Terrain Aided Localization of Autonomous Vehicles[†]

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Abstract— *This paper describes the development of a terrain-aided localization framework for autonomous land vehicles operating at high speeds in unstructured, expansive and harsh environments. The localization framework developed is sufficiently generic to be used on a variety of other autonomous land vehicles and is demonstrated by its implementation using field data collected from two different trials on two different vehicles. The results demonstrate the robustness of the proposed localization algorithms in producing reliable and accurate position estimates for autonomous vehicles operating in a variety of unstructured domains.*

Keywords— *Outdoor Localization, Map Building, Iterative Closest Point, Extended Kalman Filter, Entropy, Scale Space.*

I. Introduction

THE research addressed in this paper is concerned with the theoretical development and practical implementation of reliable and robust localization algorithms for autonomous land vehicles operating at high speeds in unstructured, expansive and harsh environments [1]. Localization is the ability of a vehicle to determine its position and orientation within an operating environment at any given time. The need for such a localization system is motivated by the requirement of developing autonomous vehicles in applications such as mining, agriculture, cargo handling and construction. The main drivers in these applications are safety, efficiency and productivity. The approach taken to the localization problem in this paper guarantees that the safety and reliability requirements imposed by such applications are achieved. The approach also aims to minimize the engineering or modification of the environment, such as adding artificial landmarks or other infrastructure, a key driver in the practical implementation of a localization algorithm [2].

In pursuit of these objectives, this paper develops a unified localization framework that uses measurements from both artificial and natural landmarks, combined with dead-reckoning sensors, to deliver reliable vehicle position estimates. The proposed localization framework is sufficiently generic to be used on a variety of other autonomous land vehicle systems. This is demonstrated by its implementation using field data collected from two different trials on two different vehicles. The first trial was carried out on a four-wheel drive vehicle in an underground mine tunnel. The second trial was conducted on a Load-Haul-Dump (LHD) truck in a test tunnel constructed to emulate an underground mine. The estimates of the proposed localization algorithms are compared to the *ground truth* provided by an artificial landmark-based localization algorithm that uses bearing measurements from a laser.

The paper is organized as follows: Section II develops an Iterative Closest Point - Extended Kalman Filter (ICP-EKF) algorithm - a map-based iconic algorithm that utilizes measurements from a scanning laser rangefinder to achieve localization. The ICP-EKF algorithm entails the development of a map-building algorithm. The development and implementation of an entropy-based metric to evaluate the information content of measurements and how this metric facilitates the augmentation of landmarks to the ICP-EKF algorithm guaranteeing reliable and robust localization is the subject of Section III. Section IV details the development and adaptation of a view-invariant Curvature Scale Space (CSS) landmark extraction algorithm. The algorithm is sufficiently robust to sensor noise and is capable of reliably detecting and extracting landmarks that are naturally present in the environment from laser rangefinder scans. The integration of the information metric, the CSS and the ICP-EKF algorithms to arrive at a minimal infrastructure localization framework is detailed in Section V. Finally, Section VI summarizes the key results.

II. Map-Based Iconic Localization

A bearing-only laser was mounted on the roof of the vehicles (for both the trials to be described in the following sections) so that it could detect strategically placed artificial landmarks (reflective stripes) in the trial environment. The exact position of these landmarks were made available from surveying using a digital theodolite. When the laser mounted on the vehicle moves through the environment, it detects the presence of these landmarks. Thus as the vehicle traverses through the environment, a sequence of bearing measurements to a number of fixed and known loca-

[†]The research reported in this paper was performed at the Australian Centre for Field Robotics, The University of Sydney, Sydney, Australia. The author would like to acknowledge the financial assistance provided towards his doctoral research by the Centre for Mining Technology and Equipment, Brisbane, Australia.

tions are made. Since the locations of these reflectors are known to the vehicle navigation system, the location of the vehicle can be computed from the bearing measurements made. Utilizing bearing measurements from a bearing-only laser in combination with dead-reckoning sensors (velocity and steering encoders and rate of change of orientation information from an inertial measurement unit), an EKF was employed to obtain ground truth.

