Ubiquitous Geo-Localization Without Infrastructure

インフラを使用しないユビキタス位置特定手法

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The primary method for geolocalization is based on GPS which has issues of localization accuracy and unavailability. We introduced a new geolocalization approach to GPS-denied indoor and outdoor environments. His approach has two principal components: public domain transport network data for outdoor and indoor available in GIS (Geographic Information System) databases; and trajectory data acquired from a mobile platform. This trajectory is estimated using inertial sensors or visual odometry. We abstract the transport map information as a graph data structure, where various types of roads are modeled as graph edges and typically intersections are modeled as graph nodes. A search for the trajectory in real time in the graph yields the geolocation of the mobile platform. The approach uses a simple visual sensor and it has a low memory and computational footprint. Our approach has the potential to completely augment, or even supplement, GPS based navigation since it functions ubiquitously in all environments.

主要な位置特定手法としてGPSがあげられるが，位置精度や適用可能範囲に課題がある。そこで，GPSが適用できない屋内・屋外環境における新しい位置特定手法を考案した。この手法には二つの基本要素がある。ひとつは，地理情報システム(GIS)に含まれる屋内・屋外の公的な道路網情報データ，もうひとつは，車両からの情報に基づく走行軌跡データで，慣性計測センサやビジュアルオドメトリを使って推定される。筆者は，道路網情報をモデル化されたグラフデータ構造で表現した。この構造では，様々なタイプの道路はグラフの線(エッジ)，交差点は交点(ノード)として表される。このグラフモデル中でリアルタイムに軌跡を探索し，車両の位置を特定する。この手法は，単純な視覚センサを使用し，小容量メモリの小型コンピュータ上で動作する。あらゆる環境で場所を選ばずに適用できることから，本手法は，GPSを使ったナビゲーションを補強し，さらにデータを補完する技術になると考える。

Introduction

Autonomous navigation is an emerging technology with a huge potential; self-driving cars are almost round the corner. This technology requires accurate geo-localization in real-time to effectively navigate urban environments. Currently, navigation technologies are time-of-flight reliant, such as Global Positioning System (GPS),[1] Ultra Wide Band (UWB),[2] Bluetooth[3] and active radio-frequency identification (A/RFID),[4] which have multiple issues. The accuracy of standard time-of-flight devices is unacceptably poor for the purposes of autonomous navigation and accurate sensors are very expensive to deploy and maintain. Especially commonly adopted GPS based solution is unreliable in several environments where transmission between the device and satellites is impeded by surrounding structures, like tall buildings in an urban environment, the so called ‘urban canyons’. In addition, GPS is unavailable indoors, underground, in tunnels, etc. and can also be degraded or denied in certain geographic regions. In order to be viable for a huge consumer market, there is a need for geo-localization solution that operates with low-cost sensors and public domain data.

We pose the problem of accurate geo-localization as a combination of accurate relative localization within a very

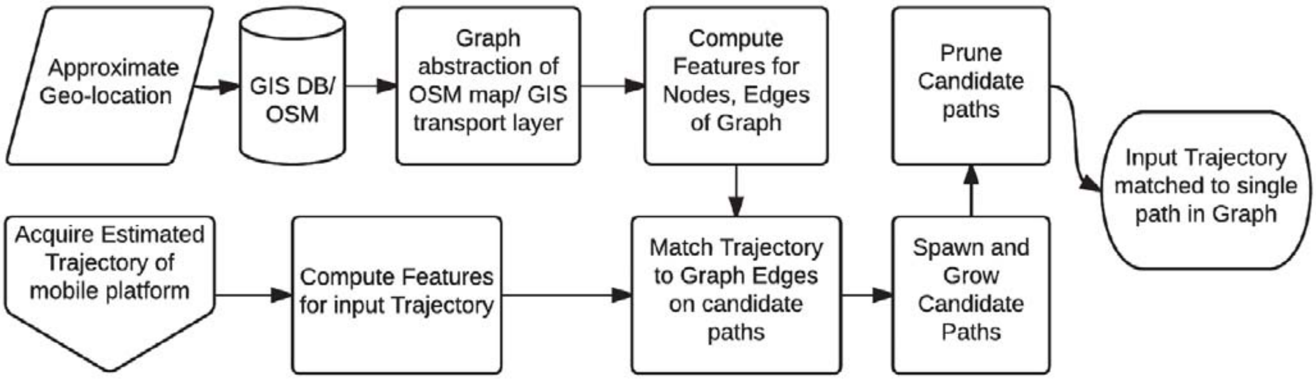

Figure 1 Trajectory Geo-Localization: VO is used to compute a trajectory in real-time which is abstracted as a sub-graph and is progressively localized by sub-graph matching in a graph abstraction of transport network map of the region of interest.

