Machine Learning Based Acoustic Sensing for Indoor Room Localisation Using Mobile Phones

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***Abstract*—We present a novel indoor localisation system that used acoustic sensing. We developed the Acoustic Landmark Locator to determine a person's current room location, within a building. Indoor environments tend to have distinct acoustic properties due to physical structure. Hence rooms in a building can have distinctive acoustic signatures. We found that these acoustic signatures can determine the position of a person. We attempted to identify location based on acoustic sensing of the surrounding indoor environment. We developed a mobile phone application that determined a person's location by measuring the acoustic levels of the surrounding environment. We used a machine learning artificial neural network based algorithm to classify the location of the person, within proximity to a landmark or room. We tested the Acoustic Landmark Locator in an indoor environment. Our tests show that the Acoustic Landmark Locator mobile phone app was able to successfully determine the location of the person carrying the mobile phone, in all test areas. It was also found that background noise caused by the presence of people does distort the landmark acoustic profiles but the artificial neural network based classifier was able to reliably determine the person's room location. Further work will involve investigating how other machine learning approaches can be used to better improve position accuracy.**

I. Introduction

Indoor localisation is a widely demanded function for numerous applications in location based services, social networking and health domains. Commonly used outdoor position tracking systems have become popular due to the availability of GPS. Indoor localisation tracking of people with unobtrusive, wearable sensors has valuable potential for applications where position tracking and motion activity monitoring is also useful. While outdoor localisation in open areas has been largely solved with the advances in satellite-based GPS systems, indoor localisation presents ongoing challenges due to the large range of variables that affect different techniques. There are no widely available or cost-effective and ubiquitous wireless solutions like GPS for indoor localisation which require no prior infrastructure. Indoor localisation systems are available, but most have difficulties operating in confined spaces.

Current solutions for indoor localisation include inertial dead-reckoning or wireless Radio Frequency (RF) trilateration. RF localisation systems can be unreliable for localisation in indoor environments due to the multi-path RF interference. RF localisation systems also tend to require dedicated infrastructure in the surrounding environment. Dead-reckoning may require extensive calibration for users, in order to be accurate and reliable. Our aim was to develop a reliable and accurate room localiser without deploying major infrastructure or requiring significant calibration.

We present a novel indoor localisation system that uses acoustic sensing. One advantage of using acoustic sensing for localisation, is that it does not depend on major sensing infrastructure. Indoor environments tend to have distinct acoustic properties due to the physical structure. Hence rooms in a building can have distinctive acoustic signatures. We found that these acoustic signatures can determine the room a person is located in. We attempted to identify a room location based on acoustic sensing of the surrounding indoor environment. We developed the Acoustic Landmark Locator (ALL) to determine a person's current indoor location, such as a room or corridor within a building. A machine learning neural network based algorithm was used to classify a person's location in proximity to a landmark.

We evaluated the ALL in a typical and realistic indoor environment. We investigated the performance aspects and advantages of the ALL in terms of:

- Landmark Location Accuracy
- Noise effect due to the presence of people within the surrounding environment

This paper is organised into the following sections. Section II discusses related work. Section III presents an overview of the ALL. Section IV discusses the classifier used in the ALL. Section V describes the operation of the ALL mobile app. An evaluation of the ALL is discussed in section VI. Conclusions and further work are presented in section VII.

II. Related Work

Various types of wireless technologies have been investigated for indoor locatisation systems. Commonly used mobile phone localisation systems include wireless and inertial sensing. Ofstad et al, [1] used the inertial sensors on a mobile phone to aid GPS localisation. Bahl et al, [2] and Youssef et al [3] explored the use of localisation using RF signal strength landmarks with Wifi. One of the drawbacks of Received Signal Strength Indicator (RSSI) localisation is the need to deploy access points or reference nodes in order to perform localisation, as highlighted in [4]. To get high accuracy, a large number of access points is typically required. This is disadvantageous in most indoor situations due to placement and power requirements of the access points. D'Souza et al [5] and Ros et al [6] highlighted the disadvantage of using RF signal strength for room localisation. One method of improving RF localisation, is to use other sensors such as inertial navigation combined with RF localisation, as shown in [7].

