GoIn – An Accurate InDoor Navigation Framework for Mobile Devices

Boaz Ben-Moshe
Department of Computer Science
Ariel University, Israel
Email: benmo@g.ariel.ac.il

Vlad Landa
Department of Computer Science
Ariel University, Israel

Nir Shvalb
Department of Industrial Engineering
Ariel University, Israel

***Abstract*—Performing a room-level positioning using $WLAM$ and Cellular cells information is a well-known methodology which was suggested and implemented by many researches. In this paper we present a general framework for accurate indoor positioning and navigation which improves the expected accuracy to a sub-meter error rate. The main algorithm is based on modified particle filter which combine RF finger-printing, odometry, visual landmarks and map constrains.The accuracy improvement achieved by using low resolution camera to track dominant landmarks such as lights. The use of "glowing-markers" allows us to accurately map relatively complex indoor buildings with compact representation. The suggested method [1] was implemented and tested on android based mobile devices and allows a robust sub-meter 3D positioning at 10-30Hz with fairly low energy consumption.**

I. Introduction

Indoor positioning and navigation has tracked a wide range of researches. Several navigation technologies have been developed including: RF-finger-printing, Pedometer, Optic Flow, Visual SLAM, Ultrasound and RF $DTOA$, Lidar Navigation and many others. A common characteristic of indoor navigation methods is the fusion of various positioning technologies in order to achieve a better altogether positioning result (see [2], [3], [4] for surveys regarding indoor positioning technologies and systems). Although there are many different types of applications which require indoor positioning, it seems that the following properties should be optimized with respect to almost any such method:

Accuracy: often the main and foremost parameter which is being tested.

High sampling rate: for a natural and intuitive navigation results, especially for highly dynamic vehicles

Energy consumption: an important property for most mobile (or battery operated) devices.

Minimal dedicated infrastructure: ideally, the solution should work without any need for additional infrastructure.

Privacy: allowing an off-line mode while avoiding using high-resolution video or photos.

Auto mapping: allowing simple and efficient crowd-sourcing for a finger-printing process (both for RF and visual).

"Bring your own device": The solution should work an standard $COTS$ devices.

Limited computing power: an important property for most mobile (or battery operated) devices.

Keep It Simple: Simplicity is a key factor in the ability to adapt the solution to various types of platforms and applications.

A. Our Contribution

This paper presents a framework for accurate indoor navigation for standard ($COTS$) android mobile devices (see Fig 1). To the best of our knowledge, this is the first paper which presents a working implementation of indoor navigation algorithm based on mapping and identification of emitting-light sources as landmarks combined with an advanced particle filter algorithm (see Fig. 2). The proposed system allows a **sub-meter accuracy** while maintaining all the above properties.

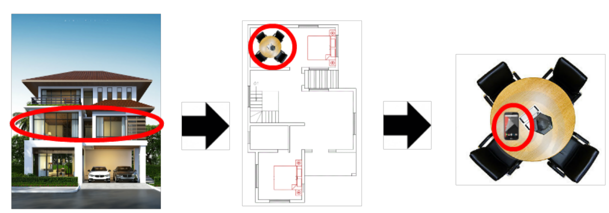

Fig. 1. Framework moving from building level to room level and the high accuracy "seat" level.

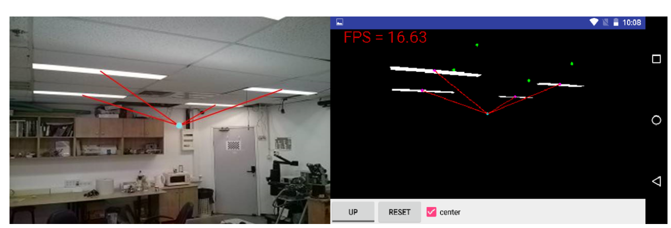

Fig. 2. An example of landmarks tracking registration which allows us to perform accurate indoor navigation using standard emitting lights.

II. Positioning Framework

Our positioning algorithm is based on a modified version of the classical *Particle Filter* (see [5] for a detailed explanation on non parametric filters). The basic positioning framework utilizes the following (well-known) building blocks:

1) Global orientation - computed by the device's 9DoF (MEMS-Gyro, MEMS-Acc, Magnetometer).
2) Inertial navigation - implemented mainly using a walking-pedometer.
3) $WLAN$ finger-printing and positioning algorithm.
4) Barometer and accelerometer - altitude change detection.
5) Visual Odometry - based on a modified $Object$ level tracker - allowing identification a robust .

