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Image Based Methods for Navigation of Intelligent Vehicles

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ABSTRACT: Intelligent vehicles are being used in transportation and robotics. Many applications of robotics and for transportation, self-position of vehicle needs to be determined. Among many methods for determining self-position, fusion of many methods offers great advantages as information obtained from one methodology cannot be obtained from others. In this paper, an attempt has been made to estimate self-position of intelligent vehicles in a cluttered environment. The methods are compared and fusion of the methods is studied to determine self-position of intelligent vehicles accurately.

KEYWORDS: Intelligent Vehicles,image matching, triangulation, GPS,self-position.

I. INTRODUCTION

Intelligent vehicles are becoming more and more popular these days because of their driver assistance services.Localization of intelligent vehicles is of utmost priority because for effective and efficient transportation of suchvehicles, their self-position needs to be known. Apart from localization of intelligent vehicles, service robots needto know their self-position before such robots perform their next task. In case of intelligent vehicles, to stay in aspecific lane, the vehicle must know its current position. The position must be known in centimetre accuracy tofollow road lane. GPS alone is not sufficient to meet the requirements of such a precise localization. Many othertechniques are used along with GPS for the purpose viz. odometry, IMU. The various methods used for localizationhave been discussed in the following sections of this paper along with their advantages and drawbacks.

II.LOCALIZATION OF INTELLIGENT VEHICLES

GPS is used for localization of intelligent vehicles. GPS consists of 24 satellites which send signals to estimate position. One satellite needs to be received for each dimension of the user’s position that needs to be calculated. This suggests three satellites are necessary for position estimate for general user (for the x, y, and z dimensions of the receiver's position) however, the user rarely knows the exact time which they are receiving at, hence four satellite pseudo-ranges are required to calculate these four unknowns. The satellite data is monitored and is controlled by the GPS ground segment - stations positioned globally to ensure the correct operation of the system. The user segment is the GPS user and the GPS reception equipment. These have advanced considerably in recent years to allow faster and more accurate processing of received data. They typically contain pre-amplification, an analogue to digital converter and DSP processors etc. [3].

Outdoor localization is a task which experiences many problems. Many sensors like laser range finders whichplay an important role in indoor localization are not suitable for outdoor localization because of the cluttered and unstructured environment. Global positioning system (GPS) discussed in Section can give valuable position information, but often the GPS satellites are occluded by buildings or trees. Because of these problems, vision has become the most widely used technique for outdoor localization. A serious problem with vision based systems is the illumination change because the illumination in outdoor environments is highly dependent on the weather conditions and on the time. In [11], the authors address the problem of long term mobile robot localization in largeurban environments where the environment changes dynamically. In their work, the authors use vision system tosupplement GPS and odometry [17] and provide accurate localization.The computations involved in vision based localization can be divided into the following four steps [14]:

• Environment sensing: For vision based navigation, this means acquiring and digitizing camera images.

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• Detect landmarks: Usually this means extracting edges, smoothing, filtering, and segmenting regions onthe basis of differences in grey levels, color, depth or motion.
• Landmark Identification: In this step, the system tries to identify the observed landmarks by searching inthe database for possible matches according to some measurement criterion.
• Calculate position: Once a match (or a set of matches) is obtained, the system needs to calculate itsposition as a function of the observed landmarks and their positions in the database.

In order for a vehicle to localize itself and to navigate autonomously in an environment, a model of that environment is needed which associates camera positions and observations. Provided that such a model (called map) has been built, a localization task can be carried out by means of ordinary statistical operations viz. regression or interpolation. Among the several sensor devices used for localization, vision provides the richest source of information, traditionally being restricted to the use of standard CCD cameras. Lately, omnidirectional vision systems are becoming increasingly popular in the mobile robots field for tasks like environment modelling, while research is active in understanding the properties of such sensors on a theoretical level. The main advantage of an omnidirectional camera compared to a traditional one is its large field of view which for localization application, allows many landmarks to be simultaneously present in the scene leading to more accurate localization. [13] The approach used in [10] consists of using integral invariant features computed on omnidirectional images and showing their interest in context of mobile robot localization. In their work the complex transformations induced by the geometry of the sensor are taken into account and integrate the virtual moments of the robot to evaluate invariant distributive features. After introducing the theoretical foundations of the integral invariant features construction, the authors presented their approach dealing simultaneously with models of omnidirectional sensor and of the effects of the robot movements on the transformed images. The experimental results presented show an improvement of the invariance of these features compared to the classical histograms, and so of the robot qualitative localization.