Acoustic based sensing for localisation, using mobile phone platforms has advantages over using RF localisation, in that reference nodes or access points are not required because the surrounding environment can provide a unique acoustic signature. Azizyan et al, [8] developed SurroundSense, a mobile phone based acoustic localisation system for determining if a user is in a particular store. Their SurroundSense was able to achieve an accuracy of 87%. Azizyan et al [9] expanded their work on SurroundSense to use a sensor network to detect light and ambient sound levels. Tarzia et al [10] developed an acoustic fingerprint or landmark localisation system that worked in conjunction with RF wifi localisation. They achieved an accuracy of 69%. Maisonneuve et al, [11] used a mobile phone to map noise pollution with GPS coordinates, in an urban environment. Such maps could be used for acoustic landmark localisation in a large urban environments.

III. Acoustic Landmark Locator Overview

We propose the Acoustic Landmark Locator (ALL) which can determine a person's position within a building, by using acoustic sensing. The resolution of the ALL was limited to estimating which room or corridor a person was located in. The ALL consisted of an Android based mobile phone, which was used to measure the surrounding environment's sound levels. Based on the ALL's current acoustic readings, the room the mobile phone's user was in, could be determined. The ALL used a machine learning based artificial neural network classifier to estimate the location.

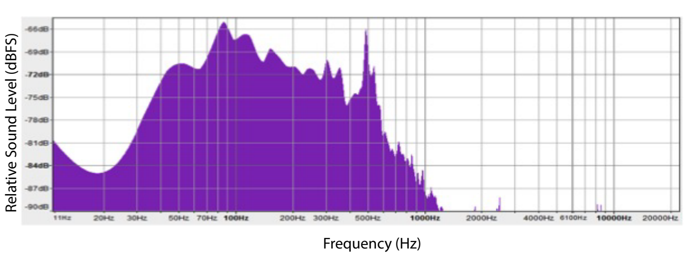

Fig. 1: Acoustic Profile of Room C with Carpet

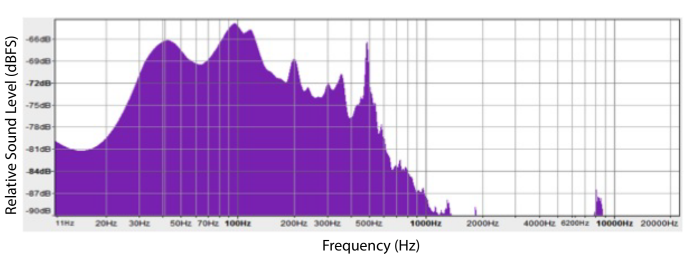

Fig. 2: Acoustic Profile of Room B with No Carpet

A map of landmarks and their associated acoustic profiles was first compiled, as seen in Figure 3. Landmarks consisted of rooms and corridors. The acoustic profiles of each landmark is unique and can be influenced by factors such as the room size, door positions and the presence of carpet. Figures 1 and 2 shows typical acoustic profiles of two different rooms. Figure 1 shows the profile of a room with carpet and Figure 2 shows the profile of a room with no carpet. The acoustic profile consisted of the audio spectrum, measured over a 1 second window, using an audio sampling rate of 44kHz.

IV. Acoustic Landmark Locator Classifier

The ALL classifier was used to determine a person's location. We used a machine learning artificial neural network based algorithm to classify the ALL mobile phone app user's landmark location. The Encog Machine Learning Framework [12], [13] was used to implement the artificial neural network classifier. For each landmark used, an acoustic profile was measured and preprocessed using an Encog neural network algorithm. The artificial neural network was trained using the recorded acoustic profiles. The ALL classifier would then determine which landmark the user was in close proximity to. Preprocessing of the acoustic profiles was done on a personal computer. A mobile phone was used to record the acoustic profiles of each landmark. The preprocessing allowed the Encog neural network to be trained. Once the neural network classifier was trained, the kernel was saved and loaded into the ALL mobile phone app. The ALL mobile phone app would use the trained neural network's kernel to process the realtime sampled acoustic signal, to determine the user's room location.

