A Cooperative Localization Technique for Tracking in Hospitals and Nursing Homes

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Abstract— **Nowadays numerous technologies such as WiFi, Bluetooth, cellular networks and magnetometer positioning are employed for tracking patients and assets in hospitals or nursing homes. Each of these techniques has advantages and drawbacks. For example, WiFi localization has relatively good accuracy but cannot be used in case of power outage or in the areas with poor WiFi coverage. Magnetometer positioning or cellular network does not have such problems but they are not as accurate as localization with WiFi. This paper describes technique that simultaneously employs different localization technologies for enhancing stability and average accuracy of localization. The proposed algorithm is based on fingerprinting method paired with data fusion and prediction algorithms for estimating the object location. Significant performance improvement was showed in practical scenarios.**

I. INTRODUCTION

In hospitals and nursing homes one of the most important tasks is a safety of patients and indoor positioning service is one of the key components of patient safety.

Most widely used solutions for indoor localization are based on WLAN received signal strength indicator (RSSI), which gives relatively accurate result under the condition of dense coverage of WiFi network in the building [1]. There are two general methods of WLAN localization: trilateration and fingerprinting. However, due to shadowing, multipath and numerous obstacles the trilateration methods cannot achieve as accurate results as fingerprinting [4]. Almost all existing WLAN indoor solutions (NavIndoors, Meredian, Ekahau, etc.) are based on fingerprinting technique, firstly described in [5], where location is estimated based on radio map.

According to numerous surveys, systems which based on fingerprinting technique have average positioning accuracy up to 1-3m [4]. Such a high precision is achievable only in environment with high WLAN coverage, when signals from several access points are available at each point of the area. Furthermore, WLAN localization cannot be used in emergencies like fire or other situations when access points are disabled. Finally, radio map, collected during preparation phase, can differ from the actual measurements, because the signal in the area could be affected by many factors such as electrical devices, elevator, heating devices etc.

These disadvantages could be overcome by combining different technologies in a single positioning system. One of the most popular hybrid positioning systems is Skyhook, which combines Cellular, GPS and WLAN signals for positioning [6]. This localization precession is good in urban areas and for devices without GPS, but it performs poorly in indoor environment.

There are hybrid solutions [7] which enhance positioning accuracy of one positioning technology (GPS, WLAN, UWB) by dead reckoning sensors, such as inertial navigation system. Commonly, these techniques are used for GPS accuracy enhancement and could be used in indoor WiFi localization as a substitute for GPS. However, WLAN localization problems, described above, cancel all advantages of this approach.

Another commonly used technique is context variable weighted fusion that defines sensor data reliability. In [9] a multisensory Kalman filter is proposed which combines GPS and inertial measurement units (IMU) data to localize an autonomous land vehicle. Here the contextual information was used, such as number of satellites in line of sight, map matching for hostile to GPS environment estimation. It is apparent that technique described in [9] cannot be used in hospital and/or nursing home environments.

In this paper we present an algorithm of combining different localization technologies with contextual information and prediction technique. The objective of this work is to develop a hybrid method, which utilizes advantages of different methods to achieve appropriate accuracy and stability.

The remaining part of the paper is organized as follows. Section II presents a description of the proposed technique. Then, in Section III the results of algorithm verification are presented. And finally, Section IV provides conclusions and plans for future research.

II. AN ALGORITHM DESCRIPTION

The main idea of the proposed algorithm is based on using different positioning technologies depending on context information. By context information we mean knowledge about error in the particular location. For simplification, in this work we used two localization techniques: WiFi and RFID. Although, system concept allows us to combine other

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technologies, such as ultra wide band (UWB), Bluetooth, cellular networks, WiMAX, etc. [8].

In Figure 1 the concept of the proposed localization algorithm is illustrated. According to this figure, we have four interacting sides. First the signal measurements are read by sensors (WLAN RSSI, RFID RSSI) and preprocessed. After that, fingerprinting technique gives several possible position estimations for each type of sensors. Then error of the each estimation is computed. Finally, according to the error variance, the data fusion algorithm calculates the mobile unit (MU) location.

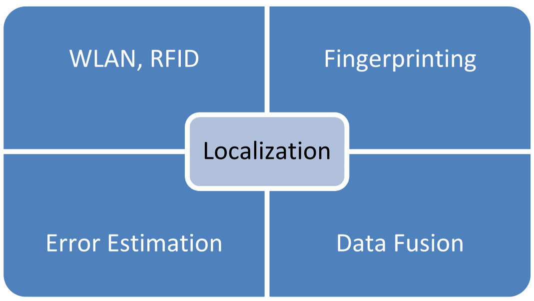

Figure 1. The proposed concept

Fingerprinting technique combined with different localization technologies (WiFi, RFID, etc.) gives several positions as an output. Of course the most applications require just one position and the next step is data fusion part which is necessary to get the final result.