The pose estimates obtained using the above artificial landmark algorithm were used to decouple the problems of map-building and map-aided pose estimation. Although it may not be appropriate to engineer the environment with artificial landmarks, it is possible to use a slow moving vehicle and a small number of landmarks to build a sufficiently accurate initial map. The reflective stripes required for the artificial landmark algorithm can be removed and the generated map can be used for vehicle localization. When the vehicle is stationary, it is easy to construct the vertices of a polyline that fit the data. When the vehicle starts moving, new range data obtained from the sensor needs to be integrated into the polyline map. Towards this, an incremental algorithm was developed for obtaining the optimal location of the vertices of the polyline in view of the new incoming data. Clearly as the vehicle moves, there will be observations that correspond to parts of the tunnel walls that were not seen before and therefore are not represented by the existing polyline. These observations were collected to expand the map by attaching line segments to either end of the polyline as the vehicle moves gradually along the tunnel. The proposed map-building algorithm is specific to this application and is not intended for high level tasks such as path planning where the required accuracy of the map would be higher. The polyline representation was chosen because of its simplicity. The curved surfaces of the environment can be represented using splines or a combination of line segments and arcs except for the fact that the additional complexity in such representations is not required for this application. As will be demonstrated, the maps obtained by the proposed map-building algorithm for both the 4WD vehicle and the LHD truck are adequate for localization.

Once the map is available, the next step towards achieving localization is map-registration. This stage is often referred to as the correspondence determination. Here, the correspondence problem involves registering the 2D laser range data to the 2D map. The Iterative Closest Point (ICP) algorithm [3] is employed to obtain the correspondence. As the iconic ICP algorithm works directly on sensed data, it does not require extraction and registering of features. The crux of the Iterative Closest Point (ICP) algorithm is to iteratively match points in one set to the closest points in another set, given that the transformation (the translation and/or rotation) between two sets is small. Here, the two point sets are the map and the laser range data, respectively. The shortcoming of the ICP algorithm is that it can only deal with cases when the first set is a subset of the second set. Zhang [3] developed a similar idea for establishing the correspondence which will be hereafter referred to as the ICP algorithm. The strength of this algorithm lies in the fact that it is capable of dealing with gross outliers in the data, occlusion and appearance and disappearance in which points in one set do not appear in the second set.

With the ICP algorithm there is no definitive way in which the uncertainty of the range data can be taken into account. Although Zhang discusses *partial* ways to accommodate the measurement uncertainty, ICP alone does not provide sufficiently reliable and accurate vehicle motion estimates. These shortcomings are overcome by combining the ICP with a post-correspondence EKF. The laser observations that do not correspond to any line segment of the map are discarded during the EKF update stage thus making it robust to errors in the map. Another attractive and appealing feature of this combined ICP-EKF algorithm is that observations from a variety of different sensors can be easily combined, since the changes are reflected only as additional observational states in the EKF [4], [5].

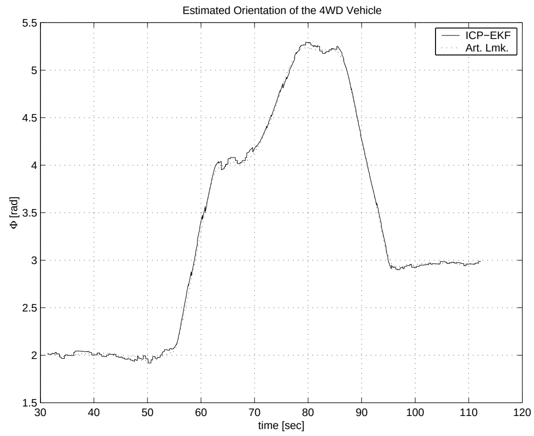
The vehicle employed in the first trial was a four-wheel drive (4WD) Troop Carrier shown in Figure 1. The estimated path of the 4WD vehicle (solid line) provided by the ICP-EKF algorithm along with the artificial landmark-based path (dotted line[1]) and the generated map using the proposed map-building algorithm is shown in Figure 2(a). Note that the map captures the geometry of the environment adequately. The curved surfaces are sufficiently modeled by shorter line segments in the polyline map. The vehicle travels a distance of 150 meters along the tunnel from right to left. The orientation estimated by the ICP-EKF (solid line) and that obtained by the artificial landmark algorithm (dotted line) are shown in Figure 2(b). The corresponding 2σ confidence bounds for the absolute error in x, y and ϕ are shown in Figure 3. It can be seen that the errors are bounded and thus the pose estimates are consistent. It is also clear that the estimated path is in close agreement with the artificial landmark-based path.

