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Outdoor mapping and localization using satellite images

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SUMMARY
Recently, satellite images of most urban settings has become available on the internet. In this study, a novel mapping and global localization approach, which uses these images, is proposed for outdoor mobile robots operating in urban environment. The mapping of large-scale outdoor environments is done by employing the satellite images acquired by remote sensing technology, and then a map-based approach, that is, Monte Carlo localization is used for localization. The novelty of proposed method is that it uses standard equipment present on almost all autonomous robots and satellite images thus it acts as an alternative to GPS data in urban environments. Extensive field tests are presented to demonstrate the effectiveness of proposed approach.

KEYWORDS: Mapping; Localization; Outdoor mobile robots; Satellite images; Remote sensing.

1. Introduction

Autonomous navigation is one of the major capabilities that a mobile robot must possess. Autonomous navigation includes many subtasks such as path planning, obstacle avoidance/reactive navigation and localization. Of all the subtasks of autonomous navigation, localization is studied in the literature as a major problem with the potential of leading to absolute autonomy.[1–12] Some researchers focused on simultaneous localization and mapping (SLAM) problem in order to localize the robot with respect to the best map obtained so far.[5–12] Some others studied localization problem assuming that *a priori map* of the environment is available.[1–4] However, the question of "*How the map is acquired?*" cannot be answered easily, even for simple indoor environments. The problem becomes more complicated in large-scale outdoor environments. It is well known and expected that the map of a local environment may not be available all the times when a robot needs to operate in that environment. This problem has been addressed from the early days of mobile research.

A number of researchers have studied localization alone[1–4] given *a priori* maps. In these studies, the position tracking of mobile robot is investigated and it is assumed that the initial pose of the robot is known. The aim is to estimate the pose of the mobile robot with a reasonable accuracy. Different sensors which have different characteristics are utilized for this purpose. The most commonly used sensors are odometer, inertial measurement unit (IMU)/inertial navigation system (INS), sonar, laser range finders, and cameras. The underlying difficulty in estimating the pose of the mobile robot stems from the fact that the sensor readings are corrupted by noise and the sensor models and the process model of the dynamic system, the mobile robot, is inaccurate. Therefore, it is inevitable that the filter which tracks the robot pose will gradually diverge as the robot operates, unless the update stage includes absolute measurements of landmarks at known locations, at regular intervals to reset the filter. The absolute measurements of known landmark also requires *a priori* map of these landmarks around.

SLAM may localize a robot without a map thus it may eliminate the need for an *a priori* map. Although there are practical applications of SLAM, some issues still require attention. First, the original SLAM run time and storage is quadratic in the number of features in the environment. Therefore, generally solution to SLAM problem cannot represent the environment in dense form but rather sparse maps are common. Another big issue related to SLAM problem is the data association:[13] when the vehicle pose uncertainty is high, data association is not an easy task.[14] Since SLAM holds unimodal belief in the robot pose and map of environment, any data association mistake will lead to catastrophic failure of the filter. The EKF filter cannot recover the true solution back.

In the light of previous qualitative introduction, the followings conclusion can be drawn: *The SLAM problem is difficult to solve and data association might be even more difficult in large-scale environments. The map representation is sparse and is not very useful for several tasks a robot has to carry out but for localization. Position tracking needs absolute measurements to reset the filter otherwise it diverges. Map based localization is considered to be solved but generation of such a map on demand is an open challenge*.

Therefore, in this study a novel solution is proposed to tackle the global localization of outdoor mobile robots operating in urban settings. This approach may be classified into map based localization. As the global urban localization of an outdoor mobile robot is investigated, the question of "*How the map is acquired?*" is answered and a way of localizing the robot on such a map is being proposed. A well-known attempt to solve mapping and localization problem in parallel which is referred to as *simultaneous localization and mapping* (SLAM) in robotics literature is avoided by focusing on localization problem alone and by using freely available satellite images as an alternative to mapping. It is believed

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that this novel method will contribute to the autonomy of outdoor mobile robots.

In this study, very large-scale urban environments are considered and the mobile robot is localized globally (the word global is used in the sense that localization is performed with respect to a fixed coordinate frame on earth). The size of the environment considered are about 1 million square meters which is far larger than a typical environment considered in previous studies. It is evident that current SLAM methods are not suitable for such environments. At this point, remote sensing provides the right answer to finding maps of vast outdoor areas. The potential use of these images which has recently appeared on internet freely is exploited for outdoor mapping. Then generated maps are used in conjunction with localization methods to globally localize the mobile robot. The *global localization* is based on the claim that in urban areas, a rough initial fix can be obtained by using the built-in cell phone infrastructure in this area. Hence, it is possible to localize one's position in a circular region of diameter which is generally about a kilometer. @Google Earth[15] cell phone application is an example application which provides such a crude localization by making use of cell phone infrastructure. Therefore, it can be assumed that ability to localize a robot in an approximate area of one million square meters is sufficient to achieve global localization when the cell phone infrastructure present in urban settings are utilized. Following this approach, the SLAM problem is avoided and localization is performed in mutually independent steps; first the map of the region of interest is obtained by making use of satellite images, second localization is achieved by using the maps obtained from these images. The scenario of the operating conditions of the mobile robot can be summarized with the *Global Urban Localization* (GUL) problem:[16]

"*A robot with a Wi-Fi enabled device (such as a laptop, a PDA or a cell phone) wakes up in an unfamiliar urban setting. In the mobile robot's foremost task is to determine its location. Luckily, a wireless Internet connection is detected in the area so that the IP address obtained through this connection can be used to identify this region. With the virtue of this wireless connection, the robot accesses a website (such as Google Earth) where the satellite images of the earth can be conveniently downloaded. By simultaneously going over the satellite images and checking out the environment using relevant on-board sensors, the robot can find common features that might pinpoint its location or at least prune the search space. Eventually, the robot performs global localization limited to urban settings. This problem will be referred to as Global Urban Localization (GUL) problem*."