The main algorithm(1) is fusing all the above sensor-data using an advanced particle filter which also uses visual emitting light as object-landmarks and compare them w.r.t. a pre-computed building-map.

Data: map_{RF}, $map_{Building}$
Result: Realtime position and orientation
Initialization: let X_0 be a set of M particles, let $WLAN_{algo}(map_{RF})$ be existing indoor location service;
while *(True)* **do**
  onWLAN($position$): update ROI;
  onAction(U_t): update $X_t(ROI, U_t)$;
  For each $x \in X_t$ Sense-and-evaluate(x, $map_{Building}$);
  Perform an impotence re-sampling(X_t);
  Calculate optimal position(X_t);
end

Algorithm 1: A general modified particle filter algorithm for computing accurate indoor position (and orientation).

In order to implement such algorithm, one need to well-define the following parameters and sub-routines

- ROI: the Region Of Interest representing the $3D$ bounded space in which the position is expected to be; in some cases this region is bounded to few meters and in other cases this region may have a diameter of over 50 meters. Denote that the ROI is not necessarily a connected volume and should be addressed as a probabilistic space.
- Map_{RF}: an RF finger printing data (e.g., $WiFi$, $BlueThooth$, LTE).
- $Map_{Building}$ a set of walls and landmarks (e.g., emitting lights) representing the building structure. This information is can be constructed as part of the fingerprinting process using methods such as structure from motion and video stitching.
- $OnAction(U_t)$: a method (callback) approximating the $6DoF$ change vector (position and orientation).
- $Sense-and-evaluate(x, map_{Building})$: a method for evaluating the likelihood (i.e.,weight) of each particle with respect to the building map, in particular the emitting lights and walls. Informally, consider the case of a particle which the action method 'moved' it through a wall - its likelihood will be reduced. On the other hand, if the a particle has a similar image of emitting lights with the actual video frame, its likelihood will be increased[1]
- $Impotence-resampling(X_t)$: use the likelihood of the particles in order to perform a weighted-resampling of the particles, i.e, creating a new set of particles - which incorporate the current likelihood probabilistic.
- $Calculate-optimal-position(X_t)$: decide the best (most suitable) current position - which is often the best particle or some weighted average over a set of closed by particles.

A key feature of the proposed algorithm is in its relatively short convergence time with relatively small number of particles (computing efficiency). This is due to intelligent action and sense functions.

III. Experimental Results and Demo setting

We have tested the presented algorithm in several use-cases and indoor scenarios (e.g., Fig. 3). The overall performance of the algorithm allows a solid sub-meter accuracy level in $3D$. In the demonstration we plan to use few WiFi (fixed) devices and perform a finger-printing (less than half an hour) in which both RF fingerprinting and structure-from-motion mapping will be captured. Both the finger-printing and the real time navigation demonstration will be performed using $COTS$ android tablets and phones. The results will also be available for performance evaluation using a GIS tool which allows a complete accuracy testing.

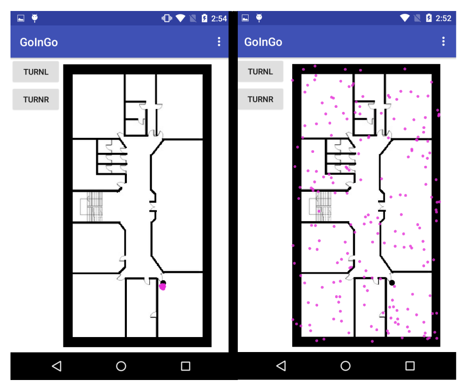

Fig. 3. An actual navigation in a room with 10-20 cm accuracy level using standard android smart-phone. Right:

References

[1] B. Ben-Moshe, N. Shvalb, *Navigation method and device*, US Patent App. 14/418,106, 2013.
[2] L. Zhu, A. Yang, D. Wu, L. Liu *Survey of Indoor Positioning Technologies and Systems* Life System Modeling and Simulation. Springer Berlin Heidelberg, 2014. 400-409.
[3] R. Harle, *A survey of indoor inertial positioning systems for pedestrians* Communications Surveys & Tutorials, IEEE 15.3 (2013): 1281-1293.
[4] M. Rainer and S. Tilch *Survey of optical indoor positioning systems* Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on. IEEE, 2011.
[5] S. Thrun, B. Wolfram, F. *Dieter Probabilistic robotics*. MIT press, 2005.

[1]The actual implementation of this stage is somewhat involved and uses visual-geometry see [1] for a general description of the algorithm.