The second vehicle that was considered for the verification of the proposed algorithms is the LHD truck. LHDs are the work horses of the mining industry. The vehicle has a front and a rear body which can rotate

[1]As the estimates and the their corresponding ground truth are very close, extra effort is required on the part of the reader to distinguish between the two.

Fig. 1. The 4WD trial vehicle used in the underground mine trials. The location of the wheel and steering encoders, two time-of-flight range and bearing lasers and the bearing-only laser is shown.

(a)



(b)

Fig. 2. ICP-EKF estimated path (a) and orientation (b) of the 4WD vehicle (solid line) and the artificial landmark-based path and orientation (dotted line). In (a), the starting location of the vehicle is at $(133.3, -17.8)$ and the direction of travel is from right to left.

relative to each other and the front and rear wheel sets are fixed to remain parallel with the body of the vehicle. Steering is achieved by driving the articulation joint located mid-way between the front and rear axles. Both the front and rear wheel sets are driven at the same speed through a single transmission. The LHD and its sensor suite are shown in Figure 4.

Unique variations in data sets are necessary to establish an unambiguous correspondence with the map. Whenever the uniqueness can not be guaranteed, the ICP-EKF algorithm can fail to produce reliable association. The ICP algorithm provides a single transformation for each registration. Given the data sets, a set of transformations satisfies the registration. In the case of long tunnels or circular regions, this is too restrictive. For the tunnel, it is the set of transformations that align the walls independently of the position along the wall. Essentially what this means is that the position of the vehicle will be uncertain along the longitudinal direction of the tunnel. When using an EKF that combines range scan registration with dead-reckoning uncertainty, the positional covariance (or the uncertainty ellipse) will be large along the directions that can not be locked down by range scan registration alone. When the vehicle encounters a region that can be reliably recognized, the positional covariance can be reduced. When such regions are not encountered, some form of external aiding needs to be provided in regions where the ICP-EKF algorithm fails.

For the LHD, the ICP fails to produce correct correspondences in certain regions of the tunnel when there are degeneracies in rigid transformations during registration. The proposed method of overcoming these deficiencies is to incorporate landmarks that provide aiding information to guarantee reliable localization. A strategy to augment the ICP-EKF algorithm with a limited number of artificial landmarks is developed in Section V. These landmarks are then detected by the bearing-only laser to overcome limitations of the ICP-EKF algorithm.

Being an iterative algorithm, the initial pose estimate that is made available to the ICP is extremely important as the resultant correspondences depend on a good initial estimate. For the 4WD vehicle, the landmark augmentation procedure was not necessary in spite of long, straight sections of the tunnel. The reason for this is two fold. Firstly, the slippage the 4WD vehicle experiences due to the undulatory nature of the terrain is less than that of the LHD. In addition to the uneven nature of the terrain, the LHD slips much more than the 4WD vehicle due to the geometry of the tunnel and the kinematics of the truck

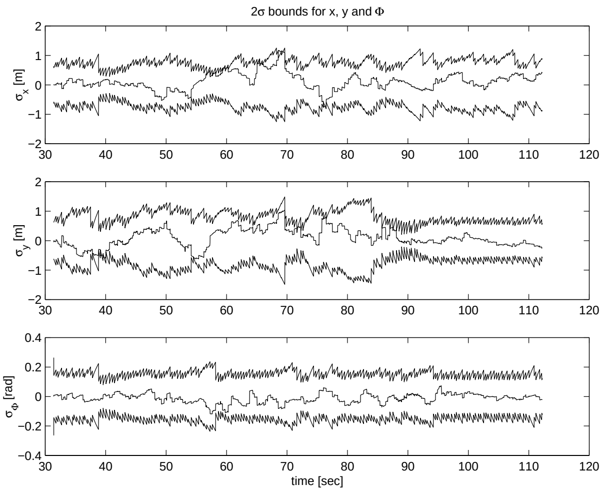


Fig. 3. The 2σ confidence bounds are computed using the covariance estimate for the error in x, y and ϕ compared to the actual error computed with the corresponding artificial landmark-based estimates for the 4WD trial.