large spatial search space without requiring any infrastructure such as deployment of antennas. The relative localization can be computed using Visual Odometry (VO) or IMU, and the large spatial search space is acquired from GIS databases.[5] The key insight is that the motion of the typical mobile platform is correlated to the associated topology of the spatial search space. For example, a car moves on roads and so the trajectory of the car for a finite distance of travel is correlated to a subset of the transport network layer of GIS in the spatial search space for that car. The use of one or more layers of GIS based on the type of mobile platform and sensors facilitates flexibility in our approach and the ability to scale the solution.

Encoding Motion

We pose the problem of accurate mobile platform geo-localization as a combination of approximate geo-localization and accurate relative localization. The approach requires an initial hypothesis of region where the mobile platform can be located, which can be indoors or outdoors. For typical use cases, the region of interest would be a country or city sized area. The approach is illustrated in the block diagram in Figure 1. The first step is to acquire map data from a public domain source such as OpenStreetMap (OSM). This data is typically given in an XML format and is structured using three basic entities: nodes, ways and relations. The nodes represent point elements in the map and are defined by their GPS coordinates. The interesting map structures for us are streets, which are modelled as ways, and can be extracted from the XML data in to form a street graph of the region of interest.

Similar to outdoor, indoor data is provided by means of a building information model (BIM) and contains similar layers of data which can be used to estimate the location of the platform indoors.

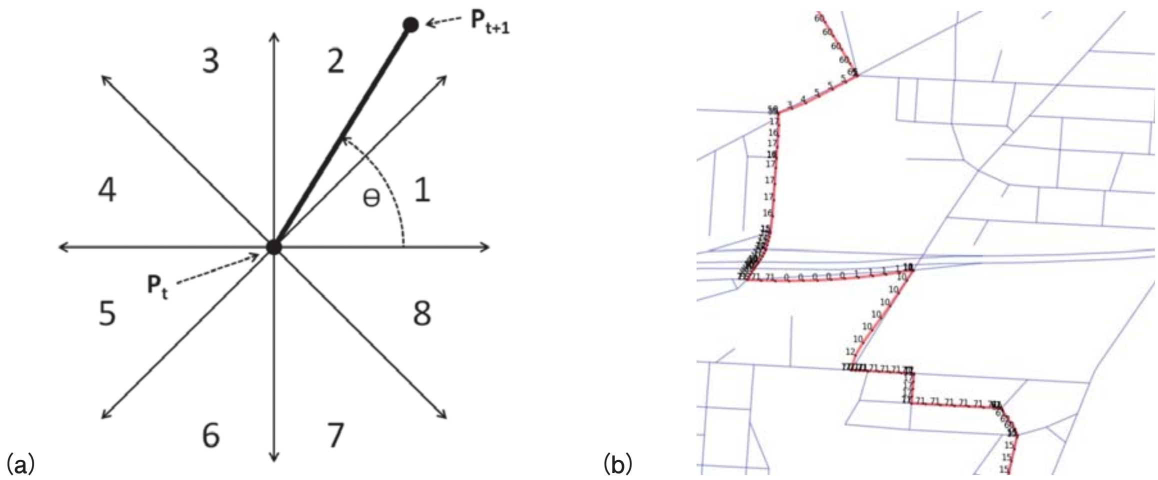

Figure 2 (a) Encoding trajectory of mobile platform and edges on graph of transport network. The motion from a point at a sampling interval to next point is measured in angle which is quantized into bins. (b) Feature descriptor for estimated 3D trajectory of mobile platform and edges of graph representing roads.

