ARIADNE: Kick-starting Indoor Localization for the Public

Georgios Pipelidis, Nikolaos Tsiamitros, Efdal Ustaoglu and Christian Prehofer
Technical University Of Munich,
Faculty of Informatics, Research Group for Software &
Systems Engineering, Munich, Germany

***Abstract*—In this paper we present Ariadne. Ariadne is a framework that provides indoor navigation in various building environments with the currently available limited open information. Ariadne is the only available framework capable of 3D localization, due to the multiple smart-phone sensor data that it combines to enable it and the use of a modified particle filter algorithm that enables this fusion. Additionally, Ariadne combines user context to improve the localization accuracy. It continuously learns its environment, in a SLAM-like approach, beginning with limited knowledge, while training multiple models that enable "on the fly" indoor localization based on various fingerprint methods. Ariadne does not require any infrastructure, while it requires very limited prior knowledge of the environment, which is usually openly available. It autonomously recognizes when the user has transit indoors and uses this information to improve its estimation.**

***Index Terms*—Indoor Localization, Sensor Fusion, 3D localization, Particle Filter**

1. Introduction

Location Based Services (LBS) have become a necessity in our daily lives. The main components of such services are a localization method and a map [6]. Unfortunately, even though we spend approximately 80% of our time indoors [7], [10], LBSs are mainly developed for the outdoor world. The main reasons are the lack of indoor localization methods and the lack of maps. Thankfully, today there is a series of initiatives that are accelerating the research of indoor LBS. Such initiatives are the Enhanced 911 [3] in United States, the Enhanced 112 in the European Union [2] as well as the European Accessibility Act [1].

Motivation. We are facing an ever-larger plethora of already deployed sensing devices in different artifacts of daily living. It is estimated that smart-phone users will exceed 6.1 billion by 2020. As a result, using approaches for localization in indoor places is essential for making better usage of those devices [4]. Moreover, considering the fact that examining "how the user is moving", provides us *"mobility context"* (i.e. *"the user is climbing stairs"* or *"the user is using the elevator"*). This context information is related to the ubiquitous computing goal of *"context awareness"* [11].

Problem. Many approaches alternative to GPS have been proposed for indoor localization, based on different technologies [12]. However, all of those approaches require highly detailed maps, annotated with the precise geometry, topology and semantics – to enable localization – of the indoor place. Additionally, most of those approaches are limited to two dimensional localization and they do not make use of the activities of the user to enhance their accuracy. All of the above have as a result none of the existing frameworks to be adopted in a large scale.

Goal. Ariadne aims to enable users to find their way inside complex buildings, where limited information is available. Ariadne's final goal is to operate as an accurate location provider indoors and outdoors. This will kick-start industries such as the indoor LBS industry, the robotic industry, which today is fixed due to the localization problem, the augmented reality industry, which is a major contributing factor in industry 4.0 and last but not least the mobile ad hoc networks industry, which can benefit by increasing the available processing capacity and energy, since the optimization of the distribution of the energy and the tasks in a mobile ad hoc network will become easier to optimize.

Contribution. The contribution of this paper can be listed as follows:

- We present the first framework that can localize people with a great accuracy in buildings for which there is no detailed map and infrastructure available.
- Our framework learns its environment, following a SLAM-like approach, while the users are navigating into it. More specifically, it extracts data which are later used to better localize users and even enable "on the fly" localization.
- Our framework is using a modification of the particle filter algorithm in order to enable the fusion between various sensors, such as WiFi, GSP and Geomagnetic as well as user context.

2. Approach

Ariadne can be divided into two main modules. The first module is responsible for the localization and its functionality is embedded in a smart-phone. The second module is responsible for detecting and localizing landmarks and keeping up-to-date a classifier that enables "on the fly" localization.

2.1. Localization Module

The localization module is responsible for localizing the user following a modified particle filter approach. The main components of this module as presented in Figure 1 are described bellow.

