Estimation Approach for AUV Navigation Using a Single Acoustic Beacon

Coupling Position Estimation and Control For Robust Navigation of the MARES AUV

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Automatic motion control often implies the measurement of relative or global variables, such as position coordinates and attitude angles. However, there are many scenarios in which such direct measurements are difficult or even impossible. Estimating these measurements is therefore a valid alternative and a common practice in robotics.

This article presents an estimation approach for navigation of the Modular Autonomous Robot for Environment Sampling (MARES) autonomous underwater vehicle (AUV) based on the range to a single beacon deployed in the operation area. The homing problem that occurs when moving toward a given reference (basis) is particularly emphasized.

Vehicle and Localization System

The MARES AUV was developed by Faculty of Engineering of the University of Porto. The vehicle has the particular abilities to hover in the water column and dive independent of its forward velocity. It features four thrusters: Vertical motion (translation and rotation) relies on two through-hull thrusters, while horizontal motion is powered by two thrusters located at the stern.

Typical MARES missions include environmental sampling and monitoring in which the vehicle sweeps a given area while collecting relevant data. To do this, the AUV carries a set of sensors, such as fluorometers, turbidity meters or conductivity, temperature and depth sensors, on board. For most of these missions, the ac-

curacy of geolocation is essential. During operation, angular variables are measured by a compass and tilt sensors, while depth is directly measured by a pressure cell. These sensors provide fairly accurate and almost noiseless measurements.

The current localization system uses a long-baseline acoustic system based on two acoustic beacons mounted on surface buoys. Each beacon answers the AUV with an acoustic pulse after having been questioned by the AUV in the same way. The distances are then computed from the times of flight of the acoustic waves, and the position of the vehicle is obtained by trilateration. This solution is robust and accurate, having demonstrated its performance through several missions in real-world scenarios, even in the presence of acoustic noise.

While the current system works well, logistics are always a major concern in AUV operation, and using a single acoustic beacon would further improve operational logistics and system reliability. Moreover, the concepts and the algorithms developed for single-beacon navigation may be directly extended to many scenarios, such as homing in on targets equipped with acoustic beacons.
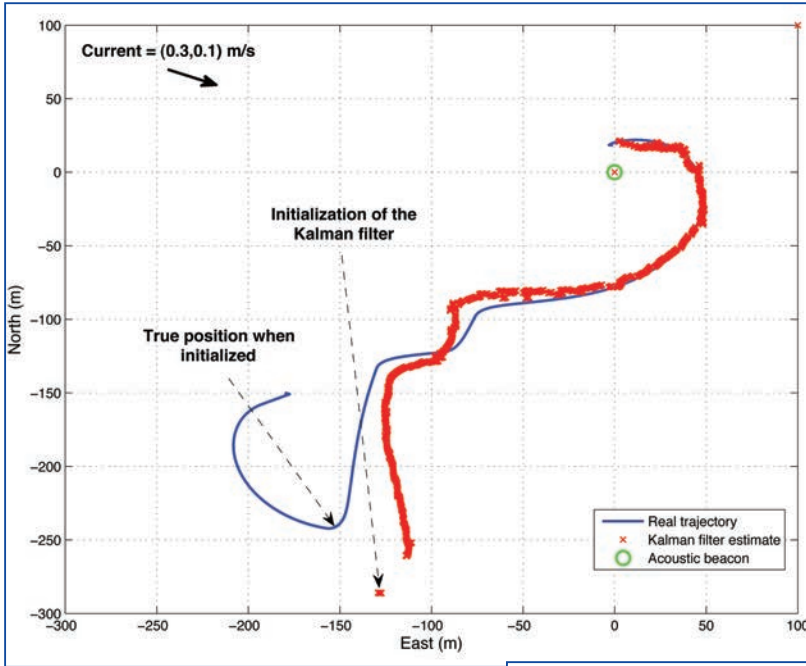
Positioning Estimation

In most mobile robotics applications, localization and positioning have the same operational importance. These two processes can sometimes be handled separately, considerably simplifying the overall navigation problem. However, in the case of single-beacon navigation, they are related, since lo-

Comparison between the EKF (above) and the particle filter (right) estimates.

oped and their benefits and limitations were analyzed. As part of the estimation process, an accurate model of MARES dynamics, which had been previously validated, is used to dead reckon the surge and the sway velocities. This mathematical model employs compass measurements as well as the estimated forces and moments applied by the thrusters.