A. Artificial Neural Network

Using an artificial neural network for the ALL classifier was advantages as it allowed noisy data to be used, with lower number of acoustic samples required. The ALL classifier's Artificial neutral network used Resilient Back Propagation (RPROP) learning [13] to train using the landmark acoustic profiles. Resilient Back Propagation was found to be sufficiently accurate to use and had low latency when computing the training kernels required for the ALL classifier. The

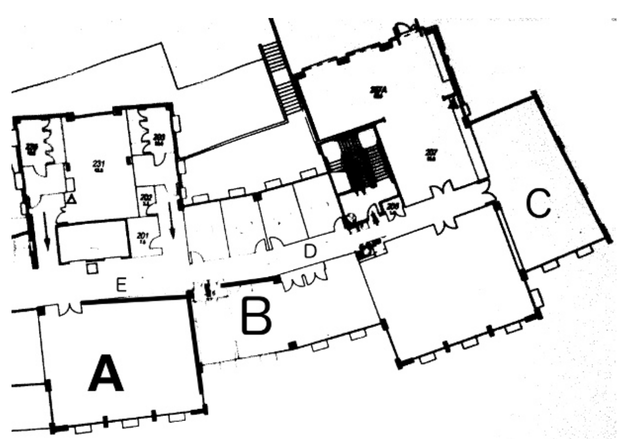

Fig. 3: Indoor Environment Testing Map Showing Landmarks (A to E)

RPROP algorithm was used by the ALL classifier's artificial neural network, to learn each landmark acoustic profiles, using an adaptive weighting algorithm, as seen in Equation 1. The artificial neural network trains with each acoustic profile and produces weightings which are saved as a kernel, to be used in the ALL classifier. The weightings are used to represent unique features related to each landmark acoustic profile. As specified by Riedmiller et al [13], the RPROP algorithm uses the signs of the partial derivatives of the weights error function (E) to update the weights (w).

$$\Delta w_{i,j}^{(t)} = \begin{cases} -\Delta_{i,j}^{(t)} & \text{, if } \frac{\partial E^{(t)}}{\partial w_{i,j}} > 0 \\ +\Delta_{i,j}^{(t)} & \text{, if } \frac{\partial E^{(t)}}{\partial w_{i,j}} < 0 \end{cases} \tag{1}$$

