Motion Model and Filtering Techniques for SVEA Vehicles with Fiducial Detection

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Abstract- **This paper is an individual report presenting the results of a group project done as a part of the applied estimation course at KTH, Stockholm. The paper addresses the problem of estimating the real-time pose (both position and orientation) of the in-house developed SVEAs (Small Vehicles for Autonomy) at the Integrated Transport Research Lab (ITRL) using an accurate motion model. In order to estimate the real-time pose, we have used the Extended Kalman Filtering (EKF) and particle filtering (PF) technique. The control input and IMU measurements are used to develop the motion model of the robot. We use the method of relative pose estimates of RGB cameras to fiducial (ArUco) markers, at a much lower frequency, as our observation measurements. The true pose of the SVEAs is determined using the Qualsyis motion capture system. The true pose is then compared to the predicted pose usiabove mentioned filtering techniques in order to find the accuracy of our proposed method. It is found that the suggested method performs well for a reasonable amount of occlusion time of ArUco markers.**

I. INTRODUCTION

At the onset of the century, many big companies started to invest in robotics technology. This was done primarily to automate simple and repetitive tasks which allowed the companies to tackle the problem of ageing society and decreased amount of labor. Today, after a couple of centuries, the above stated challenge has been almost solved but many other complex challenges such as climate change, increasing natural disasters etc. have emerged. In order to tackle these challenges, autonomous systems play a vital role and systems such as mobile robots, drones, etc. are seen as possible solutions. One of the fundamental problems of an autonomous system is its ability to localize itself in the environment, given its hardware capability.

Fiducial markers are frequently used in augmented reality research to estimate the camera pose for overlaying of virtual model to a captured video frame [1,2]. It has good properties of extracting markers from a complicated and mixed scene. This is because its tone and shape is easy to detect. The tone of fiducial markers is black and white and the vertices of fiducial markers can be easily extracted from line crossings because of its square shape.

In this work, we have developed a localization system based on motion model and fiducial detection. Our method can be used to accurately find the pose of a robot during long period of occlusion (between RGB camera and fiducial markers). Further, the method doesn't completely rely on fiducial detection and hence is robust to any false measurements of the fiducial markers. The obtained results are compared to true pose of the robot using the Qualsyis system and demonstrates that the method effectively estimates the real-time pose of the robot with high accuracy. However, the method needs to be improved for high velocity system and extended period of occlusions.

The main contribution of the method is that it uses low-cost sensors and using the above mentioned techniques develops a localization system which can be used to navigate the robot from point A to B in an environment. This kind of system can be very useful for multiple purposes such as caretakers for the elderly, self docking/ parking assist, industrial fire fighters etc.

The paper is organized as follows. In section 2, we do a literature review of the already done work in this field. In section 3, we introduce our method and it's core components. In Section 4, we present the results and try to infer from them. Section 5 gives a conclusion of our work. Finally, section 6 presents the ideas for future work.

All the equipment and setup to carry out the work was provided to us by the Integrated Transport Research Lab (ITRL), KTH- Royal Institute of Technology.

II. RELATED WORK

In order to solve the problem of localization in autonomous systems, a number of methods have been proposed. In the earlier years, localization was considered as a side effect when operating the robot under uncertainty. In that period, localization was considered as a passive phenomenon and [3] introduced the concept of active localization in mobile robots. This method was further developed in [4] where the concept of probabilistic robotics was revisited. This method treated the inherent uncertainty in robot perception, thereby necessitating the use of filters in robot localization. Filtering methods involve estimating the robot's current state (and potentially landmarks) using the set of all measurements up to the current time [5, 6]. When the process model and measurements are linear, and the noise is white and Gaussian, Kalman filtering [7] provides an optimal method (minimum mean squared error) for state estimation. But most practical robots have nonlinear system dynamics and many sensor models are also nonlinear. For such cases, an EKF can be utilized, which uses Taylor series expansion in order to linearize the system [8]. However, since the nonlinear system is linearized about the current state estimate, the EKF is, at best, only a locally stable observer. For more complex and higher order nonlinear systems, non parametric filters such as a particle filter can be used [9].