The first proposed approach makes use of a discretized EKF whose state vector is composed of the horizontal position components (x and y) and water current components. The discretized EKF follows the standard formulation: Each time a new range measurement is available, the so-called Kalman gain and the covariance matrix are updated, while the state estimate is corrected through the innovation. In the absence of range observations, the state estimate is propagated using dead reckoning, and the covariance matrix evolves according to the discretized EKF formulation. This evolution is

calization ambiguity is removed only through the motion of the vehicle. In other words, localization, as an estimation problem, is solvable only when several range measurements are taken from different positions, because range only provides information in one dimension.

These measurements are typically noisy due to natural propagation of acoustic waves in the water, where occlusions, multipath and reflections in nonhomogeneous environments cause considerable errors that are dependent on the distance to the acoustic beacon.
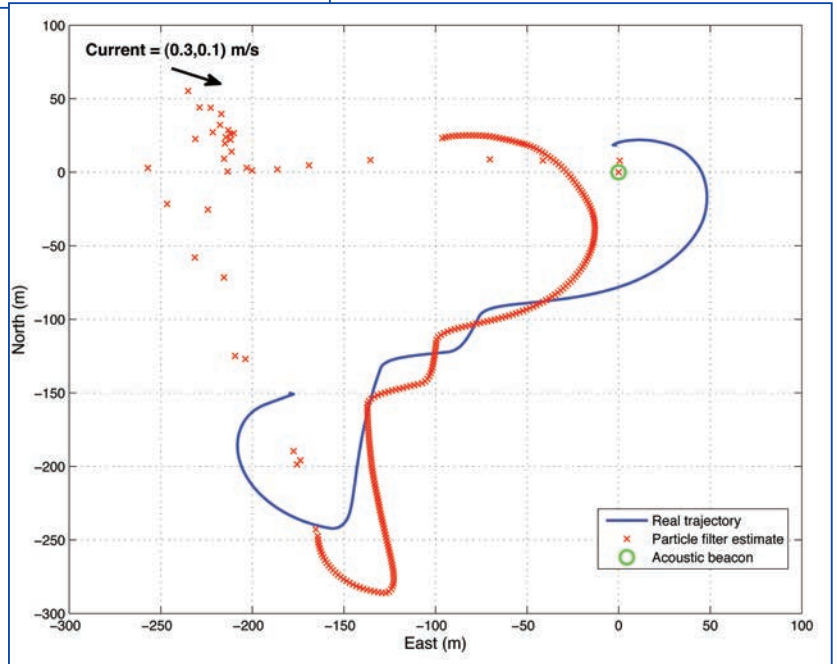
The acoustic system used in missions performed by the MARES AUV provides range measurements with errors that follow an exponential distribution, with standard deviation of about one to two meters for distances on the order of a few hundred meters.

Throughout this article, it is assumed that only one beacon is used and it is coincident with a virtual origin. For homing, the mission of the vehicle is to move to a neighborhood of the horizontal origin $(x,y) = (0,0)$ at a constant depth. The water current is assumed to vary slowly and the vehicle velocity is assumed to be sufficiently high to ensure controllability.

