A NEW METHOD FOR DATA ASSOCIATION IN 3-D LOCALIZATION: ONE-POINT RANSAC WITH EPIPOLAR CONSTRAINT

A Thesis

by

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A NEW METHOD FOR DATA ASSOCIATION IN 3-D LOCALIZATION: ONE-POINT RANSAC WITH EPIPOLAR CONSTRAINT

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ABSTRACT

The problem of Localization or Simultaneous Localization and Mapping has received a great deal of attention within the robotics literature, and the importance of the solutions to this problem has been well documented for successful operation of autonomous agents in a number of environments. Of the numerous solutions that have been developed for solving the problems, many of the most successful approaches continue to either rely on, or stem from noise filtering techniques, especially the Extended Kalman Filter method or Particle Filtering methods. Localization problems are downgraded to a data association problem after using mentioned filters. This topic has also received a great deal of attention in the robotics literature in recent years, and various solutions have been proposed. In the thesis, first mostly studied methods, such as Joint Compatibility, Sequential Compatibility Nearest Neighbor, Joint Maximum Likelihood, one point RANSAC and epipolar consistency, are studied. As the second part of the thesis a new method is presented. One-Point RANSAC with Epipolar Constraint (OPRF) is based on RANSAC and epipolar geometry. Later the performance and consistency of the method will be compared to epipolar consistency solution.

ÖZETÇE

Konum belirleme ve SLAM problemleri robotik yayınlarında yüksek ilgi toplamış ve değişik ortamlarda, bir insansız ajanın başarı ile çalışabilmesi için önemi kaydedilmiştir. Bu problemler için bulunan çözümlerin başarılı olanları genellikle Genişletilmiş Kalman Filtreleri ve Parçacık Filtreleri gibi gürültü filtreleri temellidir. Bu problemler belirtilen filtrelerin kullanımı ile temel olarak veri eşleştirme problemine indirgenir. Bu konu üzerine de son yıllardaki robotik yayınlarında yüksek ilgi toplanmış ve çeşitli çözümler önerilmiştir.Bu tez raporunda ilk olarak en çok çalışılmış veri eşleştirme yöntemleri, örneğin Joint Compatibility, Sequential Compatibility Nearest Neighbor, Joint Maximum Likelihood, one point RANSAC ve epipolar uygunluk yöntemleri incelenmiştir. İkinci bölümde ise RANSAC ve epipolar geometri tabanlı yeni bir yöntem olan One-Point RANSAC with Epipolar Constraint (OPRF) sunulmuştur. Bu metodun epipolar uygunluk yöntemi ile performans ve tutarlılık açısından karşılaştırma sonuçları da eklenmiştir.

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NOMENCLATURE

$f(.)$	system function
$h(.)$	measurement function
k	a discrete point in time
u_k	vector of control inputs
v_k	measurement noise, $\mathcal{N}(0, R_k)$
w_k	process noise, $\mathcal{N}(0, Q_k)$
x_k	vector of the actual states
y_k	vector of the measured process outputs

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Chapter I

INTRODUCTION

1.1 Motivation

Many algorithms have appeared in the literature in recent years for tracking the 3-D pose of a moving camera in real time. With the help of this advancement, simultaneously building a structural map of the surrounding environment and localization has become possible. Such vision based localization systems have huge potential in terms of providing low cost and flexible 3-D location sensing, capable of operating with agile hand held devices and in previously unseen environments. Applications are numerous, particularly in areas such as augmented and virtual reality, in which positioning and tracking technology play a key role. However, a requirement for this potential to be realized is that these systems need to operate reliably and robustly in the presence of natural human motions, including rapid accelerations, erratic motion and sudden changes in viewpoint. Providing resistance to these real-world motion characteristics is the subject of this thesis. Specifically, we investigate how to improve the data association stage of visual localization systems. Data association is the process of obtaining correct feature correspondences between any two images and is vital for stable operation. Previous approaches rely on simple but not very discriminative matching, leading to the selection of erroneous measurements, especially during fast or erratic motions. The inherent difficulty there lies in robustly resolving data association as feature tracks become highly jerky and mismatches are far more likely.

1.2 *Literature review*

There are two root causes of failures in association: First is the uncertainty in position of robot. This failure causes all the measurements to be shifted. However if a matching method which only uses relative positions of measurements is used, the effect of this uncertainty is reduced. Second cause is the uncertainty in measurements. As each measurements have different disturbance a joint solution may be hard to settle but elimination of measurements with high disturbance lowers total uncertainty. Feature point association can be handled in a sequential order or in parallel. Additionally it can be classified according to algorithm foundation as probabilistic or deterministic. After description of two foundational concepts, mostly used and successful systems will be introduced.

1. Mahalanobis distance: Used to find the distance between two random variables (positions of estimated and measured random points). The difference from Euclidian distance is that Euclidian distance doesn't take importance of axis into account however mahalanobis distance does this by using the covariance in calculations. It is calculated as:

$$\sqrt{(z-\hat{z})^T S^{-1} (z-\hat{z})} \tag{1}$$

   where measurement function is a gaussian distribution which has mean $\hat{z}$ and covariance S.

2. Validation Gate: Is a hyperellipsoid which is surrounded by the points whose mahalanobis distance to nucleus is higher than a threshold.

1.2.1 Individual Data Association

These measurements are used when we have only one target. The base attempt is used for batch processing case. For this reason base concepts are introduced by the help of these methods.

