Published in final edited form as:

Conf Proc IEEE Eng Med Biol Soc. 2015 ; 2015: 5481–5484. doi:10.1109/EMBC.2015.7319632.

Multi-Resident Identification using Device-free IR and RF Fingerprinting

Erich R. Schafermeyer,

Dept. of Electrical Engineering, Portland State University, Portland, OR, 97207

Eric A. Wan, Ph.D [IEEE Member],

Dept. of Electrical Engineering, Portland State University, Portland, OR, 97207

Shadman Samin,

Dept. of Electrical Engineering, Portland State University, Portland, OR, 97207

Noah Zentzis,

Dept. of Electrical Engineering, Portland State University, Portland, OR, 97207

Nicholas Preiser,

Dept. of Biomedical Engineering, Oregon Health & Science University, Portland, OR, 97239

John Condon,

Dept. of Biomedical Engineering, Oregon Health & Science University, Portland, OR, 97239

Jon Folsom, and

MotioSens (formerly EmbedRF), Portland, OR, 97207

Peter G. Jacobs, Ph.D [IEEE Member]

Dept. of Biomedical Engineering, Oregon Health & Science University, Portland, OR, 97239

Abstract

Remote monitoring of health and mobility is critical in the support of aging-in-place for seniors. However, it is challenging to passively monitor individuals in multi-resident homes. In this paper we present a new method for the identification of individuals using simple wall-mounted radio frequency (RF) transceivers and IR sensors with fingerprinting techniques. The approach is passive or device-free in that it does not require the person being identified to wear any transmitting device. Classification is achieved using features derived from measuring the disruption of RF received signal strength (RSS) among 4 transceivers positioned across either a hallway or doorframe. Three IR sensors provide timing information. Results are given for 3 test subjects (1 female, 2 males). The approach achieves over 98% classification accuracy in distinguishing the female from the male subjects and over 83% in distinguishing between the males using a Gaussian Mixture Model for classification. More than 2300 labeled examples per subject were used for

1 (503) 4943870, jacobsp@ohsu.edu.

Dr. Jacobs and Dr. Wan have a financial interest in MotioSens (formerly EmbedRF), a company that may have a commercial interest in the results of this research and technology. This potential conflict of interest has been reviewed and managed by OHSU.

The experimental procedures involving human subjects described in this paper were approved by the Oregon Health and Sciences University's Institutional Review Board.

training. When the training data is reduced to less than 140 examples per subject, 96% and 82% classification accuracy is still achieved respectively.

I. Introduction

Caring for seniors in their own homes is a rapidly growing sector of the healthcare industry. As the US population ages, caregivers and relatives will increasingly rely on technology for remotely monitoring the health and wellbeing of seniors living independently. Many systems designed for monitoring and safety alerts make use of wearable sensors such as pendants. One major disadvantage of these types of systems is that seniors often refuse or forget to wear such a device, which they may view as being intrusive and inconvenient. For some, remembering to charge batteries is also problematic. Alternative health monitoring systems make use of *passive* device-free monitoring approaches that do not require the use of tags. Passive monitoring is less intrusive and may provide a greater sense of independence for the seniors. Passive sensing systems include IR motion detectors for determining room level presence, bed sensors, and low-energy Bluetooth contact switches that can be placed strategically around the home to detect opening the refrigerator door, using a pillbox, leaving the home, etc. Video based systems have also been used [1] including work done using the Microsoft Kinect system to estimate gait and fall risk [2]. Seniors will oftentimes refuse to use video-based monitoring systems citing privacy concerns.

Multi-resident tracking is a particularly challenging task; most currently available systems available require a body-worn device. A background on tracking within a multiple-resident smart home can be found in [3]. At the Oregon Center for Aging and Technology (ORCATECH), work has been done using body-worn devices that use RSS from a body-worn watch relative to a base-station transceiver to identify walking speeds of multiple residents in a home [4]. Work has also been done using passive ceiling-mounted restricted IR sensors to measure walking speed differences among residents to disambiguate them [5]. A method to track multiple residents simultaneously using combined RFID and other passive sensors positioned throughout an environment is described in [6].

In recent work, we made use of RF wall-mounted transceivers and RF fingerprinting to track the location and mobility of people [7] [8] [9]. Passive monitoring of walking speed, an important metric of health, can be determined using a sequence of IR sensors [4] or a simple RF array [10]. Many of the systems and approaches developed in the research community are now being commercialized through new companies including Lively, GrandCare, CarePredict, and our affiliate company MotioSens.