The MARES AUV interprets sensor data and generates commands at a constant rate of 10 hertz. While measurements from the depth sensor and the compass are available at each time step, range measurements are performed at a lower frequency due to the speed of propagation of acoustic waves. Therefore, the available data need to be fused at different time scales, and estimators such as the extended Kalman filter (EKF) and the particle filter are promising approaches to handling this constraint together with sensor noise. Both estimators were devel-

meaningful and can be used to infer the confidence of the state estimate, since some of its entries will grow when the estimate is systematically inconsistent with the data acquired from the sensors.

The other approach employs a particle filter to estimate the position of the vehicle. In this method, the state vector is reduced: Only the position components were included. The water current components were discarded due to the nature of the particle filter, which requires more particles for more state variables, requiring a greater computational effort. Of course, it is expected that this constraint will make the estimation of the particle filter degrade. With an adequate propagation of the particles, however, a good estimation can still be reached.

Each particle is a vector with two components that represents a likely position of the vehicle. In this case, sequential
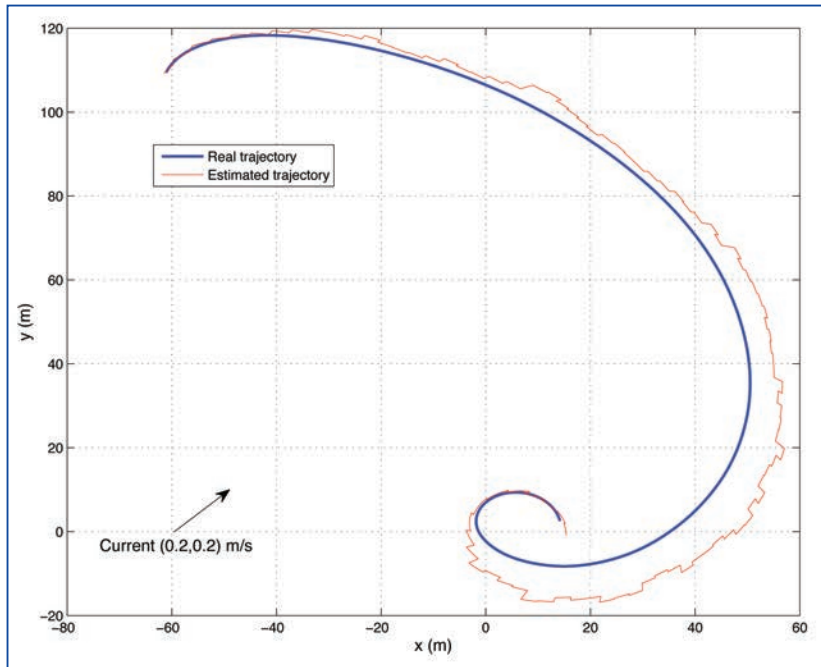
Example of a homing trajectory.

importance resampling was used. This particle filter algorithm consists of four main steps: initialization, prediction, measurement update and resampling. The initialization is carried out by spreading the particles randomly on a circle around the origin—the circle's radius is determined after having measured a sufficient number of consistent ranges. Then, at each time step, the particles are propagated through dead reckoning, generating the new prediction that is determined by the weighted sum of the particles. Weights assign an importance to the corresponding particle whenever a new range measurement is available, being functions of the consistency of the particles with respect to the range measurement.

Finally, resampling tries to avoid the well-known degeneracy problem. During the operation of the estimator, the particle weights tend to be higher for some particles than for others. In the limit, the weights will be very high for a reduced subset of particles, and the estimation will rely on these. This constitutes an issue in most cases because the spatial coverage of the particles tends to be very small. The resampling process makes it possible to randomly redistribute the particles close to the most weighted particles, with the weights being adjusted accordingly.

