Stochastic Mapping Using Forward Look Sonar

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Abstract

The goal of concurrent mapping and localization (CML) is enable a mobile robot to build a map of an unknown environment, while concurrently using that map to navigate. This paper describes the application of the stochastic mapping approach to CML \cite{10, 8, 3} to data from a high resolution array forward look imaging sonar \cite{9, 7, 2}. The objective is to test the feasibility of stochastic mapping as a method for autonomous underwater vehicle (AUV) navigation. Measurements from the forward look sonar were post-processed to yield estimates for the locations of environmental features and the trajectory of the sensor. The resulting trajectory provides an improvement in comparison to position estimates computed with an inertial navigation system. DGPS data is used as a ground-truth for comparison. The results demonstrate the potential of CML algorithms to achieve a bounded navigation error through tracking of environmental features.

1 Introduction

Navigation is one of the most challenging issues in autonomous underwater vehicle (AUV) research. Good positioning information is vital for the safe execution of an AUV mission and for effective interpretation of the data acquired by the AUV. Current methods for AUV navigation suffer serious shortcomings. Methods based exclusively on inertial navigation or dead reckoning suffer from an unbounded growth of error. To achieve bounded errors, current AUV systems rely on networks of acoustic transponders or surfacing for GPS resets. The goal of concurrent mapping and localization (CML) is enable an AUV to build a map of an unknown environment and concurrently use that map for positioning. CML has the potential to enable long-term missions with bounded navigation errors without reliance on acoustic beacons, a priori maps, or surfacing for GPS resets \cite{5, 4}.

This paper describes the application of the stochastic mapping approach to CML \cite{10, 8, 3} using real data from an underwater forward look imaging sonar \cite{9, 7, 2}. In our implementation of stochastic mapping, the AUV senses features in the environment through range and bearing measurements relative to the AUV’s current state (position and orientation). These measurements are used to create a map of the environment, which, in turn, is used to localize the vehicle.

In previous research we have analyzed the potential performance of CML for AUVs using forward looking sonar (FLS) through simulation studies of long duration missions \cite{5}. For a survey of a 1 km by 1 km area containing 50 features, position errors on the order of five meters were achieved. This paper complements this simulation study by considering the performance of CML for postprocessing of a short data set from an oceanic data acquisition exercise performed in Narragansett Bay, RI \cite{2}. The results provide evidence that a sufficient density of features can be detected in a typical operating environment and that CML can provide a feasible navigation solution for AUVs.

2 Sonar data acquisition

The data set that was processed was collected in September 1997 as part of a collaborative project between the Naval Undersea Warfare Center (NUWC) in Newport, Rhode Island, and Groupe d’Etudes Sous-Marines de l’Atlantique in Brest, France \cite{2}. An over-the-side (OTS) test rig was built to carry several typical AUV subsystems for deployment over the side of the YFRT-287, a converted U.S. Navy yard freighter. When fully deployed, the AUV subsystems
were approximately 5.5 meters below the water's surface.

The transmit transducer used for data collection was a high frequency projector manufactured by the International Transducer Corporation, operating at 87 kHz. The receive sonar array was the high resolution array (HRA) forward look sonar developed at NUWC [9]. The HRA is a forward looking planar array designed for operation in a 21-inch diameter vehicle. It consists of 1264 half-wavelength elements of 1-3 composite material (PZT-5H) configured in a 20 wavelength circular aperture (design frequency of 87 kHz). A subset of the elements consisting of two rows of 32 elements each provide single ping transmit coverage of approximately 90 degrees in azimuth by 45 degrees in elevation with a source level of approximately 205 dB. The HRA element analog outputs are processed with the data acquisition processor (DAP). The DAP conditions each of 511 analog signals, performs A/D conversion, and generates basebanded in-phase and quadrature data for the HRA element outputs. The DAP also records 511 channels of the element level HRA data. Beamforming is performed using the element level data, and subsequently range and bearing estimates to distinctive features are produced [2].

In addition to the HRA, the DAP, and the ITC transmit transducer, the following subsystems were used on the OTS test rig: an Allied Signal Model RL-34 Inertial Navigation System (INS), an Edco Model 3050 Doppler velocity sonar (DVS), a Trimble Model NT200D DGPS receiver, and a Klein 2000 SLS. Data from each of the subsystems were recorded during the exercise for further processing in the laboratory. Time-synchronization of the subsystems was accomplished via clock signals from the DGPS. Data from the INS and the DVS were input to a Kalman filter running on a workstation located onboard the YFRT-287. Data from the sensors and the filter were continuously recorded during the exercise to provide attitude and position data for the FLS. In addition to providing data to aid in the development of the FLS algorithms, these data are used to compare navigation improvements provided by the NTN approaches developed by the project team. Positional data from the DGPS are also available for comparison purposes. INS attitude data serves as input to the proposed CML approach. DGPS position data and DVS velocity estimates are also used to initialize the proposed approach. Latitude and longitude data are converted to a locally referenced Cartesian coordinate system.