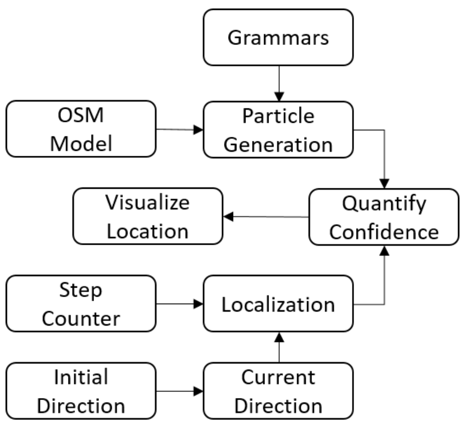

Figure 1: Localization Module Architecture.

OSM Model. Existing information from Open Street Maps is imported to enable routing and the generation of particles.
Grammars. They are heuristics following standards that help us to create a finer geometry. They are necessary due to the OSM limited information and they are inspired by [14].
Particle Generation. In this module, the newly constructed map is restructured as a set of randomly generated particles, with uniform prior distribution, which follow the Monte Carlo simulation description.
Initial Direction. The initial direction is estimated following an opportunistic approach, based on the users context (i.e. "user transit indoors", "user is ascending stairs", etc.). When this is not possible, the direction is extracted from the compass after the phone pose (i.e. on hand, in pocket etc.) has been extracted.
Step Counter. In the step counter module, the current number of steps is estimated based on the repetitive pattern caused in the accelerometer from the human bipedal movement.
Localization. Ariadne provides horizontal and vertical localization, where the horizontal localization is based on Dead Reckoning, while the vertical is based on the barometric formula.
Quantify Confidence. In every unit of time new particles are generated, weighted based on the probability of being the target's true location. Their weights are quantified based on map restrictions or model predictions.
Visualize Location. Finally, the particle with the highest probability is visualized as the real location.

2.2. Landmark Selection Module

The landmark selection module is responsible for extracting landmarks from raw sensor data that have been extracted while the user was localized from the localization module and for localizing the user once a model is available. Its components are:

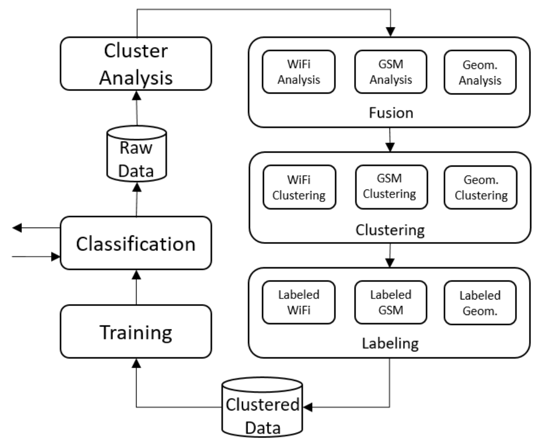

Figure 2: Landmark Selection Architecture.

Classification. In this module sensed values from WiFi, geomagnetic and GSM sensors are imported to a support vector machine classifier responsible for predicting the location of the client.
Raw Data. The raw streamed sensor values are then labeled based on their spatial coordinates, estimated from the localization module, and are stored in a database.
Cluster Analysis. A cluster analysis is performed on the collected sensed data and the optimum number of clusters is been estimated.
Fusion. Once the number of clusters has been identified, weights are assigned to the clustered values and the data are aggregated based on their proximity.
Clustering. Once the data are aggregated, they are clustered based on their characteristics, forming rectangular shapes whose edges are tangent to the walls in the map.
Labeling. The new created clusters are now labeled based on coordinates of the rectangular that they include. The size of the rectangular, in the localization phase, will indicate the localization confidence.
Clustered. The clustered and labeled data are now stored in a database.
Training. Once there are enough data and with a regular interval, a classifier is trained on them and more precise localization is enabled.

3. Results

Ariadne has been tested in various environments, such as university buildings, offices and a number of subway stations, where it performs an average error of two meters when no model is yet available. However, a detailed evaluation is the product of our current work.

A sample of the application can be seen in the figure 3. As can be seen, the client side uses basic to enable indoor routing for user. As long as there is not a generated model, the source of localization is limited from the entrance of the destination. While the user is localizing himself in this more “primitive” way, Ariadne mines data from the phone sensors that are streamed on the server.