Provided that the assumptions (i.e., relevant satellite images are downloaded via a wireless connection) are satisfied, the effort to solve the presented problem raises two basic questions: Which sensors are suitable for this localization process? How should the satellite images be processed to match with local sensory data?

This study tries to answer these questions and as a result proposes a novel technique suitable for the solution of the GUL problem. The map of the environment is obtained by processing the satellite images that are freely available on the Internet (i.e., Google Earth). For this purpose a hybrid approach employing Fuzzy C-Means (FCM) and Adaptive Network-Fuzzy Inference System (ANFIS) methodology is adapted to segment various elements in such images including buildings, forests, fields, and roads.[17] Then, the Monte Carlo Localization (MCL) technique is used along with these maps to find the pose of a mobile robot which senses around by a laser range finder.[18]

In order to successfully apply the proposed method, satellite view of the objects in scene should correlate with the observation of the mobile agent on ground. In other words, it is expected that the boundaries of the objects present in the map extracted from the satellite images match the observation of the robot in the field. In fact, this correlation is mostly achieved due to the nature of buildings, where surfaces are generally orthogonal to each other. This inherent orthogonality is the basis of correlation between robot's observation and object contours extracted from satellite images. Considering the fact that, urban environment does not change rapidly, maps extracted from satellite images can be used for extended periods of time. One exceptional situation, where projection from top view to the side view majorly differs is due to the presence of single tree or vegetation in the environment which scatters the laser beam. By using a proper filter, the effect of these objects should be omitted.

The rest of the paper is organized as follows. Section 2 reviews the related literature and justifies the GUL problem. Section 3 introduces the novel mapping technique. Section 4 elaborates on the localization approach while Section 5 describes the experimental setup. Section 6 demonstrates performance of global urban localization approach with intensive field tests. Final section presents discussions and concluding remarks.

2. Literature Review

In the literature, there are several studies that focus on the localization techniques where the maps of the environment are assumed to be already available.[1–4] In fact, MCL, Markov localization technique, and extended Kalman filter (EKF) based solutions require a map. Unfortunately, assuming that the map of the environment is available is not realistic for most situations. Therefore, problem has been extensively studied by many researchers.[5–12] Dissanayek *et al*.[5] demonstrated the convergence of SLAM methods by using linear process and measurement models. It is stated that a solution to SLAM problem does exist and that a precise map could be obtained. Despite its apparent success, the SLAM is a very difficult problem to tackle with in real time for large-scale environments especially outdoors.

Recently, several improvements to the original SLAM algorithm are proposed. Some of these approaches attempt to cut the computational cost by exploiting the structure of SLAM problem. Guivant *et al*.[6] studied localization and map building by using the information form of the Kalman filter. Guivant and Nebot[7] proposed a *compressed extended Kalman filter* (CEKF) for SLAM problem. Similarly, Thrun *et al*.[10] devised the sparse extended information filter (SEIF). Their study exploits the structure of the SLAM problem so that the update time of filter, which is irrespective of the number of features in the map, becomes constant.

Csorba *et al.*[19] developed the relative filter. In their work, the relative distance and relative angle between the landmarks are stored to develop a relative map. Hence, a simple filter (a.k.a. relative filter) is devised to update the information locally. This approach leads to a considerable computation time savings. However, the relative filter is criticized for not taking into the consideration of the cross correlations between landmarks. Consequently, the original relative filter is considered to be suboptimal.[20] On the other hand, Martenelli *et al.*[20] takes on a completely different approach. The distances and angle between point and corner landmarks, which are invariant under translation and rotation, are used in mapping. The approach requires some attention when the local invariants are transformed into a global map. Although the local invariants may be quite accurate when they are transformed into global map, the local inaccuracies may add up and the global map may turn out to be imprecise. In order to generate the global map, Newman[21] proposed the projection filter to transform the local invariants into global maps which necessitates the solution to a set of nonlinear equations. To solve the inconsistency, Martinelli *et al.*[20] proposed the EKF-based estimation.

Wang *et al.*[22] developed a decoupled solution to SLAM problem where state of vehicle augmented with the states of landmarks, is transformed into a new form. It is proven that this transformation has the effect of sparse extended information filter. Hence, the computational cost is reduced dramatically. Dissanayake *et al.*[23] devised a map management strategy for efficient computation. In this work the distant landmarks are safely deleted and later added if they are detected again. This leads to considerable cost reduction. Furthermore, Nguyen *et al.*[24] developed the orthogonal SLAM. In this study, only the parallel and orthogonal lines, which are commonly found in indoor settings, are mapped. This approach also improves computational efficiency.

Some researchers focused on data association problem. For instance, FastSLAM proposed by refs.[9,25,26] decomposes the SLAM problem into a localization problem and K independent landmark estimation problems conditioned around the robot pose estimates. It employs a modified particle filter to estimate the posterior distribution over robot paths. Each particle posses K independent Kalman filters that estimate the landmark locations around the particle's path. Thus, FastSLAM overcomes the problems associated with the Kalman filter. Just like FastSLAM, DP-SLAM proposed by refs.[12,27,28] exploits the conditional independencies. In this paradigm, both the robot poses and different possible map configurations are maintained by a particle filter. Masson *et al.*[11] studied mobile robot navigation and mapping in large environments and hybrid *architecture* of *Monte Carlo filter* and EKF based solution to SLAM is proposed. In this study, when the EKF fails, MCL is started and it continues to run until the data association problem is solved then the system switches to EKF based solution to SLAM again. Estrada *et al.*[29] studied the hierarchical SLAM. Two-level mapping is used: in the higher level, a global map, which is indeed a tree structure, is maintained. The nodes of this tree refer to the local maps and the arcs represent the adjacency and metric information about the relative distances between local maps. In the lower level, local maps are utilized to represent environment. The unique side of this study is that it imposes (loop closing) constraints whenever applicable.

