Autonomous Navigation of an Outdoor Mobile Robot in a Cluttered Environment

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Abstract: This paper proposes a modification of HybridSLAM strategy that is used to navigate an outdoor autonomous mobile robot in a cluttered environment. HybridSLAM is combining extended Kalman filter SLAM EKF-SLAM and FastSLAM to take advantage of strengths and to cover shortcomings of both filters. By the use of an unscented version of Kalman filter instead of EKF-SLAM, the formulation of the HybridSLAM is revised. Same as HybridSLAM, the new revised algorithm uses the state distribution capabilities of the unscented Kalman filter to keep the uncertainty of the system to be remembered for a long trajectory, and at each time step, FastSLAM is used to produce local maps. Presented simulations and results evaluate the performance of the proposed approach using Unscented Kalman filter in a cluttered environment.

1 INTRODUCTION

Simultaneous localization and mapping (SLAM) problem refers to a situation in which a mobile robot in an unknown environment, incrementally constructs a navigation map of its surroundings. At the same time, the robot simultaneously, and with the observations of features (landmarks), uses this navigation map for localization (Durrant-Whyte and Bailey, 2006). Due to the imperfections of the movement and observation, there are error inputs to the system. Since location of landmarks and pose of the robot are highly correlated, there will be uncertainty accumulated at next time steps to the extent that it becomes unbounded. To prevent the accumulation of uncertainty in the system, an algorithm needs register such errors. Two dominant approaches to solve SLAM problem are Extended Kalman filter SLAM (EKF-SLAM) and FastSLAM.

EKF-SLAM has been known as an optimal solution to SLAM problem for more than two decades. However, EKF algorithm has the linearity and Gaussian underlying assumptions and it suffers form two major problems; computational complexity and its sensitivity to single hypothesis data association. FastSLAM, on the other hand, can better handle non-linearity in the motion and carries less complexity. FastSLAM is also carrying the multi hypothesis data association property which makes it relatively more reliable compare to EKF-SLAM. Nonetheless, the latter is sensitive in the presence of accurate sensors and, moreover, over long vehicle trajectories such as a loop closing scenario, the algorithm becomes overconfident by not considering the existing uncertainty. A combined (Brooks and Bailey, 2009) called “HybridSLAM” uses a Hybrid mapping to add up strengths of both filters where the FastSLAM is employed to construct a local map and reduces the ambiguity of the motion. However, experimental results prove that for a very large loop, the use of EKF as a back-end in HybridSLAM causes a complexity in the computation of the global map. This paper takes advantage of the same strategy that was used in HybridSLAM to combine two filters used as front-end and back-end but instead of EKF-SLAM, an unscented version of Kalman filter (UKF) is combined with a Rao-Blackwellised particle filter. A loop closing scenario in a cluttered environment is presented in this study. Several experimental results are presented and three SLAM strategies are compared.

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2 HYBRIDSLAM

By combining EKF-SLAM and FastSLAM (Thrun, and Montemerlo, 2004), HybridSLAM (HS) was introduced (Brooks and Baily, 2009). HS is taking advantage of strengths in both filters and helps to overcome their limitations and weaknesses. The resultant algorithm acts as a modified filter. The use of EKF-SLAM on the side, helps FastSLAM not to become over-confident. As a result, by combining EKF-SLAM and FastSLAM, the modified filter performs much better in comparison with either its component. FastSLAM needs to be presented as a continuous (Gaussian) form so that it can be combined with EKF-SLAM. The modification may be done in a way that FastSLAM builds local maps and is allowed to run for long enough to disambiguate associations. Before the path becomes so long that particle diversity becomes problematic, a single dimensional Gaussian is computed from the FastSLAM posterior. At the end, this Gaussian local map can be fused into the global map to be represented as a whole. State of the system in FastSLAM representation at time step k can be expressed as

$$ {}^{\mathrm{n}}\mathrm{x}_k = \{ {}^{\mathrm{n}}\mathrm{X}_k^R, {}^{\mathrm{n}}\mu_{k,1}, {}^{\mathrm{n}}\sigma_{k,1}, \ldots, {}^{\mathrm{n}}\mu_{k,M}, {}^{\mathrm{n}}\sigma_{k,M} \} \tag{1} $$

and the weighted sample for particle n is:

$$ {}^{\mathrm{n}}\hat{w}_k = P(\mathbf{Z}_k \mid {}^{\mathrm{n}}\mathbf{X}_k^R, \mathbf{Z}_{k-1}, \mathbf{U}_k, \mathbf{x}_0^R) \tag{2} $$