(a) Indoor Map. (b) Indoor Localization.

Figure 3: Screenshot from Ariadne client side. In figure 3a can be seen the indoor map (in black) and the indoor route (in red). In 3b can be seen the indoor route (in red) and the estimated position (in blue).

4. Related Work

Mapping indoor places is a challenging process, since it requires the description of the geometry, the topology and the semantics of a place. Various approaches for crowd-sourcing such process have been suggested [5], [15] and [9], while, many products are made for this task [8] and [13]. However, those approaches and products are focusing on extracting the geometry and the topology of indoor places and not on extracting the semantics (e.g. the function of an elevator).

5. Conclusions

In this paper we presented Ariadne. Ariadne is using a modification of the particle filter algorithm, in order to enable precise 3D localization. Ariadne is a localization framework that uses a SLAM like approach to keep the geometry, semantics and topology of the a map always up-to-date. Ariadne does not require any infrastructure, while it requires very limited prior knowledge of the environment, which is usually openly available. Ariadne provides the least resource demanding way to map indoors, since it requires limited information for routing and localization.

References

[1] European Accessibility Act - Employment, Social Affairs & Inclusion - European Commission. http://ec.europa.eu/social/main.jsp?catId=1202.

[2] European Commission - PRESS RELEASES - Press release - Commission pushes for rapid deployment of location enhanced 112 emergency services. http://europa.eu/rapid/press-release_IP-03-1122_en.htm?locale=en.

[3] Wireless E911 Location Accuracy Requirements. https://www.fcc.gov/document/wireless-e911-location-accuracy-requirements-3, Dec. 2015.

[4] I. Afyouni, C. Ray, and C. Claramunt. A fine-grained context-dependent model for indoor spaces. In *Proceedings of the 2Nd ACM SIGSPATIAL International Workshop on Indoor Spatial Awareness*, ISA ’10, pages 33–38, New York, NY, USA, 2010. ACM.

[5] M. Alzantot and M. Youssef. Uptime: Ubiquitous pedestrian tracking using mobile phones. In *Wireless Communications and Networking Conference (WCNC), 2012 IEEE*, pages 3204–3209. IEEE, 2012.

[6] K. Axel et al. *Location-based services: fundamentals and operation*. John Wiley & Sons, Chichester, England ; Hoboken, NJ, 2005.

[7] E. Building. the environment: A statistical summary. *US Environmental Protection Agency*, 2004.

[8] Google. Tango. https://get.google.com/tango/. 2017-06-12.

[9] W. Guo, N. P. Filer, and S. K. Barton. 2d indoor mapping and location-sensing using an impulse radio network. In *Ultra-Wideband, 2005. ICU 2005. 2005 IEEE International Conference on*, pages 296–301. IEEE, 2005.

[10] N. E. Klepeis, W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern, and W. H. Engelmann. The national human activity pattern survey (nhaps): a resource for assessing exposure to environmental pollutants. *Journal of Exposure Science and Environmental Epidemiology*, 11(3):231, 2001.

[11] P. Lukowicz, A. S. Pentland, and A. Ferscha. From context awareness to socially aware computing. *IEEE Pervasive Computing*, 11(1):32–41, January 2012.

[12] R. Mautz. Indoor positioning technologies, 2012.

[13] Microsoft. Path Guide. https://play.google.com/store/apps/details?id=com.microsoft.msra.followus.app, June 2017.

[14] D. Philipp, P. Baier, C. Dibak, F. Durr, K. Rothermel, S. Becker, M. Peter, and D. Fritsch. Mapgenie: Grammar-enhanced indoor map construction from crowd-sourced data. In *Pervasive Computing and Communications (PerCom), 2014 IEEE International Conference on*, pages 139–147. IEEE, 2014.

[15] G. Pipelidis, C. Prehofer, and I. Gerostathopoulos. Adaptive bootstrapping for crowdsourced indoor maps. In *Proceedings of the 3rd International Conference on Geographical Information Systems Theory, Applications and Management - Volume 1: GISTAM,*, pages 284–289. INSTICC, ScitePress, 2017.