Due to their computational cost, the SLAM methods cannot produce dense maps. Although sparse representation of the environment is sufficient for localization and mapping, it is not adequate for navigation. To overcome these difficulties, Guivant *et al.*[30] developed a hybrid metric map (HYMM). In their study, the sparse maps of features, produced by solving SLAM, are combined with occupancy grid (OG) maps to represent the environment more accurately. The features/landmarks in the environment are used to divide up the environment into a set of connected local triangular regions (LTR). These LTR are solid regions on which several properties can be represented in the form OG maps. Nieto *et al.*[31] addressed the dense representation of environment. The feature based sparse landmark maps can be delimited to small LTRs in which a dense representation of the environment is possible.

Consistent landmark detection is difficult in outdoor environment. It is relatively easier to find natural landmarks in indoor environments such as corners and walls. However, outdoor settings do not have so many distinct and structured features. Madhavan and Durrant-Whyte[32] proposed the utilization of maximum curvature points as natural landmarks in unstructured outdoor environments so as to yield robust and stable landmarks.

As mentioned earlier; despite successful applications, the SLAM algorithms are not practical in large-scale environments such as the ones considered in this paper. Note that another important limitation of SLAM is that only the maps of the previously explored regions are available to the robot. Whereas, the maps obtained from satellite images can enable the robot to devise mission plans on a much larger scale. Similar efforts in literature, which make use of satellite images, can be found in refs.[33,34] Booker[33] correlated millimeter radar data with aerial images and Guivant *et al.*[34] computed the path of a mobile robot by matching inertial navigation system data to road networks found on satellite images.

Remote sensing promises an alternative solution to outdoor mapping. The remote sensing technology (RST has been successfully applied to a broad range of applications. In fact, RST has been used to monitor the environment and human activities, that is, urban development and the natural resources, for years. In refs. [35, 36] the remote sensing technique is used to monitor the forest activities and marine pollution. The estimation of the urban population is critical as urban development has major impact on nature, water resources, and climate. Such effects cannot be detected from ground; therefore, RST is being used extensively to estimate the extent of urban development and the degree of damage to the nature.[37,38] Agriculture is yet another field where remote sensing finds its use such as water requirement predictions and yield estimation.[39,40] Remote sensing is also used to monitor the structure of the earth.[41,42] It is employed to study archeological sites,[43,44] that is, archeological inheritance dispersed in vast areas, which cannot be assessed from the ground. Natural hazards are one of the hottest topics of remote sensing; remote sensing can be utilized to identify the damage level of catastrophic events.[45] Similarly, it can be also facilitated to identify the quality and quantity of water resources.[46]

Among all of these studies listed for RST above, none of them focused on creating maps that are suitable for outdoor mobile robot navigation. For this purpose, a mixed (a.k.a. "hybrid") approach that makes use of the FCM and ANFIS is proposed to identify various objects present in satellite image describing a scene, in which the robot is to operate. Next section will introduce the proposed novel method for obtaining such maps that are suitable for outdoor mobile robot localization and navigation.

3. Map Creation Using Satellite Images

In this work, the mapping is considered as a separate step independent of the localization process. Hence, the coupled problem of localization and mapping is reduced to a localization problem over a preconstructed map. In the proposed technique, satellite image(s) of an operational urban area is processed into a meaningful form that can be used by a robot for navigation purposes. During mapping, geometric information as well as the structural information associated with the segmented parts is included in this representation.

Analysis of satellite image is performed by a combination of unsupervised and supervised techniques; the satellite images are first clustered in feature space by using an unsupervised clustering technique, namely, Fuzzy C-Means (FCM) then boundaries between different fuzzy cluster regions are drawn by an Adaptive Network-Fuzzy Inference System (ANFIS) thus both of them constructs the structural regions in the environment useful for localization purpose.[17,47–50]

Fuzzy clustering, for example, Fuzzy C-Means (FCM) is used to generate the meaningful fuzzy clusters that represents mass number of the pixels with diverse characteristics, these initial clustering serve as a rough guess for the membership's functions in a FIS. Since, FIS cannot be trained, at this stage, in order to estimate the membership function's parameters of the FIS precisely, an ANFIS is constructed/trained by a hybrid learning scheme. Note that the ANFIS considered at the second stage of the hybrid classifier attaches the fuzzy data clusters found by FCM in the first stage autonomously to information classes, that is, labels of objects in the scene (objects in scene are labeled with integer numbers; field = 1, building = 2, forest = 3, road = 4) The flowchart of this cascaded system is shown in Fig. 1.

The benefit of unsupervised classification method can be justified by its data compression characteristics. Hence, the supervised system running on a compact data set reduces the training time dramatically.