In recent years, localisation using vision positioning technology based on artificial landmarks is having a very huge impact. Compared to natural landmarks, it avoids large calculations and has higher real-time performance [10]. ArUco markers are modern variants of earlier tags like ARTag [11] and AprilTag [12]. The utilization of AruCo markers is shown by Bacik, J. et al. in [13]. Our work extends this idea and we develop a mobile robot with ArUco marker detection.

III. METHODOLOGY

A. EXPERIMENTAL SETUP

Motion Capturing System from Qualisys [14] was used to get the true pose of the SVEAs. The system does a multiview 3D construction of passive IR markers. The system is based on the fact that if a point in space is seen from at least two different viewpoints with calibrated cameras of known position, the position of the point in 3D can be calculated. Position of each marker is computed from 2D images of four tracking cameras of the Qualisys. Cameras are mounted in each corner of the room and in a circular setup. The speed of the MoCap system was set to 10 Hz (100 frames per second). Markers used were small reflective balls which are seen in the camera image as bright dots.

Fig 1. SVEA mobile robot

Fig 1. shows the SVEA mobile robot that was used for experimental purposes. It has an onboard IMU, Nvidia Jetson Xavier, Arduino and a USB camera. A 3D printed ArUco marker was attached to the platform in order to facilitate fiducial detection. The robot is driven using DC motors and was not tested at its maximum velocity because of increasing complexity of detection of ArUco marker with respect to speed.

B. PROBLEM FORMULATION

In this paper, we propose to problems in order to validate our results. These are:

- In the first problem, we will be calculating the estimated pose of a SVEA using a stationary vision camera. It detects the ArUco marker placed on the SVEA vehicle which is being driven remotely inside the Smart Mobility Lab

(SML). There will be long periods of occlusion, so an accurate motion model will be critical.

- For the second problem, we will estimate the pose of the original SVEA using a camera in a dynamic environment. This will be accomplished by placing the vision camera on a second SVEA vehicle driven remotely near the original SVEA.

C. CONTROL METHOD

In order to control the movement of the SVEAs, we don't rely on predefined trajectories and instead use a joystick in order to move the robot. This is done primarily because we think that by using a joystick as a control signal input, we can control the movement of the robot at any time instance and hence introduce more randomness in order to better test our algorithm.
The output state of the robot is taken to be it's velocity (both angular and linear). We are using a bicycle model for the SVEAs and the acceleration is assumed to be constant for our model. Hence, we get a continuous output state.

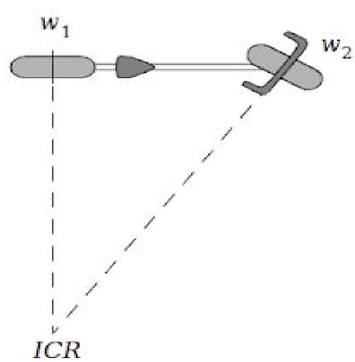

Fig 2. The bicycle model

D. FILTERING TECHNIQUES

1. EXTENDED KALMAN FILTER

Extended Kalman filter is a popular estimation technique and has been largely investigated for state estimation of nonlinear systems.[8] The EKF consists of using the classical Kalman filter equations to the first-order approximation of the nonlinear model about the last estimate. The process model has a state vector x ∈ R n and is governed by the non-linear stochastic difference equation

$$x_k = f(x_{k-1},\ u_{k-1},w_{k-1}) \qquad (1)$$

with a measurement z ∈ R ^{m} that is

$$z_k = h(x_k,\ v_k) \qquad (2)$$

where random variables w_k and v_k independent of each other. Variables w_k and v_k represent the process and measurement noise (respectively). They are assumed to be white, and with normal probability distributions

$$p(w) \sim N(0, Q)$$
$$p(v) \sim N(0, R)$$

where Q is process noise covariance and R is measurement noise covariance. The non-linear function f in the difference equation (1) relates the state at the previous time step k-1 to the state at the current time step k. Along with the noise it also sometimes includes any driven function u_{k-1} . The non-linear function in the measurement equation (2) h relates the state x_k to the measurement z_k . Since in practice individual values for the noise v_k and w_k at each time step are not known, one needs to approximates the state and the measurement vector without those values.

