Smartwatch Based Indoor Localization

László Árvai
Department of System Development
Bay Zoltán Nonprofit Ltd. for Applied Research
Miskolc, Hungary
laszlo.arvai@bayzoltan.hu

Abstract **— The hardware platform for the indoor pedestrian navigation systems are usually smartphones. They are suitable for the infrastructure-less indoor localization systems since they have several sensors built-in like magnetic compass for direction sensing, gyro and acceleration sensor for motion analysis and Wi-Fi or Bluetooth radio module for fingerprint-based position determination. Some application fields, like monitoring elderly patient's movement, motion path and health condition require more convenient and wearable device like a smartwatch. The smartwatch usually has limited number of sensors and their wearing position make motion sensing less accurate therefore special localization, filtering and data processing algorithms are required. In this article the algorithms, filtering methods and tuning procedures are explained of a smartwatch based indoor localization system.**

Keywords — indoor localization, fingerprint localization, smartwatch localization

I. Introduction

The recently emerging smartwatch technology with very powerful hardware and very versatile Android operation system makes possible to use smartwatch as a monitoring device, sensor device in elderly care or home care systems. Many of the smartwatches has several sensors and communication interfaces with the flexibility of the programing ability provided by the Android operation system. In the case of elderly care, the wearable sensors have very high importance and since the watches are well known and well accepted by elderly people, they don't need to have special experience to use it. And since they have a custom anyway to wear a watch it is not a strange or even "dangerous" looking electrical gadget, but something which they were used to it for decades. Therefore, according to our experience, the smartwatch is one of the most accepted wearable devices by elderly people.

Unfortunately, more and more elderly people live with dementia, which puts more and more burden to their relatives and overall to the society. Therefore, any effort to expand the period of their life which they can be spend at their home independently or any effort to reduce the workload of the caregivers by using IT solutions is getting high importance.

Based on those thoughts we have developed a smartwatch based multi sensor application for elderly care, especially considering the needs of elderly people with dementia.

II. Smartwatch in Elderly Care

Using smartwatches in elderly care is not a new idea. But to create a smartwatch-based system for elderly people which would be a well-accepted and would be used day-by-day is not a simple problem. As [1] states there are several special requirements for a smartwatch-based system for the elderly. Just to mention a few requirements, the price is very important, the simplicity of user interface, the device design is also important. The functionality provided by such a system is even more important, not just the elderly users but for the family members, relatives and all caregivers. The appropriate functionality makes their life easier, removes some burden from their shoulder and helps them to be sure their beloved elderly is in good and safe condition. Considering the functionality the possibilities of a sport watch are very limited even it can be efficiently use in elderly care, especially for elderly with dementia or Alzheimer's disease [2] but their functionality is very limited and usually there is no or reduced possibility to write application to it, so the factory implemented functionality cannot be expanded.

There is some very sophisticated solution for elderly monitoring using wearable sensors [3], they provide a lot of different kind of measurement data and data analysis, including indoor localization, but requires several wearable sensors which makes the comfortability questionable.

There are solutions focusing on a thin area of application like fall detection, fall risk assessment using smartwatch [4]. Even this kind of usage is important and useful, it is just using a few features, few possibilities of the smartwatch-based solutions.

The commercially available smartwatches also can provide support for elderly. The Apple Watch has several functions for elderly [5] however the high price of this device will make difficult to widespread among elderly users.

There are some systems using smartwatches for indoor localization [6] but they are just using smartwatch as an additional device for the mobile phone localization, not a standalone localization device.

The [7] proposes a system for smartwatch based indoor localization but it mainly relies on Bluetooth beacons which needs some kind of infrastructure creation and maintenance.

III. System Implementation

The complete elderly care system is composed of a smartwatch and its software, a server application and a browser-based user interface for the caregivers (Fig. 1).

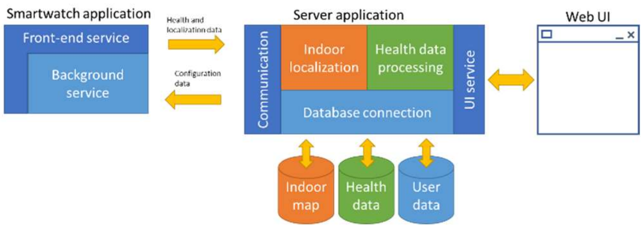

Fig. 1. The system architecture

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The smartwatch is responsible for all the data collection and senses the condition in a certain extent of the elderly. It is communicating with the server, transferring the collected data for further processing and storage. The server is responsible for data storage, processing and provides a user interface for the caregivers to access the collected data, analyze and display it. Since the indoor localization has relative high resource requirements it is also runs on the server side. In certain case, especially in alarm conditions the smartwatch directly can communicate with the caregiver by sending SMS.