V. Acoustic Landmark Locator Mobile Phone App

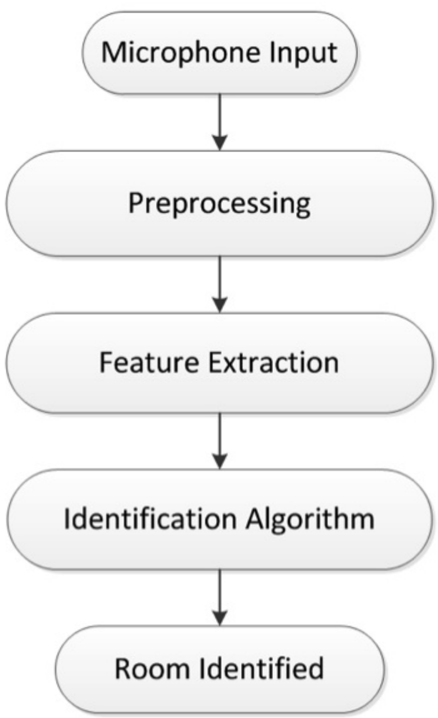

Fig. 4: Acoustic Landmark Locator Mobile Phone App Overview

The ALL mobile phone app was used to capture and process the current sound levels, using the mobile phone's microphone. An overview of the ALL mobile phone app can be seen in Figure 4. One second of audio samples were captured using the microphone. The sampling rate was at 44 kHz, which allow audio frequencies up to 22kHz to be measured. The acoustic profile of the captured audio samples was computed by calculating its power spectrum. The mobile phone app would then apply a moving average of five frames, to the power spectrum. This was repeated for until there was sufficient data samples to determine a match. The mobile phone then used the preprocessed Encog neural network kernel to classify the room location. The mobile phone user's location would then be displayed, as shown in Figure 5.

TABLE I: Acoustic Landmark Locator Correct Matches

Landmark	Correct Match (%)
A	91
B	90
C	99
D	71
E	71

TABLE II: Landmark Characteristics

Landmark	Type	Size	Flooring
A	Room	Large (15m x 15m)	Carpet
B	Room	Medium (15m x 5m)	No Carpet
C	Room	Medium (15m x 6m)	Carpet
D	Corridor		No Carpet
E	Corridor		No Carpet

VI. Evaluation

The ALL was tested in an indoor environment as shown in Figure 3. The test areas were the main corridor and rooms. We tested the ALL by having a user walk through a known path whilst carrying a mobile phone. In Figure 3, the user walked from Room C, through corridor D, Room B, corridor E and room A. The tests were conducted during normal business hours, on week days and so consisted of people walking through the corridors and utilising the test areas. We consider the test environment to be realistic for evaluating the ALL. The duration of the test path track was between 5 to 10 minutes (including time for ground truth measurements). Table II lists for each landmark, the type, size and flooring type (carpet or no carpet). Table I shows the correct match percentage for each landmark tested. The correct match refers to the percentage match to a landmark acoustic profile. The ALL smartphone app was able to successfully determine a person's location, in all test areas. For landmark B and C, the matches were 90% and 99%. The match for landmark C was higher than for landmark B. This can be due to the presence of carpet in Landmark C, which would reduce the amount of reverberation.

A. *Landmark Occupancy Effects*

We measured the acoustic profile of landmark C (room C), with different occupancy levels (number of people present in room). The landmark acoustic profile of Landmark/Room C was measured in the middle of the room, for a period of 10 minutes. Figure 6 displays the landmark acoustic profile for when the room is empty. Figures 7 and 8 show the acoustic profiles for when the room has a small occupancy and when it is half occupied. The presence of higher frequencies above 1kHz can be seen in Figures 7 and 8, was due to the presence of people which distorts the landmark acoustic profiles. Using an artificial neural network for classification, would allow the ALL to still determine the correct landmark.

VII. Conclusions and Further Work

We developed the ALL to determine a person's current indoor location, such as a room or corridor within a building. The ALL used mobile phone based acoustic sensing to determine

