Indoor Positioning using Visual and Inertial Sensors

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***Abstract*—Indoor positioning system is a rapidly emerging technology. Unlike outdoor positioning, which uses triangulation from satellites in line-of-sight, current indoor positioning methods attempt triangulation using Received Signal Strength Indicator (RSSI) from indoor transmitters, like WiFi and RFID. These methods, however, are not accurate and suffer from issues like multi-path and absorption by walls and other objects. In this paper we propose an alternate and novel approach to indoor positioning, that combines signals from multiple sensors. In particular, we focus on visual and inertial sensors that are ubiquitously found in mobile devices. We utilize a Building Information Model (BIM) of the indoor environment as a guideline for navigable paths. The sensor suite signals are processed to generate a trajectory of device moving through the indoor environment. We compute features on this trajectory in real-time and data mine pre-computed features on BIM's navigable paths to determine the location of the device in real-time. We demonstrate our approach on BIM in our university campus. The key benefit of our approach is that unlike previous methods that require installation of a wireless sensor network of several transmitters spanning the indoor environment, we only require a floor-plan BIM and cheap ubiquitous sensor suite on board a mobile device for indoor positioning.**

Keywords—indoor positioning, Simultaneous Localization and Mapping, Building Information Model, Inertial Measurement Unit, Visual sensor, Visual Odometry.

I. INTRODUCTION

In the age of automation technology, the ability to navigate persons and devices in indoor environments has become increasingly important for a rising number of applications. With the emergence of global satellite positioning systems, the performance of outdoor positioning has become excellent, but many mass market applications require seamless positioning capabilities in all environments. Therefore, indoor positioning has become a focus of research and development during the past decade.

The goal of positioning is to determine the physical coordinates of a single sensor or a sensor network. These coordinates can be relative or global, such that they are aligned with some external reference frame. Typically, beacon nodes are a necessary prerequisite to localizing a network in a global coordinate system. Beacon nodes are ordinary sensor nodes that know their global coordinates a priori. This knowledge could be hard coded, or acquired through some additional hardware like a GPS receiver. At a minimum, three non-collinear beacon nodes are required to define a global coordinate system in two dimensions. However, the use of beacon nodes have inherent disadvantages. GPS receivers are expensive. They also cannot typically be used indoors, and are confused by tall buildings or other environmental obstacles. GPS receivers also consume significant battery power, which can be a problem for power-constrained sensor nodes.

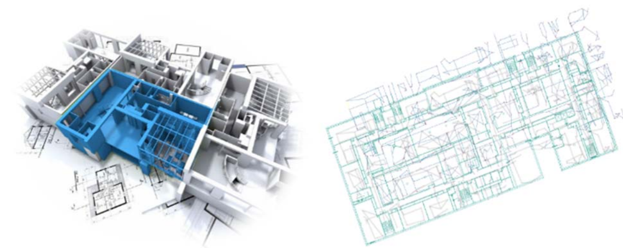

Figure 1: Building Information Model. The floor plan from BIM is used to create set of navigable paths in that building environment.

In wireless sensor networks, every sensor is equipped for radio frequency transmitting capabilities. In theory, the energy of a radio signal diminishes with the square of the distance from the signal's source. As a result, a node listening to a radio transmission should be able to use the strength of the received signal to calculate its distance from the transmitter, which is referred to as Received Signal Strength Indicator (RSSI). However, RSSI ranging measurements contain noise on the order of several meters. This noise occurs because radio propagation tends to be highly non-uniform. For instance, radio propagates differently over asphalt than over grass. Physical obstacles such as walls, furniture, etc. reflect and absorb radio waves. As a result, distance predictions using signal strength have been unable to demonstrate the precision obtained by other ranging methods such as time difference of arrival when used in an outdoor environment. Some of the issues in localization algorithm design using current approaches are: resource constraints like battery life and transmitter power; sensor network node density; non-convex topologies of static sensor installations; and environmental obstacles and terrain irregularities.

Among these issues, the principal challenge towards scaling current methods for positioning in any indoor environment is the necessity of installation of numerous static wireless transmitters in that indoor location. In this paper, we propose an alternate and novel approach to sensor localization, that does not require a network of transmitters installed across the building. Instead, we use the Building Information Model (BIM). A typical BIM is a CAD drawing that provides a floor plan of the building. We use the CAD drawing to infer a set of navigable paths in that building. As the sensor moves, its trajectory will be a subset of this set of navigable paths. Now, every point in the navigable path has a known location since it is computed from the BIM. By discovering a match between the sensor trajectory and BIM navigable paths, we are able to localize the sensor in real-time as it moves through the building.