For implementing the EKF on the SVEA platform, we used the robot localization library in ROS [15]. The library gives the flexibility to fuse odometry data with IMU data, which is precisely what we wanted to achieve. The library helped expedite the process of implementing EKF but did not necessarily make it easy.
In order to achieve a good amount of accuracy with EKF, we needed to choose the right control input. The IMU data as well as the output state of the control method were considered as an input to the process model of the EKF. The output of the EKF was the pose of the robot. Observation model used is the pose given by the ArUco marker detection. For getting a good accuracy, the process noise covariance (Q) and the measurement noise covariance (R) needed to be fine tuned. The initial estimate of these values is done using calculations, for e.g., it can be approximated for the process noise covariance that how much maximum displacement it could have by looking at the maximum possible acceleration and frequency of input signal (30 Hz in our case). Further, the accuracy is improved by the hit and trial method on the covariance values.

It is found that the EKF performs well for a good amount of driving time until the error starts to grow where it finally diverges. Further, it is found that the EKF is less sensitive to the observed ArUco marker than expected.
The above mentioned problems led us to test particle filter for estimating the real-time pose of the SVEAs

2. PARTICLE FILTER

The particle filter is an alternative nonparametric implementation of the Bayes filter. Just like histogram filters, particle filters approximate the posterior by a finite number of parameters. However, they differ in the way these parameters are generated, and in which they populate the state space. The key idea of the particle filter is to represent the posterior $bel(x_t)$ by a set of random state samples drawn from this posterior [8].

In our implementation of particle filter, as shown in Fig 3., we fuse the velocity from the control method and the IMU data using the EKF itself and use the particle filter in order to address the issue of low sensitivity of EKF to ArUco marker detection as described above. Further, our method also addresses the issue of growing error in the EKF since during particle re-initialization, the less weighted particles are dropped.

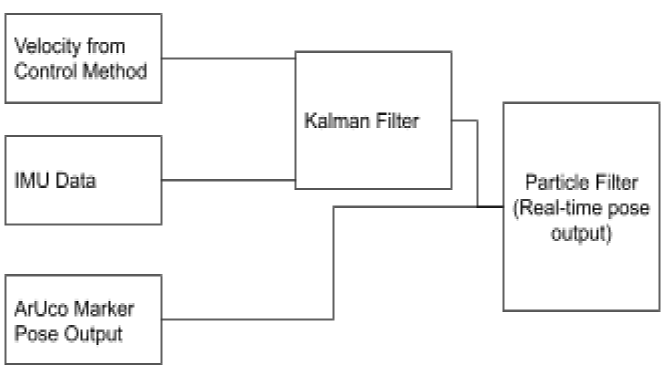

Fig 3. Particle Filter Implementation

IV. RESULTS AND DISCUSSION

As described in Sect III (B), the method is tested on two independent problems in order to validate its performance. The initial position of the robot is the same for both the problems as well as for both the filters. The base position of the robot is shown in Fig 4. with the assumption that the robot is facing the North direction.

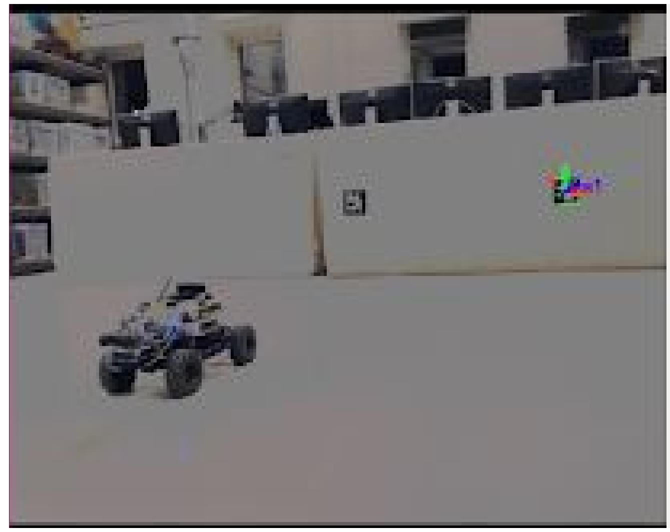

Fig 6. EKF implementation (Blue-EKF pose)

A. Problem 1

As described above, in problem 1, we address the issue of camera being mounted in a static location with respect to the robot.
In Fig 5. And Fig 6., the performance of EKF and PF is compared when the drift introduced in the robot is less. This is achieved by driving the robot at a continuous acceleration and in a smooth trajectory.

