Towards an interval fingerprinting approach for indoor localization.

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Introduction

The omni-present availability of sensor-rich smartphones along with the fact that people spend 80-90% of their time in indoor environments has recently boosted an interest around the so called *Internet-based Indoor Navigation (IIN)* [12]. These comprise of indoor models, such as floor-maps and points-of-interest, along with Internet of Things (IoT)-based raw data, such as wireless, light and magnetic signals, used to localize and track mobile users and targets.

There is a large variety of localisation methods that exhibit diverse quality performance levels regarding precision, accuracy, cost, reliability, scalability, energy efficiency and robustness [1, 9]. One reason behind low performance usually observed in localization accuracy or robustness is the noisy nature of the IoT raw data used. For instance, the WiFi received signal strength (RSS), which is most commonly used by indoor localisation techniques, is in fact susceptible to multipath effects and interference, hence shows high variability over time. These variations may naturally introduce errors and jolts in reconstructed locations. To smoothen the location estimates and improve consistency, state-of-the-art localisation techniques work either with averaged signal data, or rely on more advanced probabilistic or Bayesian approaches [6, 11].

Other approaches use as well hybrid approaches combining RSSi-fingerprinting with inertial tracking systems as in [7] where the WiFi-based and the IMU-based location estimates, along with the associated uncertainties are provided as inputs to a data fusion module that implements the hybridization scheme by means of a particle filter. In practice however, the true probability distribution to use as Likelihood or a priori in the Bayesian methods are often unknown hence need be approximated using Gauss or uniform distributions. It is therefore appealing to consider an alternative description of the errors and disturbances acting on the measurements.

In this note we will report on a preliminary investigation on alternative methods to deal with the uncertainty in the measured signals by working directly with interval data, i.e. data ranges or data sets computed from the raw data with no assumption of the probability distribution within the interval. We will discuss a new method for IIN based on interval fingerprinting [10].

Interval fingerprinting

In this section, we discuss ways to exploit the interval measurements data in Wi-Fi Radiomap-based indoor localization techniques. We focus on techniques such as the ones implemented in Anyplace software [12].

Anyplace uses Wi-Fi Radiomap-based in-

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door localization, which stores radio signals from Wi-Fi APs in a database at a high density. The localization subsystem of Anyplace utilizes the following routine:

In an offline phase, a logging application records the so called *Wi-Fi fingerprints*, which comprise of *Received Signal Strength (RSS)* indicators of Wi-Fi Access Points (APs) at certain locations (x, y) pin-pointed on a building floor map (e.g., every few meters).

Subsequently, in a second offline phase, the Wi-Fi fingerprints are joint into a $N \times M$ matrix, coined the *Wi-Fi RadioMap*, where N is the number of unique (x, y) fingerprints and M the total number of APs.

Finally, in the online phase, a user can compare its currently observed RSS fingerprint against the RadioMap in order to find the best match, using known algorithms such as K-nearest neighbour (KNN) or weighted KNN (WKNN) [6].

Contrariwise to standard approaches, we further assume that at each unique location l, $l = 1, ..., N$, the range of variation of the signal intensity is captured, e.g. by sampling data during short time windows. The *RadioMap* (*RM*) now contains *interval fingerprint* $[\vec{v}_l]$ measured at location l. The actual coordinates of location l may also be subject to bounded uncertainty, i.e. $\vec{p}_l \in [\vec{p}_l] = ([x_l], [y_l])$. The thus obtained *interval*-RM is stored in a database, where each entry T_l has the form

$$T_l = ([\vec{p}_l]; [\vec{v}_l]) \tag{1}$$

Finally, the observed RSS fingerprint during online phase is taken as an interval vector $[\vec{v}_o]$.

Classification with interval data

Since both the radiomap data and the signal measured by the mobile unit are interval data, we need to extend the WKNN approach to measure dissimilarities between interval vectors.

This idea is not new. A KNN classification method using interval data is proposed in [8], where the method mainly relies on identifying possible and necessary neighbours using the *partial* orders induced by some distance metrics computed with intervals. By construction, the method yields ambiguous decisions.

To the contrary, other authors addressed the issue using *total* orders for clustering interval data in [4, 2] and also in the framework of fuzzy sets in [3]. In these works, the distance metric used for comparing two interval vectors was the Hausdorff distance, associated with the Chebyshev metric as it seems explicit formulas were readily available for online computation. However, when other metrics were used, the distance used was not the most appropriate to interval data. The reason it seems, is that the authors of these works did not find explicit formulas for computing the Hausdorff distance associated with the other metrics.

Actually, Jahn [5] gives explicit formulas that allow online computation of the Hausdorff distance h_p associated with the Minkowski norms (2)

$$d_p(x, y) = \left(\sum_i |x_i - y_i|^p \right)^{1/p}. \tag{2}$$

Classical WKNN can then be used to estimate the location of the mobile unit using the k nearest neighbours

$$[\hat{\vec{p}}_o] = \frac{\sum_{i=1}^{k} [\vec{p}_i]/d_i}{\sum_{i=1}^{k} 1/d_i}, \tag{3}$$

where the distance are given by

$$d_i = h_p([\vec{v}_l], [\vec{v}_o]). \tag{4}$$

Concluding remarks

The preliminary evaluation of our new method on an actual interval radio map containing N = 52 interval fingerprints obtained at positions covered by M = 206 unique AP, shows that first, it can work directly with interval data, and second, the estimates it provides are smoother and more consistent than the ones provided by state-of-the-art methods.

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