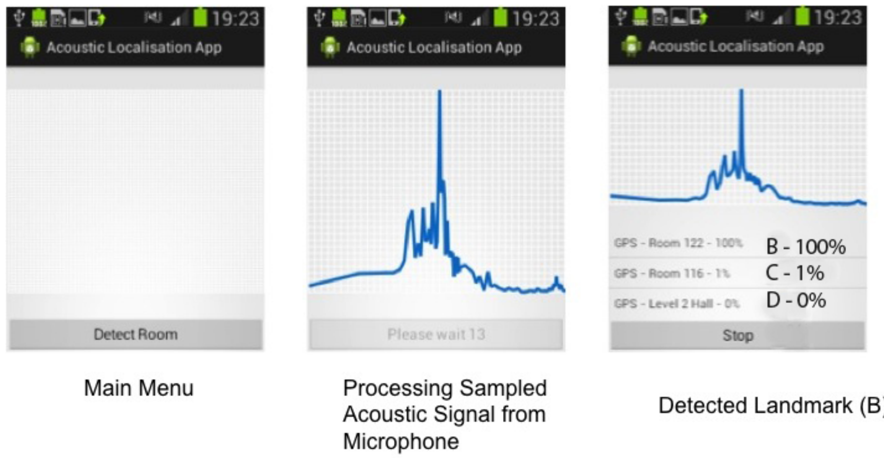

Fig. 5: Acoustic Landmark Localiser Mobile Phone App

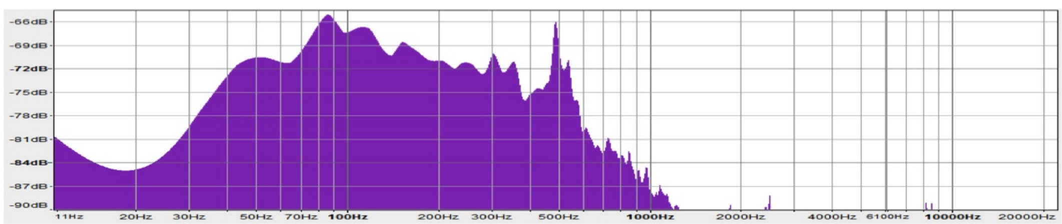

Fig. 6: Acoustic Profile of Landmark (Room C) with no occupancy

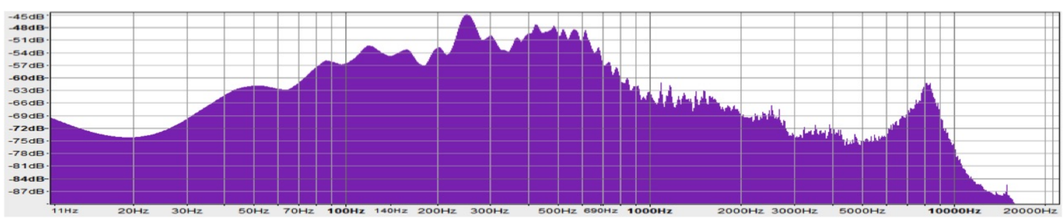

Fig. 7: Acoustic Profile of Landmark (Room C) with small occupancy

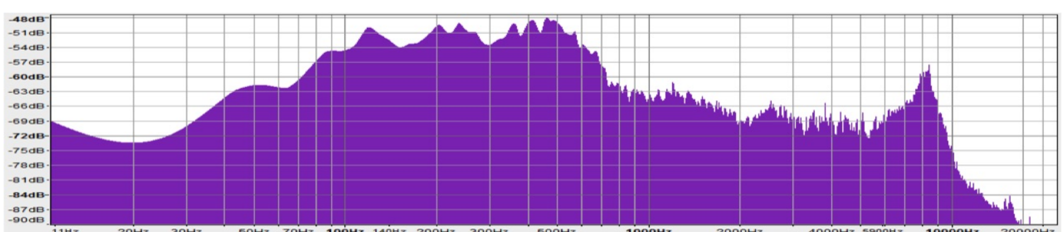

Fig. 8: Acoustic Profile of Landmark (Room C) with half occupancy

a person's location. The ALL used an artificial neural network based classifier to determine the most likely landmark that the user was near. The ALL classifier was implemented using the Encog Machine Learning Framework. For each landmark used, an acoustic profile was measured and used to train an Encog neural network algorithm. The ALL classifier would then determine which landmark the user was in close proximity to. Once the neural network classifier was trained, the kernel was saved and loaded into the ALL mobile phone app. The ALL mobile phone app used the trained neural network's kernel to determine the user's room location.

The ALL was tested in an indoor environment of a corridor and three rooms. Our tests show that the ALL mobile phone app was able to successfully determine the location of the person carrying the mobile phone, in all test areas. It was also found that the presence of people does distort the landmark acoustic profiles but the ALL classifier was still able to correctly determine the person's position.