Fig. 4. The Load-Haul-Dump truck and its sensor suite. The LHD was fitted with two two-dimensional time-of-flight range and bearing lasers. The bucket is in front of the vehicle. A bearing-only laser scanner, as in the case of the 4WD trials, detects the presence of artificial landmarks. Encoders were used to measure the vehicle velocity and the articulation (steering) angle.

itself. Secondly, the 4WD vehicle model produces good prediction estimates enabling the ICP to provide accurate correspondences thus obviating the need for landmark augmentation. For the articulated LHD, dead-reckoning is not as good as that for the 4WD vehicle. Even explicitly taking into account wheel slippage with the inclusion of the two slip variables, α_v and β_v [1], the dead-reckoning estimates that are the initial estimates to the ICP are poor and accordingly the correspondences are no longer accurate. For these reasons, external landmark aiding becomes necessary for the LHD.

III. Landmark Selection and Augmentation

The proposed method for the selection of a particular landmark is based on localization information offered by a particular landmark from a given vehicle pose. This method implicitly takes into account the uncertainty in the vehicle pose estimate while computing the information content of the landmark. The concept of entropy is employed to facilitate landmark augmentation.

The entropy $h(\,\cdot\,)$ is a measure of the average uncertainty of a random variable and thus represents the *compactness* of the probability distribution. Subsequently, it is a measure of the *informativeness* of the distribution where *information* is defined as the negative of entropy. The entropy is minimum when information is maximum. It is conventional to seek minimal entropy when actually maximum information is sought. A mathematical expression for the entropy of a Gaussian distribution is to be developed. For an n-dimensional state vector $\mathbf{x}_k$ conditioned on a stacked observation vector denoted by $\mathbf{Z}_k \triangleq [z_1, z_2, \ldots, z_k]$ where $z_1, z_2, \ldots, z_k$ are individual sensor measurements, the *posterior entropy* can be derived to be [6]:

$$\begin{aligned} h_{k|k} &\triangleq h\left(p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)\right) \\ &= \mathrm{E}\left\{-\ell n\; p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)\right\} \\ &= 0.5\; \ell n\left[(2\pi e)^n \left|\mathbf{P}_{k|k}\right|\right] \end{aligned}$$

Thus for a Gaussian (normal) vector distribution all that is required to compute its entropy is its length, n and covariance, $\mathbf{P}$.

The *posterior* and *prior* information metrics can then be defined as:

$$\begin{aligned} im_{k|k} &\triangleq -h\left(p\left(\mathbf{x}_k \mid \mathbf{Z}_k\right)\right) \\ &= -0.5\; \ell n\left[(2\pi e)^n \left|\mathbf{P}_{k|k}\right|\right] \\ im_{k|k-1} &\triangleq -0.5\; \ell n\left[(2\pi e)^n \left|\mathbf{P}_{k|k-1}\right|\right] \end{aligned}$$

The resultant information contribution, ic, from measurements, is thus given by the relation:

$$ic_{k|k} \triangleq im_{k|k} - im_{k|k-1} \tag{1}$$

To overcome cases in which the ICP-EKF algorithm has insufficient information, the system is augmented with a limited number of artificial landmarks along certain sections of the tunnel. To realize this goal, the following three questions need to be answered: 1) When should a landmark or landmarks be added for external aiding? 2) How to select potential landmarks in order to overcome the divergence of the ICP-EKF estimates? Additionally, given a set of landmarks, how to select a landmark or landmarks that are optimal in the sense of increasing the robustness of localization? 3) Given a set of optimal landmark(s), how to incorporate these external aiding measurement(s) from the landmark(s) into the existing ICP-EKF framework?

The first two questions are answered in the following paragraphs and the landmark augmentation methodology is detailed in Section V.

• Landmarks are introduced when the estimated pose covariances exceed a predefined bound. The growth in covariance is a direct result of inaccurate correspondences provided by the ICP. Without additional landmarks, this would eventually lead to filter divergence.

The issue of computing a potential landmark set that can be employed to provide aiding measurements is addressed as follows:

• Potential landmarks can be computed from a given vehicle position since the artificial landmark locations are available as is the direction of vehicle travel. By discarding landmarks that are farther than a predetermined distance (proportional to the range of the bearing-only laser when artificial landmarks are to be augmented or to that of the range and bearing laser when natural landmarks are to be augmented), a landmark set can be arrived at and denoted by: $\mathbf{L}_{pl}$:($\mathrm{X}_{i_{pl}}$,$\mathrm{Y}_{i_{pl}}$), $i_{pl} = 1 : n_{pl}$, where n_{pl} is the number of landmarks in the set.

• From the current vehicle position, for all the landmarks in the set $\mathbf{L}_{pl}$, the predicted bearing measurement (range and bearing measurements in the case of natural landmarks) is computed and is checked to see if this measurement is acceptable.