1.2.1.1 *Individual Compatibility*

This is the most basic one it just checks if the measurement is in validation gate or not. The method is also called as Gating. Gating is the first step of almost all calculations to find association candidates. [1]

1.2.1.2 *Nearest Neighbour*

It is based on likelihood function::

$$f(i,j) = \frac{1}{\sqrt{(2\pi)^n|S|}} e^{\frac{-1}{2}(z-\hat{z})^T S^{-1}(z-\hat{z})} \tag{2}$$

Then to find the nearest neighbor the measurement which makes $f(i,j)$ maximum is chosen:

$$e_j = argmax_i(f(i,j)) \tag{3}$$

This method's computation is complex. For this reason a simplified (based on $ln(f(i,j))$) version is used. After the simplification matching becomes:

$$e_j = argmin_i(N_{i,j}) \tag{4}$$

$$N_{i,j} = (z-\hat{z})^T S^{-1}(z-\hat{z}) + ln|S| \tag{5}$$

where $N_{i,j}$ is called as normalized distance, which is based on equation (1). The method is also known as Maximum Likelihood. [2]

1.2.1.3 *Combined Individual Compatibility and Maximum Likelihood*

NN calculation is computationally heavier than IC and some of the measurements can be out of the validation gate, it is useful first eliminate outliers by gating. After that the association is calculated by NN.[2]

1.2.1.4 Probabilistic Data Association

This method calculates the association probabilities of all of the candidate measurements (in validation gate). By using these probabilities the individual measurements' innovations are integrated into a combined innovation and filtering/tracking can be carried on using combined innovation. [3]

These methods are being used for just one target. From now on we will focus on "Batch Data Association" meaning solution to data association problem of many targets simultaneously.

Prior to method description we must define a new matrix called as "joint association matrix(JAM)". The values of these matrix are normalized distances of the candidate associations, idividall compatibility satisfied pairs. [4]

1.2.2 Deterministic Methods As Batch Processing

This data association algorithm family searches for one association list which is not to be changed in feature.

1.2.2.1 Sequential Compatibility Nearest Neighbour

It is the application of "Nearest Neighbour" method of single target to many targets in a greedy manner. The implementation is based on application needs. Most simplistic method:

1. Construct JAM.
2. Choose pair with smallest normalised distance and remove all candidates with the same measurement and landmark from table.
3. Repeat second step until all the measurements have been assigned.

This algorithm is fast but not optimal (there can be a better result) as the nature of greedy algorithms.

1.2.2.2 Global Nearest Neighbour

After construction of JAM, a modified version of Munkres algorithm[5], which supports rectangular cost matrix, is used to find minimized total normalized-distances. [6] This method is also known as Joint Maximum Likelihood.

1.2.2.3 Joint Compatibility

Global nearest neighbor checks each possibility but just checks in pairs, so the result is not "global". This problem is caused by a hidden assumption behind design of NN: measurements are not correlated. This problem is handled by the concept of "joint compatibility". This method is analogous to NN case, but uses joint innovation to calculate distance. [7]. It can be calculated as:

$$D^2_{H_i} = \nu_i^T C^{-1}_{H_i} \nu_i \tag{6}$$

where ν is the innovation and C_{H_i} is the covariance of the joint innovation, defined as:

$$C_{H_i} = H_{H_i} P H^T_{H_i} + R_{H_i}$$

where H_i is the measurement matrix and R is the measurement matrix. The method constructs a tree structure (interpretation tree). The nodes are landmark-observation pairs and they are individually compatible. Each level of the tree denotes a measurement and each path from root to leaf builds up a hypothesis. General algorithm can be summarized as:

```
function Best_H = JCBB
Best_H = []
JCBB_Recursive ([], 1);


function JCBB_Recursive (H, i)
if leaf node?
```

```
        if length(H) > length(Best_H)
            Best_H = H
else
     foreach individually compatible j
         if jointly_compatible([H j])
             //(i,j) is accepted
             JCBB_Recursive([H j], i+1)


        if remaining obs are enough
            //star node: i not paired
            JCBB_Recursive([H 0], i+1)
```

where jointly_compatible function checks if D^2 (6) is less than $\chi^2_{d,\alpha}$. The last term is a Chi-squared distribution and d is dependant on length of hypothesis and where α is the desired confidence level (0,95 by default). [8]

1.2.2.4 Combined Constraint Data Association

CCDA uses two different constraints. They are absolute constraint, similar to individual compatibility, and relative constraint, similar to joint compatibility but between two pairs. CCDA algorithm uses a graph structure also. The graph's nodes are pairs those are checked with absolute constraints or all the possible pairs. The edges of the graph denotes that relative constraints between corresponding two nodes are ensured.Then the largest joint compatible association set may be found by performing maximum clique search. [4]

1.2.3 Probabilistic Methods As Batch Processing

1.2.3.1 Joint Probabilistic Data Association

The key difference of JPDA compared to PDA is the use of joint probability of the measurements. Then the method integrates the measurement with using the modified weights(probabilities) similar to PDA. [3]

1.2.3.2 Multi Hypothesis Data Association

MHDA is also called as multi hypothesis tracking (MHT) and it is based on a different [9] concept. It is a framework to let use (test) of many hypotheses first then the best ones will be chosen to survive. As it is a framework instead of a method different implementations exist. One of them can be summarized as:

1. Receive measurements

2. Hypotheses generation: Compare measurements to existing landmarks by gating. If it is a not in gate of a landmark create a new Kalman filter as it is a new landmark. Then associate measurements.

3. Reduce the number of hypotheses: In this item hypotheses are divided into clusters so the problem is reduced into smaller ones.

4. Hypotheses probability evaluation

5. Hypotheses management (i.e. pruning, elimination, creation): Hypotheses with low probability are eliminated.

6. State update

1.2.3.3 1-Point RANSAC for EKF

This [10] is a complete SLAM which integrates extended Kalman filtering steps into an iterative model selection called RANSAC[11]. This method will be detailed on thhe section 3.1.1 .