While the particle filter has a well-defined procedure for automatic initialization, the EKF has to be initialized manually with a fairly good estimate. Of course, this reduces the autonomy of single-beacon navigation. Therefore, automatic initialization would be convenient. Previous works have tackled this problem using the least-mean-square estimator. However, this method strongly relies on accurate dead reckoning, and an implementation of the least-mean-square estimator revealed that initialization is very sensitive to model uncertainties. Nevertheless, the initialization estimation can be achieved using the particle filter's estimate, which is fairly accurate after a small number of iterations. In order to do so, an initial maneuver is defined: First, the vehicle moves in a straight line with an arbitrary direction for 30 seconds after the particle filter has been initialized, then it describes an arc of circumference (typically

180°), and finally, the EKF is initialized using the particle filter's estimate.

Vehicle Control

For an ideal case in which the vehicle position is perfectly known along the trajectory, the control law would simply ensure that the followed path is a straight line to the origin. However, the position is estimated in real time, being affected by errors during operation. Moreover, the motion in a straight line to the origin lacks observability along the axis that is orthogonal to the motion. Thus, another type of trajectory that ensures observability should be described in the approach to the origin. A curvilinear trajectory would be adequate in this context.

Making use of velocity controllers developed previously, it can be assumed that the surge velocity and the yaw rate can be directly commanded. Thus, from the position estimate, it is possible to determine the (estimated) heading angle, ψ, that makes the vehicle point to the origin. Curvilinear trajectory can be achieved by setting the heading reference equal to ψ plus a predefined offset: $\psi_{ref} = \psi \pm \psi_{off}$. Taking this fact into account, a control law that assigns a variable reference to yaw rate is derived using Lyapunov theory and the backstepping technique.

The sign of the offset described above will define the origin-approach side and can be used to improve estimations. Allowing this sign to change according to the confidence of the estimate will balance the observability of the two axes. As stated before, this confidence can be obtained from the covariance matrix of the EKF, being inversely proportional to its diagonal entries. This approach makes the sign of the offset change whenever these values grow above a defined threshold.

Results

In order to compare their behavior, both particle filter and EKF approaches were implemented and tested through realistic simulation of sensors and vehicle dynamics. The tests occurred in the same conditions, with the two estimators operating concurrently. Water currents were considered and errors were voluntarily added in the dead-reckoning model to assess the robustness of the estimators.

The EKF operation resulted in robust estimation, since the initialization is adequately made using the particle filter estimate. Nevertheless, even in the presence of large initialization errors (about 50 meters), the EKF estimate converges to the real position and real current components after a few iterations. This method has also been demonstrated to be robust for modeling uncertainties: dead-reckoning model parameters varied by 30 percent around their nominal values and the estimation remained adequate. Though this effect causes an erroneous estimate of the water current, it is not critical, since it evolves according to the heading angle.

On the other hand, particle filter estimation resulted in satisfactory estimates only for the first iterations. In most cases, the estimate starts by converging to the real position, but sometimes the dead reckoned result tended to dominate, resulting in divergent estimates. Repeatability is, therefore, not ensured,

and consequently, robustness is not achieved. The divergent behavior originates from the lack of spatial coverage of the particles: After a few iterations, the particles cover only a very small area due to resampling, and their propagation is not sufficient to prevent divergence.

This behavior can be overcome by significantly increasing the number of particles while including the water current components in the state estimation and making the propagation larger. In these tests, however, even a 10 times increase in the number of particles—with a corresponding increase in the computational effort—revealed no significant improvement in the estimation performance.

Conclusions

The problem of AUV navigation with a single beacon was addressed in this article by developing two estimators of different natures. The particle filter is a promising estimator that does not rely on any assumptions about noise, but its performance is related to the number of particles, which directly influences computational requirements. On the other hand, the EKF assumes certain properties of the kind of noise affecting measurements, needs and adequate initialization, but demands less computational capabilities. To take advantage of the two methods, both estimators were combined and, together with a control strategy that ensures observability along AUV trajectories, a robust solution for single-beacon navigation was obtained.

Field experiments are currently being conducted with MARES to evaluate the accuracy of the proposed algorithm. During operations, traditional long-baseline positioning data is being recorded on board for later comparison with the single-beacon navigation estimates.

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