The main structure of segmentation procedure implemented here can be summarized as:

- A number of satellite images are obtained/downloaded from the region of interest and converted to HSV color spectrum
- The images are divided into two groups:
  - Training images
  - Test images

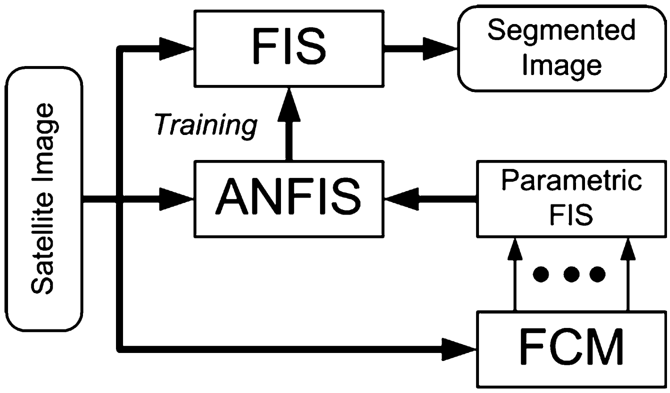

Fig. 1. The structure of hybrid classifier.[17]

- The pixels values of training images are classified by FCM clustering algorithm into a fixed number of clusters. Note that this part is an unsupervised classification
- Rough FIS is constructed from the clusters found by FCM
- The ANFIS is constructed for the FIS and is trained to compute the parameters of the FIS. This part is a supervised training hence the information class of training images, for example, field, forest etc. are known and ANFIS learns the nonlinear relation between pixel values and information classes codes, for example, field = 1, building = 2, etc.
- The trained system ANFIS/FIS is applied on the test images to label the pixels, for example, pixel (x,y) = information class (ground = 1, building = 2, ...).

A detailed description of FIS and ANFIS structure used in this study is presented in ref. [51].

4. Localization

Localization of a mobile robot, that is the estimation of the pose of robot, $\{x, y, \theta\}$ coordinates of the robot and its heading, respectively, is best explained as a dynamic Bayesian network (DBN) where the robot pose/state is the hidden variable. This hidden variable can be represented with a first-order Markov process. A complete description of a Markov process requires specification of three probability measures, namely; state transition model $P[x_{t+1}|x_t, a]$, observation model $P[y_t|x_t]$, and *a priori* distribution $P[x_0]$. Given the Markov process, the question to be answered is: Given an observation sequence, $y_{1:t}$ how do we find a state sequence, $x_{0:t}$ which explains the observations best?

Bayesian models can be used to estimate hidden states from given observations. Thus, posterior distributions of states can be obtained from Bayes' theorem and inference can be made about the states (i.e., maximum likelihood). Assuming that the Markov process is available, at any time t, the posterior distribution is given by Bayes theorem.[52] The expression for the marginal distribution $P[x_t|y_{1:t}]$ satisfies the following recursion.[53]

Prediction:

$$P\left[x_t|\, y_{1:t-1}\right] = \int P\left[x_t|\, x_{t-1}, a_t\right] P\left[x_{t-1}|\, y_{1:t-1}\right] \mathrm{d}x_{t-1}. \tag{1}$$

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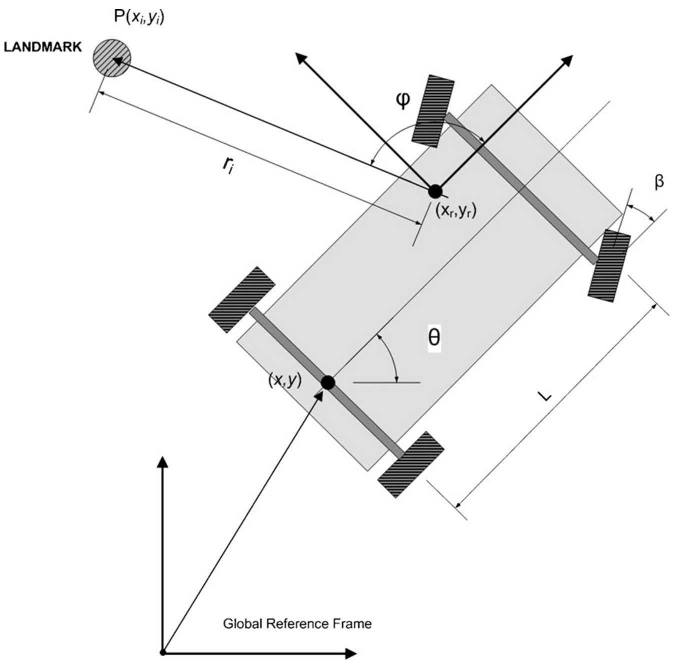

Fig. 2. The vehicle model.[6]

Updating:

$$P\,[x_t|\,y_{1:t}] = \frac{P\,[y_t|\,x_t]\,P\,[x_t|\,y_{1:t-1}]}{\int P\,[y_t|\,x_t]P\,[x_t|\,y_{1:t-1}]\,\mathrm{d}x_t}. \tag{2}$$

Next the discrete time process and measurement models and probabilistic state transition model of the mobile platform and observation model of sensors used in this study are developed. The kinematic model of a mobile robot can be expressed as[6]

$$\begin{bmatrix} x_{t+1} \\ y_{t+1} \\ \theta_{t+1} \end{bmatrix} = \begin{bmatrix} x_t \\ y_t \\ \theta_t \end{bmatrix} + \begin{bmatrix} v\cos\theta_t \\ v\sin\theta_t \\ \frac{1}{L}v\tan\beta \end{bmatrix} + \begin{bmatrix} N(0,\sigma_x) \\ N(0,\sigma_y) \\ N(0,\sigma_\theta) \end{bmatrix}, \tag{3}$$

where $\{x, y, \theta\}$ are the coordinates and heading of the mobile robot and $\{v, \beta\}$ are the translational velocity and steering angle of mobile robot, respectively. $N(0, \sigma_x)$ is a zero-mean Gaussian PDF for noise characteristic of state-x. The robot kinematic model is illustrated in Fig. 2. Equation (3) may be expressed in compact form as

$$x_t = f(x_{t-1}, a_t, w_{t-1}). \tag{4}$$

In order to reduce the computational complexity, the robot's heading is measured by a compass which changes within certain (absolute) bounds. Throughout this study, the nominal value of the compass measurement is used as heading angle data.