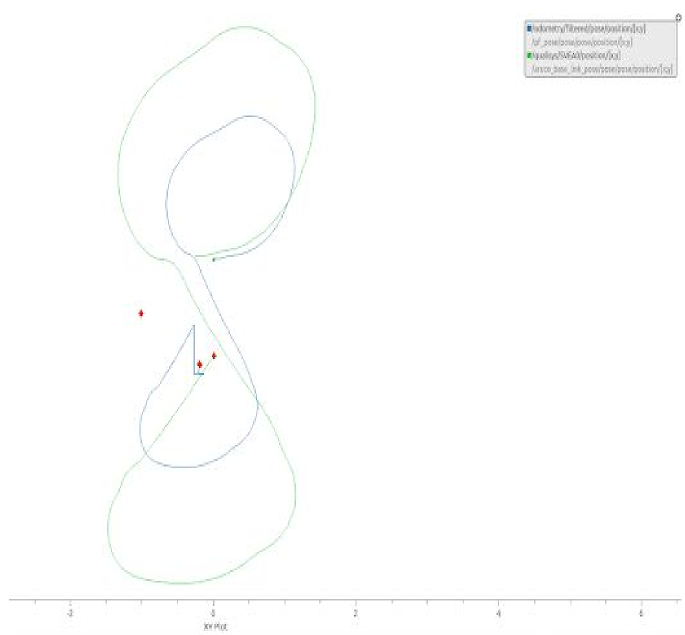

Fig 5. EKF implementation (Blue-EKF pose)

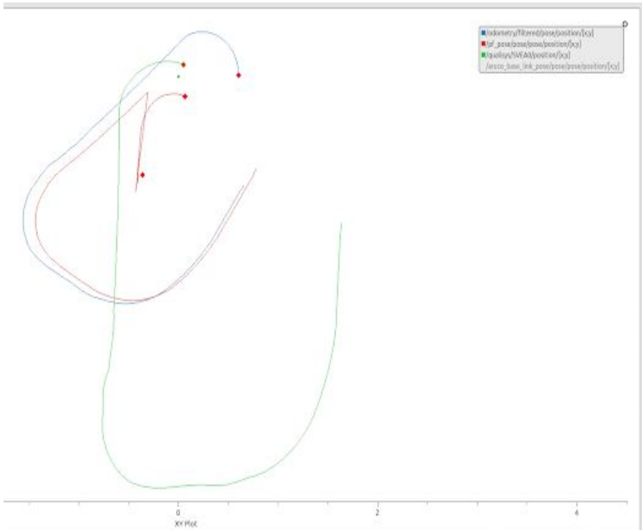

Fig 6. PF implementation (Red-PF pose)

It can be observed from Fig 5. and Fig 6. that both the filters perform as expected and we get a highly accurate estimated pose of the robot. Furthermore, it can be observed that the particle filter decreases the error as soon as ArUco marker is detected.

Fig 6. highlights the importance of observation update and its performance in both EKF and PF.

