to set up. Many of these systems are designed for specific clinical populations, so they are only designed to capture specific data relevant to evaluating patients with specific ailments.

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Here, an Internet-enabled smart home monitoring system is presented that is capable of measuring a wide variety of phenomena while providing room-level localization of the user. The goal of the system is to achieve continuous evaluation of ADLs and the IADLs, thus enabling proactive healthcare interventions. The intended outcome is to allow the elderly to remain in their homes longer as they age and avoid costly nursing home care or hospitalization.

The proposed system only requires that the user wear a standard form-factor wrist watch. Data is continuously sent from the watch to the wireless sensor network, where it is then streamed over the Internet to a centralized server to be processed and analyzed automatically. A one-time calibration procedure done in the living space, which uses simultaneous localization and mapping (SLAM), provides both an accurate floorpmap and a means for calibrating the localization system. Experimental results are given to demonstrate that this method is capable of providing accurate real-time room-level localization of the user.

This is the first step towards building a system that will perform a wide array of behavioral classification.

II. RELATED WORK

The functions of a smart home can generally be broken down into the following types of monitoring [3]:

- Physiological: Directly analyzing vital signs
- Functional: Activity and behavioral classification
- Safety: Detection of environmentally hazardous events
- Security: Intruder alert; detecting wandering patients
- Social: Interaction with others and integration into the community

Mature systems already exist for safety and security; and social monitoring is nearly impossible for a smart home to parameterize, since it oftentimes takes place outside of the house, varies greatly from person to person, and is highly contextual [4]. Thus, the majority of recent smart home research has focused on developing systems for monitoring physiological and functional parameters.

Although established methods exist for measuring physiological parameters, solutions for measuring functional parameters remain highly disjoint [5]. Skubic et al. implemented their system in 17 apartments and continuously recorded data over a two year period in the TigerPlace eldercare facility [6]. Their system localizes the subjects using passive infrared (PIR) sensors, bed sensors, and video cameras.

Brownsell et al. [7] and Glascock et al. [8] demonstrate the usefulness of commercial products for position and activity

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tracking, and further demonstrate that these technologies can be used for preventative care.

Kaye et al. performed an extensive study in which 233 participants agreed to have PIR detectors installed in their home to detect position and gait speed [9]. The system also tracked computer usage and exterior door opening and closing. This study revealed well-defined baseline parameters among different demographics in terms of both age and medical condition. It represents the largest known smart home deployment of its kind, paving the way for future clinical evaluation in this area.

While not always explicitly discussed, almost all smart home research systems employ some form of *indoor localization*, which refers to techniques used to determine the location of objects and people indoors. The majority of smart home researchers use PIR sensors to detect the position of subjects in their home [10] [5], however, these sensors – which are best known for use in residential and commercial motion-activated lighting applications – lack sophistication; they only produce a binary "present/not-present" output, and they are incapable of distinguishing between different living subjects (including pets), which is a critical system requirement for most practical deployments.

Received signal strength indication (RSSI) localization is an inexpensive indoor localization method that balances mote cost, deployment complexity, functionality, and localization precision. The basic premise of active-mode RSSI localization is to deploy sensors in an environment that measure the received signal strength of a transmitting tag. Generally, mote density is slightly higher when compared to PIR sensors, but better-than-room-level accuracy is possible and, most importantly, individuals wearing unique radio tags can be distinguished from each other (and from the movements of other individuals and pets that are not tagged).

The most accurate localization systems relying on the strength of received signals use RSSI fingerprinting as a way to determine location from a set of received RSSI values [11], [12]. The RSSI fingerprinting model assumes the environment is static — i.e., whatever environmental characteristics affect the signal will continue to affect the signal in the same manner forever. As long as this condition is met, this model predicts that returning the tag to a specific position will always produce a specific RSSI output at each mote. Therefore, the tag can be localized by comparing received RSSI data to RSSI data collected at known locations. These known locations make up the allowed *states* the tag can be in – these states may or may not be distributed uniformly in space. Because of this, localization resolution depends on the state density around the tag's location.

III. METHOD

Home monitoring systems can provide input data for a wide array of classification algorithms. In this work, the focus is the localization component of the system – which is the key to many behavioral classification challenges.