The measurement model of the mobile robot is expressed as

$$\begin{bmatrix} O_{k,1} \\ O_{k,2} \end{bmatrix} = \begin{bmatrix} \sqrt{[x_{k,L} - x_r]^2 + [y_{k,L} - y_r]^2} \\ a\tan\left[\dfrac{y_{k,L} - y_r}{x_{k,L} - x_r}\right] + \theta \end{bmatrix} + \begin{bmatrix} N(0,\sigma_{k,1}) \\ N(0,\sigma_{k,2}) \end{bmatrix}, \tag{5}$$

where $\{x_r, y_r, \theta\}$ are the states of mobile robot, $O_{k,(1,2)}$ and $\{x_{k,L}, y_{k,L}\}$ are the range and bearing measurement to the kth landmark, and the coordinates of the considered landmark, respectively. Equation (5) may be expressed as

$$y_t^k = h_k(x_t, v_t). \tag{6}$$

Next the computation of $P[x_t|x_{t-1}, a_t]$ and $P[y_t|x_t]$ is explained. Here the probabilistic motion model, $P[x_t|x_{t-1}, a_t]$ which is a *first-order Markov Process*, is defined by the *process model* $x_t = f(x_{t-1}, a_t, w_{t-1})$ and the known statistics of process noise w_{t-1}[52]

$$P\,[x_t|\,x_{t-1}, a_t] = \int \delta\,[x_t - f(x_{t-1}, a_t, w_{t-1})] \times P\,[w_{t-1}]\,\mathrm{d}w_{t-1}. \tag{7}$$

Probabilistic observation model $P[y_t^k|x_t]$ are defined by the *measurement model* $h_k(x_t, v_t)$ and known statistics of measurement noise, v_t Both process, w_{t-1} and measurement, v_t, noises are zero mean, temporally uncorrelated white Gaussians:[52]

$$P\,[y_t|\,x_t] = \int \delta\left[y_t^k - h_k(x_t, v_t)\right]P\,[v_t]\,\mathrm{d}v_t, \tag{8}$$

where $\delta(.)$ is a Dirac-delta function. Both equations require that we are able to sample from process and measurement noise.

The necessary probabilistic models to simulate DBN modeling the mobile robot localization problem are explained next. Since the *lost robot* case is assumed, there is no prior information about the initial pose of the robot, and the initial distribution is assumed to be uniform.

The probabilistic motion model, $P\,[x_{t+1}|\,x_t, a_{t+1}]$ is assumed as a Gaussian distribution about the nominal incremental move measured by the odometer. It can be expressed as:

$$P[x_{t+1}|x_t, a_{t+1}] = \det(2\pi R_t)^{-1/2}\exp\left\{-\frac{1}{2}A^T R_t^{-1} A\right\}. \tag{9}$$

A can be given as follows:

$$A = [x_{t+1} - f(x_t, a_{t+1})]\,, \tag{10}$$

where a_t is the action command; x_t, is the pose of the robot prior to the execution of the action and x_{t+1} is pose of the robot pose after action command is executed. a_t is the nominal distance traveled by the robot as it is commanded by the action, and R_t is the covariance matrix of the process noise. Equation (9) is a direct consequence of Eqs. (4) and (7).

The robot scans the environment at constant angular sectors. The measurement model is computed by a joint probability of these single measurements along each angular direction. Thus, the measurement model for a single landmark can be expressed mathematically as:

$$P\left[y_t^k\middle|\,x_t\right] = \det(2\pi Q_t)^{-1/2}\exp\left\{-\frac{1}{2}B^T Q_t^{-1} B\right\}, \tag{11}$$

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where

$$B = \left[y_t^k - h_k(x_t)\right] \tag{12}$$

and Q_t is the covariance matrix of the measurement noise.

Assuming conditional independence between successive measurement, the measurement likelihood, $P[y_t|x_t]$, can be computed as

$$P\left[\,y_t|\,x_t\right] = \prod_{k=1}^{K} P\left[\,y_t^k\middle|\,x_t\right], \tag{13}$$

where K is the total number of angular sectors which sums up to gross angular scan, Q_t is the covariance matrix of the uncertainty in the laser scanner measurement, y_t^k is the range and bearing measurement to kth landmark in gross measurement y_t observation, made by real laser scanner, $h_k(x_t)$ is the kth range and bearing measurement in gross measurement $y_t$observation, made by virtual laser scanner located on the map whose pose is x_t. Since the scale of environment map obtained from satellite images and the real environment scale does not match, the virtual scans made by virtual laser scanner on the map is calibrated before, such that unit distance measured by the real laser scanner on the robot and the virtual laser scanner on the hypothetical robot on the map, is the same. The joint conditional probability Eq. (13) can be computed from Eqs. (6) and (8).

In this paper, buildings and dense vegetation are used as landmarks. It has been observed that dense tree groups and man-made objects such as buildings are detected by the laser scanner in the field and they can be safely used for localization purpose. Thus, a satellite image is segmented accordingly into four categories: building, forest, field, and roads. The color codes of four categories are arranged such that the virtual laser scanner operating on the map extracted from satellite images is sensitive to the first two categories, building and dense tree groups and is insensitive to last two categories in the map, that is, field and road.[18]

Once $P[x_{t+1}|x_t, a_{t+1}]$ and $P[y_t|x_t]$ are obtained from the process and measurement models, MCL can be implemented to run the Bayes filter.

5. Experimental Setup

To test the performance of the proposed method, a mobile platform is designed to collect data outdoors. The mobile platform is equipped with a SICK LMS 291-S05 laser scanner, a notebook, and a battery pack. Custom software is specifically developed to communicate with this laser scanner and to record the 180° polar scan for the scanner. In the experiments, these polar plots are to be recorded at equal distances of travel. Note that the direction of the laser scanner is aligned with the motion of the mobile platform. 180° angular sector is scanned with increments of half degrees; however, the data are then under-sampled with increments of 3° to speed up the simulation process.

