Detecting if a Smartphone is Indoors or Outdoors with Ultrasounds

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Introduction

Current mobile phones provide, beyond communication functionalities, location and context-aware services. Smart-phones carry a lot of sensors from which they can infer a multitude of context clues. However, they may have different availabilities, energy, and accuracy profiles in different environments. An effective Indoor/Outdoor (IO) detection scheme can provide primitive environment information for a variety of mobile applications and thus potentially improve their performance. For example, in location-based applications, people usually employ GPS for an accurate location reference when they are in the outdoor environment. In contrast, it has been proved that GPS performs poorly without line-of-sight paths to satellites, i.e. when mobile devices are inside buildings. The proposed detector can provide a useful essential information to upper level mobile applications. For example, being the performance of GPS poor outdoors, a localization application can check whether the user is outdoors before turning on the GPS interface and, if the user is detected indoors, decide not to turn it on and use other indoor localization methods. In mobile data services, mobile phones normally observe more WiFi access points (APs) with strong signals inside buildings, whereas it is unlikely to have good WiFi connections in outdoor environments. Therefore, knowing whether the environment is indoors or outdoors can help to make smarter decisions regarding whether to perform or not an AP scanning.

Feature Extraction

It is impossible to identify the direction of the echoes being the microphone (as well as the phone speakers) non-directional. The idea is that, as it is outlined in Fig. 2, the indoor number and the intensity of the echoes should be higher than outdoors due to the higher number of obstacles. Translating such an idea into a practical Indoor/Outdoor detector means finding those features that model such behaviour. Rather than trying to exactly locate the position of the obstacles, the proposed method extracts 9 features that are statistically related to number and the amplitude of the echoes.

Classification

Weka, a wide used software for machine learning, has been used for testing four different classifiers: Naive Bayes, Logistic Regression, Decision Tree and Support Vector Machine. Table I reports the confusion matrices. All the classifiers have good performances in terms of accuracy, being all above 88%. Indoor and Outdoor classes have similar recognition rate meaning that the classifiers are not biased towards one class. The SVM is the classifier that exhibits the higher accuracy (94.9%).

Results

The Naive Bayes classifier is used as baseline and tested because of its simplicity and intuitiveness. In Fig. 3 the accuracy of the system has been studied with respect to $M_{p}$, the number of consecutive pings waited before taking a decision. A cubic interpolation has been reported along the measured accuracy values to show the trend. The more echoes are averaged together so the accuracy increases. On the other hand the system takes more time to retrieve a response, thus, it is a accuracy vs. latency trade-off. It can be seen that the accuracy does not increase much with $M_{p}$ > 10.

System Description

The proposed solution is an active system. The phone generates an ultrasonic ping and, using its in-built speakers, periodically emits it. At the same time it continuously listens for the echoes using its microphone. A band-pass filter is used to separate the echoes of the emitted signal from the environmental noise. A digital fifth order Butterworth filter centered around the ping frequency is applied to the recorded signal in order to isolate the echoes.

References