The proposed home monitoring system comprises four components: a smart watch, several fixed-position WSN motes, an Internet-enabled WSN gateway, and an Internet-visible centralized server. While in the home, the user wears a smart watch (Chronos, Texas Instruments running custom firmware), which broadcasts accelerometer data to the WSN installed in the user's home. Each WSN mote receives the smart watch's accelerometer data and measures the wireless signal strength of the smartwatch. Both of these data are relayed to the gateway, which forwards it to a centralized server over the Internet. The server stores and analyzes this data to determine the user's position and activity.

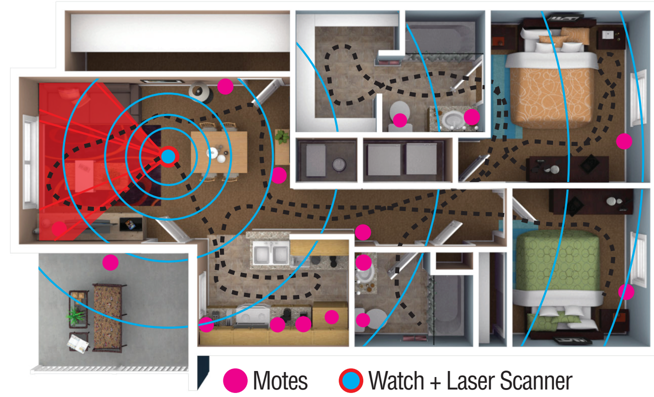

Fig. 1. An illustration of the proposed RSSI fingerprinting procedure. The user calibrates the system by traversing through the living space with the smart watch mounted to a laser scanner while WSN motes installed throughout the home record the signal strength of the watch. The laser scanner allows the system to generate a floor map of the space while providing the location of the watch at all times.

A. RSSI Fingerprinting

For each message the watch sends, the system records a vector $\mathbf{r}_t$ comprising the RSSI reading of the watch's signal strength obtained by each mote. To calibrate the system, the smart watch is moved around to different rooms in the living area while periodically sending packets to the system. Each $\mathbf{r}_t$ is associated with a room label $v_{t,i}$ that corresponds with the room the watch was located in at time t. To avoid the tedious task of manually associating the data with the location during calibration, the proposed system automates the process by localizing the watch using a simultaneous localization and mapping (SLAM) system (Fig. 1).

The system uses the Hokuyo UTM-30LX scanning laser rangefinder, capable of providing accurate (with a resolution of 2 cm and $0.25°$) measurements in a circular arc. In general, when using a scanning laser rangefinder, SLAM is achieved by matching the latest scan to a map made by previous scans and then adding information from the latest scan to the map. Specifically, HectorSLAM [13] is used to achieve high-quality real-time tracking and mapping results. To train the system to predict room labels from RSSI readings, a set of radial basis function (RBF) neural network coefficients are computed using linear optimization. The shape of the RBFs is chosen to be Gaussian and their means and variances are found by applying k-means clustering to the entire set of RSSI readings. The flowchart shown in Fig.

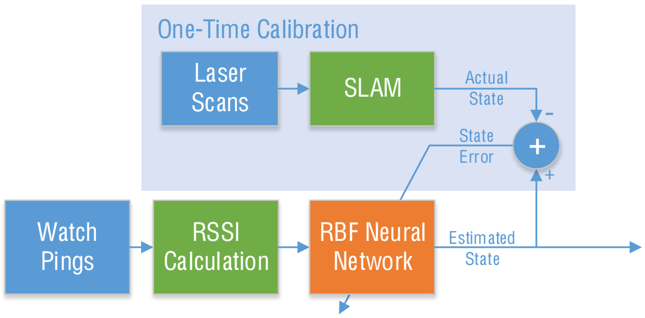

Fig. 2. A flowchart of the proposed RSSI fingerprinting method. The section denoted "one-time calibration" is used to derive the parameters of the RBF neural network. Once calibrated, the system is capable of performing localization using only RSSI measurements of the watch pings as inputs.