• For all acceptable measurements, the individual information contributions are computed according to Equation (1). Finally, the landmark that provides the maximum information from the potential set of landmarks is selected for augmentation.

IV. Multiscale Natural Landmark Extraction

Feature or natural landmark-based methods for autonomous localization have become increasingly popular as they do not require infrastructure or other external information to be provided to the vehicle for operation. Feature-based localization methods require that natural landmarks can be robustly detected in sensor data, that the localization algorithm can reliably associate landmarks from one sensor observation to the next, and that the method can overcome problems of occlusion, ambiguity and noise inherent in measurement data. In indoor environments, features such as walls (line-segments), corners (diffuse points) or doorways (range discontinuities) are used as landmarks. In outdoor environments however, similar simple features are sparse and infrequently observed. In unstructured or natural outdoor environments a more general notion of a landmark or navigation feature is required. Given a (laser) range scan of an environment, one natural measure of feature or landmark significance is the local curvature in this range data. Rapidly changing range data indicates either a significant physical discontinuity or a prominent geoform. The use of local curvature as an interest measure is well known in the computer vision community. Further, and most important for navigation, curvature extrema are well known to be view-point invariant. Practically, this means that points of maximum curvature can be used as robust point landmarks in localization.

Scale space filtering is a qualitative signal description method that deals with the problem of *scale* by treating the size of a *smoothing kernel* as a continuous parameter [7]. The main idea of multiscale representation is to successively suppress fine scale information and thus to progressively remove the high frequency information which results in the signal becoming gradually smoother. The common way of constructing a scale space is by convolution with a Gaussian kernel. The essential requirement here is that a signal at a coarser (higher) scale level should contain less structure than at a finer (lower) level of scale. In scale space methods, a qualitative description of the signal is obtained by studying the behavior of the extrema over the continuum of scales. Also the extrema that survive over larger smoothing extents are considered to be more significant than others. Attenuation of the noise in the signal is realized by convolving the signal with the Gaussian kernel.

A Curvature Scale Space (CSS) algorithm was developed to identify, extract and localize landmarks characterized by points of maximum curvature at successive geometric scales. The CSS algorithm can be used to extract curvature extrema from laser scan data corresponding to landmarks at different scales that are: 1) invariant to rotation and translation of the shape (signal) under consideration 2) robust to noise and 3) reliably detected and localized. The basic principle of the CSS algorithm to identify dominant points is: "Convolve a signal with a Gaussian kernel and impart smoothing at different levels of scale (the scale being proportional to the width of the kernel). From the resulting convolved signal, identify the dominant points (curvature extrema)." For various degrees of smoothing of the curve (segmented range scan), it is desired to find the curvature extrema. A parametrization of the curve is necessary to compute the curvature at varying levels of detail (for segmentation and parametrization procedures see [8]). A parametrization is possible by considering a path length variable along the curve and expressing the curve in terms of two functions $x(s)$ and $y(s)$ such that $C = \{x(s), y(s)\}$ with s being a linear function of the path length ranging over the closed interval $[0, 1]$. The curvature, κ, is given by:

$$\kappa(s,\sigma) = \dot{X}(s,\sigma)\ddot{Y}(s,\sigma) - \dot{Y}(s,\sigma)\ddot{X}(s,\sigma)$$

where $\left\{\dot{X}(s,\sigma), \dot{Y}(s,\sigma)\right\}$ and $\left\{\ddot{X}(s,\sigma), \ddot{Y}(s,\sigma)\right\}$ are obtained, respectively, by convolving $x(s)$ and $y(s)$ with the first and second derivatives of the Gaussian kernel. The Gaussian kernel is given by: $g(s,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-s^2/2\sigma^2}$ where σ is the width of the kernel. By employing the CSS algorithm, dominant points are extracted based on the persistence within a scan and over consecutive scans. Features that exist only at finer scales and disappear at higher scales do not correspond to stable features and thus do not qualify as reliable candidates for subsequent detection and tracking during the vehicle localization stages. Persisting dominant points enable the construction of a natural landmark map based on which natural landmark-based localization is achieved.

V. Landmark Augmented Minimal Infrastructure Localization

This section describes the localization of the LHD using both artificial and natural landmarks. Natural landmarks characterized by dominant points of curvature were extracted from laser rangefinder scans and a natural landmark map was built using the curvature scale space algorithm as detailed in Section IV. Such a natural landmark map can then be used to augment the ICP-EKF framework thereby reducing the number of artificial landmarks that are required for reliable and robust localization.