1.3 Comparison of Batch Data Association Techniques

We should define our focus and environment before comparison. Our environment will include moving objects(people). If these are handled as feature points as the locations of them will change according to statics it will lead tracking and mapping failures. This problem can be avoided by marking moving objects as outlier but practically it is impossible to classify all objects as static or moving correctly. For this reason it is better to search for joint compatibility constraints. For this reason we can eliminate SCNN and GNN. JCBB (Joint Compatibility Branch and Bound) is the most widely used data association in EKF SLAM implementations as in [8]. CCDA's results are similar to JCBB but only relative constraints are required but with a severe computational burden.

JPDA is designed for tracking moving targets so it is not directly applicable to SLAM problems. It can be extended for SLAM but results of JCBB are better. MHDA is a different concept just to use/test as many as possible hypotheses. The concept is similar to particle filters and it has several good implementations as in [12]. The same concept with inclusion of RANSAC is implemented in [10], and it is computationally more feasible and better matches to EKF.

1.4 Contribution of the thesis

This thesis is concerned with the robustness and tractability issues for practical stochastic localisation in large-scale, particularly outdoor, environments. Specific contributions are made towards reliable data association within an Extended Kalman Filtering framework. The principal contribution of this thesis is the development of a new method for 2-D feature matching based on a combination of the epipolar constaint and a RANSAC based hypothesize-and-test procedure.

1.5 Outline of the thesis

This thesis describes the progress towards solving the data association problem in localization associated with a scene appearance approach. The rest of the thesis is composed as follows: Chapter 2 summarizes the background knowledge on Kalman Filter and Extended Kalman Filter and various solutions to data association problem.

Chapter 3 presents the proposed method for 2-D feature matching for data association. Experimental results are given in Chapter 4. Chapter 5 concludes with a summary of the contributions of the thesis and provides a general discussion of ideas for future research.

Chapter II

BACKGROUND

In this chapter Extended Kalman Filters and their base Kalman Filters will be described. Then most important data association techniques which are available on literature and in conjunction with Kalman Filtering approaches will be described.

2.1 Overview of Kalman Filtering

Kalman Filters(KF) are a form of process state estimator as a predictor-corrector loop.

Aim of KF is to estimate unmeasured states and the actual process outputs solving below two equations at the same time.

$$x_k = A_k * x_{k-1} + B_k * u_k + w_{k-1} \tag{7}$$

$$y_k = C_k * x_k + v_k \tag{8}$$

KF assumes A_k, B_k, C_k are constant matrices and the noises w_k, v_k are independent of each other.

The Kalman filter uses a two step predictor-corrector algorithm. The first step involves projecting both the most recent state estimate and an estimate of the error covariance (from the previous time period) forwards in time to compute a predicted (or a-priori) estimate of the states at the current time.

$$\hat{x_k^-} = A_k * \hat{x_{k-1}} + B_k * u_k \tag{9}$$

$$P_k^- = A_k * P_{k-1} A_k^T + Q_k \tag{10}$$

The second step involves correcting the predicted state estimate calculated in the first step by incorporating the most recent process measurement to generate an updated (or a-posteriori) state estimate.

$$K_k = P_k^- * C_k^T * (C_k * P_k^- * C_k^T + R_k)^{-1} \tag{11}$$

$$\hat{x_k} = \hat{x_k^-} + K_k * (y_k - C_k + \hat{x_k^-}) \tag{12}$$

$$P_k = (I - K_k * C_k) * P_k^- \tag{13}$$

In the above equations P_k is an estimate of the covariance of the measurement error and K_k is called the Kalman gain.

2.2 Overview of Extended Kalman Filtering

The drawback of KF is the necessity of linearity of system equations. To overcome this necessity, second and higher order terms of system equations' Taylor expansion replacement is removed and linearity is conserved.

And the system functions are more generalized forms as:

$$x_k = f(x_{k-1}, u_k, k) + w_{k-1} \tag{14}$$

$$y_k = h(x_k, u_k, k) + v_k \tag{15}$$

However, due to the non-linear nature of the process being estimated the covariance prediction and update equations cannot use f and h directly. Rather they use the Jacobian of f and h.

As with the original Kalman Filter, the Extended Kalman Filter uses a two step predictor-corrector algorithm. The first step involves projecting both the most recent state estimate and an estimate of the error covariance (from the previous time period) forwards in time to compute a predicted (or a-priori) estimate of the states at the current time.

$$\hat{x_k^-} = f(\hat{x_{k-1}}, u_k, k) \tag{16}$$

$$P_k^- = F_{k-1} * P_{k-1} * F_{k-1}^T + Q_k \tag{17}$$

where:

$$F_k = \left.\frac{\partial f}{\partial x}\right|_{(\hat{x_k}, u_k, k)} \tag{18}$$

The second step involves correcting the predicted state estimate calculated in the first step by incorporating the most recent process measurement to generate an updated (or a-posteriori)state estimate.

$$K_k = P_k^- * H_k^T * (H_k * P_k^- * H_k^T + R_k)^{-1} \tag{19}$$

$$\hat{x_k} = \hat{x_k^-} + K_k * (y_k - h(\hat{x_k^-}, u_k, k)) \tag{20}$$

$$P_k = (I - K_k * H_k) * P_k^- \tag{21}$$

where:

$$H_k = \left.\frac{\partial h}{\partial x}\right|_{(\hat{x_k}, u_k, k)} \tag{22}$$

In the above equations Pk is an estimate of the covariance of the measurement error and Kk is called the Kalman gain.

If the process is linear then the above equations collapse to the equations of the original (i.e. linear) Kalman Filter. However, unlike the Kalman Filter, the Extended-Kalman Filter is not optimal in any sense. And further, if the process model is inaccurate then due to the use of the Jacobians – which essentially represent a linearization of the model – the Extended-Kalman Filter will likely diverge leading to very poor estimates.