During the experiments, the mobile platform is moved along a certain path. Man-made objects (like buildings and walls) allow precise measurements whereas certain elements of nature (vegetation, trees, bushes etc.) are potential sources of difficulty. For instance, the laser beam scattered by the vegetation has considerable noise content in the measurements so the acquired data may not be directly used for localization. To overcome this difficulty, a custom filter, which compares the derivative (i.e., the first-order difference) of the range signal to a selected threshold, is designed, which estimates the new range signal by considering the minima of that region.

The experiments were conducted by placing a laser scanner on the top of a vehicle (emulating a mobile robot) which is far above the height of an average passenger car on the road. Hence, the nonquasi-static elements in the scene are effectively eliminated. Note that there are some events whose period extends well beyond the capture frequency of satellite images like construction sites. However, the experiments in this study are conducted in a well-developed urban setting to avoid such instances. The following section discusses the localization performance of the proposed technique.

6. Experimental Results

A district, Dikmen, in the city of Ankara (Turkey) is selected because the nature of this region represents a true urban scenario. The experiment is conducted late at night when the sensor is not disturbed by nearby moving objects. In a way, the requirement of a quasi-static established environment is satisfied. A utility vehicle (Fiat Doblo), whose roof is far above the height of the any passenger cars, is employed to eliminate nearby cars (and other objects) since these objects are not truly modeled in satellite images, note that at the time of experiments, most cars on the street are parked. However, some trucks and busses are passing from time to time which in turn disturbs the characteristics of measurements. However, the simulations have shown that their effects on the results are quite insignificant.

Although the experiments are conducted in an old part of the city where urbanization has been almost completed; there are some building-construction sites appearing to be unoccupied in the satellite images (due to their low sampling/update rate). For those instances, the discrepancies are corrected manually in accordance with our observations.

The utility vehicle is driven to follow the prescribed path at a constant speed of 10–12 km/h. The path of robot path is plotted on the satellite image of the local region in Fig. 3. As illustrated in Fig. 4, the satellite images were segmented into four elements: buildings (in black color), forest (light gray), and field (dark gray), and road (white) by following the procedure introduced by Dogruer *et al.*[17] During the experiments, the GPS coordinates are obtained from a GPS receiver and the laser range finder measurements are recorded at constant time intervals. Notice that the method suggested for the solution global localization of a mobile robot/platform requires the odometer- and compass (heading) data. Hence, these data are to be computed indirectly utilizing the GPS data.

To assess the performance, the (filtered) range data recorded in the field are fed into the simulation software (an M-script in Matlab 7.1) as if the robot were actually moving around the track where the data were originally collected.

The experimental results are presented in a systematic way. First, the results of simulations are printed in discrete simulation steps, because it is almost impossible to print

Fig. 3. Satellite image and the robot path, coordinates of image origin is 39° 52′ 47.98″ N; 32° 49′ 58.20″ E.

all simulation steps on one image. The numerical check is performed by using entropy metric

$$H(X) = \sum_{x \in X} P[x] \log P[x] \tag{14}$$

and KL-divergence:

$$D[P(x)|Q(x)] = \sum_{x \in X} P[x] \log \frac{P[x]}{Q[x]}. \tag{15}$$

Entropy metric is suitable for checking statistical characteristics of localization whereas KL-divergence checks the characteristics and distribution of particle with respect to a model/GPS data.

The particle distribution at different simulation steps are shown in Figs. 4–6. The successive particle distribution shows that the true robot pose is achieved in the 20th steps. The rest of the analysis is a position tracking. The robot closes the path successfully. Although the final error in closed path seems big, with respect to the area of the region this amount is

Fig. 4. Simulation step: 5,10,15,20,25,30.

Fig. 5. Simulation step: 40,50,60,70,80,90.

reasonable. The successive locations are shown with a color wheel.

Figures 7 and 8 show the entropy metrics and KL-divergence computed for the same path, respectively. Graphs of these metrics support the particle distribution. Note that entropy metric computes how compact the distribution is and cannot be used to assess that the true position is recovered or not. KL-divergence metric compares two data sets, the GPS data and the simulation result and it can tell if the simulation recovers the true position.

Figures 9 and 10 show the Cartesian coordinates (x, y) of the robot with one sigma confidence limit. The GPS data are also printed to compare the simulation results with the GPS (a.k.a. ground truth data). It is observed that the simulation results are good in agreement with the ground truth data.

With respect to the cost of simulation; the computational load associated with the proposed technique can be assumed reasonable considering that the size of the field being searched is vast: $\sim$1 million m^2. Notice that the presented technique is in fact suitable for real-time operation provided that the mobile robot is equipped with a number of fast processors and that the satellite images are pre-processed to create the virtual laser scans on the map.

Fig. 6. Simulation step: 100,110,120,130,140,150,163.