A. Natural Landmark Observation Model

The laser rangefinder provides both range and bearing to a landmark and accordingly an equation relating both of them to the vehicle (laser) location is required. The predicted range and bearing, respectively, for each natural landmark j at discrete time-instant k is given by the non-linear model:

$$\begin{aligned} R^j_{n\ell_k} &= \sqrt{\left[x^j_{n\ell} - x_{L_k}\right]^2 + \left[y^j_{n\ell} - y_{L_k}\right]^2} \\ \theta^j_{n\ell_k} &= \tan^{-1}\left[\frac{y^j_{n\ell} - y_{L_k}}{x^j_{n\ell} - x_{L_k}}\right] - \phi_{v_k} \end{aligned}$$

where $(x^j_{n\ell}, y^j_{n\ell})$ is the cartesian location of landmark j and (x_L, y_L) is the location of the laser rangefinder on the vehicle. The observation model for a natural landmark is thus given by:

$$Z^j_{n\ell_k} = \begin{bmatrix} R^j_{n\ell_k} \\ \theta^j_{n\ell_k} \end{bmatrix} + \begin{bmatrix} v^R_{n\ell_k} \\ v^\theta_{n\ell_k} \end{bmatrix} \qquad (2)$$

where $v^R_{n\ell_k}$ and $v^\theta_{n\ell_k}$ refer to the uncertainty present in the range and bearing measurements and are modeled as zero-mean uncorrelated Gaussian sequences with constant variances, $\sigma^2_{R_{n\ell}}$ and $\sigma^2_{\theta_{n\ell}}$, respectively.

B. Entropy-based Artificial Landmark Selection and Augmentation

During the vehicle localization stage, for every range and bearing scan, natural landmarks are extracted and are associated with those in the map. Details of natural landmark matching and discriminance procedures are detailed in Section V-C. When the information provided by these natural landmarks is not enough to curtail the growth of the pose covariances, the entropy-based landmark selection and augmentation method is adopted to select the required artificial landmarks. Whenever it is determined that the ICP-EKF framework requires additional external aiding, all the landmarks that are visible from the current vehicle position are examined and the landmark that contributes the maximum information is then selected.

C. Natural Landmark Matching and Discriminance

Whenever a range and bearing scan becomes available, there is the need to decide whether the scan should be used for a) Natural landmark-based localization or b) ICP-EKF based localization. The same scan should not be used for both as this amounts to using the same information twice. To avoid such reuse of information, the entropy-based information content measure is utilized to determine to decide upon (a) or (b). The pertinent localization procedure is arrived at by looking at the information contribution provided by both (a) and (b) and selecting the one that provides maximum information towards localization.

When natural landmarks are used for localization, it is essential that the extracted natural landmarks from a scan are reliably matched to those in the map. Whenever a range and bearing laser scan is received, the dominant point landmarks are extracted in the same fashion as described in Section IV. Locations of all the extracted dominant points above a certain scale level are then compared with the natural landmark map. Two landmarks that differ only slightly in their position should be identified as distinct within the limits imposed by the sensor noise. Such discriminance is achieved by checking if the computed innovation sequences pertaining to both the range and bearing of a matched natural landmark fall within the normalized innovation gate by using the natural landmark observation model given in Equation (2).