A. *The smartwatch application*

The smartwatch we have selected to use in this work is the Kingwear KW88 type device [8]. This smartwatch is ideal for health application since it has heart rate, pedometer sensor, acceleration sensor, GPS and very capable communication interfaces for data transmission over 3G GSM, Wi-Fi and Bluetooth. The watch runs Android 5.1 operation system on a quad core, 1.3GHz processor with 0.5GByte RAM and has 4GB flash file storage. It is still convenient and lightweight to wear.

The smartwatch runs two applications developed by us. The front-end application provides a conventional looking watchface (Fig. 2.) which can be configured as a modern looking digital watch or more conventional “analog” like display with rotating hands. The display has very minimal functionality it only shows the current time, shows the battery charge information and have a big SOS button in order to make emergency call.

Fig. 2. Smartwatch with the application screen

The front-end application has another function, making itself to the only runnable application by the user. This is the startup application and all methods are disabled to exit from the application or start another application. There is a special way with a PIN code protection to close the application for maintenance or configuration.

The background application is also an Android application developed by us and it starts automatically with the front-end application. It is responsible for all data collection and communication function of the smartwatch and has several submodules, each responsible for a specific function (Fig. 3).

The localization mode selector module is responsible for determining the environment where the localization must be used. It compares the currently connected Wi-Fi access point (AP) name (SSID) with a list of predefined names. If the any of the name on the list it is matches with the name of the AP this is considered as a known indoor environment. In this case the outdoor localization module is shut down and indoor module is initiated. If no matches occur the location considered as outdoor condition the outdoor localization module is started while the indoor module is stopped.

The indoor module scans for Wi-Fi access points and Bluetooth beacons and sends the MAC addresses together with their field strength (Received Signal Strength Indication – RSSI) value to the server. The indoor localization is done on the server in order to save the smartwatch’s battery power.

The outdoor localization module is based on the built in GPS, to be more exact the built-in localization service of the Android operation system. To use this localization mode no external data connection is required all measured outdoor position data is collected and uploaded to the server when Wi-Fi data connection is available again. The outdoor mode also handles the geofence protection. There is a possibility to define a geofence in the web-based UI and the geofence is downloaded the smartwatch on order to be available even in the case of no mobile data connection. The outdoor module continuously compares the outdoor position with the predefined geofence and sends an SMS message of warning data to the caregiver to avoid outdoor wandering of the patient.

The operation of other modules is common for indoor and outdoor mode. The health data collector continuously collects heart rate data and logs the activity (step count) information. The fall detection module monitors the acceleration sensor data looking for a signal pattern that suggesting the user has fallen.

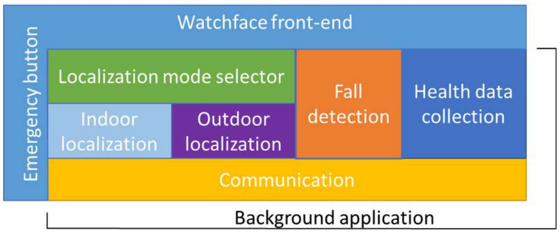

Fig. 3. Smartwatch software modules

The communication module is responsible for transferring all the collected data from the smartwatch to the server and receiving configuration data from the server. The communication module also responsible for the optimal usage of battery power for the communication as well as optimal usage of the available bandwidth and data usage limit.

In order to save battery power in indoor mode the data is sent in batches so the communication data transfer frequency can be reduced. In outdoor mode the mobile data communication can be disabled. In this case the collected data is temporary stored on the smartwatch and once the Wi-Fi connection is available again all stored data is streamed to the server.

B. *Server application*

The main responsibility of the server application is receiving data from smartwatches and store it in the appropriate database. It also stores the user information and device assignment data, since the smartwatch always sends the data packet with a device specific ID, which is assigned to a person only at the server side. If the data packet captured before reaching the server, no user information can be obtained only a device specific id.

The server has a module serving the UI part of the system. The user interface makes possible to access the stored data, configure the system, view or analyze the collected data.

The server is also responsible for the indoor localization. In order to save battery power, the smartwatch only collect the Wi-Fi field strength measurements sends it to the server and all the calculations are done on the server.

IV. Indoor localization

The indoor localization is based on the fingerprinting method. This means the environment where the localization needs to be applied is mapped in advance (so called off-line or fingerprinting phase) collecting and mapping all measurable and location specific properties of the environment.

Once the fingerprint phase is done and all required data is available for the localization algorithm the system is ready to use, it can determine the smartwatch position from the measurement data provided by the watch.