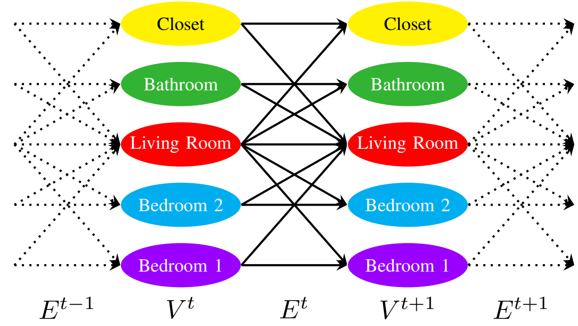

Fig. 3. An example of a trellis used to refine localization estimates obtained by RSSI fingerprinting. It is assumed that the user's movement is restricted to connected paths through the trellis.

2 illustrates how SLAM is used to calibrate the RBF neural network used for RSSI fingerprinting.

Once the system is trained, it can be used to estimate the probabilities $P(v_{t,i}|\mathbf{r}_t)$ at all times t for each state i. From the probabilities, it is possible to assign the room estimate to the one with the highest probability in a sample-by-sample fashion, where states are considered independent from each other. However, because the system is built to measure human movement, the sequence of paths should be resolved in a global fashion.

B. Refinement

Between any two instances of time, the user can either stay in the same room or move to another, neighboring location. The floor map generated during the calibration stage can be used to define the boundaries of each room and determine the set of all possible room-to-room transitions. As a result, a directed graph $G = (V, E)$ is created where the set of vertices $V = \{v_1, \ldots, v_N\}$ represents all distinguishable locations and E is a set of edges e_{ij} representing all possible room-to-room transitions from state v_i to v_j. An example of a temporal representation of the state diagram is given in Fig. 3. This graph represents the allowable movement within the living space. In the field of channel coding, this type of graph is referred to as a trellis and the maximum likelihood sequence of hidden states (path) through the trellis can be found by applying the Viterbi algorithm [14].

Before applying the Viterbi algorithm, it must be assumed that the user's movement is restricted to connected paths through the trellis. At each moment in time, the Viterbi algorithm finds the probability (or some monotonic function of probability) of the most probable path that ends in each state. This is represented by the recursive equation

$$x_{t,i} = P(\mathbf{r}_t|v_{t,i}) \times \max_{j \in V} (a_{j,i} \times x_{t-1,j}), \qquad (1)$$

where $x_{t,i}$ is the probability of the most probable path that ends in state v_i at time t and $a_{j,i}$ is the probability of transitioning from state $v_{t,j}$ to $v_{t,i}$. For the purposes of optimal path selection, the probability $P(v_{t,i}|\mathbf{r}_t)$ found by applying the RBF neural network can be used in place of $P(\mathbf{r}_t|v_{t,i})$. In this work, the *a priori* probabilities of being in each state are considered equal, however, it would be easy to incorporate unequal *a priori* probabilities using Bayes' rule. It is important to note that applying the Viterbi algorithm directly to probabilities can lead to an underflow of floating point numbers, therefore, it is best to compute the logarithm of (1) for software implementation.

While recursively applying (1), the best paths leading to each state are recorded. At the end of the sequence, the final state with the highest probability is linked to the maximum likelihood path through the trellis.

IV. RESULTS

To holistically evaluate the system's functionality and performance, the system was deployed in a large, three-story fraternity for University of Nebraska Medical Center students. A resident of the fraternity served as a test subject for this experiment. The system was deployed on August 14th, 2013 and ran for approximately 2 weeks. Twenty motes, one smart watch, and one gateway device were deployed in the home. Before the experiment started, the system was calibrated using a Chronos watch coupled with the proposed Laser SLAM method, which provided training data to the proposed RSSI fingerprinting method.

Fig. 4 shows the floor maps produced by SLAM that are used for analysis where color coding was added to illustrate the separation between rooms. The results demonstrate the SLAM implementation's ability to accurately generate floor maps. The white areas in the floor map represent mirrors and windows, which are known to "fool" laser scanners into thinking that space exists beyond the walls. While these areas distort the floor map, they are typically easy to identify and remove in post processing.

