Internet of Hospital Things: Infrastructure-less Localization

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Abstract

The goal of this project was to create an infrastructure-less indoor self-localization system that could be used in a hospital, or a device that could identify its location without requiring additional hospital-installed components. This is important because most currently available locator devices for hospitals require expensive RFID infrastructure set up throughout the hospital to work.

Two localization methods were investigated:

- **Ambient method**: machine learning algorithms were applied to ambient data collected from the environment to predict the location. The results indicated that the audio features were the most prominent ambient environmental data for accurately predicting location.
- **Phone method**: all hospitals have phones already installed everywhere. The locating device would listen for identifying noises emitted by the phones and use the unique tone heard to pinpoint its location. For this method, the method of tone identification was tested and results showed that the device could accurately identify DTMF tones that a phone could emit.

Testing Method

Hardware: The core of the device was a Particle Photon, an inexpensive wifi connected microcontroller, with sensors attached. The audio was collected with a smartphone to achieve a 44.1 kHz sampling rate.

Ambient method: Environmental data was collected in 3 distinct places

- UCF Partnership 3 Lab (Lab): relatively quiet room with few people passing through to mimic a hospital room
- Outside in Knights Circle Apartment (Outside): representative of outside of the hospital
- UCF Student Union (Union): busy public setting that mimics a hospital cafeteria or other public area

In each location, 40 data points were collected in a 2 hour period. Of these 120 total points, 96 were used to train an SVM classifier, and 24 were used in a testing set.

Each sample was taken over a 3 minute period. For the non-auditory feature points (in figure), the data was averaged over these 3 minutes. For the audio features, the features (figure) from 10 frames of the 3 minute ambient noise recording were used, for a total of 5 non-audio and 340 audio feature points per sample.

Phone method: DTMF (dual tone multi frequency) tones from the 1, 5, and 9 phone keys were recorded along with audio of background chatter. This was played from a speaker while audio was recorded in all parts of a small room (in order to mimic a hospital room). Then audio features (figure) were extracted from 1000 samples of length 25ms. Machine learning was again used to predict which DTMF tone the sample contained. Of these samples, 900 were included as the training set in another SVM classifier and 100 were used as the testing set.

Audio features [34 total]: zero crossing rate, energy, entropy of energy, spectral centroid, spectral spread, spectral entropy, spectral flux, spectral rolloff, MFCC's (13), chroma vector (12), chroma deviation

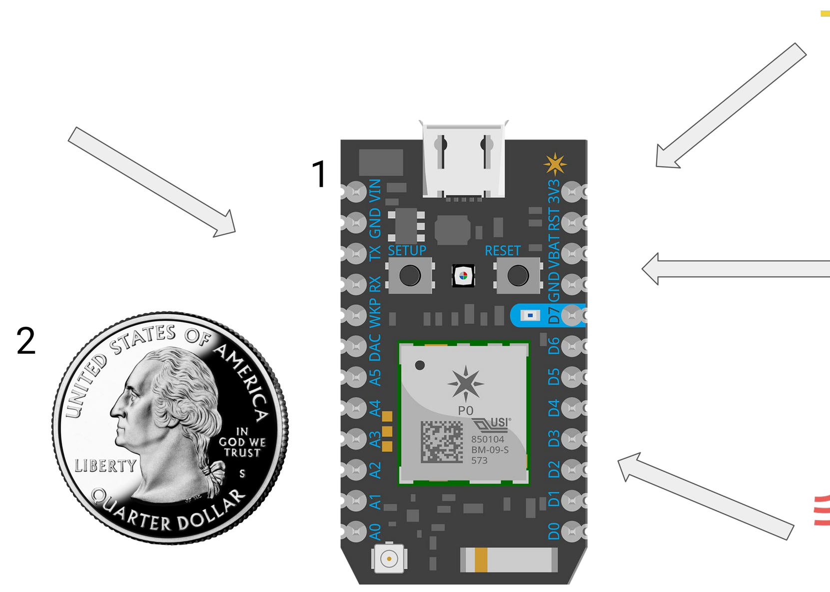

Figure: Particle Photon next to quarter for size.

Light sensor data: light temperature and lux

Atmosphere data: air temperature and pressure

Motion sensor data: movement around device

Non-Audio features [5 total]

Results

Ambient Method:

Audio features only

Location	Tested Samples	Accurate Predictions	Percentage Accuracy
Lab	8	8	100
Outside	8	8	100
Union	8	8	100

Audio features and non-audio features

Location	Tested Samples	Accurate Predictions	Percentage Accuracy
Lab	8	8	100
Outside	8	8	100
Union	8	4	50

Conclusion: In ambient method, the audio features alone were the more prominent feature points in training the classifier to make accurate predictions. 50% of the time, when both audio and non-audio feature points were used, the classifier misidentified union samples as outside.

Phone method: For 99% of the test samples, the correct DTMF tone was identified. Thus, the tone identification stage of making a localization system is complete.

Future Work

- Improving the classifier: from fine tuning the parameters, to trying different classification methods, or different variations of the SVM classifier.
- Testing more locations for the ambient method, and collecting more samples to have larger testing and training sets.
- Identifying the least obtrusive phone sound in a hospital setting for the phone method
- Testing other controllable non obtrusive signals, such as lighting
- Using the successful phone method tone detection from this investigation in an experiment that actually attempts localization

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Image References:

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2. https://upload.wikimedia.org/wikipedia/commons/a/a3/United_States_quarter,_obverse,_2004.png