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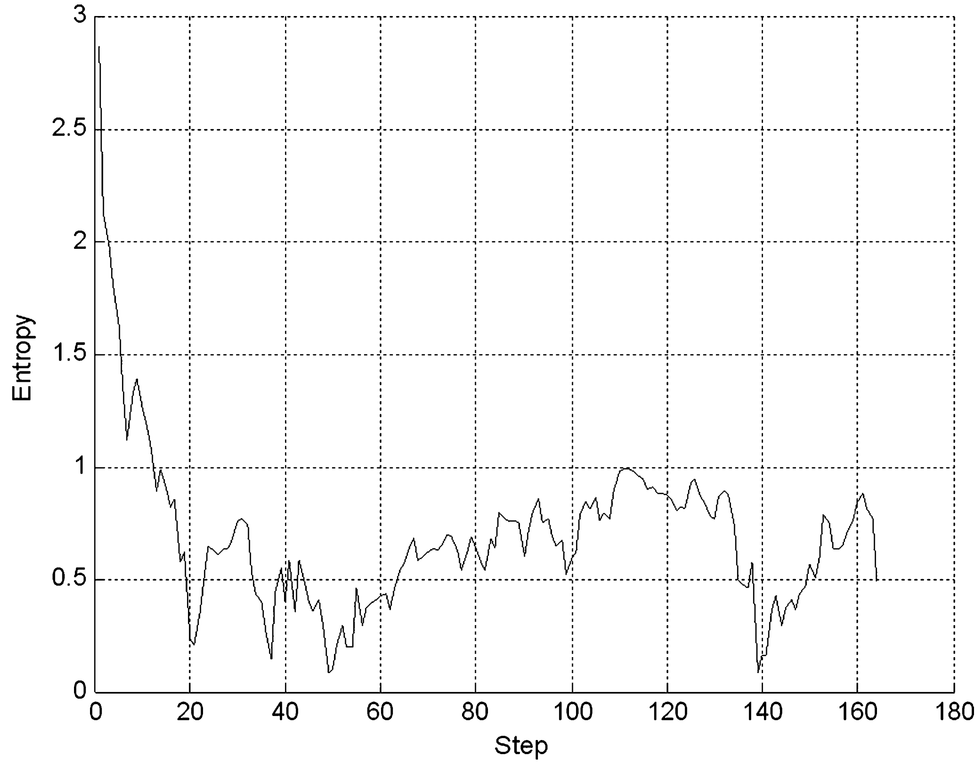

Fig. 7. Entropy metric for Dikmen path.

7. Conclusion

In the last decade, the satellite images of most urban areas have become available publicly on the Internet. Hence, this study has focused on a novel localization method for mobile robots that make use of such images.

In this study, it is shown that a two-dimensional laser scanner and a simple odometer system can be used along with maps created from satellite images to localize mobile robot in large-scale environments. The tested environments are larger than most of the environments used in previous studies.

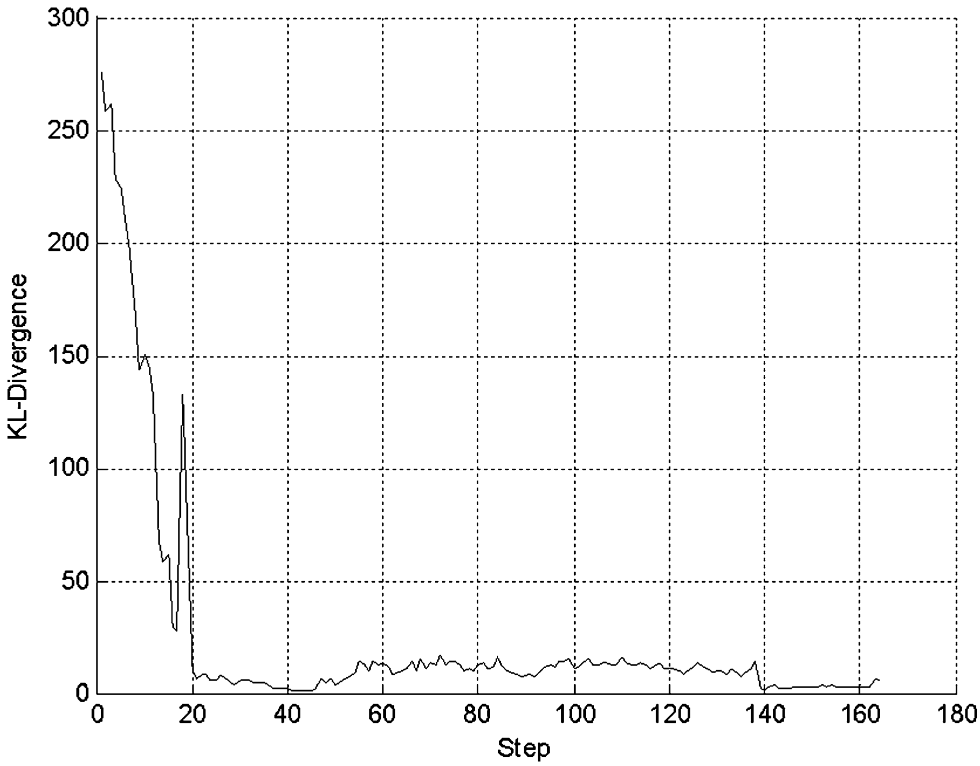

Fig. 8. KL-divergence metric for Dikmen path.