However, in practise, and when used carefully, the Extended-Kalman Filter can lead to very reliable state estimation. This is particularly the case when the process being estimated can be accurately linearized at each point along the trajectory of the states.

2.3 Description of the RANSAC Algorithm

RANSAC is an abbreviation for "RANdom SAmple Consensus". It is an iterative method to estimate parameters of a mathematical model from a set of observed data which may contains outliers. It is a non-deterministic algorithm in the sense that it produces a reasonable result only with a certain probability, with this probability increasing as more iterations are allowed. The algorithm was first published by Fischler and Bolles in 1981.

The basic assumption is that the data consists of "inliers", i.e., data whose distribution can be explained by some mathematical model, and "outliers" which are data that do not fit the model. Outliers could be considered points which come from noise, erroneous measurements or simply incorrect data. RANSAC also assumes that, given a set of inliers, there exists a procedure which can estimate the parameters of a model that optimally explains or fits this data. The basic algorithm is summarized as follows:

- Select randomly the subset of points required to determine the model
- Calculate the model
- Determine how many points from the set of all points fit with a predefined tolerance
- If the fraction of the number of inliers over the current maximum, update loop limit and set it as current maximum
- repeat first four steps until loop limit is reached

The number of iterations, N_{hyp}, is chosen high enough to ensure that the probability p (usually set to 0.99 but can be lowered) that at least one of the sets of random samples does not include an outlier. Let u represent the probability that any selected data point is an inlier and $v = 1 - u$ the probability of observing an outlier. N_{hyp} iterations of the minimum number of points denoted m are required, where

$$1 - p = (1 - u^m)^{N_{hyp}} \tag{23}$$

and thus with some manipulation,

$$N_{hyp} = \frac{\log(1 - p)}{\log(1 - u^m)} \tag{24}$$

2.4 Fundamental Matrix

Below figure shows the formation for stereo vision. The application of projective geometry to this situation results in the epipolar geometry approach. The three points COP_1, COP_2, P form what is called an epipolar plane and the intersections of this plane with the two image planes form the epipolar lines. The line connecting the two centers of projection COP_1, COP_2 intersects the image planes at the conjugate points e_1 and e_2 which are called epipoles. For a 3D point P, that projects into the two image planes as the points p_1 and p_2 which are expressed in homogeneous coordinates $u_1, v_1, 1$ and $u_2, v_2, 1$ respectively. After some manipulations, the main result of the epipolar geometry is that the following linear relationship can be written.

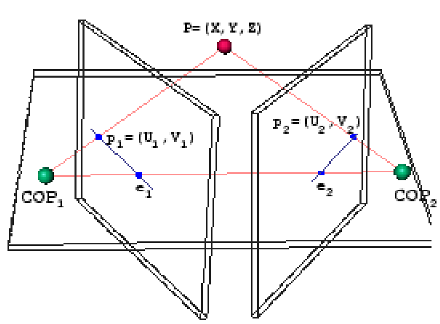

Figure 1: Epipolar geometry

$$(p_1)^t * F * p_2 = 0 \tag{25}$$

Here, F is the so-called fundamental matrix which is a 3 x 3 entity with 9 parameters. However, it is constrained to have rank 2 (i.e. $\|F\| = 0$) and can undergo an arbitrary scale factor. Thus, there are only 7 degrees of freedom in F. It defines the geometry of the correspondences between two views in a compact way, encoding intrinsic camera geometry as well as the extrinsic relative motion between the two cameras. In addition, the structure of the scene is eliminated from the estimation of F and can be recovered in a separate step. Given the matrix F, identifying a point in one image identifies a corresponding epipolar line in the other image.

The fundamental matrix defiines the replacement of corresponding pixels in different frames. Therefore using the calculated replacement it can be calculated. In described method fundamental matrix is calculated by using the model (EKF update output) by using the formula:

$$F = (K^T)^{-1} * R * [R^T t]_x * K^{-1} \tag{26}$$

Chapter III

METHOD

3.1 Data Association Techniques Used in EKF Based Tracking

In this section a brief introduction to the system base to OPRF is found.

3.1.1 1-Point RANSAC for EKF

This [10] is a complete SLAM which integrates extended Kalman filtering steps into an iterative model selection called RANSAC[11]. Before describing the method RANSAC should be introduced.

RANSAC is a non-deterministic method as it tests many hypothesis, model, which are initiated by randomly selected samples. The algorithm can be summarized as follows:

1. Randomly select the points, and determine model parameters. (number of the points is m)

2. Determine the number of inlier for the selected model.

3. Repeat first two steps enough number, N_{hyp}, times.

4. Choose the model with highest number of inlier, discard others.

5. Update model parameters using selected inlier.

For RANSAC the number of required hypotheses (N_{hyp}) is the most critical parameter that define number of iterations. And the relation between N_{hyp} and m is given as:

$$N_{hyp} = \frac{log(1-p)}{log(1-(1-\epsilon)^m)} \tag{27}$$

1	initialize hypothesis number (N_{hyp}) as a big value
2	randomly pick one match and update model
3	reproject all matches by using new model
4	calculate Euclidian distances for each pairs
5	mark pairs as inlier or outlier by using a threshold
6	if the inlier number is more than inlier set1 then update inlier set1 as inlier and update N_{hyp}
7	repeat steps 2-6 N_{hyp} times
8	update model by using inlier set1
9	reproject all matches of outlier set1 by using new model
10	calculate Euclidian distances for each pairs
11	mark pairs as inlier or outlier by using a threshold
12	if the inlier number is more than inlier set2 then update inlier set2 as inlier and update N_{hyp}
13	merge both inlier sets

Table 1: One Point RANSAC

where p is the probability that at least one spurious-free hypothesis has been tested, and ϵ is the outliers ratio and m the minimum number of data points necessary to instantiate the model. Therefore hypotheses number is lowered exponentially by lowering m.