Using the two above equations:

$$ \begin{aligned} {}^{\mathrm{n}}\mathrm{x}_k &= \{ {}^{\mathrm{n}}\hat{w}_k, {}^{\mathrm{n}}\mathrm{X}_k^R, {}^{\mathrm{n}}\mu_{k,1}, \ldots, {}^{\mathrm{n}}\mu_{k,M}\ {}^{\mathrm{n}}\sigma_{k,1}, \ldots, {}^{\mathrm{n}}\sigma_{k,M} \} \\ &= \{ {}^{\mathrm{n}}\hat{w}_k, ({}^{\mathrm{n}}\mathrm{X}_k^R, \mathrm{m}), {}^{\mathrm{n}}\mathrm{C}_k \} \end{aligned} \tag{3} $$

Equation (3) represents RBPF as a Gaussian mixed model in which each particle is a Gaussian component with weight ${}^{\mathrm{n}}\hat{w}_k$, mean (${}^{\mathrm{n}}\mathrm{X}_k^R$,m), and covariance matrix ${}^{\mathrm{n}}\mathrm{C}_k$. With the use of moment matching process, the final result of pose of the robot with covariance C_k extracted from all particles can be expressed as

$$ \mathrm{x}_k = \sum_n {}^{\mathrm{n}}\hat{w}_k\ {}^{\mathrm{n}}\mathrm{x}_k \tag{4} $$

$$ \mathrm{C}_k = \sum_n {}^{\mathrm{n}}\hat{w}_k [{}^{\mathrm{n}}\mathrm{C}_k + ({}^{\mathrm{n}}\mathrm{x}_k - \mathrm{x}_k)({}^{\mathrm{n}}\mathrm{x}_k - \mathrm{x}_k)^{\mathrm{T}}] \tag{5} $$

Since the observation sensor includes noise, ${}^{\mathrm{n}}\mathrm{C}_k$ represents the covariance of the map produced by every individual particle. Due to noisy motion $({}^{\mathrm{n}}\mathrm{x}_k - \mathrm{x}_k)({}^{\mathrm{n}}\mathrm{x}_k - \mathrm{x}_k)^{\mathrm{T}}$ represents variation between the map produced by particles. At each time step, a new local map is developed by RBPF and fused into global map (the map produced by EKF-SLAM). Constrained Local Sub-Map Filter (CLSF) technique is used to integrate a local map to a global map (Williams, Dissanayake, Durrant-Whyte, 2002).

3 UKF VERSUS EKF

The use EKF-SLAM in HybridSLAM has its own estimation limitations and it has its approximation issues when facing nonlinearity of the system (Monjazeb, Sasiadek, Necsulescu, 2011). An improved version of EKF was introduced and called unscented Kalman filter (UKF) (Julier, Uhlmann, 2004). Applying UKF in Hybrid SLAM addresses the approximation issues in constructing a global map and will result in a more reliable map in the fusion step. By replacing UKF with EKF in HS the approximation of the state distribution using a Gaussian random variable can be done except for the case where it propagates the state distribution analytically through the third order linearization of a non-linear system. EKF optimization may lead to suboptimal performance resulting in failure of the filter since it generates substantial error in the posterior mean and covariance of the system. UKF represents the state distribution of the system based on a Gaussian random variable and a deterministic sample approach. Unscented transform eliminates calculation of Jacobians in UKF by which the complexity of computation is reduced substantially. The system can be expressed as an augmented form of estimated state and system covariance as follows:

$$ \mathbf{x}_{k-1}\,(\text{augmented}) = [(\hat{\mathbf{x}}_{k-1}^{+})^{\mathrm{T}}\ \mathrm{E}[\mathbf{w}_k^{\mathrm{T}}]]^{\mathrm{T}} \tag{6} $$

$$ \mathbf{P}_{k-1}^{-}\,(\text{augmented}) = \begin{bmatrix} \mathbf{P}_{k-1}^{+} & 0 \\ 0 & \mathbf{Q}_k \end{bmatrix} \tag{7} $$

For more detail see (Julier, Uhlmann, 2004)