Currently, many passive monitoring systems have a major shortcoming: the inability to separate multiple people in a single home. When a caregiver or friend visits, their presence corrupts the monitoring of the resident. When monitoring the number of trips that a resident takes to the bathroom in a given day, it is critical to know that it is the resident making the trip and not a spouse or visitor. If there is a couple living together, it is essential to be able to associate health and mobility metrics for each individual.

The solution presented in this paper makes use of the same non-intrusive wall-mounted RF transceivers that we previously used for both walking speed and location tracking [8] [10]. Our system uses a small network of RF transceivers placed in hallway or doorframe to detect the unique signatures of individuals (see Fig. 1). As a person walks past the sensors, the received signal strength (RSS) between transceivers is distorted. Unlike a simple IR switch, RSS measurements capture aspects of a person's body and movement caused by the absorption, and multipath reflection of RF energy. To successfully identify a person, the signal's attributes are processed to extract a variety of relevant features or *fingerprints*. During a calibration phase, recorded features for each person of interest are used to fit a classifier; we tested both a Gaussian Mixture Model (GMM) and a feedforward neural network (NN). The classifier can then be used to identify individuals in real-time as the person passes the sensors. Details of the system, derived features, classification training, and results are provided in the remaining sections of this paper.

II. Methods

A. Hardware and System Configuration

The sensor system consists of 4 RF transceivers, referred to as access-points (AP), arranged in a doorway or on the walls of a hallway as shown in Fig. 1. The RSS signal recorded between each pair of APs is defined as a "link". In our experiments, a 1 m wide doorframe was simulated using wooden posts to position 2 APs at 1 m height (~ waist level) and 2 APs at 1.75 m (~ head level). This provides a total of 4 links (direct links A and B, and cross links C and D). In addition to the RF transceivers, 3 narrow-beam IR range sensors (Sharp GP2Y0A02YK0F) were used for the purpose of synchronizing the data acquisition system and for obtaining an estimation of walking speed.

The APs themselves were built by MotioSens (Portland, OR) and programmed to transmit data at 912 MHz with a transmission rate of 20Hz (see Fig. 2). Periodic transmission allows all APs to function at very low power levels (*i.e.*, sleep whenever not transmitting) and last for up to a year on a single set of batteries. One of the APs also acts as a hub, which relays data to a laptop running custom data acquisition software. For this study, data was recorded and processing was performed offline. However, the system is also capable of transmitting recorded data to a cloud server for real-time remote processing and monitoring. The total cost of the system hardware is less than \$150.

B. Data Processing, Feature Extraction, and Classification

The RSS waveforms acquired at 50ms intervals for each link serve as the data input to the classification algorithm. An example of RSS waveforms recorded as 3 different subjects walked past the sensors is shown in Fig. 3. RSS signals are converted from dBm into power (Watts):

$$RSS_w = 10^{RSS_{dbm}/10} \quad (1)$$

Next, “background subtraction” is performed in which the long-term mean is subtracted from each signal (a variance threshold is used to avoid including data when a person is nearby in the long-term mean calculation). Using the IR trigger (IR2), a 2 second (41 sample) centered window of data is extracted each time a person walks past the sensors.

The features used for classification are derived from the windowed data of the RSS for each of the 4 links. Classification performance depends on finding good features that discriminate well between people and maintain high generalization over time. We started with a large candidate number of possible features, including spectral representations of the signal, principle component analysis (PCA), mean, variance, skew, kurtosis, and others. Additional heuristic features such as peak magnitude and difference in peak magnitude between links, were also included. In total, 81 different unique features were considered. We then performed a simple, popular feature selection procedure called *sequential forward selection* to select a smaller subset of the most relevant features. This involves first choosing the single best feature out of the 81 candidates that had the highest classification performance. A GMM was used for classification (trained and tested using cross-validation on approximately 7,000 examples collected from 3 subjects see next section for details). Once the single best feature had been selected, each of the remaining 80 features were tested again in combination with the best feature in order to select the best 2 feature pairs. The process of adding features and testing was repeated until adding more features resulted in only a marginal improvement in classification performance. This procedure resulted in selecting the following 10 best features in order:

1. The area under the curve for the link C RSS; area is calculated as the sum of the RSS magnitude squared.
2. The first 5 principle components from the link A signal.
3. Number of unique peaks in link B RSS signal.
4. The max minus the min value of link A RSS signal.
5. Walking speed as approximated by the timing difference between IR sensor firings from IR1 and IR3.
6. The skew of link B RSS signal.
7. The standard deviation of link B RSS signal.
8. The max minus the min value of the difference between link A and link B RSS signals.
9. The mean of link C RSS signal.
10. The difference in std between link B RSS signal before and after the primary peak of link B RSS signal.