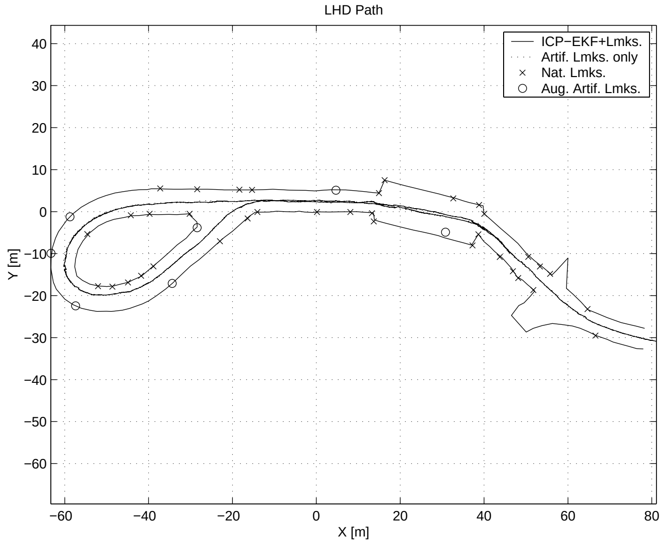
If the observations fall within the prescribed limits, then the landmark is accepted as a match. Subsequently, this observation is used to update the vehicle states using the range and bearing innovation sequences that are obtained as a direct consequence of the matched landmark measurement. The resultant information contribution from a matched natural landmark, $ic_{n\ell}$, and that after the ICP-EKF updates for the same scan, $ic_{icp-ekf}$, are computed by using Equation (1). Based on $ic_{n\ell}$ and $ic_{icp-ekf}$, the procedure that provides the maximum information is chosen. The combined algorithm thus bounds the natural degradation of the ICP registering results when there are no distinguishable landmarks along the longitudinal direction and ensures that the lateral matching (crucial for vehicle guidance) is not deteriorated.

D. Results and Discussion

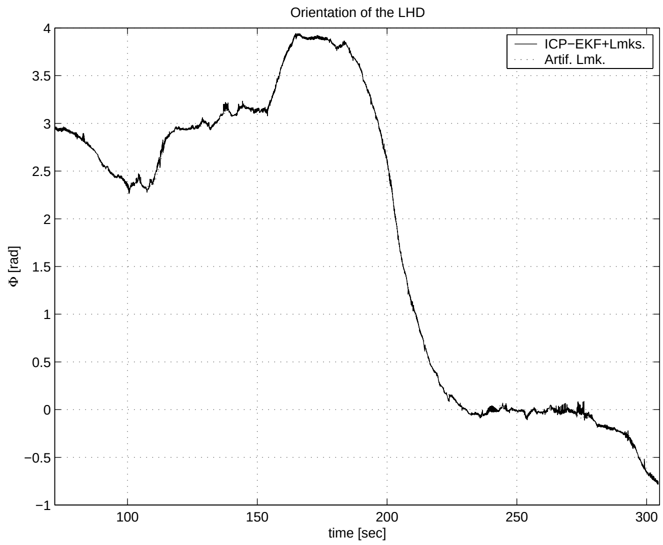
The results when both natural and artificial landmarks are employed towards localization of the LHD are discussed now. Figure 5(a) and (b) show the estimated path and orientation of the LHD by the ICP-EKF natural and artificial landmark-augmented algorithm (solid line). It should be emphasized here that the natural landmarks need to be extracted only once. For localization in a tunnel over several trials, the natural landmark extraction can be done on an exploratory trial run and such landmarks can then be utilized. From Figure 5(a), it can be seen that the landmark-augmented ICP-EKF algorithm provides estimates that are similar to the ground truth. Note that natural landmarks have taken the place of artificial landmarks along the straight sections of the tunnel. Unfortunately, in the circular loop section of the tunnel, there were not many persistent extractable natural landmarks and this necessitated the inclusion of artificial landmarks. Nevertheless, the important point to note here is that the number of required artificial landmarks have been successfully reduced (by a factor of four [1]). In environments where the extraction of persistent dominant landmarks is possible, the artificial landmarks can be totally eliminated[2]. Figure 5 (b) shows the orientation of the two trials (solid line) along with those provided by the artificial landmark algorithm (dotted line).

Figure 6 shows the absolute pose errors computed with the aid of the ground truth and the corresponding 2σ (95%) confidence bounds. It is evident that the errors remain white and are well within with the prescribed bounds representative of consistent estimates. Absolute error estimates of half a meter were achieved in the position estimates with the corresponding error in the orientation estimate being less that 5 degrees.

Figure 7 depicts the validated range and bearing innovation sequences along with the 1σ and 2σ bounds. The discontinuity in the innovation sequences corresponds to periods where there were no updates performed as there were no natural landmarks available during such periods. For example in Figure 7, the discontinuity from $177 - 200$ seconds in both the range and bearing innovation sequences corresponds to the loop section of the tunnel where the external aiding is predominantly provided by the artificial landmarks. It can be seen that both the range and bearing innovation sequences also remain white and are well within the defined bounds.