The integral method used to build invariant has the advantage of being more direct than differential or geometricalmethods. The integral method requires neither image segmentation as in geometrical methods nor derivativecomputation as in differential methods. The starting point of the invariant building is the Harr integral. It consistsof a course through the space of the transformation group parameters. It is typically expressed as

$$I_{Harr} = \frac{1}{|G|}\int_G f.g(x)dg \text{ with } \quad |G| = \int Gdg \qquad (1)$$

Where G is the transformation group, and g(x) the action of g, an element of G, on vector x. This invariant has been used in image query in case of Euclidean motion and for mobile robot localization although the Harr integral was not explicitly used. The authors interest concerns transformations of the image obtained with an omnidirectional camera. The type of transformations is due to the robot movements and to the projection process. In their work, the study of the robot movements is limited to translations on the floor. Nevertheless, other transformations such as rotations or illumination changes could have been considered but have not been presented in their paper. Translations transform 3D point x (expressed in robot reference frame) into point x + t with t = (t1, t2, 0) a translation in the (Ox, Oy) plane. The camera is endowed with an omnidirectional sensor, generating transformations that can be divided into a projection on its parabolic mirror and an orthopaedic projection on to the image plane. The projection of point x on the mirror is modelled by the following equation.

$$\begin{bmatrix} x_m \\ y_m \\ z_m \end{bmatrix} = \alpha \begin{bmatrix} x_m \\ y_m \\ z_m \end{bmatrix} \qquad (2)$$

where x m defines the corresponding point to x on the mirror surface. In [8], authors propose an omnidirectional camerabased localization system that does not involve the use of historical position estimates. A modified hue profile is generated for each of the incoming omnidirectional images. The extracted hue regions are matched with that of the reference image to find corresponding region boundaries.As the reference image, exact position of the reference point and the map of the workspace are available, the current position of the robot can be determined by triangulation. The method was tested by placing the camera setup at a number of different random positions in a 11.0m x 8.5m room. The average localization error was 0.45m. No mismatch of features between the reference and incoming image was found.

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In [9], authors make use of omnidirectional camera for map building and localization of a robot. The image sequences of theomnidirectional camera are transformed into virtual top-view ones and melted into the global dynamic map. After learning the environment from training images, a current image is compared to the trainingset by appearance based matching. Appropriate classification strategies yield an estimate of the robot's current position.

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III.LOCALIZATION BASED ON MAP OF THE ENVIRONMENT

In many urban navigation applications, high accuracy localization of moving vehicles is achieved using maps of urban environments. One such technique has been proposed by Jesse Levinson et al [1]. This approach integrates GPS, IMU, wheel odometry and LIDAR data acquired by an instrumented vehicle to generate high resolution environment maps. The idea of their work is to augment inertial navigation by learning a detailed map of the environment, and then to use a vehicle's LIDAR sensor to localize itself relative to this map. The maps are 2-D overhead views of the road surface, taken in the infrared spectrum. Such maps capture a multitude of textures in the environment that may be useful for localization such as lane markings, tire marks, pavement and vegetating near the road (e.g. grass). The maps are acquired by a vehicle equipped with a state-of-the-art inertial navigation system (with GPS) and multiple SICK laser range finders.

IV.LOCALIZATION BASED ON MAPPING OF ROAD

The vehicle transitions through a sequence of poses. In urban mapping, poses are five dimensional vectors, comprising the x − y coordinates of the vehicle, along with its heading direction (yaw), roll and pitch angle of the vehicle (the elevation z is irrelevant for this problem). Let x (t) denote the pose at time t. Poses are linked together through relative odometry data, acquired from the vehicle's inertial guidance system.

$$x_t = g(u_t, x_{t-1} + \epsilon_t) \tag{3}$$

Here g is the non-linear kinematic function which accepts as input a pose xt−1 and a motion vector u (t), and outputs a projected new pose x (t). The variable ϵt is a Gaussian noise variable with zero mean and covarianceR_t.In log-likelihood form, each motion step induces a non-linear quadratic constraint of the form.

$$(x_t - g(u_t, x_{t-1}))^T = R_t^{-1}(x_t - g(u_t, x_{t-1}))^T \tag{4}$$

These constraints can be thought of as edges in a sparse Markov graph. For any pose x (t) laser angle relative to the vehicle coordinate frame α, the expected infrared reflectivity can easily be calculated. Let $h_i(m, x_t)$ be this function, which calculates the expected laser reflectivity for a given map m, a robot pose x (t) and a laser angle α. The observation process is modelled as follows

$$z_t^i = h_i(m, x_t) + \delta_t^i) \tag{5}$$

Here δ_t^i is a Gaussian noise variable with mean zero and noise covarianceQ_t .In log-likelihood form, this provides a new set of constraints, which are of the form.

$$(z_t^i - h_i(m, x_t))^T = Q_t^{-1}(z_t^i - h_i(m, x_t))^T \tag{6}$$

The unknowns in this function are the poses x (t) and the map m.

V. LOCALIZATION BASED ON 3D ENVIRONMENT

The location estimation of a vehicle with respect to a 3D world model finds applications which include automaticnavigation, automatic integration of new information into a modelling system, the automatic generation of modelto image overlays. All of these will become increasingly important as modelling systems, such as Google Earth,progress towards more accurate 3D representations [23]. The 3D models are constructed from automatically

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aligned 3D scans acquired using a Leica HDS 3000 LIDARscanner, which also produces the model image set {γM}, acquired using a calibrated camera [2]. Model imagesare pre-processed to extract SIFT keypoints[5], filtering the results spatially to reduce the keypoint set. Keypointlocations are back-projected onto the model surfaces. Each of these 'model keypoint' has an associated 3D location,scale and 3D surface normal. In addition a plane π is fit to the LIDAR points in a reasonably large surface area(80s x 80s, where s is the LIDAR sample spacing on the surface) surrounding the keypoint using a M-estimator.