All features are scalars except for feature 2, which is a vector of 5 values. Features 1 and 3 are derived from the RSS signal in dbm while features 2, 4, 7–10 are derived from the RSS signal in units of Watts. Fig. 4 shows the subject histograms for feature 1, which indicates that with just a single feature the female subject (Subject A) is well separated, whereas there is a large overlap between features for the male subjects (Subjects B and C). Our approach

makes use of all 10 features as the fingerprint for input to the classifier. Both GMM and feedforward NN classifiers were evaluated as discussed in the next section.

III. Experiments and results

Three volunteer subjects were used to record data and evaluate performance. Subject A was a 5'3" 145 lb female, subject B was a 5'11" 185 lb male, and subject C was a 6'1" 195 lb male. Subjects were asked to walk for an hour continuously back and forth down a 7 meter hallway at varying speeds, each time passing the sensor system. This was repeated on 5 separate days. Subjects wore different shoes and clothing on each day but were instructed not to carry a bag or purse. Subjects were allowed to carry (and use) a cellphone. Approximately 460 walks per subject past the sensors were recorded each day for a total of approximately 2,300 recordings per subject over the 5 days.

Classification performance was compared for a GMM versus a feedforward NN, both using the same set of 10 best features (see previous section). For the GMM, a different model with 15 Gaussians (determined experimentally) was fit for each of the 3 subjects using expectation maximization (EM). 15 hidden neurons were used for the NN classifier. Accuracy was evaluated by using a 5-fold daily cross validation. This involved using 4 days for training (~1,840 examples per subject) and the remaining day for testing (~460 examples per subject). This was repeated 5 times to find the average daily classification performance. In this way we were assured that none of the training data came from the same day as testing. This validation resulted in a final classification accuracy of 98.1% for the GMM and 98.6% for the NN when separating male versus female and 83.8% for the GMM versus 82.0% for the NN when separating male versus male.

Reducing the amount of labeled training data was also investigated to characterize performance as summarized in Fig. 5. This involved Monte-Carlo sampling by randomly drawing a percentage of the training data (from the 4 training days), while still evaluating all available data for the test day. For small amounts of training data the GMM clearly outperforms the NN. When only 6% of the available labeled training data was used (approx. 140 walks per subject) the GMM still achieved 96.4% accuracy (male-female classification) while the NN achieved only 93.5% accuracy. This difference is most likely due to the feed-forward NN over-fitting the training data. In the male-male case the GMM achieved 82.8% accuracy with only 6% training data while the NN achieved only 71.6%.

To further evaluate performance, the subject classification confusion matrices are shown in Table 1 for 100% labeled training data and Table 2 for 6% labeled training data for the GMM. The classifier is most successful at recognizing subject A, the female subject. Using all labeled training data, female-male classification has a sensitivity of 0.97 and a specificity of 0.99. By reducing the amount of labeled training data to less than 140 observations the sensitivity drops to 0.94 and the specificity drops to 0.98. This suggests that a reduction in training data does not significantly affect the classifier's ability to separate male versus female. However, subject C and Subject B, the two male subjects who are of similar height and the same weight were not as well separated. In this case, sensitivity was 0.87 and the

specificity was 0.80 when using all data. This dropped to 0.85 sensitivity and 0.80 specificity when using only 140 observations for training.

The above analysis assumes that classification is performed on all observations. Alternatively, we may discard some data based on setting a confidence threshold for the GMM output. By discarding approx. 20% of the data, both sensitivity and specificity is increased to 0.97 and 0.99 respectively for the male-female classification and to 0.89 and 0.86 for the male-male classification, again using only 140 observations per subject for training.

IV. Discussion and Conclusion

In this paper we have developed a new method for passively identifying people within a home environment. The approach uses small low-cost sensors to detect patterns in RSS signals as a person walks between wall-mounted access-point transceivers. Using four APs and two IR sensors placed in a hallway or doorframe a person can be identified and separated from other residents in the home. Preliminary experiments with 3 subjects showed high classification accuracy (0.97 sensitivity, 0.99 specificity) in separating the female subject from both the male subjects. However, separating the 2 male subjects, who were of similar build, was more challenging (0.87 sensitivity, 0.80 sensitivity). This would indicate the applicability of the approach to distinguishing between couples living together that are distinct in stature. A surprising result was that good classification performance was still maintained with relatively few training samples (140 examples per subject). This would make the system practical to calibrate in the home. For example, a senior living at home might only need to walk back and forth past the sensors for less than 5 minutes to register approximately 20 examples. This would be then be repeated every day for a week in order to fully train the system.