(a) Estimated path of the LHD



(b) Estimated orientation of the LHD

Fig. 5. Natural landmark-augmented ICP-EKF estimated path (a) and orientation (b) of the LHD (solid line) and the artificial landmark-based path (dotted line). In (a), the traversed path runs right to left. The direction of travel is in the anti-clockwise direction around the loop at the left end of the figure. The circles represent the augmented artificial landmark locations and the crosses represent the natural landmark locations. The starting location is at $(81.1, -30.9)$.

[2]In fact, this claim was substantiated by a third trial run on a Utility vehicle in an outdoor area populated by people and moving cars in the University of Sydney campus [8].

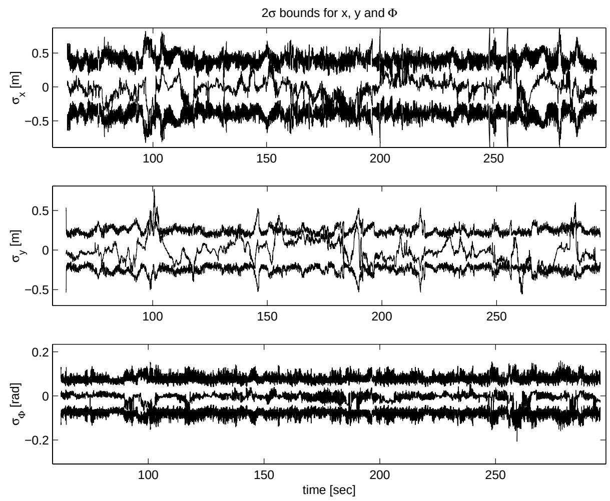


Fig. 6. Natural landmark-augmented ICP-EKF pose errors and the 2σ confidence bounds computed using the covariance estimate for the error in x, y and ϕ compared to the actual error computed with the corresponding artificial landmark-based estimates.

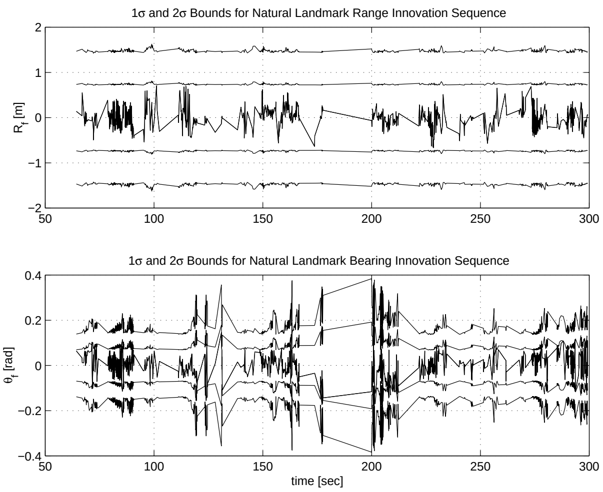


Fig. 7. Range and bearing innovation sequences for the natural landmarks matched during the LHD trial. The 1σ and 2σ confidence bounds are also shown.

VI. Conclusions

This paper discussed the development of a unified terrain-aided framework for achieving minimal infrastructure localization of high speed vehicles operating in unstructured and harsh environments.

The first step in the achievement of this goal was the development of a map-based ICP-EKF localization algorithm utilizing measurements from a scanning laser rangefinder in combination with dead-reckoning sensors. The next step was the identification of shortcomings of the ICP-EKF algorithm and the development of an entropy-based landmark augmentation metric to overcome the deficiencies. Using this metric, evaluation of information content of measurements was possible and thus facilitating the acceptance or rejection of a particular landmark measurement. The metric was shown to be an optimal way of efficiently utilizing measurements by implicitly incorporating the landmarks' utility towards reducing localization error. A view invariant multiscale natural landmark extraction algorithm was developed to extract point landmarks characterized by dominant curvature points from laser scans thus facilitating reliable detection and extraction of persistent natural landmarks. Attenuation of noise inherently present in laser scans was achieved by convolving the scans with a Gaussian kernel. The algorithm was also shown to possesses the attractive property of being invariant to rotation and translation effects that the laser scans under consideration might experience due to vehicle travel over harsh terrains.

Finally, the paper detailed the integration of the information metric, the CSS and the ICP-EKF algorithms to arrive at a unified localization framework. The developed localization framework has the ability to use measurements from both artificial and natural landmarks as and when they become available and was shown to be sufficiently generic to be used on a variety of autonomous land vehicles, by its application to a 4WD vehicle and an LHD truck. The results demonstrated the reliability and robustness of the proposed framework.

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