By this fact the method uses one point and priori information of the state.

In the algorithm a sample match is selected randomly from all available matches for that frame. Using that match and priori state information new state is calculated by the help of EKF update procedure. Then by projecting all the matches distance between feature point and landmark is calculated. If the distance is lower than a threshold, the pair is marked as an inlier. If inlier number is higher than mark the set as inlier and update hypothesis number. As a second stage of the algorithm the a new state is calculated by using inliers, and all steps are repeated on outliers. Table 1 illustrates the algorithm.

3.1.2 Data Association by Fundamental Matrix Calculation

Data association is basically inlier detection. This definition also holds for Fundamental Matrix calculation. Current method also utilizes RANSAC to test subgroups

1	initialize hypothesis number (N_{hyp}) as a big value
2	randomly pick m match and calculate fundamental matrix
3	calculate epipolar consistency
4	mark pairs as inlier or outlier by using a threshold
5	if the inlier number is more than inlier set then update inlier set as inlier and update N_{hyp}
6	repeat steps 2-5 N_{hyp} times

Table 2: Data Association by Fundamental Matrix Calculation

of required size. The flow can be summarized as:

1. Randomly select the points, and determine Fundamental matrix. (number of the points is m)

2. Determine the number of inlier for the selected model.

3. Repeat first two steps enough number, N_{hyp}, times.

4. Choose the model with highest number of inlier, discard others.

5. Update model parameters using selected inlier.

The outputs of this algorithm is the model [13] (Fundamental matrix) and inlier set. Fundamental matrix determination requires a determined size of input points. Therefore large size requirements make RANSAC to test many combinations which will make all the system to be slow. Table 2 illustrates this algorithm.

3.2 Proposed Method For Data Association in EKF Tracking

The method is selected to be probabilistic typed because the deterministic ones can propagate position and measurement uncertainties further. Probabilistic approaches might lower the failures by applying try-see concept. However this gain must be over-bound as incrementing the number of trials may increase success ratio but also increases the time exponentially. For this reason the parameters that has effect on this ratio must be selected while application scenario is in mind. The method is based on RANSAC algorithm to generate subsets of measurement points to update robot position by the help of EKF update and to check the consistency. The subsets are used to generate model or robot position. Then this model is used to find the consistent points out of the measurements for associated frame. The model generation is achieved by an EKF update procedure. The selected subset and outputs of EKF prediction, prior to the data association are the inputs of this step. Output position of EKF update is the model to be used in consistency calculations. The next step is to count consistent points. To calculate it all the map landmarks which match to current feature points are projected to frame coordinates using the model. Then the distances are calculated between feature points and reprojected landmark matches by using $(p_1)' * F * p_2$ formula. In this formula p_1 and p_2 are measurements and landmark projections and F is the fundamental matrix calculated by the model.The matches which have distances lower than a threshold is assumed to be consistent. This threshold is predetermined value, which is set according to sensor and application environment. Lowering the value will lower probability that the chosen match will be consistent. Therefore more selections will be tested and this will increase the overall time. However a very big value will enable wrong matches to be associated.

Here is the overview of whole system:

