USING ULTRASONIC AND VISION SENSORS WITHIN EXTENDED KALMAN FILTER FOR ROBOT NAVIGATION

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1. INTRODUCTION

One of the recent and consistently interesting topics in robotics research community is the simultaneous localization and map-building (SLAM) problem. It requires an autonomous mobile vehicle starting in an unknown environment. Then the vehicle incrementally builds an environment map and simultaneously localizes its pose within this map.

Wolter and his colleagues point out that any approach to master the SLAM problem can be decomposed into two aspects: handling of map features (extraction from sensor data and matching against the (partially) existing map) and handling of uncertainty (Wolter et al. 2004). Therefore, robotic research community keeps tackling the SLAM problem in these two aspects. As for the first aspect, some sensing systems can successfully interpret natural features for mapping, such as ultrasound, computer vision, laser and their fusion. As for the second aspect, some probabilistic methods are proven to minimize the SLAM uncertainties (Thrun 2002).

In this study, we address the problem of robot SLAM within extended Kalman filter (EKF) framework, which falls into the second aspect. Two types of sensing systems, ultrasound and computer vision, which handle the first aspect, are mounted separately on the robot to perceive the environment so as to simultaneously localize the robot and build the landmark map.

2. METHODS

2.1 Extended Kalman Filter

The Kalman filter (KF) is a linear, discrete-time, finite dimensional system endowed with a recursive structure that makes a digital computer well suited for its implementation (Hayin 2002). While state vector of the KF is suitable only for a linear model, EKF can deal with the nonlinear models in which the majority of the real world applications lie. The conversion from KF to EKF is through a linearization procedure based on first order Taylor approximations (Hayin 2002).

The key reasons for using EKF in SLAM are due to the facts as follows: firstly, EKF directly provides a real-time solution to the navigation problem and to on-going estimation of the uncertainty acquired from vehicle motion and landmark observations; secondly, a number of methods and experience have been developed in aerospace, subsea, and other navigation applications that robotics research community can study. Such wide application is due to the fact that EKF is an optimal minimum mean square error (MMSE) estimate method and its covariance matrix is proven to converge strongly (Dissanayake et al. 2001).

A classic two-stage EKF algorithm is as follows:

Prediction Process (Chen & Samarabandu 2005):

$$
\begin{aligned}
\hat{\mathbf{x}}(k|k-1) &= \mathbf{f}(\hat{\mathbf{x}}(k-1|k-1), \mathbf{u}(k)), \\
\mathbf{P}(k|k-1) &= \nabla\mathbf{F_x}\mathbf{P}(k-1|k-1)\nabla\mathbf{F_x}^T + \nabla\mathbf{F_u}\mathbf{Q}\nabla\mathbf{F_u}^T, \\
\mathbf{z}(k|k-1) &= \mathbf{h}(\hat{\mathbf{x}}(k|k-1)).
\end{aligned}
\tag{1}
$$

Update Stage:

$$
\begin{aligned}
\hat{\mathbf{x}}(k|k) &= \hat{\mathbf{x}}(k|k-1) + \mathbf{K}\nu(k) \\
\mathbf{P}(k|k) &= \mathbf{P}(k|k-1) - \mathbf{K}\mathbf{S}\mathbf{K}^T,
\end{aligned}
\tag{2}
$$

where

$$
\begin{aligned}
\nu(k) &= \mathbf{z}(k) - \mathbf{z}(k|k-1) \\
\mathbf{K} &= \mathbf{P}(k|k-1)\nabla\mathbf{H_x}^T\mathbf{S}^{-1} \\
\mathbf{S} &= \nabla\mathbf{H_x}\mathbf{P}(k|k-1)\nabla\mathbf{H_x}^T + \mathbf{R}.
\end{aligned}
\tag{3}
$$

Interested readers can refer (Chen & Samarabandu 2005) for more details of this probabilistic framework.

2.2 Ultrasonic Sensing System

Ultrasonic sensors provide a cheap and reliable means for robot localization and environmental sensing when the physical principles and limitations of their operation are well understood.

In this study, beam pattern of an ultrasonic range finder is modeled in a 2-D plane, which will be further discussed in Section 3. Considering the speed of sound is much faster than that of the wheeled robot, the robot movement is omitted between the time interval when transmitter fires and receiver receives the echo. Kleeman *et al.* develop algorithms to localize and classify the features (Kleeman & Kuc 1995), which indicates that sonar is one of the good tools for robotic feature detection. After detecting the feature range of the landmark as well as bearing (from an other sensor, e.g. computer vision or compass) are fed to EKF in Equations. 2 and 3 in order to localize the robot.