The second step is to compute feature descriptors for the 3D trajectory of the platform and the transport network graph. We chose a contour tangent shown in Figure 2a as the uniform sample distance. In order to aid scalability of the solution, we opted for a descriptor that is both fast and good for search trajectory in the graph. A trajectory is assumed to be consisted of points at roughly uniform sampling distance. The quantization associated with sampling distance is relevant in terms of sensitivity to the motion of the mobile platform. The choice of quantization level is based on optimizing sensitivity to mobile platform motion while minimizing effect of noise. Figure 2b shows a trajectory encoded in this manner.

Trajectory Search in Graph

With the aim of facilitating a generalized solution that does not require knowledge of geographic coordinates or global direction information of the mobile platform, we assume that the trajectory estimated by VO is in its simplistic form a sequence of points with relative distance measure. This means the most reliable mode of encoding the trajectory is change in angle of motion of the mobile platform which is equivalent to contour angles of a spline approximation of the acquired sequence of points. A graph abstraction of this trajectory is created using the control points as nodes of the graph and set of points between control points comprise an edge of the graph. Since the mobile platform travels on the road network the trajectory graph can be assumed to be a sub-graph of the map graph. Our approach to searching for a match in this large graph is to introduce path graph. Searching for a trajectory is equivalent to search for a sub-graph of the larger graph. So, we compute a similarity score between the trajectory graph and path graph for all path graphs in the map graph. The best matching path graph is then selected as the solution.

We consider the problem of geo-localization in real-time. Note that the estimated trajectory continuously grows with time and consequently the trajectory graph also grows with time. Consequently we formulate our trajectory search solution according to a sub-string matching algorithm.[6] The trajectory is a sequence of quantized edge-orientations we described earlier. Each graph path is also similarly encoded as a sequence of quantized edge-orientations. The key benefit of using string matching is that partial matches also produce a reasonably good similarity score. This formulation makes robust to noise, missing data, erroneous vehicle motion like swerving, map registration flaws, etc. The motivation for this approach is derived from the popular Bag-of-Words method in computer vision that has also been used for Simultaneous Localization and Mapping.

Experiments

We found that abstraction of trajectory and map to graph structure should be based on the scale and frequency of occurrence of significant features. To improve efficiency of the implementation we begin with an analysis of the topology of the map data. There results were used to tune the parameters of our geo-localization pipeline which is evaluated on several datasets for different parts of the world.

We acquired maps for regions of interest from OpenStreetMap to evaluate the performance of our approach for different types of transport network topologies including urban, semi-urban and country roads, and scale of the search region. We selected maps for: ‘Franklin county, Ohio’ which provides a typical U.S. county sized map; ‘Washington DC’, which is a highly urban region with a lattice grid structured road network; and ‘Montpellier, France’, which is a semi-urban and country spaghetti shaped road network of a state sized region. Some of the results of our experiments for each of these regions is illustrated in Figure 3. Initially, the estimated trajectory is short as the mobile platform begins moving. We compute a similarity score and observe that there are several matching paths, shown in the first column of the Figure for each region. As the estimated trajectory grows the number of candidate paths reduce based on our empirically determined threshold, shown in the center column in the figure. Subsequently, a single path with the highest similarity score remains, which is our matched path in the map graph. The right column for each region in the figure shows the matched path in the graph for the corresponding mobile platform trajectory. In our experiments we found that quick search depends on the uniqueness of the trajectory and the nature of the map graph.

Conclusions

A novel approach for geo-localizing position of a mobile platform is presented. We have proposed a modified approach to classical visual odometry pipeline with indoor and outdoor map data in a unified framework. We have described the algorithmic and implementation details of our method and demonstrated it on several different types of maps from different regions of the world. We have demonstrated excellent results on our proposed visual odometry pipeline on a benchmark dataset. Our results show that the proposed system is able to provide fully automatic global localization at a low infrastructural cost. Building on this work, we plan to further investigate the use of maps, especially different layers of a GIS database such as building, hydrology, relief maps, etc. We also plan to integrate outdoor and indoor GPS-denied navigation