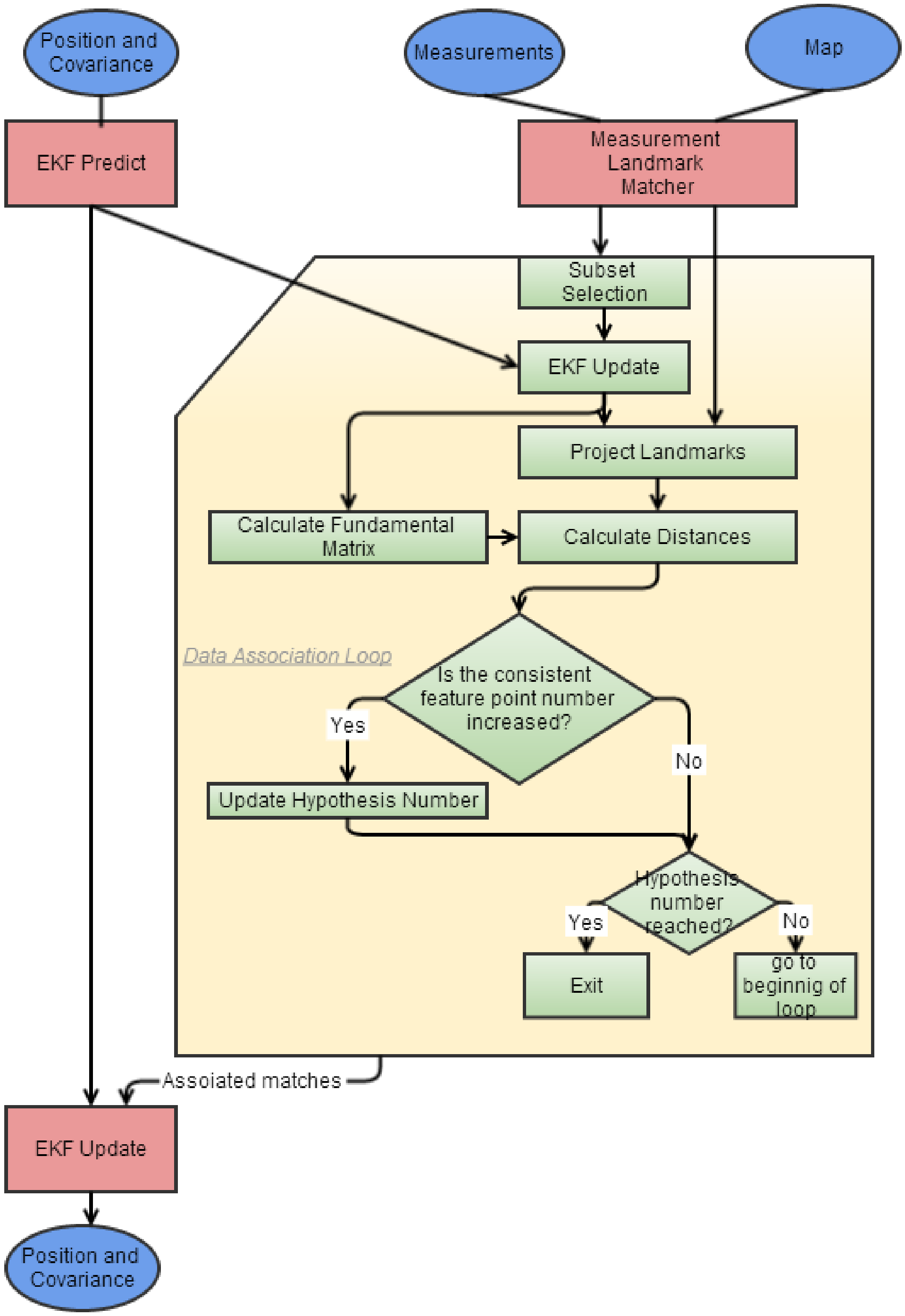

Figure 2: The whole system

The steps of data association are

Subset Selection: Randomly select one pair from all matches.

EKF Update: Update the state with the selected pair as measurement. Update procedure is same as EKF measurement update stage.

Project Landmarks: Project matched landmarks by using the new state.

Calculate Fundamental Matrix: Calculate it by using the equation (26)

Calculate Distances: The distances are the output of epipolar consistency equation (25)

Is the feature point number increased: Count the consistent pair number and check if it is larger than the best.

Update Hypothesis Number: Update hypothesis number by using equation (24) and mark the set as the best.

Hypothesis number reached: Are the above procedures repeated hypothesis number times?

Chapter IV

RESULTS

The algorithms are tested in an EKF loop for localization and the prerecorded ground truth values with additional noise. Therefore real use scenario with controlled noise can be simulated.

First step of the main loop is introducing noise on input. This step is very important to be able to evaluate algorithm performance as a function of noise level. Then normal loop begins with an EKF predict procedure. After that data association step is completed and position is updated by EKF update procedure as the last step.

The test loop is implemented as:

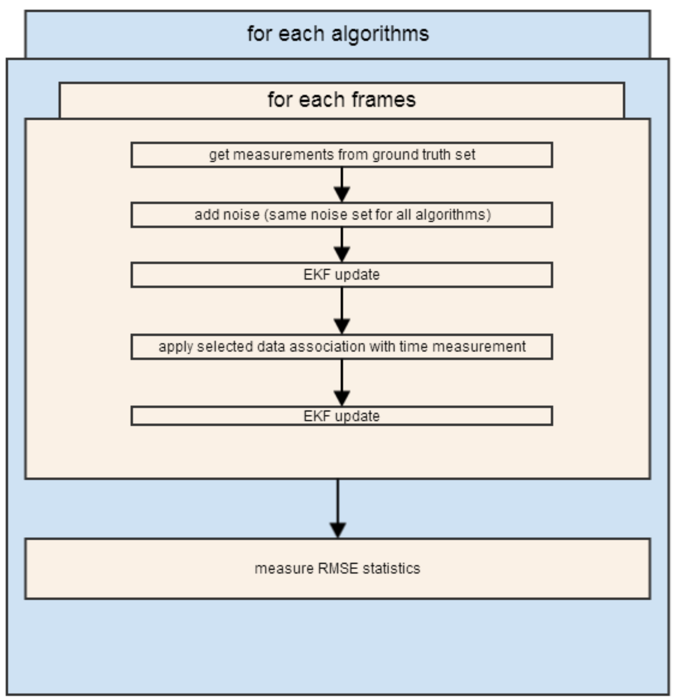

Figure 3: Environment for test evaluation.

In this loop there are two different criteria to be used to compare the method. First is the time spent in data association, next is "root mean square error" of output position of one loop step.

The main sources of noise can be classified as three different types. First is the noise in measurements,second is the noise in control input and the last one is failures in matching proses before the loop step. In our tests measurement noise and matching error has ranges from 5 to 20 percents, and the noise on control input is ranged from 0 to 10 percent. These values are selected to simulate real use better.

The measurements those are used as evaluation parameter are the average of data association process times and RMSE of EKF output position. Comparison of these values for the selected algorithms are demonstrated for each noise type to be able to criticize them.

Test results will be categorized into three groups according to noise applied input. First group is variable noise levels on measurements, second is variable noise levels control inputs and the latter is variable noise levels on measurement-landmark matches.

The next figure shows the effect of noise of measurements on process time of suggested(OPRF) and fundamental matrix data association algorithms.