The simplest solution could be averaging of inputs, but that gives inaccurate result because accuracy of technologies is not constant in space. For instance, WiFi localization can gives 2 meter mean error in one part of a corridor, but can gives 6-7 meter error in another part of a corridor. Therefore, applying weighted averaging method like *weighted least squares* and knowing error of each technology, the accuracy of the final result could be improved.

The next three parts give more details for fingerprinting, error estimation and data fusion algorithms, used in this work.

A. Fingerprinting technique

Location fingerprinting is the technique for calculating location of the MU, which has signal strength measurement capabilities. Location fingerprinting has two phases: offline phase for calibration and online for location estimation. In offline phase the Received Signal Strength Indicator (RSSI) from several access points (AP) is measured at the selected locations, called calibration points (CP). These measurements are called the fingerprints of the calibration points. All collected fingerprints from the building create radio map. In the second phase of location estimation the measurements collected in calibration points and current measurements of mobile unit (MU) are used for localization estimations.

One element of the radio map can be written in the following form:

$$\mathcal{M}_i = \left(b_{i1}, b_{i2}, \{a_{ij} \middle| j \in N_i\}, \theta_i\right), \qquad i = 1, \dots, M,$$

where a_{ij} is the list of RSSI data measured from access point AP_j, N_i is a set of APs in range at the ith calibration point, that means that APs is available from the calibration point in offline phase of the algorithm. Thus the number of APs is the dimension of the list N_i. The number of RSS values measured from AP_j is the size of the list a_{ij}. In this work only 2-dimentional location is used and b_{i1}, b_{i2} denote coordinate of location in the building.

The goal of location estimation phase is to calculate the state x from the received measurements y, which represent value of RSSI from the each of APs in the system. Depending upon the system and its energy consumption requirements the measurements could be taken with different frequency, however, for the sake of simplicity, in our experiments we assume homogeneous clock of one sample a second. The measurements could be represented as:

$$y = \{y_j \middle| j \in N_y\} \in R,$$

where y_j is the measurements from access point j.

In online phase the current RSSI values of mobile unit (MU) are compared with the radio map, formed during the offline phase.

There are two groups of methods to estimate location by fingerprints: deterministic and probabilistic. The first one includes methods such as K nearest neighbors, neural networks, and support vector machine [11]. These methods have one point as a result (in some cases with standard deviation), which is not a correctly approximated MU location. The probabilistic methods, in the opposite, have location pdf as an output and describe the possible MU location more accurately. In our work we are interested in the second group, because location estimation is just a first step of the positioning process and we need as high accuracy about MU location as possible.

The basic idea of probabilistic methods of location fingerprinting is to compute the conditional pdf of the state x given measurements y. The pdf of the random variable $x|y$ is defined as

$$p_{x|y}(x|y) = \frac{p_{x,y}(x,y)}{p_y(y)},$$

where $p_y(y) > 0$. The definition of the Bayes rule has the form

$$p_{x|y}(x|y) = \frac{p_{y|x}(y|x)p_x(x)}{p_y(y)} = \frac{p_{y|x}(y|x)p_x(x)}{\int p_{y|x}(y|x)p_x(x)dx},$$

For simplicity let's denote pdf of random variable x as

$$p_x(x) \triangleq p(x).$$

In Bayes formula the function $p(y|x)$ is *likelihood* function of the received measurements. This function represents information retrieved during the offline phase of location fingerprinting. The function $p(x)$ is called the *a priori* (this functions is independent of the measurements) and could represent background information about the localized object movement history, $p(x|y)$ is called the *a posteriori* of the state x. Prior distribution $p(x)$ in location fingerprinting is often uniform distribution.

There are several implementations of the likelihood function, such as kernel function, histograms, histogram comparison. In this work we used kernel function approximation, because, according to the numerous surveys, this method gives more accurate results [1]. In general, the a priori function is uniform and posterior distribution of location depends only of likelihood function. Therefore the most important task is to approximate physical nature of distribution of signal strength as accurately as possible.

In the Kernel method, the likelihood function represents sum of kernel functions of observations divided by a number of observations at a given location. As a result, probability density function for an observation in a given location is a mixture of n kernel functions, where n is number of observation in the location:

$$p(y|x_i) = \frac{1}{n}\sum_{t=1}^{n} K(y, a_i^t),$$

where $p(y|x_i)$ – the pdf of RSSI (likelihood function) at location x_i, $K(\cdot,\cdot)$ –kernel function, a_i^t – fingerprint in the location, t – total number of fingerprints in the given location [3].

Generally the Gaussian function is used as a kernel function:

$$K_{Gauss}(y, a_i^t) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(y-a_i^t)^2}{2\sigma}\right),$$

where parameter σ is determined experimentally.