Figure 1: Over-the-side test rig.

Figure 2: Narragansett Bay area around NUWC (top), and the run area (bottom). The data processed in this paper was acquired on leg A3, shown in the lower left of the bottom figure.
A series of data collection legs approximately 1 kilometer in length were conducted in the exercise. With a 20 second pulse repetition rate and typical YFRT-287 speeds of approximately 2 knots, HRA data were collected about every 20 meters. The current paper describes CML processing of data from leg A3, consisting of 36 pings of data. The data set was collected from Narragansett Bay in Rhode Island in an area known as Halfway Rock. Figure 2 depicts the Narragansett Bay area around NUWC. The steep slope along the east of the Halfway-Fiske shoal gives way to a shipping channel. The bathymetry in the test area varies from 15 to 0 meters deep (Halfway Rock branches the surface). Since the area is well inside Narragansett Bay, it is shielded from much of the ocean swell, and unwanted ship motions are minimized.

3 Stochastic mapping algorithm

The feature-based CML algorithm used to process the data is an augmented form of Stochastic Mapping (SM), a Kalman filter-based method for CML first proposed by Smith, Self, and Cheeseman [10] and first implemented by Moutarlier and Chatila [8]. Stochastic mapping assumes that point-like features are present in the environment and can be effectively detected and tracked. Our implementation augments SM by adding a nearest-neighbor data association strategy and logic-based track initiation and deletion strategies [1,4]. Figure 3 shows a flow-chart representation of the algorithm. More details of the implementation can be found in Feder et al. [4].

The robot and the map are represented by a single state vector, $\mathbf{x}$, with an associated estimate error covariance $\mathbf{P}$ at each time step. As new features are added, $\mathbf{x}$ and $\mathbf{P}$ increase in size. Measurements are taken every $t = kT$ seconds, where $T$ is a constant period and $k$ is a discrete time index. The dynamic model of the motion of the vehicle is an important input to a stochastic mapping algorithm. For this experiment, the following simple dynamic model was used:

$$
\begin{align*}
X_{k+1} = f(X_k, u_k) + d_x = & \begin{bmatrix} x_k + \delta v_k T \cos(\phi_k) \\
y_k + \delta v_k T \sin(\phi_k) \\
\phi_k + \delta \phi_k \\
v_k + \delta v_k 
\end{bmatrix} + d_x,
\end{align*}
$$

(1)

where $d_x$ is a white Gaussian noise process. The control input at time $k$, $u_k = [\delta \phi, \delta v]^T$, is represented by a change in heading, $\delta \phi$, and a change in speed, $\delta v$, and was backed out from the change in heading and velocity that had to occur in order for a vehicle with the dynamic model $f$ of Equation (1) to get from the integrated INS position estimate at time $k - 1$ to the integrated INS estimated position at time step $k$. The INS position estimates were used to model the unrecorded control input to the vessel, rather than the more natural choice of using the INS readings as observations in a dead reckoning model. This was done as no vessel dynamic model or control input was recorded. In order to perform stochastic mapping on-board in real-time, a dynamic model should be developed, the control input would be available and the INS measurements would be used directly in a dead reckoning model. Such a system would yield more accurate results that obtained in this paper.

The sonar measurements consist of a sequence of range and bearing measurements to high signal-to-noise ratio scatterers using a process described by Carpenter [2]. To accommodate clutter and dropouts, the initiation of new feature tracks is performed using a logic-based track initializer [1, 5]. All measurements that have not been matched with any feature over the last $N$ time steps are stored. At each time step a search for clusters of more than $M \leq N$ measurements over this set of unmatched measurements is performed. For each of these clusters, a new feature track is initiated. A cluster is defined as at most one measurement at each time step that gates with all other measurements in the cluster. Features gate when their 95% highest density regions overlap.