2.3 Multiple View Geometry

For the purpose of study and comparison, multiple view geometry (MVG) technique is utilized within EKF framework to solve the SLAM problem. Singular value decomposition (SVD) based factorization is applied to 2-D snapshot pictures to reconstruct the landmark in 3-D world coordinates. Map is augmented by the adding reconstructed landmarks.

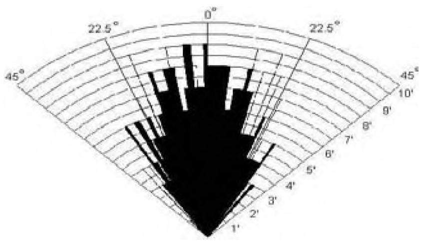

Fig. 1. A Devantech SRF04 sonar range finder beam pattern

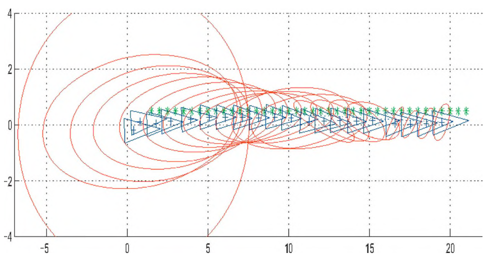

Fig. 2. The trajectory of a mobile robot with ultrasonic sensor for localization

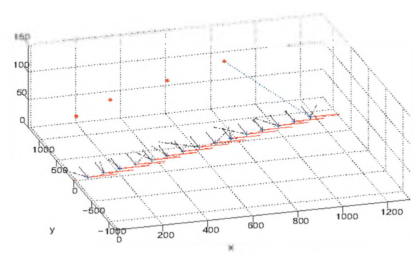

Fig. 3. SLAM by MVG-EKF

TABLE I

AVERAGE ERRORS WHEN $\sigma_{\mathbf{z}} = 0.002$.

	MVG-EKF	MVG	Map
Smooth trajectory	1.7403	4.3289	4.6907
Sharp trajectory	5.8833	14.0874	12.1794

The camera position is estimated using a direct reconstruction technique. This reconstruction outcome is optimized by EKF. Robot navigation uncertainty is reduced (Chen & Samarabandu 2005).

3. RESULTS

Simulations are performed in both sensing systems. For the ultrasonic system, a Devantech SRF04 sonar range finder beam pattern is simulated, which is illustrated in Figure 1. It is apparent that the angular scope of the ultrasonic sensor is narrow. Thus a quite large number of ultrasonic sensors is required to mount on the robot and make sure that the robot can "observe" all 360° of its environment. In the simulation, observation Gaussian noise with $\sigma_{\mathbf{z}} = 2.8$ is added to the ultrasound detection. In Figure 2, the triangles represent the robot trajectory. The asterisks represent features the robot detected, and the ellipses are the uncertainties of robot locations. This shows that the uncertainties decrease as the robot moves. The final average error can be as small as 0.22m. This indicates that the ultrasonic sensors are reliable for robot navigation. However, its short range detection property (less than 10 ft) restricts it to local measurement. Additionally, a non-scanning ultrasonic sensor can only build a 2-D map.

Computer vision technique is suitable for high resolution and long range measurements. MVG integrated with EKF framework is also implemented with observation noise $\sigma_{\mathbf{z}} = 0.002$ (Figure 3). Simulation results show that EKF can improve the localization accuracies, and recursively build the environment map for robot navigation (Table I).

4. DISCUSSION

For robotic SLAM problem, ultrasonic and computer vision sensors have their own advantages. For example, ultrasonic sensors are cheap and reliable for short distance detection. Computer vision does well in high resolution and long range measurements, and provides rich research results in feature detection and recognition. Of course, each has their own drawbacks. For ultrasound, its short distance, narrow angular scope of detection and 2-D properties limit its application. For computer vision, it is sensitive to observation noise.

In the SLAM research community, ultrasound based techniques are well established. On the other hand, MVG has a promising future in 3-D SLAM, as the algorithm can be easily applied to single or multiple camera sensing system. If applied to monocular vision-based system, it is benefited from redundant information and avoids unnecessary calibration. MVG-EKF based technique can reduce the robot localization estimation errors compared to using MVG solely.

Future work will include different sensor fusion, e.g. computer vision with ultrasound sensor. Other works will focus on real-time implementation of MVG-EKF algorithm.

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