A. *Fingerprinting*

In our case the measurable location specific value is the Wi-Fi field strength and Bluetooth beacon field strength (if available). The system also requires the floorplan to be created in advance. It is used for the measurement of the fingerprint data and also used by the localization [9]. For the floorplan creation we are using the Open Street Maps data format and tooling. This is an open source outdoor, indoor mapping solution. There are several editor for creating maps, we are using the Java Open Street Map Editor (JOSM) [10] since it is very user friendly, easy to use and the maps are available in well documented XML format.

The fingerprint data collection is done by using a mobile phone application developed by us [9]. For the data collection requires to walk along the pathway where (or close to) the localization needs to be applied. While the user walks with the mobile phone the phone collects the Wi-Fi field strength information and Bluetooth beacon field strength at each step and assigns them to the given position of the map.

Once the measurement is done, the floorplan is combined with the fingerprinting data (Fig. 4). The figure shows a digital floorplan of an elderly home with the heat map display of the field strength value of one selected Wi-Fi access point. The floorplan and field strength together specify the infostructure file which is the bases for the indoor localization and contains all information required by the localization algorithm.

Fig. 4. Floorplan and Wi-Fi fingerprinting measurements

The infostructure file is then stored on the server. Since the system is not limited to localize only in one building, several infostructure file can be stored on the server in the indoor map database.

After this preparation step the system is ready to use the indoor localization service. The localization service runs on the server side in order to save battery power at the smartwatch side. The server can parallelly run several indoor localization algorithms independent of the localization belongs to the same or different building.

The localization algorithm has several consecutive stages and each preliminary stage must be done to switch to a new stage, it follows a pipe like operation. Wi-Fi scans are going to its input and each stages of the pipe processes the data and generates intermediate data for the next element of the pipe while the last element provides the location information.

B. *Building determination*

The first processing element of the localization data pipe is the building determination module. It receives the Wi-Fi scans from the smartwatch, collects the MAC addresses of the APs included in the scan and looks up them in a database table containing the collection of the APs for each building. The database table is automatically updated when a new building map is added to the system. Once the building is identified the building map (floorplan together with the fingerprint data) is loaded into the memory and all data is passed to the next processing element which determines the floor of the given building.

C. *Floor detection*

Once the building is identified the next step is to determine the floor. The floor detection uses k-nearest neighbors search for the measured Wi-Fi field strength and a voting algorithm in order to provide robust solutions even the environment is noisy. For the quick search a k-d tree is constructed when building data is loaded. The tree contains all previously measured AP and signal strength data together with the floor index where the measurement was taken. The floor detection algorithm finds the three closest matching measurement positions by calculating the distance between the measured AP's signal strength value and between the measured values on the fingerprinting data. Each floor which belongs to the best matching level gives a score. This procedure is repeated by three times (for three consecutive Wi-Fi scan data) and the level with the highest score is chosen as the current floor of the smartwatch.

Once the floor is determined the measurement data of the given floor is loaded and made available for the localization algorithm. But before it is passed to the localization algorithm the fingerprint data is filtered and restructured for the fast and reliable localization

D. *Fingerprint data filtering*

The fingerprint data preparation and filtering are also a multi-step procedure. The first step is recognizing the virtual access points (VAP). The virtual access points are very common is the wireless network structure, it means one physical access point server two or more different SSID, different network. Out system always identifies the APs based on their MAC address but in the case of VAP the MAC addresses are different for each wireless network even it is served by one physical access point. It means the signal of one physical access point would be considered twice or more since just based on their MAC address, they would be identified as a separated A-Ps. Therefore, it is important to recognize the virtual access point from the measurement data which means we have to determine the similarities between the measurement belongs to two different access point with different MAC address. If this similarity measurement is too strict the virtual access points will not be recognized and if it too permissive than APs with no relation will be recognized as virtual access points pairs. Therefore, we have developed a similarity measurement technique which provides reliable recognition. In our experiment it provides high VAP recognition ability (>95%) and low misidentified VAP (<5%) after investigating more than hundreds of VAPs. The algorithm compares the field strength at all measurement position for all APs that were measured there. If the field strength distance is less than 5dBm and both APs are visible at the 80% of the measured positions then they considered as VAP pairs, they measurement data is handled as they are only one AP.

The next preparatory step is filtering out the AP which seems to be unreliable for the indoor localization purposes. In a regular home or office environment there are several visible APs. They can be APs from the neighbors or some household, IT or IoT device equipped with Wi-Fi connection. So, the APs are classified by their probable reliability with the following algorithm: all measurement point is investigated and three strongest AP is selected and they are marked in the list of all APs. Only APs which has mark will be used for the localization the others will be neglected. According to our experience it is efficiently filters out unreliable (APs with temporary existence) APs.