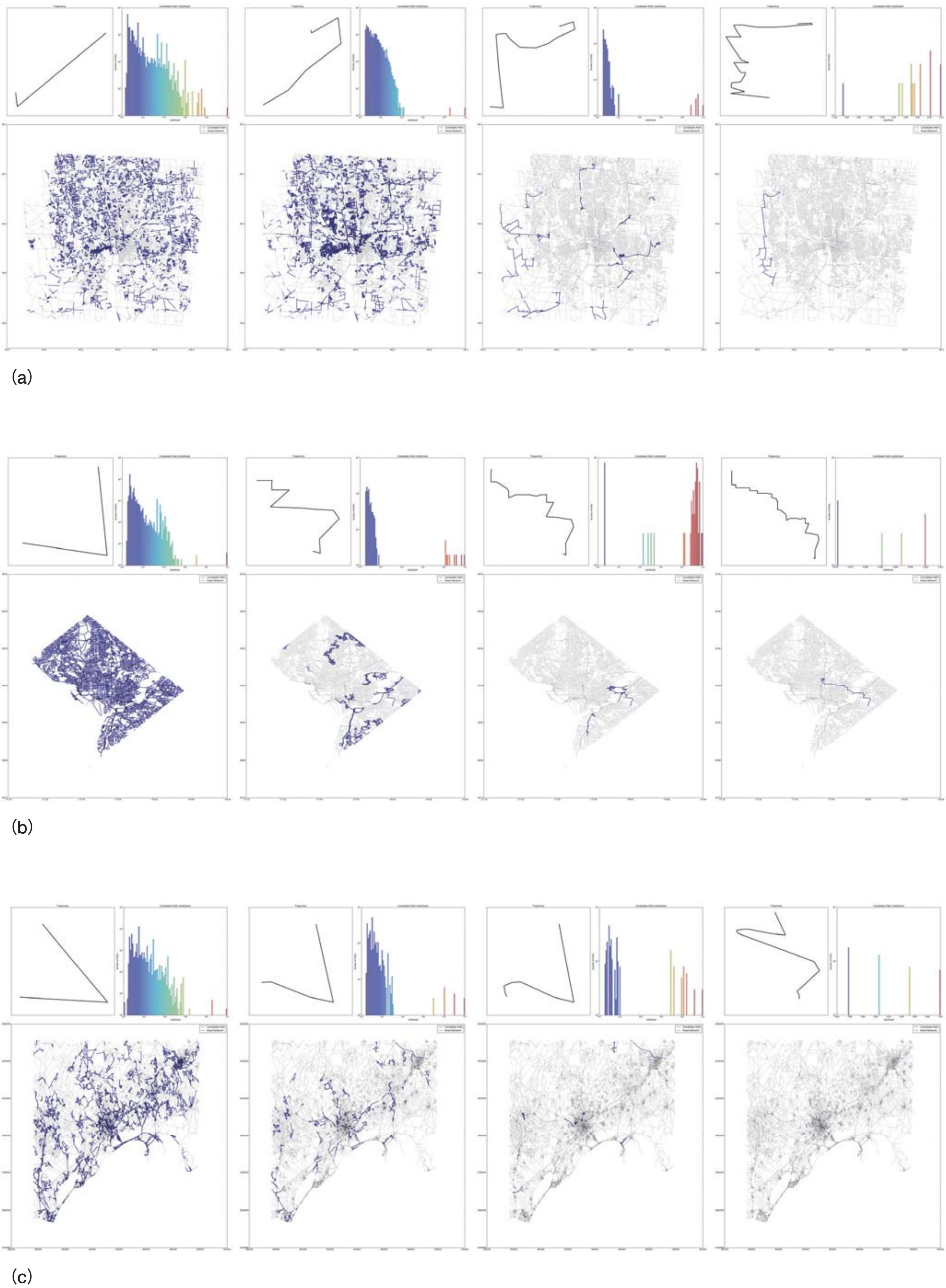

Figure 3 Geo-localization of mobile platform trajectory. (from top to bottom) For the geographic regions of 'Franklin County, Ohio', 'Washington DC, US', and 'Montpellier, France'. The estimated trajectory of the mobile platform is shown on the top left; the histogram on the top right shows the match score of each candidate path; and the map shows the current candidate paths. In the first column, the initial trajectory is small and several candidate paths are spawned. The similarity match score is shown in the histogram graph. As trajectory grows several candidates are pruned. Finally, the best matching path remains, shown in the right column, which is used for inferring geo-location of the mobile platform.

for seamless uninterrupted geo-navigation in all locations and environment conditions.

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