II. METHODOLOGY

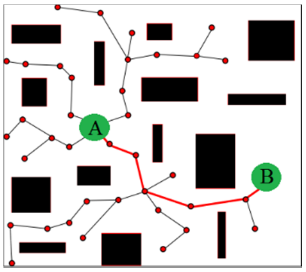

Figure 2: Topological Map.

A. Underlying concept

The concept behind our approach is depicted in Figure 2. The path adopted by a mobile sensor in any environment is dependent on the positions of stationary and moving objects or obstacles present in that environment. Consequently, the traversal of the mobile sensor is correlated to available navigable paths. For short durations, this traversal is non-informative and indistinguishable from numerous subsets of navigable paths in the environment. However, as the mobile sensor moves for longer durations, the traversal gradually becomes more `unique' with fewer potential matching paths. Our approach is inspired by the method referred to as the Simultaneous Localization And Mapping (SLAM), that has been used to address autonomous navigation using a sensor suite on a robot [1]. SLAM techniques construct a 'map' of the local environment of a robot and estimates its location within that environment in real time. It performs well for relatively small sized novel environments.

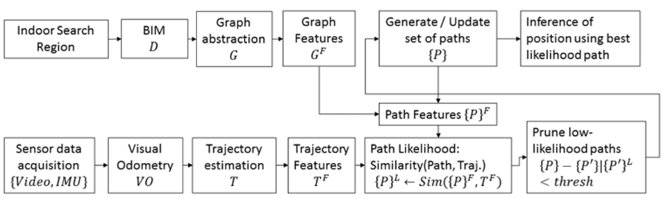

Figure 3: Sensor positioning system block diagram

B. Our sensor positioning system

A block diagram of our multi-sensor fusion based positioning method that combines Visual Odometry [2] and BIM is shown in Figure 1. First a set of navigable paths are created using the BIM, as shown in Figure 1. The navigable paths constitute a graph structure, where graph traversals correspond to possible trajectories of sensors in that indoor environment. We pose trajectory search in a BIM as a progressive sub-graph matching problem, where we use a probabilistic framework to update likelihood of a pool of candidate traversals until the trajectory is uniquely matched to a sub-graph from which we infer the position of the sensor. This approach is illustrated in the block diagram in Figure 4.

C. BIM and sensor trajectory features

The trajectory of a moving sensor is encoded using change in angle of the tangent at points on the trajectory. Similar change

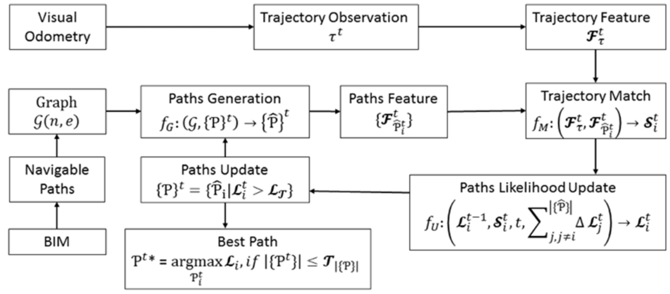

Figure 4: Matching sensor trajectory with BIM navigable paths. Candidate paths are spawned and pruned until most likelihood path remains.

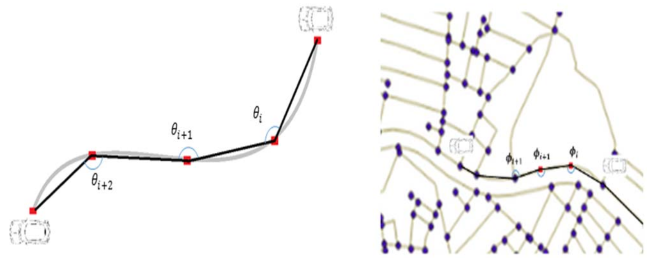

Figure 5: Computing features of sensor trajectory in real-time and similar features for navigable paths in BIM a-priori

in orientation features are also computed for the graph of the indoor environment, depicted in Figure 5. The trajectory matching step in our approach, shown in Algorithm 1, computes the difference between the tangent angle based features computed for the trajectory in real-time and the BIM model.

