35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

# A Hybrid Localization Technique for Patient Tracking

Denis Rodionov, George Kolev, Kirill Bushminkin*

*Abstract*— **Nowadays numerous technologies are employed for tracking patients and assets in hospitals or nursing homes. Each of them 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. The core idea of the algorithm is technology fusion using error estimation methods. For testing accuracy and performance of the algorithm testing simulation environment has been implemented. Significant accuracy 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 of indoor positioning problem 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) to find location of autonomous 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 main objective of this work is to develop a hybrid method, which utilizes advantages of different methods to achieve appropriate accuracy and stability.

## II. An algorithm description

The main idea of the proposed algorithm is based on using different positioning technologies depending on context information combined with utilization of location prediction as auxiliary information. For simplification, in this work we used three localization techniques: WiFi, RFID and magnet field based localization. Although, system concept allows us to combine other 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, the sequence of processing steps is following. First the signal measurements are read by sensors (WLAN RSSI, RDID RSSI and magnitude). After that, the location probability density function (pdf) is approximated by fingerprinting technique. Then error estimation technique provides accuracy of each of used technology. Finally, the data fusion algorithm calculates the mobile unit (MU) location by means of four pdf (prediction, WLAN, RFID, Cellular).

* Denis Rodionov (rodionov.lancs@gmail.com), Lancaster University, School of computing and communications, InfoLab21, United Kingdom,
Dr. George Kolev (mail@kolev.us), Center of Coordination of International Scientific Education Programmes,
Kirill Bushminkin (kbushminkin@gmail.com), Lancaster University, School of computing and communications, InfoLab21, United Kingdom

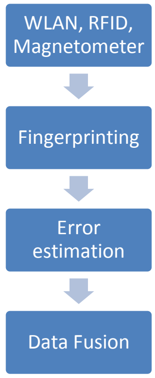


**Figure 1. The proposed concept**

*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 RSSI from different access points (AP) is measured at the selected locations. Locations with RSSI are called calibration points (CP). These measurements united from several APs in one location are called fingerprints. 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 RSSI measured from $AP_j$, $N_i$ is a number of APs available at the $i$th calibration point, that means that APs is available from the calibration point in offline phase of the algorithm. Thus the amount of APs is the dimension $N_i$. The number of RSS values measured from $AP_j$ is the size of the list $a_{ij}$. Here only 2-dimentional location is used so $b_{i1}, b_{i2}$ denote coordinate of location in the building.

The goal of location estimation stage is to calculate the state $x$ by means of 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 for fingerprinting is to calculate the conditional pdf of the state x with given measurements $y$. The conditional random variable pdf 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 $x$. Prior distribution $p(x)$ in 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 $\sigma$ is determined experimentally.

One of the natural choices of determining location by means of calculated posterior distribution is to find the argument of maximum posterior estimation of the location: $\hat{x}_{MAP} = argmax\ p(x|y)$

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. Prediction*

In the previous section the position has been estimated with unitary *prior* $p(x)$. According to [1] the prior pdf can be constructed by

- map matching (MU cannot jump from one room to another, the number of the next possible locations is restricted)
- direction of movement (if the MU's speed is not zero, the most probable location is located on the direction of the movement)

In case of large sensor measurement interval the several-step prediction algorithms could be used [2].

### *C. Error estimation*

Because commonly we do not have the same coverage in any point of the building 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.

According to [11], the following algorithm can be used to calculate an error at each location:

- Build a fingerprinting map using all locations except one(location $p$)
- Each fingerprint in location $p$ used as an online measurement in algorithm with radio map where location $p$ was excluded.
- Calculate the error for each fingerprint
- Calculate the error estimate for position p as the average of observed errors added to double standard deviation of observed errors.

### *D. Data Fusion*

The described localization algorithm we have $N$ localization methods, which works separately and provide results with different accuracy. Here we have a linear observation model [9]:

$$y_k = H_k x + e_k,$$

where $y_k$ – estimation of k-th localization algorithm (WiFi, RFID, etc.,) $H_k$ – in this particular example is identity matrix, $e_k$- error of the method. The most appropriate solution for final location estimation is weighted least square data fusion with unitary $H$ matrix:

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

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

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

The error covariance of the final estimated position is

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

## 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. Simulated environment considers only one floor of the home with size 40x20m. For result simplification we used WiFi and RFID localization technologies. In order to show algorithm performance, Wi-Fi and RFID coverage is uneven across the floor. The Kernel method is implemented 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, $\eta$ is a slope index (in this work we used $\eta = 1.8$ which typically for indoor environment. $\mathrm{d}_k$ is a distance to base station and $\upsilon_k$ 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.

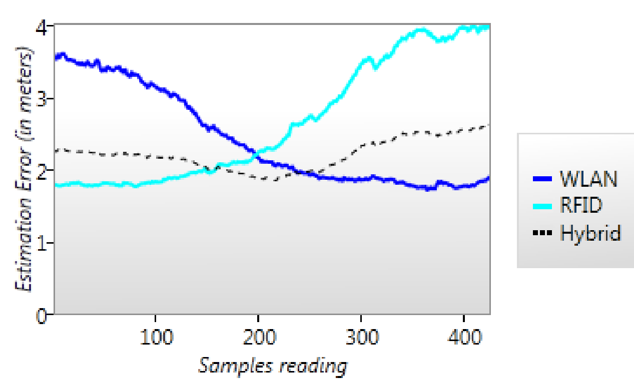


**Figure 2. Accuracy comparison**

On the Figure 2 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 some places is more accurate than others of used algorithm.

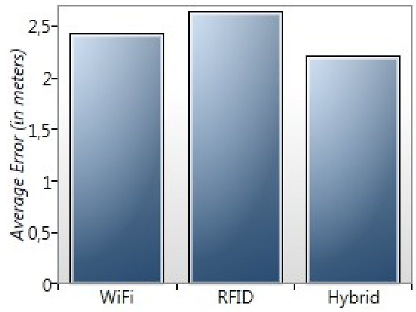


**Figure 3. Accumulated error of each of the methods**

In Figure 3 the comparison of the mean 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.

## IV. DISCUSSION

The specified technique could be improved by using united fingerprinting technique, where sensor measurements from different sources (Wi-Fi, RFID, etc) are combined in one fingerprint. This approach requires implementing another error estimation technique allowing to remove measurements which increase overall error of the system.

## V. 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 utilizing additional sensors, such as accelerometer or gyroscope.

## ACKNOWLEDGMENT

We acknowledge the support from the [European Community's] Seventh Framework Programme [FP7/2007-2013] under grant agreement No 238710 (Monte Carlo based Innovative Management and Processing for an Unrivalled Leap in Sensor Exploitation) and Rinicom Ltd., UK.

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