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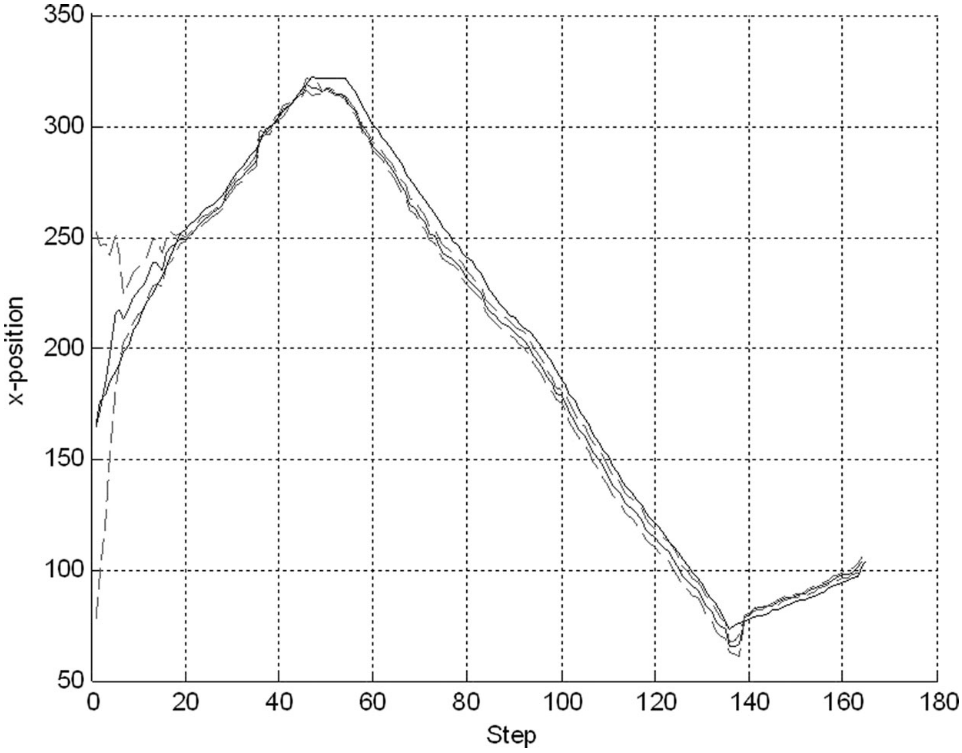

Fig. 9. x-position mean (—), the one sigma confidence limit (- - -), and the GPS data (**—**).

Localization results are found quite satisfactory for all intensive purposes. It is expected that the widespread use of this approach will reduce the setup time of outdoor mobile robotics applications in large-scale urban environments. It may eliminate the map crafting totally. This novel localization and mapping method, which uses satellite images for mapping and cell phone infrastructure to make an initial crude localization, may serve as an alternative to GPS technology. Although, initial crude localization in GUL problem requires the cell phone towers, the rest of the operation of the mobile robot do not require any external information source. Maps of these large landscapes may

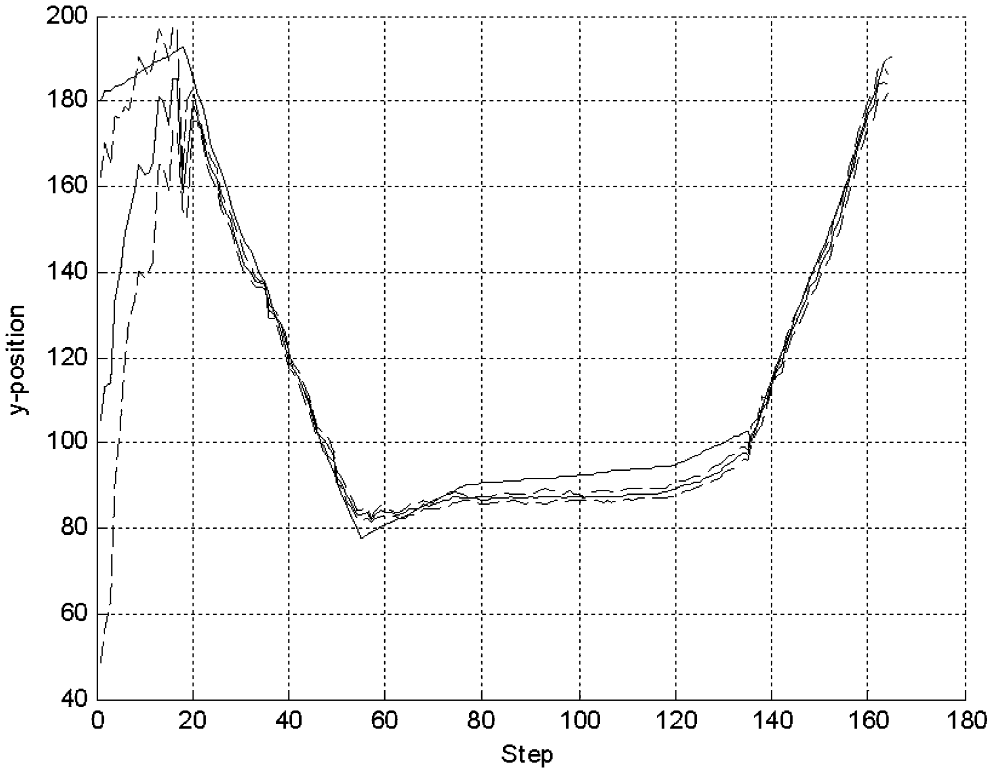

Fig. 10. y-position mean, the one sigma confidence limit and the GPS data. Legend is the same as given in Fig. 9.

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be uploaded to robot memory so robot does not need to communicate with main server, hence can operate in off-line mode. In cases where the robot is to operate in large yet restricted environments, proposed method can also be used fully off-line without requiring cell phone towers on the expense of elongated localization times. From the practical point, many robotic applications (such as perimeter surveillance, reconnaissance, package delivery, etc.) are done within areas the limits of which are known *a priori*. Hence, it is possible to load regional maps upfront and use the proposed method in completely off-line manner.

Proposing this method as an alternative to GPS, does by no means imply that it is a direct substitute of a GPS device. Yet, GPS signals are not guaranteed to be present under all circumstances in all urban environments all around the world. GPS signal strength might significantly change as the robot moves as well. However, the maps extracted from satellite images contain features belonging to urban regions that do not tend to change rapidly in time. In addition to the fact that, laser scanners and odometers may be considered as standard pieces of equipment used in most mobile robots, the proposed method offers an alternative localization method for mobile robots operating in urban environments. GUL can be used to assist or verify existing localization techniques, or as shown in this work, it can also be used on its own to localize a mobile robot in an urban environment.

Lastly, the presented approach is the first attempt of solving a novel problem defined in this paper, namely, *Global Urban Localization*.

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