VI. LOCALIZATION BASED ON STORED MEMORY

In [12] and [19], the authors propose a self-localization method that extracts information which is identical forthe position of a sensor and invariant against the rotation of the sensor by generating an autocorrelation image froman observed image. The location of the sensor is estimated by evaluating the similarity among the autocorrelationimage of the observed image and stored autocorrelated images. The similarity of autocorrelated images is evaluatedin low dimensional eigenspaces generated with stored autocorrelated images. They conducted experiments with realimages and examined the performance of their method.

VII. LOCALIZATION BASED ON NATURAL LANDMARKS

Natural landmarks are features extracted from the image sequences without any changes made to the environmentalmodel. The use of natural landmarks in localization is limited because of appreciable errors encountered due tochange in illumination, camera occlusion and shadows etc.

Artificial landmark localization approach makes use of landmarks which are inserted purposely in the environmentalmodel and these landmarks could be some visual patterns of different shapes and sizes. Artificial landmarksovercome the problem of illumination changes which occurs in natural landmark methods. The disadvantage ofusing artificial landmarks is that the environment has to be engineered, what in turn limits the flexibility andadaptability to different operational sites. However, this problem can be avoided by using simple, cheap andunobtrusive landmarks, which can be easily attached to walls of buildings in most of the environments. In [24], amobile robot localization system which uses passive visual landmarks to enhance the recognition capabilities of theon-board camera has been discussed and the focus is on the evaluation of the spatial localization uncertainty withtheoretical analysis and presentation of experimental results.

VIII. LOCALIZATION BASED ON APPEARANCE BASED METHOD

In this approach, the appearance of an object is used for comparing images. Here, an appearance is a view of anobject from a certain position and direction. This approach consists of two steps:

(1) Storing images and corresponding positions in a database.

(2) Finding an image having a similar appearance to the input image from the database and obtaining its corresponding position.

Compared to landmark based approach, the appearance based approach does not require geometrical objectposition. However these methods cannot estimate a vehicle's lateral position since they assume that the trajectoryof the self-positions is the same as the trajectory when the database was constructed.In [4], authors use local feature descriptors and its experimental evaluation in a large, dynamic, populatedenvironment where the time interval between the collected set is upto two months. The overview of the proposedmethod has been shown in the following diagram. The input is the current omni-image and the current odometryreading. The database consists of poses (x, y, θ) of the database images together with the extracted features. Output is the current estimate of the robot position based on the weight and distribution of particles.In [6], the authors addressed the issues of outdoor appearance based topological localization for a mobile robotover different lighting conditions using omnidirectional vision. Their databases, each consisting of large number ofomnidirectional images, have been acquired over different day times in dynamic outdoor environments. Two differenttypes of feature extractor algorithms, SIFT and the more recent SURF [20, 21], have been used to compare theimages, and the two different approaches, WTA and MCL [22] have been used to evaluate performances. Given thechallenges of highly dynamic and large environments, general performances of localization system are satisfactory.

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IX. LOCALIZATION BASED ON APPEARANCE BASED METHOD

The simultaneous localization and mapping (SLAM) problem asks if it is possible for a robotic vehicle to be placedat an unknown environment and for the vehicle to incrementally build a consistent map of this environment whilesimultaneously determining its location within this map. A solution to the SLAM problem has been one of thenotable success to the robotics community. A two part tutorial of SLAM aims to provide a broad introduction toSLAM [15, 16].The main steps in SLAM are:

• Define robot initial position as the root of the world coordinate space or start with some pre-existing featuresin the map with high uncertainty of the robot position.

• Prediction: When the robot moves, motion model provides new estimates of its new position and also theuncertainty of its location positional uncertainty always increases.

• Measurement: (a) Add new features to map. (b) Re-measure previously added features.

• Repeat steps 2 and 3 as appropriate.

In [18], a system for Monocular Simultaneous Localization and Mapping (Mono-SLAM) relying solely on videoinput. The method makes it possible to precisely estimate the camera trajectory without relying on any motionmodel. The estimation is completely incremental- at a given time frame, only the current location is estimatedwhile the previous camera positions are never modified. In particular, simultaneous iterative optimization of thecamera positions is not performed and they have estimated 3D structure (local bundle adjustment). The key aspectof the system is a fast and simple pose estimation algorithm that uses information not only from the estimated 3Dmap, but also from the epipolar constraint [7].

X. SUMMARY

Automated methods for self-position estimation of intelligent vehicles have progressed a lot. Each of the methods suffers from its own drawbacks. Combining many methods to give a hybrid approach to self-position estimation finds many applications. Among all the methods, image matching based methods are very accurate and efficient for self-position estimation. Some of the challenges in image based methods, for example, illumination changes among various images in the database can be handled using robust feature detectors and feature descriptors. This paper has surveyed various aspects of the advancements madeso far in machine vision field for estimating self-position of robotic and intelligent vehicles.

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