4 SIMULATIONS AND RESULTS

In this experiment, the range sensor was able to detect approximately 6 point landmarks per meter, meaning that the shortest distance between two nearby landmarks is approximately 0.20 meter same as (Monjazeb, Sasiadek, and Necsulescu, 2008). In all simulation experiments, the sampling time is considered as T=0.2s. Velocity of the robot is set at 3.0 m/s and in agreement with a real instrumentation. The maximum range for the range/bearing is set as 50m. In a simulated scenario the robot is travelling on a road that is curved and depicts a loop closing situation. Position of detectable landmarks simulates a cluttered environment. The systematic error of the motion This figure illustrates a loop closing scenario with given waypoints and detectable landmarks that represent a two dimensional (250,000m^2) cluttered environment. 200 detectable landmarks are randomly distributed and a set of waypoints is defined through a passageway. With the assumption of unknown data association for a HybridSLAM algorithm, 30 particles are incorporated in the calculation of local map and fused to the global map using both EKF-SLAM and UKF-SLAM. Figures 2 and 3 depict a situation that the loop is closed and the Root Mean Square (RMS) position error is calculated. Figure 2 shows how the vehicle observes landmarks with uncertainty involved in the algorithm. In Figure 3-a, the accuracy of HybridSLAM is shown using EKF-SLAM as a back-end. The RMS position error average is around 0.6m. Figure 3-b depicts the RMS position error in the same situation using UKF-SLAM except for, this time, the accuracy of HybridSLAM is substantially improved. The RMS position error using UKF is 0.3m which is 30cm less than the situation in which the algorithm uses EKF-SLAM as a global map fusing strategy. Figures 4 shows the orientation error for both versions of KF an for the same scenario; the use of EKF-SLAM and UKF-SLAM as the back-end to fuse the local map to the global map. Results indicate that in terms of the orientation error, UKF is outperforming EKF. The average of orientation error as a result of using UKF-SLAM is around 0.03rad and the difference with that of EKF-SLAM is 0.01rad. The simulation of the same scenario was run for 20 iterations. Figure 5 demonstrates a comparison between HybridSLAM with a use of EKF-SLAM and HybridSLAM with a use of UKF-SLAM. The accuracy of both algorithms is computed in terms of the RMS position error average.

It should be noted that the performance of HybridSLAM in the presence of either Kalman filter will depend on motion parameters as well as the measurement model. Results indicate that UKF-SLAM performance is better than EKF-SLAM infusing the local map into the global map.

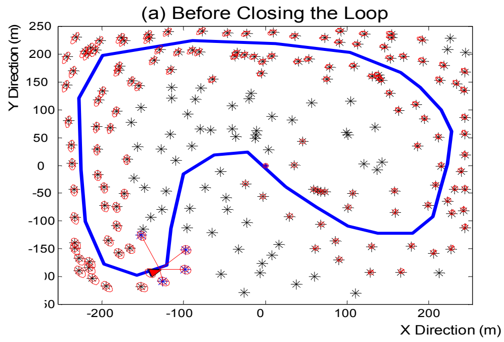

Figure 1: An autonomous mobile robot travelling in a cluttered environment. (a) before the loop is closed (b) after the loop is closed.

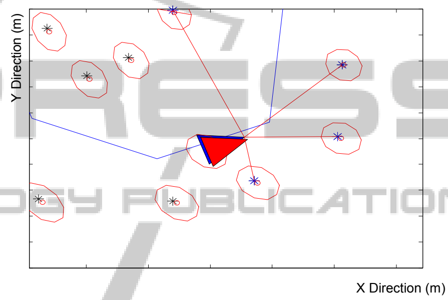

Figure 2: Uncertainty that arises in the heart of SLAM problem.

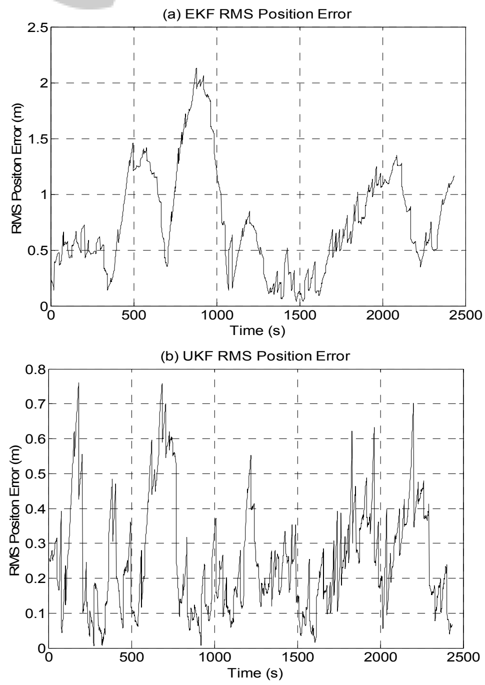

Figure 3: (a) RMS position error for EKF-SLAM as the back-end in HybridSLAM (b) RMS position error for UKF-SLAM as the back-end in HybridSLAM.