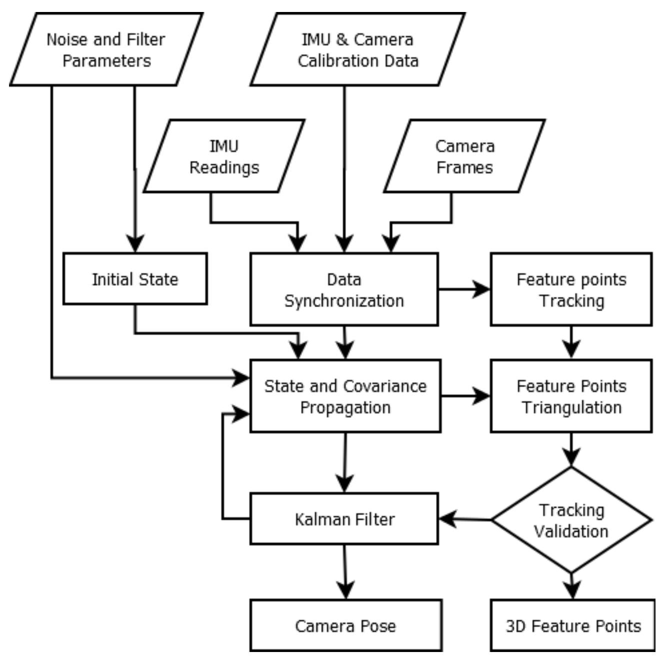

Figure 6: Sensor trajectory estimation

D. Sensor trajectory estimation

We adapt Visual Odometry based approach to estimate trajectory of mobile sensor in real-time. A block diagram of this approach is shown in Figure 6. We utilize the popular Scale Invariant Feature Transform (SIFT) as descriptors for the visual sensor signal [3]. A Multi-State Constraint Kalman Filter (MSCKF) to combine the IMU sensor and monocular vision-based sensor measurements [4].

Algorithm 1 Graph Path Search

Input: $\mathcal{G}(n,e)$ (graph), $\{\mathcal{P}\}^t$ (paths), $\{\mathcal{L}\}^t$ (likelihoods)
Output: $\mathcal{P}^*$ (best matching graph path)
Initialize: $t \leftarrow 0$, $\{\mathcal{P}\}^t = \{e_j | e_j \in \mathcal{G}\}$, $\mathcal{L}_i \leftarrow 0 \forall i \in \{1,\ldots,|\mathcal{P}^t|\}$
repeat
  $t \leftarrow t+1$
  Input: τ^t , (trajectory from visual odometry)
  Compute: $\mathcal{F}^t_\tau$, (trajectory feature)
  Update: $\{\hat{\mathcal{P}}\}^t \leftarrow f_p(\{\mathcal{P}\}^t, \mathcal{G})$, (generate candidate paths)
  Compute: $\mathcal{F}^t_{\hat{\mathcal{P}}_i}$ $\forall i \in \{1,\ldots,|\hat{\mathcal{P}}^t|\}$, (graph path feature)
  Compute: $\mathcal{S}^t_i \leftarrow f_s(\mathcal{F}^t_\tau, \mathcal{F}_{\hat{\mathcal{P}}^t_i})$ $\forall i \in \{1,\ldots,|\hat{\mathcal{P}}^t|\}$ (similarity score)
  Update: $\mathcal{L}^{t+1}_{\hat{\mathcal{P}}_i} \leftarrow f_l(\mathcal{L}^t_{\mathcal{P}_k}, \mathcal{S}^t_i, t, \sum_{j,j\neq i}^{|\{\hat{\mathcal{P}}^t\}|} \Delta\mathcal{L}^{t+1}_{\hat{\mathcal{P}}_j} \ni \hat{\mathcal{P}}^{t+1}_i \leftarrow f_p(\mathcal{P}^t_k, \mathcal{G})$ (likelihoods of candidate paths)
  Prune: $\{\mathcal{P}\}^{t+1} \leftarrow \{\hat{\mathcal{P}}^t_i | \mathcal{L}^{t+1}_{\hat{\mathcal{P}}_i} > \mathcal{L}_{threshold}\}$ (eliminate low-likelihood paths)
until $|\{\mathcal{P}^{t+1}\}| \leq |\{\mathcal{P}\}|_{threshold}$
$\mathcal{P}^* \leftarrow \arg\max_{\mathcal{P}^{t+1}_i} \mathcal{L}^{t+1}_{\mathcal{P}_i}$
return $\mathcal{P}^*$

Algorithm 1: Search for candidate path in BIM that matches sensor trajectory in real-time.