Once the APs are filtered the fingerprinting vectors can be constructed from using the list of remaining APs and belonging measurements. The fingerprint vectors always contain the measured RSSI values in fixed order of APs, this order is determined and fixed after filtering out the alias and unreliable APs. Then all the fingerprint vector is stored in a quadtree. Each leaf of the quadtree is storing fingerprint vectors for the given position. The quadtree makes fast to find fingerprint vectors for the given position which will be essential for the localization algorithm.

E. Localization algorithm

The localization algorithm is based on a particle filter method [11]. The particle filter used for this purpose uses several assumptions about the location of the smartwatch, so called particles. We have found for an average size building (home, or nursing home) 300 particles are sufficient. The steps of the algorithm are the following:

Step 1:
At initialization, when no measurement is available, particles are placed randomly over the measurement positions

Step 2:
When Wi-Fi scan is received from the smartwatch it triggers the iteration of the particle filter algorithm. The iteration starts with the prediction of the position of the particles. Since the smartwatch can't provide the motion vectors of the user the prediction is based on a random procedure. However, the watch can determine is the user is moving or not moving, since it has a step detector. If step is detected the user is considered as moving, if no step detected for at least 2s the user considered as standing. The position is updated before processing the Wi-Fi scan using the equation (1):

$$\vec{p}_{k+1} = \vec{p}_k + \vec{r}(m) \tag{1}$$

where $\vec{p}_k$ is the position vector (with x,y position components) in the current (k) or the next $(k+1)$ iteration. The $\vec{r}(m)$ is a function which gives a random vector based on the motion state of the user. When $m = true$ the user is moving when $m = false$ when the user is standing. The function behavior is shown on (2):

$$\vec{r}(m) = \begin{cases} rv(l_m, \sigma_m), \ m = true \\ rv(0, \sigma_s), \ m = false \end{cases} \tag{2}$$

The $rv(l, \sigma)$ function is generating a vector pointing in random direction and has a random length with the given expected value (l) and has a normal distribution with the given variance (σ). When the user is moving a random vector is generated with the length of the average human step length which is calculated by the time step between each iteration step multiplied with the average human walking speed which is 1.2m/s in our case. We have found the variance $\sigma_m = 4$ gives the best result. In the stationary case the vector has zero expected value and much lower variance $\sigma_s = 2$ for the length which provides more precise result once the user stops the motion.
Once the vector is calculated the positions can be updated. There is one more filtering activity here. When the particle position is updated it is compared to the floorplan of the building and a geometrical calculation is executed in order to check if the new position is possible. if the particle should go through a wall to reach the new position the particle movement marked as a low chance update. If the new position is reachable because it is not crossing any wall or passes thru a door the position update has high chance.

Step 3:
Once the position updates the measured data is compared to the fingerprint data. For all particles the three closest (by position) fingerprint data is retrieved from the quadtree. Their fingerprinting distance from the measured Wi-Fi scan is then calculated and they receive a reverse proportional weight after the distance. it means the better match receives a close to one weight while worst matches receive close to zero weight.

Step 4:
The particle collection is then resampled based on their weight. If a particle has higher weight (close to one) it has a higher chance to be in the resampled collection, while a particle with low weight (close to zero) has a low chance to be in the resampled collection (sequential importance resampling)

Step 5:
The position is determined from the resampled collection using the best 30% of the particles (particles with the highest weight). The indoor position is the weighted sum of the position of particles where the weight in the sum is same as the particle weight.

Step 6:

The iteration restarts from the Step 2.

Then the indoor position data is stored in the database for further processing.

V. Results

We have tested the indoor localization method in an elderly home. Using the Wi-Fi only localization method the average precision was between 3-4 meter with the appropriate Wi-Fi coverage. It means from all relevant position of the localization at least six Wi-Fi AP must be visible. If better accuracy is requiring Bluetooth beacons needs to be installed. With the application of the Bluetooth beacon the accuracy can be increased 2-3 meter.

VI. Conclusions

The smartwatch is a useful device for elderly care with its sensors it can provide valuable information or can provide various alarm message when the elderly people is in danger. Most of the sensors are available on a smartwatch, but for the indoor localization there is no widely accepted solution is existing. Therefore, we have developed our own indoor localization system based on the Wi-Fi fingerprinting data if the indoor environment. The indoor localization data is a valuable extension of the sensors of the smartwatch since it can provide information for the wandering detection, activity recognition functions, can provide position information if the elderly people falls down or has serious medical condition can be sensed by the heart rate sensor. In these cases, knowing their whereabout might save their life or bring then a quicker medical assistance.

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