One of the natural choices of determining location by means of calculated posterior distribution is to seek the argument of maximum posterior estimate of the location, that is

$$\hat{x}_{MAP} = argmax\ p(x|y)$$

Usually, the fingerprinting technique is used in the context of MU localization task in WLAN network. But this technique can be successfully applied for geo-magnetic positioning technique as shown in [10].

B. Error estimation

Generally coverage vary from one part of the building to another, therefore we have different errors which are location specific. In order to have information of error at any location we need to store error map for each of the used methods.

An error map could be created by using idea that some regions have similar signal properties. Signal strength deviations of this area are almost the same as the deviations in one of locations of this area. Because signal noise prevent find true location in the area, error of localization is equal the area of the region.

The following algorithm divide location map for clusters, representing the described regions:

1. Initially every location represents a separate cluster.

2. After that random cluster is chosen and compared with adjacent cluster by similarity function. If the value of similarity function lies above a given threshold, the clusters are merged into one new cluster.

3. The previous step is repeated until no clusters can merged any more.

4. All clusters which include only one location are merged with the most similar adjacent cluster without considering the threshold.

5. The remaining clusters represent regions with similar signal properties. The error of each location of cluster could be deduced from size of the area.

The similarity function, mentioned in step 2, is calculated in the following way: For each access point of which RSSI measurements are contained in the clusters, a mean value and standard deviation is calculated. By these values a normal distribution pdf are constructed. After that, the overlapped area of distribution probability functions is computed by the flowing way. First the intersection points of functions are found:

$$\frac{1}{\sqrt{2\pi}\sigma_1}\exp\left(-\frac{(\mu_1-x)^2}{2\sigma_1^2}\right) = \frac{1}{\sqrt{2\pi}\sigma_2}\exp\left(-\frac{(\mu_2-x)^2}{2\sigma_2^2}\right),$$

where μ_1, μ_2 – mean and σ_1, σ_2 – standard deviations of pdf,

$$\frac{(x-\mu_2)^2}{2\sigma_1^2} - \frac{(x-\mu_1)^2}{2\sigma_2^2} = \frac{1}{2}\ln\frac{\sigma_1^2}{\sigma_2^2},$$

$$(\sigma_1^2-\sigma_2^2)x^2 + 2(\mu_1\sigma_2^2\text{-}\mu_2\sigma_1^2)x + (\mu_2^2\sigma_1^2 - \mu_1^2\sigma_2^2 - \sigma_1^2\sigma_2^2\ln\frac{\sigma_1^2}{\sigma_2^2}) = 0,$$

Obviously, square equation gives two solutionsx_1, x_2. Then using cumulative distribution function (CDF) the overlapping area is calculated:

$$S = F_1(x_1) + \big(F_2(x_2) - F_2(x_1)\big) + \big(1 - F_1(x_2)\big),$$

where $F_1, F_2 (\sigma_1 < \sigma_2)$ are CDF of the given distributions. On Figure 2 the overlapped area is showed. The procedure is repeated for all access points, and finally an average size of overlapped areas is calculated. This value serves as a similarity function for two clusters.

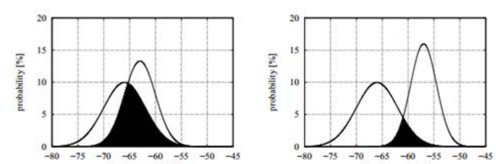

Figure 2. Overlapped area of two pdf

The threshold, mentioned in step 2 can be varied. The higher threshold entails smaller clusters, which helps to decrease difference between estimated and actual error. But this raises probability of wrong region selection. Experimentally found optimal threshold 0.63.

Figure 3 illustrated resulting clusters for RFID localization algorithm with RFID readers in the left part of the floor. Big clusters have red tints and small clusters have green tints. Obviously localization algorithm works better in green areas because they have smaller error. In yellow and red areas another localization technique should replace RFID.

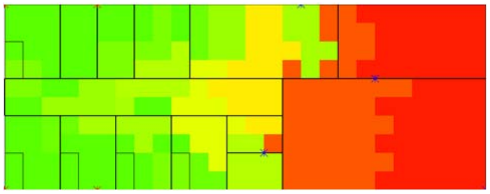

Figure 3. Accuracy map

C. Data Fusion

The described localization algorithm we have N localization methods, which works separately and provide results with different accuracy. According to [9] the optimal solution to this task is weighted linear least squares (WLLS) with model:

$$y_k = H_k x + e_k,$$

where y_k – estimation of k-th localization algorithm (WiFi, RFID, etc.,) H_k – unitary matrix, e_k- error of the method. The estimation of true position by WLLS is as follows:

$$\hat{x}^{WLS} = (\sum_{k=1}^{N} H_k^T R_k^{-1} H_k^{-1})^{-1} \sum_{k=1}^{N} H_k^T R_k^{-1} y_k =$$

$$= (\sum_{k=1}^{N} R_k^{-1})^{-1} \sum_{k=1}^{N} R_k^{-1} y_k$$

where R_k – error covariance (accuracy estimation) of the k-th method which has been received in section B, $\hat{x}^{WLS}$ – final estimated position of MU, N – number of localization methods.