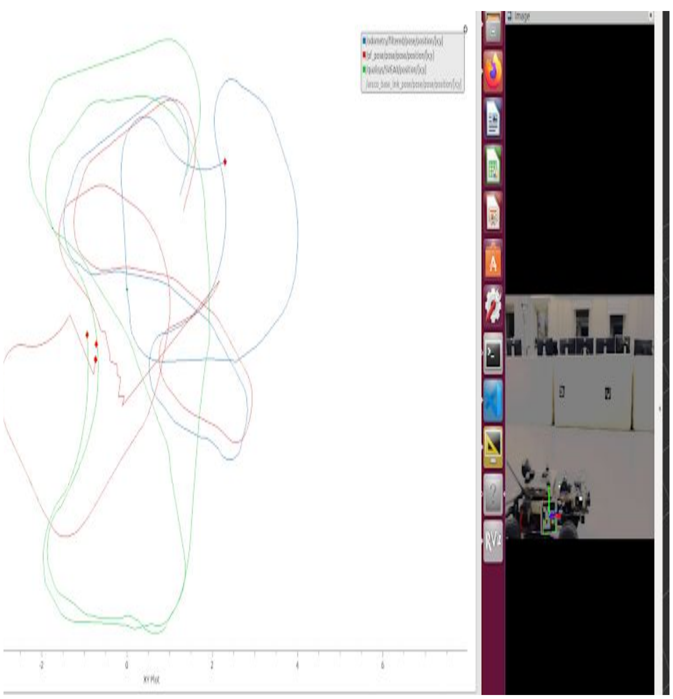

Fig 7. Observation Update (Red-PF pose)

It can be observed from Fig 7. that as soon as the ArUco marker is detected, the estimated pose of the robot by the particle filter (red line) gets updated whereas the motion model (blue line) is way off.

B. Problem 2

As described above, in problem 2, we address the issue of camera being mounted in a dynamic position (on a robot) with respect to the SVEA.

Fig 8. And Fig 9. show the results of EKF and PF applied to problem 2 respectively.

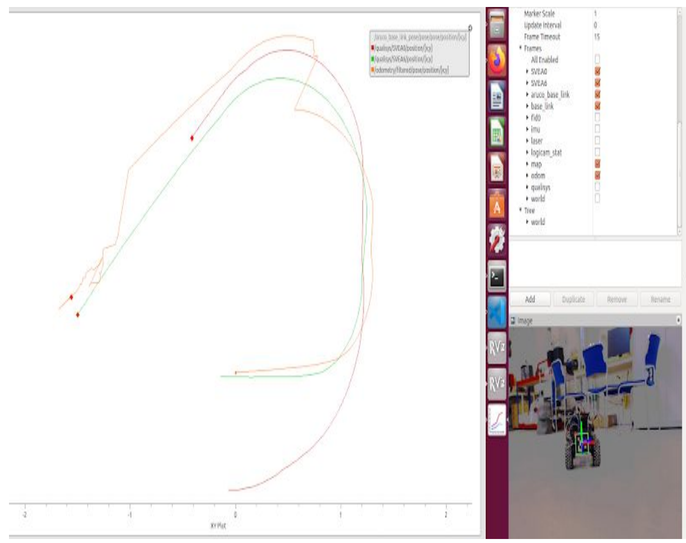

Fig 8. EKF implementation (Orange-EKF pose)

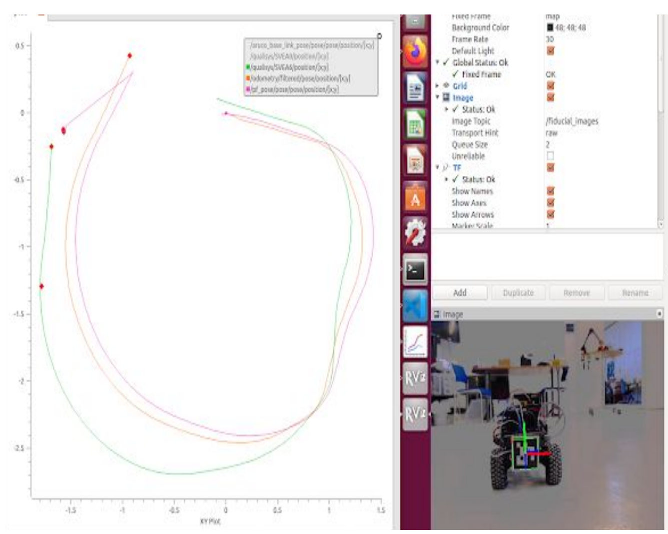

Fig 9. PF implementation (Pink-PF pose)

It can be observed in Fig 9. that although the particle filter was diverging, as soon as it saw the ArUco marker, it updated its position.