Further work will involve investigating how other machine learning approaches can be used to better improve position accuracy and increase the number of sample spaces significantly. We will also look into creating and updating, in realtime, acoustic profiles for use in acoustic landmark localisation.Other avenues of investigation will also look at how 2-dimensional localisation can be achieved with additional acoustic sensing information.

REFERENCES

[1] A. Ofstad, E. Nicholas, R. Szcodronski, and R. R. Choudhury, "Aampl: Accelerometer augmented mobile phone localization," in *Proceedings of the First ACM International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments*, ser. MELT '08. New York, NY, USA: ACM, 2008, pp. 13–18. [Online]. Available: http://doi.acm.org/10.1145/1410012.1410016

[2] P. Bahl and V. Padmanabhan, "RADAR: An In-Building RF-based User Location and Tracking System," in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies*, vol. 2, 2000, pp. 775–784 vol.2.

[3] Youssef M. and Agrawala A., "The Horus WLAN Location Determination System," in *In Communication Networks and Distributed Systems Modeling and Simulation Conference*, 2005, pp. 205–218.

[4] M. D'Souza, T. Wark, M. Karunanithi, and M. Ros, "Evaluation of realtime people tracking for indoor environments using ubiquitous motion sensors and limited wireless network infrastructure," *Pervasive and Mobile Computing*, vol. 9, no. 4, pp. 498 – 515, 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1574119212000478

[5] M. D'Souza, T. Wark, and M. Ros, "Wireless Localisation Network for Patient Tracking," in *Intelligent Sensors, Sensor Networks and Information Processing, 2008. ISSNIP 2008. International Conference on*, 15-18 2008, pp. 79 –84.

[6] M. Ros, J. Boom, G. de Hosson, and M. D'Souza, "Indoor localisation using a context-aware dynamic position tracking model," *International Journal of Navigation and Observation*, vol. 2012, no. 293048, pp. 1 – 12, 2012.

[7] M. D'Souza, M. Ros, and M. Karunanithi, "An indoor localisation and motion monitoring system to determine behavioural activity in dementia afflicted patients in aged care," *electronic Journal of Health Informatics*, vol. 7, no. 2, 2013.

[8] M. Azizyan, I. Constandache, and R. Roy Choudhury, "Surroundsense: Mobile phone localization via ambience fingerprinting," in *Proceedings of the 15th Annual International Conference on Mobile Computing and Networking*, ser. MobiCom '09. New York, NY, USA: ACM, 2009, pp. 261–272. [Online]. Available: http://doi.acm.org/10.1145/1614320.1614350

[9] M. Azizyan and R. R. Choudhury, "Surroundsense: Mobile phone localization using ambient sound and light," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 13, no. 1, pp. 69–72, Jun. 2009. [Online]. Available: http://doi.acm.org/10.1145/1558590.1558605

[10] S. P. Tarzia, P. A. Dinda, R. P. Dick, and G. Memik, "Indoor localization without infrastructure using the acoustic background spectrum," in *Proceedings of the 9th International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '11. New York, NY, USA: ACM, 2011, pp. 155–168. [Online]. Available: http://doi.acm.org/10.1145/1999995.2000011

[11] N. Maisonneuve, M. Stevens, M. E. Niessen, and L. Steels, "Noisetube: Measuring and mapping noise pollution with mobile phones," in *INFORMATION TECHNOLOGIES IN ENVIRONMENTAL ENGINEERING (ITEE 2009), PROCEEDINGS OF THE 4TH INTERNATIONAL ICSC SYMPOSIUM, THESSALONIKI, GREECE, MAY 28-29, 2009*. Springer, 2009, pp. 215–228.

[12] Heaton Research, "Encog Machine Learning Framework," "www.heatonresearch.com/encog", 2015.

[13] M. Riedmiller and H. Braun, "A direct adaptive method for faster backpropagation learning: The rprop algorithm," in *IEEE INTERNATIONAL CONFERENCE ON NEURAL NETWORKS*, 1993, pp. 586–591.