GoIn – An Accurate InDoor Navigation Framework for Mobile Devices

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***Abstract*—Performing a room-level positioning using $WLAN$ 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 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. Such light-map is the basis of our modified particle filter navigation algorithm. The suggested method [1] was implemented and tested on android based mobile devices (such as phones and tablets). The implementation is using on low resolution video feed ($QVGA$) fused with IMU-sensors which combined allowed a robust landmark tracking and navigation in $10-60Hz$, even on low-end devices.**

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 general framework which allows for accurate indoor navigation for standard ($COTS$) android mobile devices. 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. The proposed system allows (in most cases) a **sub-meter accuracy** while maintaining all the above properties.

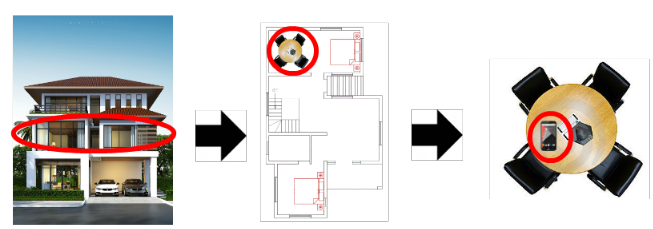

Fig. 1. Level of positioning accuracy : Left - building level accuracy ($3G, 4G, GNSS$), Middle - floor level ($WiFi, Bluetooth$), Right - sub-seat level accuracy (visual $landmarks$).

II. Positioning Framework

Our positioning algorithm is based on a modified version of the classical *Particle Filter* (see [5] for a detailed explanation

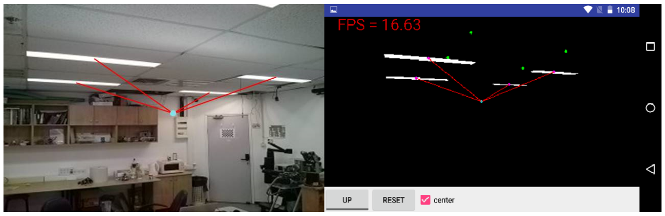

Fig. 2. An example of landmarks tracking registration which allows us to perform accurate indoor navigation using standard emitting lights.

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) RF finger-printing commonly implemented on $WLAN, BlueTooth$ or $Cellular$ signals and positioning algorithm.
4) Barometer and IMU - altitude change detection.
5) Visual object identification - based on a modified $Object$ level detection - and using them as robust landmarks.

The main algorithm(1) fuses all the above sensor-data using an advanced particle filter which also uses visual light as object-landmarks and compare them w.r.t. to precomputed building-light-map.

Data: RF_{map}, $Bulding_{map}$
Result: Realtime position and velocity
Initialization: let X_{t_0} be a set of n particles, let $WLAN_{algo}(RF_{map})$ be existing indoor location service;
while *(True)* **do**
  onWLAN($position$): update ROI;
  onStep(U_t): update $X_t(ROI, U_t)$;
  onFrame(F_t) : detection visual landmarks.
  For each $x \in X_t$ sense-and-evaluate(x, $map_{Building}$);
  Perform an impotence resampling(X_t);
  Calculate optimal position(X_t) and velocity;
end

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

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 it 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.
- RF_{map}: 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 not may be constructed during the fingerprinting process using methods such as structure from motion and video stitching.
- $OnStep(U_t)$: a method (callback) for approximating the $6DoF$ motion vector (position and orientation).
- $onFrame(F_t)$: a method (callback) for detecting the visual landmarks in the frame and computing the world $3D$ vector to each landmark.
- $Sense-and-evaluate(x, Building_{map})$: a method for evaluating the likelihood (i.e.,weight) of each particle with respect to the building map, in particular the 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 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. 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. The finger-printing (RF,$Ligths_{map}$) and the real time navigation demonstration will be performed using $COTS$ android devices.

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.

[6] Montemerlo, Michael, and Sebastian Thrun. "FastSLAM 2.0." Fast-SLAM: A scalable method for the simultaneous localization and mapping problem in robotics (2007): 63-90.

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