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Indoor Human Localization and Gait Analysis using Machine Learning for In-home Health Monitoring

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***Abstract*— Homes equipped with ambient sensors can measure physiological signals correlated with the resident's health without requiring a wearable device. Gait characteristics may reveal physical imbalances or recognize changes in cognitive health. In this paper, we use the physical interactions with floor to both localize the resident and monitor their gait. Accelerometers are placed at the corners of the room for sensing. Gradient boosting regression was used to perform localization with an accuracy of 82%, reasonably accounting for inhomogeneity in the floor with just 3 sensors. A method using step time variance is proposed to detect gait imbalances; results on induced limps are presented.**

Keywords: Indoor Localization, Classification, Machine Learning, Signal processing, Smart Homes, Gait

I. Introduction

Ambient intelligence is a developing research field that explores the interaction between sensed environments and their inhabitants [1]. Smart sensor technologies deployed in the home environment introduce ambient intelligence applied to monitoring the resident's wellbeing. The sensed activities of daily living performed in home environments can reveal indicators of a resident's mental and physical health.

In this paper, we explore a means of monitoring the resident's movements and activities. Changes in movement patterns have been linked to mental health or depression. Depression is widely prevalent; about 7.6% of the US population aged 12 years and over has depression in any 2-week period [2]. Amongst those that seek treatment, up to 80% show an improvement in their symptoms [3]. Despite its success rate, nearly 2 in 3 people suffering from depression do not actively seek nor receive proper treatment [3]. This may be due to the negative stigmas around mental health. For example, depressive symptoms shown by men in their everyday lives may be misinterpreted as expressions of masculine ideals [4]. Activity curtailment is a risk factor, while engagement and a close social network are described as protective factors from depression [5].

Moving slowly, restlessness, and change in sleeping patterns are symptoms of major depressive disorder [6]. We hypothesize that monitoring the resident's movements and habits can detect possible depressive symptoms. A resident's habits can be tracked through their locations in the home over time. Increase of time spent in bed, or frequent pacing, can only be monitored in the home.

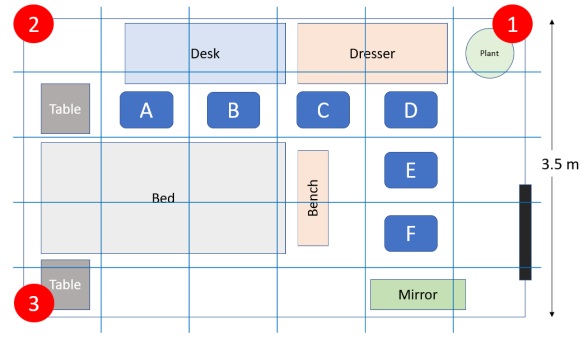

Fig. 1: Diagram of the experimental setup room with furniture. Red circles represent the 3 accelerometer sensors. The subject walked on the blue squares indicating the 6 different locations within the grid. The floor is hardwood.

Gait and balance symmetry may change over time. Because a gradual change in gait is difficult to self-detect, a smart home sensing system could alert the resident of any problematic changes in gait over time. One application of gait monitoring is for patients of Parkinson's disease, who are susceptible to Parkinson's gait. Patients have reduced gait speed, increased axial rigidity, and impaired rhythmicity [7]. The treatments create further challenges because they cause fluctuations in motor response [7].

We propose that both location and gait properties of the resident can be monitored through the natural physical interactions between a resident and their floor through footfalls. This approach is a non-invasive and continuous mode of monitoring. We capture and analyze data from footfalls with a minimal number of sensors.

A. Background

Related methods to monitor movement include vision based approaches such as infrared sensors [8] or depth cameras [9]. Some view these methods as a breach of privacy and are ineffective if line of sight is obscured. One recently developed non-contact solution is RT-Fall, which uses WiFi signal sensing [10]. Although effective, the detection deteriorates if the environment changes, such as if movement of furniture blocks the line-of-sight of the signal. Several approaches to localization have been made with accelerometers on the floor. Footsteps on a concrete floor were localized with 56% success rate when locations were discretized into 1 m by 1 m grids [11].