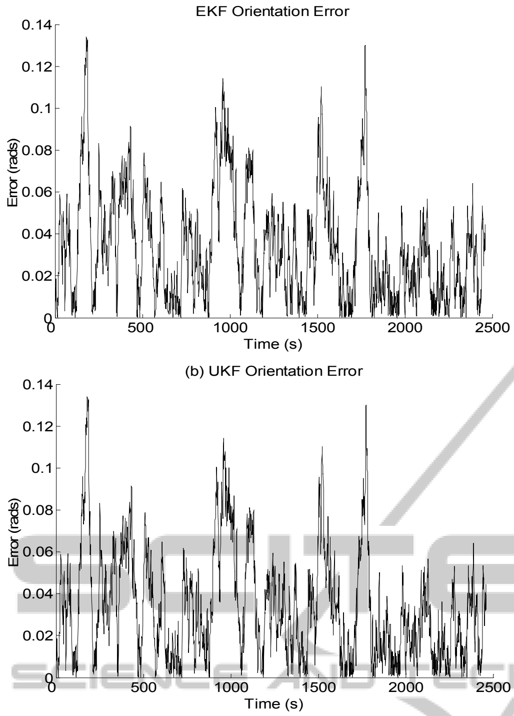

Figure 4: (a) Orientation error for EKF-SLAM as the back-end in HybridSLAM (b) Orientation error for UKF-SLAM as the back-end in HybridSLAM.

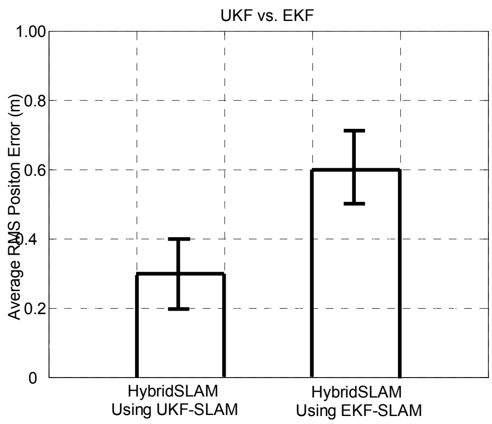

Figure 5: A comparison between EKF-SLAM and UKF-SLAM in a HybridSLAM algorithm.

5 CONCLUSIONS

In this paper, the performance of HybridSLAM strategy is examined using two different versions of Kalman filter as the back-end algorithm to fuse local map into a global map. Results show that with a use of UKF-SLAM, Root Mean Square (RMS) position and orientation errors decrease substantially in comparison with EKF-SLAM. Applying Unscented Kalman Filter (UKF) allows the state distribution to be propagated analytically through the third order linearization of a non-linear system. The performance of proposed method is compared with a standard HybridSLAM and accuracy of the process is examined through 20 iterations. In addition, simulations and results show that for a non-linear motion, the use of UKF-SLAM would drastically increase accuracy of the estimation for a long trajectory specified in a loop closing case.

REFERENCES

Monjazeb, A., Sasiadek, J. Z., Necsulescu, D., Autonomous navigation among large number of nearby 2011, landmarks using FastSLAM and EKF-SLAM; a comparative study, *Proc. of 16th International Conference on Methods and Models in Automation and Robotics*, pp. 369-374, Miedzyzdroje, Poland.

Brooks, A., Bailey, T., 2009, HybridSLAM: Combining FastSLAM and EKF-SLAM for reliable mapping, *Springer Tracts in Advanced Robotics*, Volume 57, pp. 647-661.

Sasiadek, J. Z., Monjazeb, A., Necsulescu, D., 2008, Navigation of an autonomous mobile robot using EKF-SLAM and FastSLAM, *Proc. of* 16th *Mediterranean Conference on Control and Automation*, pp. 517-522, Ajaccio, France.

Durrant-Whyte H., Bailey T., 2006, Simultaneous localization and mapping (SLAM): Part I the essential algorithms, *IEEE Robatics and Automation Magazine*, Vol. 13, No. 2, pp. 99-108, June.

Thrun, S., Montemerlo, M., Koller, D., Wegbreit, B., Nieto, J., Nebot, E., 2004, FastSLAM: an efficient solution to the simultaneous localization and mapping problem with unknown data association, *Journal of Machine Learning Research*.

Julier, S. J., Uhlmann, J. K., 2004, Unscented filtering and nonlinear estimation, *Proceedings of IEEE Journal*, Vol. 92, Issue 3, pp. 401-422, March.

Vander Merwe, R., Wan, E., Julier, S., 2004, Sigma-point Kalman Filters for nonlinear estimation and sensor-fusion: Applications to integrated navigation", *Proceedings of the AIAA Guidance, Navigation and Control Conference, Providence, Rhode Island, August*.

Williams, S. B., Dissanayake, G., Durrant-Whyte, H., 2002, An Efficient Approach to the Simultaneous Localisation and Mapping Problem", *Proceedings of the 2002 IEEE International Conference on Robotics & Automation*, Washington DC.