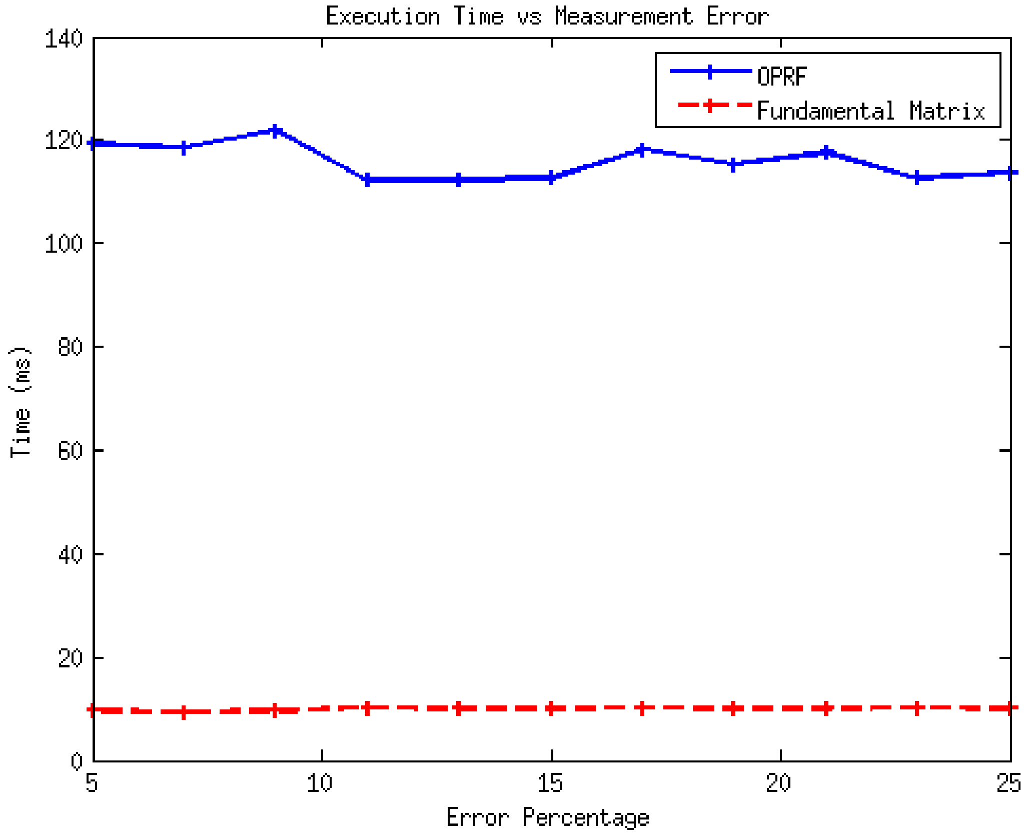

Figure 4: Time change according to measurement noise.

In the above figure it seems that measurement noise level almost has no effect on times, but if the consistency threshold levels were selected as lower, times will increase as increasing noises.

The next figure shows the effect of noise of measurements on result correctness of suggested(OPRF) and fundamental matrix data association algorithms and no data association.

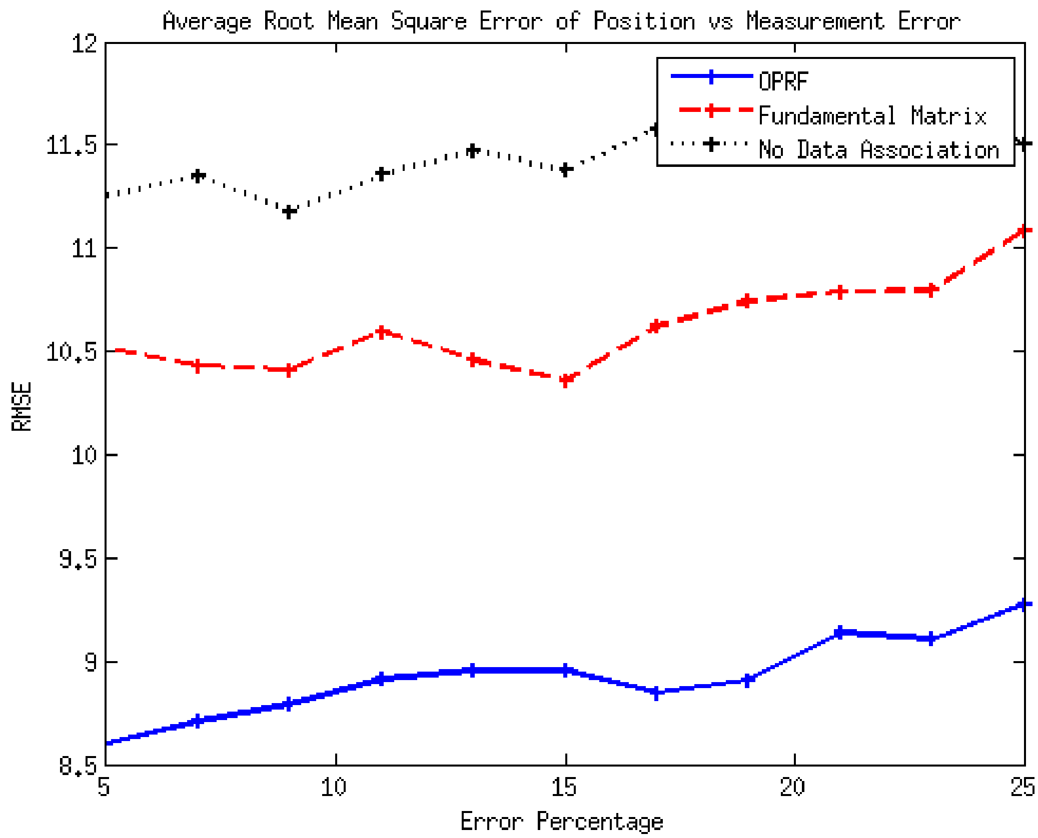

Figure 5: Error in position according to measurement noise.

In the above figure it seems that measurement noise level almost has linear but little effect on RMSE. Also it can be noted that OPRF has a better quality

The next figure shows the effect of noise of control inputs on process time of suggested(OPRF) and fundamental matrix data association algorithms.