Devices such as smart watches and smart phones may detect the user's location and their walking [12]. However,

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this relies on the user physically wearing the device, which may be cumbersome for many, especially in the comfort of their own homes.

In this paper, we present the results of indoor human localization and gait analysis from the ambient floor sensor design shown in Fig. 1, as follows: In Section II, we describe the design and performances of machine learning algorithms to localize human footsteps. In Section III, we analyze different gait imbalances. In Section IV, we discuss our results and the future work involving smart floor design.

II. INDOOR LOCALIZATION

A. Experimental Setup

Three accelerometers were placed in the corners of a 4 m by 3.4 m bedroom with furniture as shown in Fig. 1. The bedroom has hardwood floors and is furnished with a heavy bed and other furniture as shown. Three high sensitivity low frequency seismic accelerometers by PCB Piezoelectronics (model 393A03) were placed in the corners of the room to detect the vibrations on the floor. The number of sensors were kept to a minimum to increase the scalability of this approach while detecting enough signal. The data was collected through National Instruments (NI) cDAQ-9174 and NI 9230 data acquisition modules. The sampling frequency was 12.8 kHz. We used a frequently used walking path in this room to gather barefoot walking data with footfalls placed at 6 different 0.5m by 0.5m grid locations. This study was performed under Committee on the Use of Humans as Experimental Subjects (COUHES) protocol 2011000269. This walking path was repeated by the same subject 50 times, totaling 300 footsteps. This gave 50 discrete datapoints at each of the 6 grid locations.

B. Feature Extraction

Signal processing was performed on the data to extract the desired features, which were then used to run the classification algorithm. To remove noise, we used a finite impulse reponse (FIR) lowpass filter with cutoff frequency of 0.3π rad/sample. We took the absolute value of the signal and used windowing to find the peaks of each footfall impact and their corresponding impact onset times. Example data and signal processing results are shown in Fig. 2.

The extracted features are as follows: the peak magnitudes in Volts of each impact for each of the 3 sensors, the differences between the two largest magnitudes and the smallest magnitude between the 3 sensors, and the time differences in the impact onsets. The time differences were calculated by subtracting the earliest onset time between the 3 sensors from the onset time of the other two sensors. For example, if the onset times were 12.05s, 12.08s, and 12.01s for sensors 1,2, and 3 respectively, the time difference feature values would be 0.04, 0.07, and 0. Therefore the feature vector for a single footfall impact has 9 elements.

The data were split between training and testing data using 10-fold cross validation with stratification to maximize the size of the dataset while keeping the distribution of location labels consistent throughout the folds. We used L1

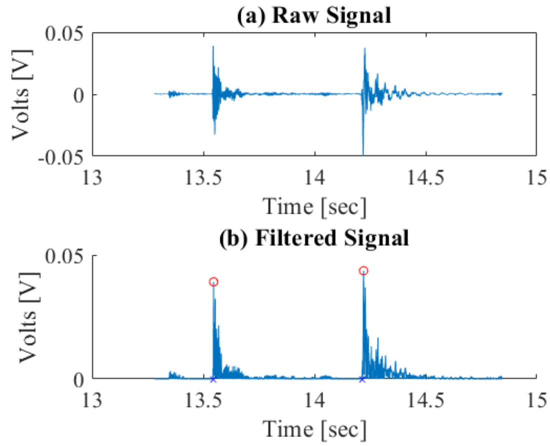

Fig. 2: (a) Example of a raw signal picked up by sensors from two footfalls. (b) Example of processed signal where x indicates the impact onset time and the red o indicates peak magnitude.