One important observation in both the problems was the importance of setting the right values for both process noise covariance and observation covariance. This is shown in Fig 10. and 11. respectively.

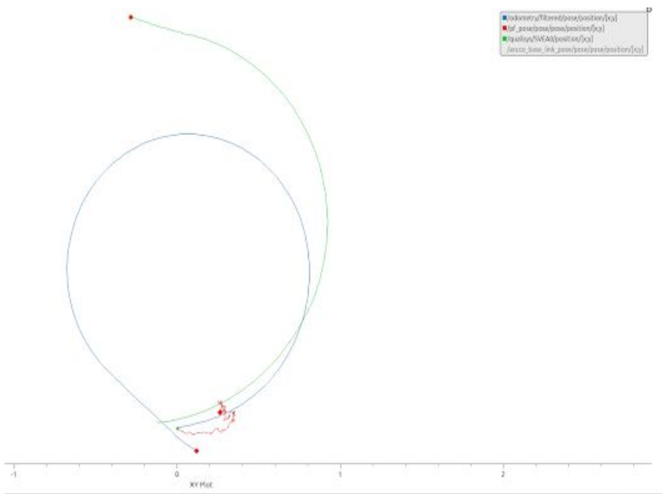

Fig 10. PF implementation (high process covariance)

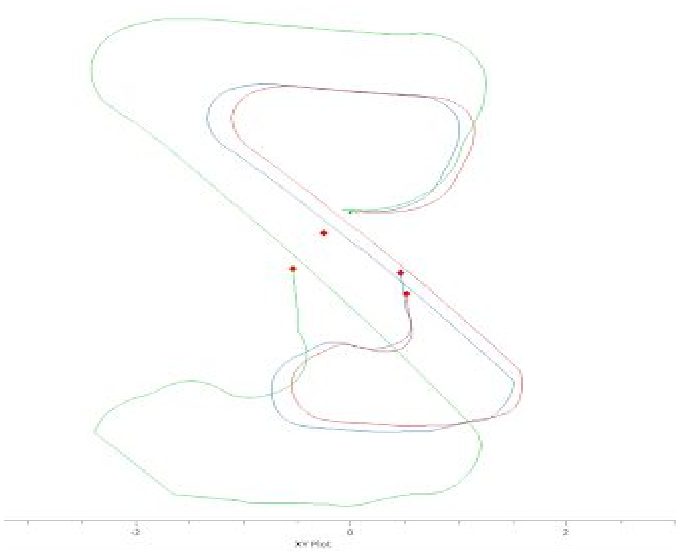

Fig 11. PF implementation (high obs. covariance)

It can be observed from Fig 10. that high process covariance leads to particle filter relying highly on no displacement at all and that all the input information is noise. Here, no aruco marker detection takes place.
Whereas, in Fig. 11, due to high observation covariance, the filter assumes that it's position is accurate enough and no update happens even though ArUco marker detection takes place.

V. CONCLUSION

This paper addresses the problem of the problem of estimating the real-time pose estimation of a mobile robot using an accurate motion model. It presents a method based on fiducial detection and different filtering techniques. It is found out that artificial landmarks such as ArUco markers work quite well in the localization problem of the mobile robot. But they have their own problems such as occlusion, intrinsic parameters calibration etc. These problems are addressed using filtering techniques such as Extended Kalman Filter and Particle Filter. It is found that the particle filtering technique works better as compared to the EKF alongside ArUco marker detection. Hence the overall system serves as a good solution to the robot localization problem. Hence, it can be concluded that we can develop a highly accurate and robust motion model using fiducial detection and filtering techniques.

VI. FUTURE WORK

In future, we would like to develop a non-linear acceleration based control method of the robot and test it at its extreme performance (velocity in our case).
Further, we would like to extend this work to a swarm of robots where only the leader of the swarm has all the necessary sensors and the other robots follow the leader using filtering methods applied to their fiducial detection and motion model

VII. REFERENCES

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