A hybrid method for indoor user localisation

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Abstract. In this work we describe an approach to indoor user localisation by combining image-based and RF-based methods and compare this new approach to prior work [1]. This paper details a new algorithm for indoor user localisation, demonstrating more effective user localisation than prior approaches and therefore presents the next step in combining two different technologies for localisation in indoor type environments.

Key words: SURF, Image localisation, Image matching, RF localisation, Nokia N95, Gaussian distribution, data fusion

1 Introduction

The main goal of this work is to investigate whether the combination of two complementary localisation methods gives better results than single modality localisation and to compare these results with previous work in data fusion. The ability of a digital device to perform automatic user-localisation enables it to provide location-aware functionality, enhancing the user experience. Outdoor localisation, using GPS and GSM, makes it feasible to provide sightseeing and/or tracking applications [2]. Indoor localisation is more challenging given the weak GPS signals and the high spatial accuracy required. An approach targetted at indoor applications, such as a museum or an exhibition scenario, was developed in [1] by combining image information with signal strength readings from a WLAN 802.11 network. In this paper, we also use these complementary data sources but develop a more accurate and computationally efficient algorithm. We use the Nokia N95 cellphone as a testbed, since it is capable of processing both RF and image data. Additionally, our set of test locations has more complex surroundings and obstacles, compared to [1]. We improve on prior work by using a more accurate Bayesian method, a Gaussian distribution and a different, more efficient hybrid method.

2 System Overview

The system we developed is presented in Fig. 1 and can be divided into two streams: an image stream and RF stream. The RF section utilizes signal strength

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measurements and processes them in order to get a descending array of possibilities for the user's location. This leads to a smaller search space on which the image localisation algorithms will be performed. As the search space is narrowed, the results are more accurate and the processing is faster. This gives the final estimated localisation of the user. The system presented here has a flexible architecture, which allows the processing to be performed on the phone or on a server, depending on the phone's capabilities.

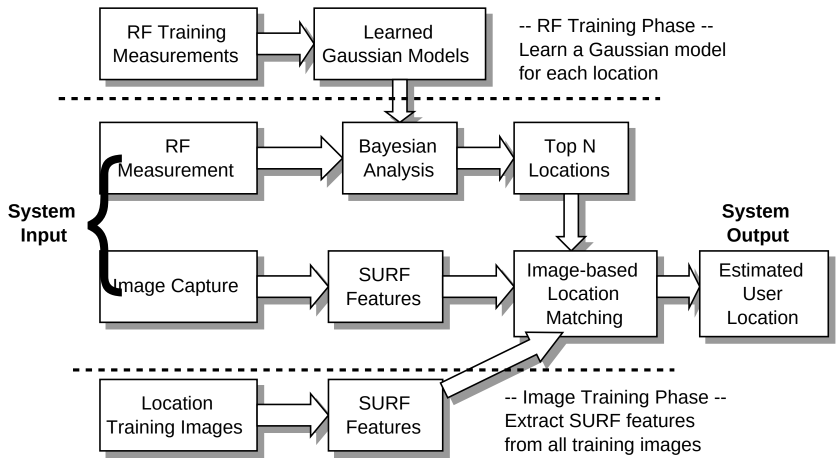

Fig. 1. System overview

3 RF localisation

Various approaches to RF localisation have been described in prior literature. In [4] indoor positioning was achieved using Bayesian analysis; an indoor experimental setup was given in paper [5] and a positioning method based on IEEE 802.11 in [6]. In this paper signal strength measurements were measured at specific locations from the same four access points of a 802.11 WLAN network. A set of signal strengths gathered at a location is used to build a histogram model of signal strength values for that location and later for approximating it with a Gaussian distribution. Let S_i represent a location, $1 \leq i \leq I$, and O_j is the current observed signal strength data from access point j, where $1 \leq j \leq J$. Additionally, $P(S_i|O_j)$ is probability of being at position S_i given the observed O_j signal strength data. Since there are several access points, one has to calculate these values for all of them. With a given access point j, for a set of locations $1 \leq i \leq I$, Bayesian probability equations can be written as:

$$P(S_i|O_j) = P(O_j|S_i)P(S_i)/P(O_j) \tag{1}$$

where $P(O_j)$ is given by:

$$P(O_j) = P(O_j|S_1)P(S_1) + P(O_j|S_2)P(S_2) + ... + P(O_j|S_I)P(S_I) \tag{2}$$

for every $1 \leq j \leq J$. Also, for every access point there is a (different) Gaussian function (which gives $P(O_j|S_i)$). An array is formed where i^{th} element is given by equation 3 (right side of the equation is analyzed). Since $P(S_i)$ and the denominator are constant values from Gaussian distributions the other part of the numerator is obtained, which is only needed for the calculations. The maximum value of the array gives the estimated location.

$$\begin{aligned} &P(S_i|O_1)P(S_i|O_2)...P(S_i|O_J) = \\ &= P(O_1|S_i)P(O_2|S_i)...P(O_J|S_i)P(S_i)^J/(P(O_1)P(O_2)...P(O_J)) \end{aligned} \tag{3}$$

4 Image matching and localisation

The image matching uses the well-known SURF (Speeded Up Robust Features) algorithm [3] which is implemented and installed on the cell phone. SURF is a scale, noise and rotation-invariant interest point descriptor. It was inspired by and several times faster than the SIFT descriptor [7]. Interest points are selected at distinctive locations in the image such as corners, blobs, and T-junctions. Next, the neighbourhood of every interest point is represented by a feature vector. The SURF descriptor is robust to noise, lighting and other geometric/photometric deformations. Finally, the descriptor vectors are matched between different images calculating the Euclidean distance between them. If the distance is less than a given threshold then a match is confirmed. The process is repeated for all vectors in one pair of images (an example is shown in Fig. 2 left). It proceeds in the same way with all other images in the database. As a result an array of correct matches between given image and our set of images is formed. The maximum value of this array indicates the image with most matches, and thereby provides a good location estimate.

5 Experiments and Results

The test sites for our experiment are a set of locations which are scattered throughout DCU (3 locations on the first and 4 on the second and the third floor). For the RF localisation, the Camaignr software [8] was installed on the N95 cellphone. For data collection 11 locations with 4 orientations of the cell phone for each location were used. We combined the measurements from all 4 orientations into one model. Campaignr was set to measure signal strengths every 30 seconds and the N95 was being used for approximately 15 minutes at the same location with a fixed orientation. The cellphone was rotated 90 degrees clockwise every 15 minutes to account for variation in antenna orientation. Photos of the exhibits were taken from various angles, with different rotation, scale and with different object variation in order to simulate images captured by a real user at a museum exhibit. At each location $6-8$ images were captured (74 images in total). The hybrid technique is based on applying image matching on the smaller set of locations, which are generated by applying Bayesian analysis to the RF signal strength readings. We compared our combined approach to single modality localisation and to prior work [1]. The results are presented in fig. 2:

	Previous [1]	Proposed
RF only	59.83 %	63.64 %
Image only	74.90 %	81.8 %
Hybrid	79.21 %	87.5 %

Fig. 2. (left) SURF location matching, (right) Table of user Localisation results.

6 Conclusion

The proposed approach to combining RF and image information was shown to outperform prior work in this area and to provide a significant improvement over single-modality localisation. Future work will focus on applying the Bayesian approach to image-based localisation to further improve results.

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