normalization on each of the split training data to minimize sensitivity to outliers. We ran XGBoost [13] with default values to find the the F scores of features, which indicate their importance in classifying the locations. Features with F scores under 90 were omitted. The included features had F scores above 340. The ineffective features were magnitude differences at sensor 3, time differences at sensor 1, and absolute magnitude values at sensor 1 and 2. Sensor 3 was placed near a heavy piece of furniture, so the accelerometer vibrations were most likely dampened. Therefore the sensor 3 magnitudes were irrelevant because they were always near 0. Conversely, sensor 1 was in the most open area, so it was the most sensitive. It frequently felt the vibration first, so the time differences at sensor 1 is often 0. Lastly, sensor 1 and sensor 2 absolute magnitudes are irrelevant because the magnitude differences in the other features already record these values, so they are duplicates.

Once these four features were omitted, we used both classification and regression to predict the locations. As a classification problem, we label the test datapoints into distinct location buckets. We ran random forest classifier (RF) and k-nearest-neighbors classifier (KNN) [14] using randomized search with 50 iterations for hyperparameter optimization. We selected these classifiers because of their simplicity due to the relatively small number of datapoints. As a regression problem, we note that the locations are linearly spaced, as shown by the blue crosses in Fig. 1, and have correlated signals and features due to their physical proximity. For example, locations A and B are more likely to have a related set of features than locations A and F. We used 1D gradient boosting regression (GBR) due to the small amount of datapoints and used randomized search with 20 iterations for hyperparameter optimization. A comparison of the accuracy of the classifiers and regression is shown in Table I.

C. Results and Discussion

RF and GBR performed similarly with around 82% accuracy. However, the root mean squared error (RMSE) is important to consider for our application. Classifying a location incorrectly but still predicting a close location is less problematic than predicting a location that is very far away. We conclude that gradient boosting regression method performs the best with 82% accuracy and an RMSE of 0.285m.

TABLE I: Location Classification Results

	Accuracy	RMSE [m]
KNN	76%	0.351
RF	82%	0.439
GBR	82%	0.285

III. GAIT ANALYSIS

Analyzing stride length and step time are important because both can be indicative of a person's stability and fall risk [15]. Building on the localization method shown in Sec. II, calculating stride length, and it's change over time, is straightforward. We count the number of impacts between the first and last step and calculate the distance between those locations.

Conversely, step time is more difficult to find. We used the same experimental room and sensors for this purpose, as described in this following section.

A. Experimental Setup

We gathered different walking data with varying step times for gait analysis. The dataset from Section II was performed with normal walking gait. We repeated walking on the same path with one foot wearing sneakers and the other barefoot. The sneaker heel height is 3 cm. The shoe was used to emulate slight limping due to leg length differences. To simulate a severe limp, we repeated the experiment but this time with a boot on one foot and barefoot on the other. The boot heel height is 6 cm. These limping walking paths were repeated 20 times each, resulting in 120 datapoints for each limp. The shoes worn for these experiments are shown in Fig. 3.

Fig. 3: Different shoes used to mimic severe limp and slight limp by different leg lengths. Only one shoe was worn; the other foot was barefoot.

B. Gait Imbalance Detection

The challenge of detecting step time abnormalities lies in distinguishing between the left and right leg. Assuming the limp is caused by the same leg each time, the problem arises when the resident of a home stops and starts walking frequently. There is no guarantee that the resident will always start walking with the same foot. Therefore, the floor is unable to distinguish between the left and right leg. Data are shown in Fig. 4 to demonstrate this issue. In order to detect a limp, there needs to be a method to combine the different walking segments such that the limp is determined from a larger number of datapoints rather than one episode of walking. Given that there are furniture in the home, the resident will rarely walk long enough to determine if there is a gait imbalance just from one walking episode.

We propose a novel approach to determine step time imbalances by using the distribution in time between heel strikes from left-to-right and right-to-left of all combined impacts. By using the impact onset times as described in Section II-B, we calculate step times by using the time difference between the current and previous impact. By analyzing the distribution of these step times, we determine any changes in gait over time as well as detecting if a gait imbalance meets a certain threshold.