Once tracks are initiated, data association is per-
Table 1: Parameters used for augmented stochastic mapping post-processing.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>sampling period, $T$</td>
<td>20 sec.</td>
</tr>
<tr>
<td>range measurement std. dev.</td>
<td>1 m</td>
</tr>
<tr>
<td>bearing measurement std. dev.</td>
<td>0.6°</td>
</tr>
<tr>
<td>speed process std. dev.</td>
<td>4 cm/T</td>
</tr>
<tr>
<td>heading/INS proc. noise std. dev.</td>
<td>0.9°</td>
</tr>
<tr>
<td>INS speed measurement std. dev.</td>
<td>4.4 cm/T</td>
</tr>
<tr>
<td>gate parameter $\gamma$</td>
<td>10</td>
</tr>
<tr>
<td>track initiation parameters $M = 5, N = 4$</td>
<td></td>
</tr>
</tbody>
</table>

formed by finding the single sonar return closest to each track [1]. It is assumed that a sonar return originates from not more than one feature. After the closest return to each feature is found, this return is gated with the estimated feature position. In regions of high clutter, multiple instances of the same feature or non-existing features may be initiated. For this reason, track deletion is incorporated. In this paper, we have utilized a simple track deletion strategy that checks for consistency of the estimated features. In previous work we have utilized more sophisticated track deletion algorithms [4].

4 Results

The parameters used in the augmented stochastic mapping algorithm are shown in Table 1. Figure 4 shows all the returns from the data set. There are three known features, marked by ‘x’, located near the final position of the vehicle in addition to environmental features. The sonar returns are quite dispersive and it is hard to pick out single objects by eye. Tracks for many environmental features are initiated by the algorithm. The close-up view at the bottom of Figure 4 illustrates that quite good estimates of the known features were obtained. Also, the estimated position of the vehicle performing CML is closer than that of INS to the “true” DGPS position. Figure 5 displays the vehicle’s position as estimated from DGPS, CML and INS, along with the $3\sigma$ error ellipses for all the modeled environmental features as well as two of the known features. The error ellipses are, however, quite large, and thus provide relatively poor positioning information. The reason for the relatively large uncertainty in feature estimates is due to the very low re-observation rate of features that occurred during this mission, as can be seen from Figure 6.

The superiority of CML over dead-reckoning is illustrated by Figure 7, where the INS error grows linearly without bound, and the CML error remains bounded. At $t = 120$ seconds, CML yields a worse estimate than the INS due to a data association error. Figure 8 shows the errors and $3\sigma$ errors bounds for the position, heading and velocity estimates produced by post-processing of the data through the algorithm. The increase in uncertainty in position towards the end of the run is due to the fact that no new features were observed during the last part of the data collection.

5 Conclusion

This paper has described the postprocessing of an oceanic forward look sonar data set using the stochastic mapping algorithm for concurrent mapping and localization. The results demonstrate that salient features useful for navigation can be detected and tracked to provide effective navigation in a shallow-water operating environment. Improved positioning in comparison to a system using only inertial navigation is achieved. The potential to achieve bounded positioning errors is demonstrated.

Considerable future research is necessary to realize the goals of implementing CML onboard an actual AUV. Some of the research issues that must be considered include the development of better methods for detection of features from natural terrain [7], techniques for mapping of large environments [6], and the implementation of appropriate sonar feature detection algorithms in a real-time computer system onboard an actual AUV.

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References

Figure 4: Result of post-processing of augmented stochastic mapping performed from the data collected at Narragansett Bay in September, 1997. Returns from the HRA sonar are shown by small dots, the DGPS position fixes at each measurement point are shown by triangles, the CML result is drawn as a solid line, the INS result is shown by small circles, the three known features are represented by ‘x’ signs, and the estimated feature locations are shown by ‘+’ signs. Top figure: The result for the entire mission. Bottom figure: A magnification of the last 12 measurement points and estimates for the mission.

Figure 5: The estimated features locations, marked by ‘+’, along with the 3σ (99% highest confidence region) ellipses for each of these estimates for post-processing of the data from leg A3, shown in Figure 4.


Figure 6: The number of returns from the HRA sonar that were used for track updating, track initiation and the returns that were rejected at each time step. Notice that only a very small number of returns were used for track updating and thus for improving mapping and localization in the environment. With the data association strategy employed in augmented stochastic mapping, many returns are discarded because their origin is considered too ambiguous. However, improved navigation is realized with only a small number of correctly associated measurements.

Figure 7: A comparison of root mean square error when relying on the inertial navigation system only versus the CML result produced by augmented stochastic mapping as a function of time. (DGPS data is used for ground-truth.)

Figure 8: Errors and $3\sigma$ bounds (99% highest confidence bounds) for the position, heading and velocity estimates produced by post-processing the data from leg A3 with the augmented stochastic mapping algorithm.