The error covariance of the final estimated position is

$$Cov(\hat{x}^{WLS}) = (\sum_{k=-1}^{N} R_k^{-1})^{-1}$$

III. SIMULATION

In order to verify accuracy of the proposed algorithm the following simulation has been conducted. We created a typical nursing home environment with rooms and corridors where several access points were placed. For result simplification we used WiFi and RFID localization technologies which were based on Kernel method with 2 meter grid cell. The signal propagation model was based on Okumura Hata model with RSSI measurements modeled as the following function:

$$z_k = z_0 - 10\eta \log_{10}(\mathrm{d}_k) + \upsilon_k$$

where z_0 is a constant characteristic of the transmission power of base station, η is a slope index (in this work we used $\eta = 1.8$ which typically for indoor environment. d_k is a distance to base station and υ_k is a logarithm of the noise component (we used 4 dB as a standard deviation of the Gaussian noise).

In the experiment we model the person movement from one room to another through a corridor. The person has WiFi and RFID RSS sensors. For testing purposes some areas of the person route have stronger WiFi signal coverage then RFID one. In another part of the route the situation is the opposite.

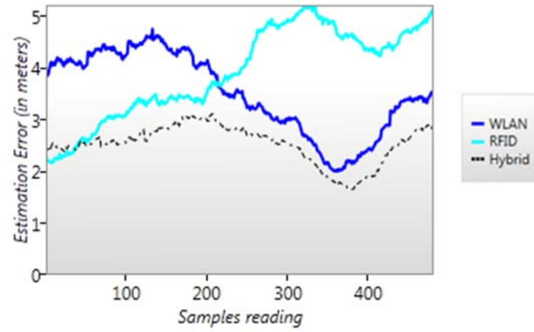

Figure 4. Accuracy comparison

On the Figure 4 the accuracy of the three methods is compared during the route of the modeled person. It can be observed that in the first part of the route WLAN fingerprinting method provides large error due to the lack of WiFi coverage. Then as the coverage improves the WLAN imposed errors go down. The opposite situation we have with RFID localization. Nevertheless the proposed hybrid method has stable 2-3 meter error and in the most places is more accurate than others of used algorithm.

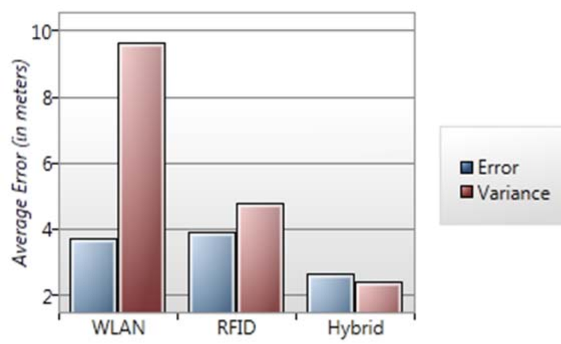

Figure 5. Accumulated error and variance of each of the methods

In Figure 5 the comparison of the accumulated accuracy is shown. As it following from these results, the proposed fusion algorithm in general provides better accuracy compared to WLAN and RFID localization techniques. In the main paper we will present more detailed results for a number of practical user cases and will provide quantitative assessment of achieved accuracy in these scenarios.

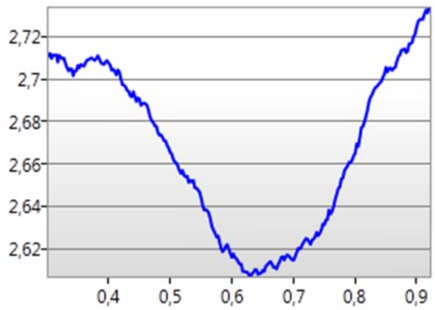

Figure 6. Thresold optimal value

Illustration of error dependency of threshold choice is shown on Figure 6. Value 0.63 was optimal for the experiment.

IV. Conclusion

In this paper we describe the technique that simultaneously employs different localization technologies for enhancing stability and average accuracy of localization. The proposed algorithm is based on fingerprinting technique paired with data fusion and prediction algorithms for estimating the object location. We present performance results showing significant performance improvement in practical scenarios. More specifically, we show that the proposed technique is appropriate for indoor localization (2-3 meter accuracy) and allows reliable localization of patients in hospital and/or nursing home environments. In the main paper we present results showing that the achieved accuracy could be improved further by prediction model used in [2] and by utilizing additional sensors, such as accelerometer or gyroscope.

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