III. Experiment and Result

We acquired BIM model for each floor of a building in our university campus. This BIM file was a CAD drawing file of the floor plan that we used to infer navigable paths. An example of the results of these steps in shown on right in Figure 1. As the sensor begins to move through the building, there are initially several probable locations of the sensor. Each candidate location and its associated sub-graph has a likelihood score based on its match with the sensor trajectory. This is shown in the top of Figure 7. Every iteration, more candidate paths are spawned based on the number of outgoing edges from a node in the graph. Our approach keeps computing the likelihood of every sub-graph in the current pool of candidate paths. Those paths that have low likelihood are pruned out of the set of candidates. After a short traversal through the building, the trajectory of the sensor becomes sufficiently unique and therefore only matches one sub-graph with high likelihood. The algorithm then stops and infers the current position of the sensor as the most recent node added to the most likely candidate path.

IV. Conclusion

We proposed a method for positioning of sensors in an indoor environment that is significantly different than other approaches. While other methods estimate position within a wireless sensor network in terms of RSSI and suffer from multi-path, and unpredictable signal absorption, our approach uses a BIM model and does not need to transmit or received signals for the purpose of localization. Most importantly, BIM models are easy to acquire and process to create a graph based database of navigable paths. It is more expensive and time consuming to install static sensor network in buildings. Our approach is scalable and it can be used for indoor positioning in a previously unvisited building as long as a BIM or floor plan of that building is available.

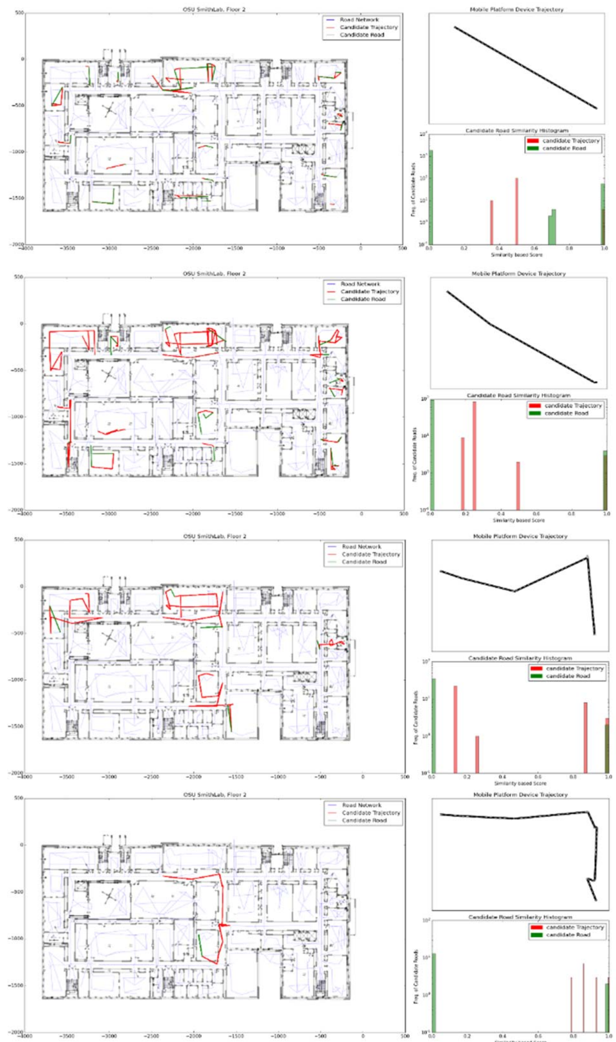

Figure 7: Indoor Positioning of mobile sensor. The figure on the top right shows the trajectory of the sensor as it moves in the indoor environment. The figure on the left shows candidate paths based on trajectory at any given time. The figure on the bottom right shows the histogram of candidate paths based on their likelihood scores. Those paths with lower likelihood are on the left are pruned. The remaining path is used to infer sensor position.

V. References

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