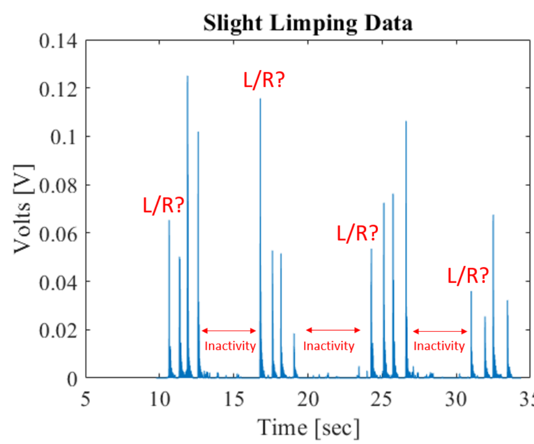

Fig. 4: Processed signal from slight limping. The subject walked 4 steps back and forth. The 4 steps are not enough to determine if there is a limp. The different episodes of walking must be combined, but the left and right legs cannot be labeled.

C. Results and Discussion

The step time distributions of normal walking, slight limp walking, and severe limp walking is shown in Fig. 5. The mean step time, standard deviation, and bimodality coefficients for these distributions are summarized in Table II. Though the distributions follows a unimodal distribution, the standard deviation increases for the slight limp when compared to the normal walking distribution. The bimodality coefficient is also larger in the slight limp step times when compared to the severe limp step times. This approach bypasses the need to label every impact with the correct leg to analyze the resident's gait.

Further, the severe limping distribution clearly shows a bimodal distribution with a large standard deviation and bimodality coefficient. This demonstrates that one leg had a significantly larger step time than the other. With this approach, a threshold using standard deviation and bimodality coefficient can be set to alert the resident of a newly developed limp. This threshold can be a function of gradual change over time.

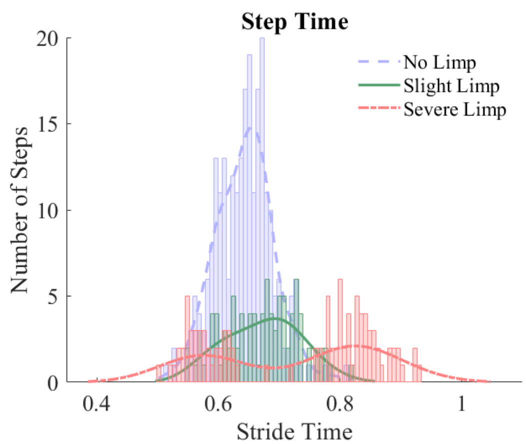

Fig. 5: Three histograms showing the distribution of normal walking, slight limp walking, and severe limp walking. Normal and slight limp both follow unimodal curves, but the slight limp distribution is wider. Severe limp shows a distinct bimodal distribution corresponding to the two different legs.

TABLE II: Gait Imbalances Results

	Mean [s]	Std. [s]	Bimod.
Normal	0.65	0.052	0.290
Slight Limp	0.67	0.065	0.407
Severe Limp	0.72	0.40	0.699

IV. Conclusions and Future Work

We have demonstrated in this paper that using 3 sensors in the corners of the room can locate the resident to 82% accuracy. We also proposed a novel approach to detect step time asymmetries of the resident by using the bimodality of the step time distribution.

The number of sensors were kept to a minimum for better scalability of this approach. Further analysis of how the number of sensors affect the signal accuracy could be performed. With the growing aging population, another concern for residents in a home is emergency health monitoring such as detecting a fall. The proposed technique could be extended toward distinguishing between a fall that results in serious injury, trips that the resident quickly recovers from, and everyday objects dropped on the floor. With successful detection, a smart home could automatically call for an emergency medical response with improved detection accuracy.

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