Once the system was calibrated, the subject wore the Chronos watch while journaling his timestamped location as he moved around his house; at the same time, the Chronos watch was set to chirp every second, providing RSSI data to the motes deployed. Results shown in Fig. 5 illustrate the localization accuracy when using the proposed RBF neural network with and without the proposed refinement method. Accuracy was computed by matching each set of RSSI data (occurring every second) with the subject's last-recorded journal entry. This time window was chosen to illustrate

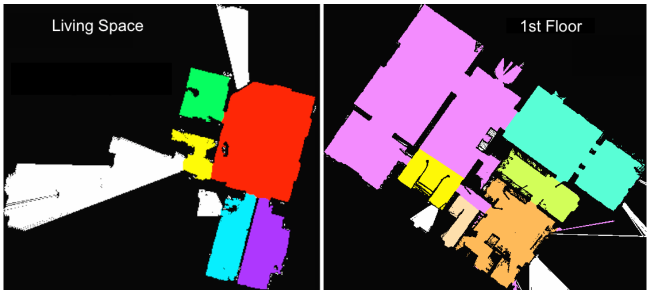

Fig. 4. Floor maps of an indoor space that were generated using laser scanner simultaneous localization and mapping. Colors have been manually added to the illustration to show the separation between rooms considered by RSSI fingerprinting.

the the accuracy of the proposed system at a time when the user changed locations often. Overall, when applying the proposed refinement method, the system produced 91% accuracy against the subject's journal. This improved localization performance by 15% over the performance without refinement. In particular, it is apparent that the refinement process removed errors in localization that correspond to sporadic movements that often violated the movement restrictions inherent in the living space. It is important to note that the value of $a_{i,j}$ used in (1) was $\frac{1}{40}$ when $i \neq j$ and $\left(1 - \sum_{k \neq i} a_{i,k}\right)$ when $i = j$. This parameter, linked to the probability that the user remains in or leaves a room, is vital for improving localization accuracy with refinement.

V. Conclusion

A complete system and method have been presented for performing real-time localization of a user in their home using a low-cost, non-intrusive wireless sensor network. This serves as a first step toward smart home health monitoring and behavioral classification. Experimental results demonstrate that the system can accurately track the location of the user within their home using combination of RSSI fingerprinting and a novel method for temporal refinement. The smart watch firmware implementation only transmits single accelerometer readings, however, the quality of data transmitted could be improved by performing on-board dominant frequency analysis of the accelerometer readings. The watch could also be modified to allow for bidirectional communication so the system can automatically send textual messages to the watch's display to provide clinical feedback to patients. While the current system provides accurate 2D floor maps, the system's ability to categorize behavior can be greatly enhanced with a full 3D model of the house, which would provide information about furniture arrangement.

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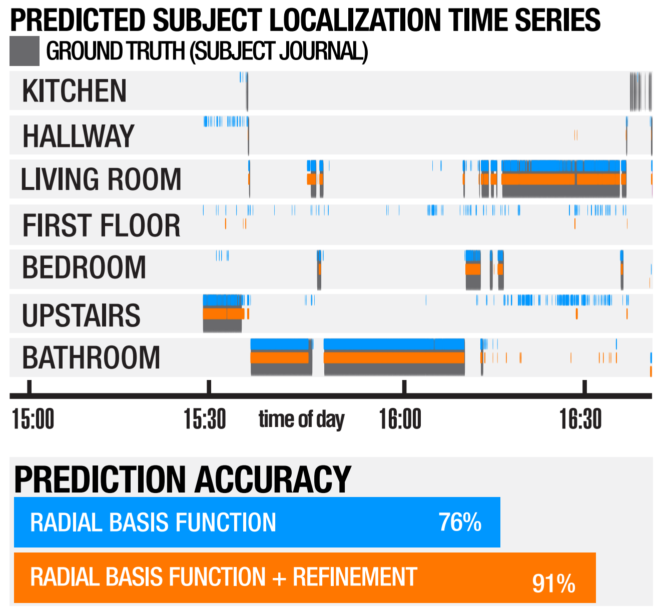

Fig. 5. Results of the proposed method for RSSI localization when compared to the ground truth positions obtained through journaling.

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