We are currently investigating alternative feature representations, more sophisticated feature selection schemes, semi-supervised learning, and different sensor array configurations in order to further improve performance. Additional studies are planned to further evaluate robustness to environmental conditions that could affect RSS stability and to test the system's ability to distinguish a single subject from an arbitrary number of people.

Our approach provides a critical solution for passively identifying people and is intended for use with in-home health monitoring system that must operate with multiple-residents and visitors. While our primary focus is on monitoring seniors to support aging-in-place, other uses may include passive identification for security purposes, or to augment smart-home systems that interact and respond to specific individuals.

Acknowledgments

This research was support in part by grant no. 1R41AG035400 from the National Institute for Aging and grant no. ETAC-12-239042 from the Alzheimer's Association. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Center for Aging or the National Institute of Health.

V. REFERENCES

1. Wang F, Stone E, et al. Toward a Passive Low-Cost In-Home Gait Assessment System for Older Adults. *IEEE J Biomed Health Inform.* 2013;346–355. [PubMed: 24235111]
2. Stone EE, et al. Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect. *IEEE Trans Biomed Eng.* 2013; 60:2925–2932. [PubMed: 23744661]
3. Cook DJ, et al. Tracking Systems for Multiple Smart Home Residents. *Human Behavior Recognition.*
4. Pavel M, , et al. Continuous Assessment of Gait Velocity in Parkinson's Disease from Unobtrusive Measurements. *Int IEEE EMBS Conference on Neural Eng;* 2007; Kohala Coast, HI. 700–703.
5. Austin D, , et al. *Journal of Ambient Intelligence and Smart Environments.* Vol. 3. IOS Press; 2011. On the disambiguation of passively measured in-home gait velocities from multi-person smart homes; 165–174.
6. Galatas, et al. Multi-person identification and localization for ambient assistive living. *Lecture notes on computer science.* 2013; 8028:109–114.
7. Jacobs PG, , et al. EmbedRF Position Tracking and Mobility Assessment System: A low-power and low-cost system for indoor pedestrian tracking and mobility assessment. *ION GNSS;* September, 2011; 3461–3469.
8. Jacobs PG, , et al. Measuring in-home walking speed using wall-mounted RF transceiver arrays. *EMBC 2014;* August, 2014; 914–917.
9. Paul AS, , et al. MobileRF: a robust device-free tracking system based on a hybrid neural network HMM classifier. *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing;* September, 2014; 159–170.
10. Wan EA, , et al. Tag-Free RSS Based Indoor Localization. *Proceedings of the 2012 International Technical Meeting of The Institute of Navigation;* 2001; 940–944.

Figure 1.

Access-points (AP) transceivers are arranged in a hallway. As a person walks past, the RSS disruptions between links are measured and used to recognize the person. IR sensors provide timing information to extract walking speed.

Figure 2.

(a) MotioSens 915 MHz, wireless transceiver used for the access points and hub (1.5 grams, 10 payload byte, 15m range). (b) Enclosure used to hold the transceiver and mount on the wall.

Figure 3.
Example RSS waveforms for three different subjects.

Figure 4. Histograms from three subjects' data for feature 1: the area under the RSS curve for diagonal link C.

Figure 5.

Percent classification accuracy versus amount of labeled training data used for both a GMM and feed forward NN.

Table 1

Confusion matrix of three subjects (A-female, B-male, C-male) classified using a GMM trained on all available labeled observations. 5-fold daily cross validation.

E	Subject A	Subject B	Subject C
T			
Subject A	96.97	1.68	1.35
Subject B	1.76	85.43	12.81
Subject C	0.58	20.79	78.64

Table 2

Confusion matrix of three subjects (A-female, B-male, C-male) classified using a GMM trained on approximately 140 labeled observations (6% of data) per subject. 5-fold daily cross validation with Monte-Carlo sampling.

E	Subject A	Subject B	Subject C
T			
Subject A	94.06	4.43	1.51
Subject B	2.67	82.47	14.87
Subject C	1.95	19.29	78.76