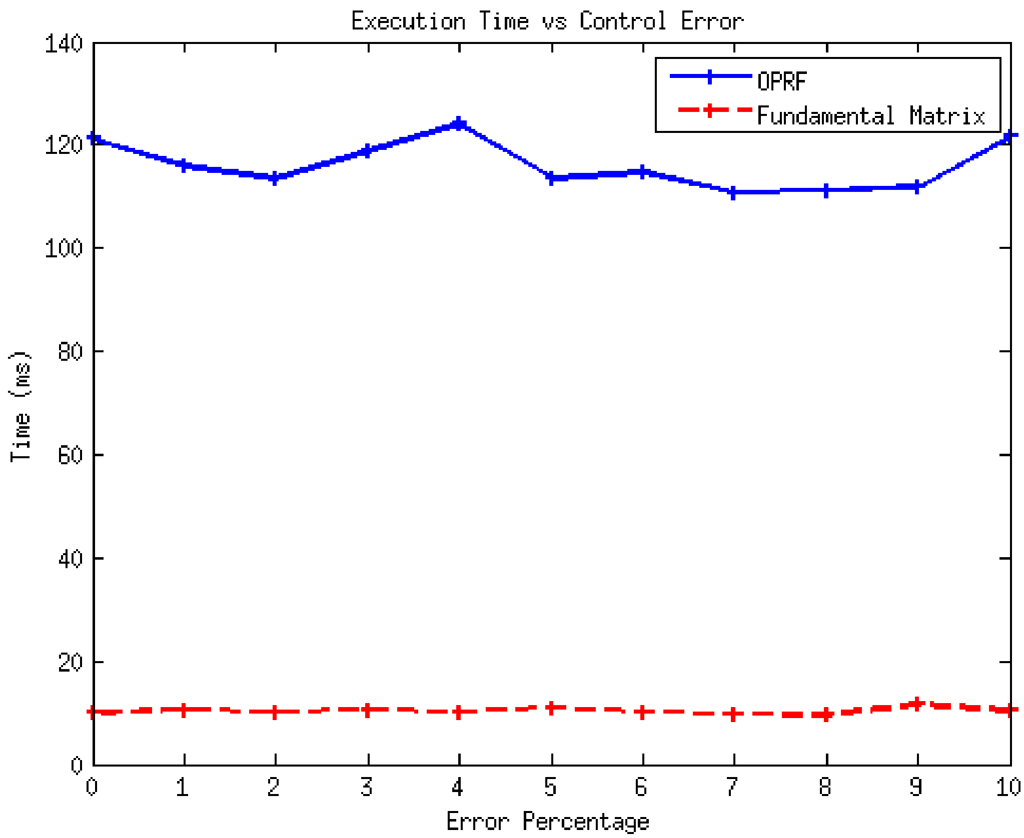

Figure 6: Time change according to control input noise.

In the above figure it seems that different noise levels on control input almost has no effect on times.

The next figure shows the effect of noise of control inputs on result correctness of suggested(OPRF) and fundamental matrix data association algorithms and no data association.

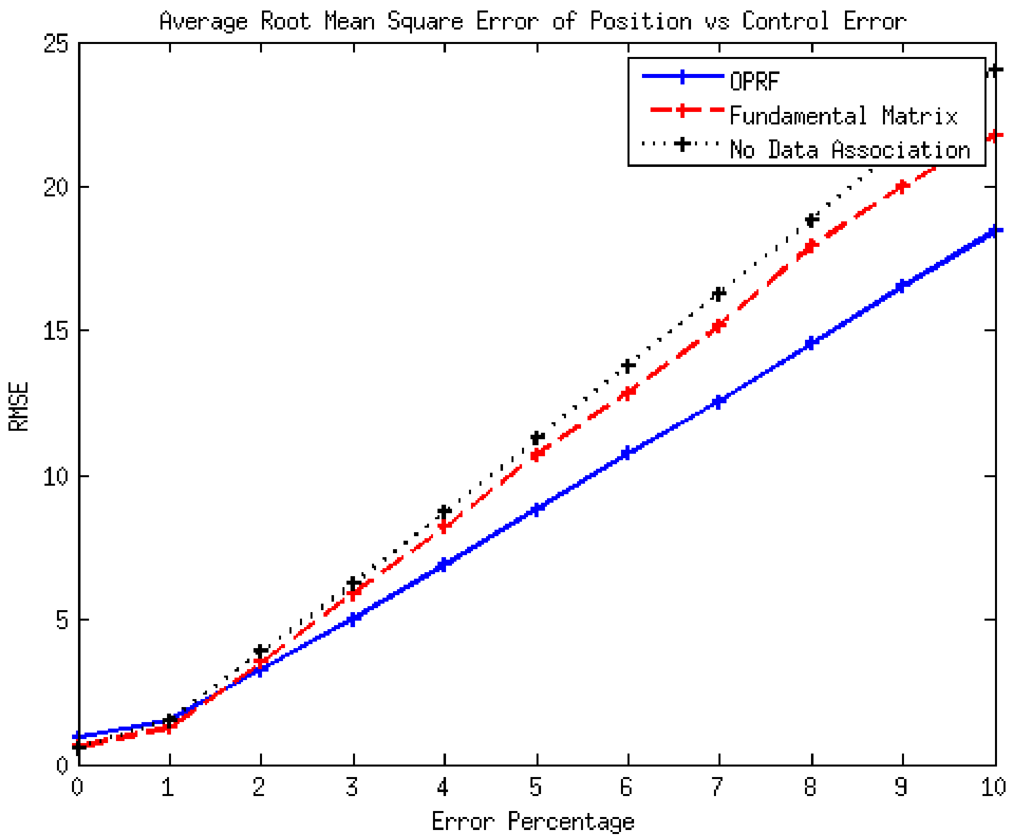

Figure 7: Error in position according to control input noise.

In the above figure it seems that different noise levels on control input almost has linear effect on RMSE. Also it can be noted that OPRF has a better quality

The next figure shows the effect of noise of matchings on process time of suggested(OPRF) and fundamental matrix data association algorithmse.

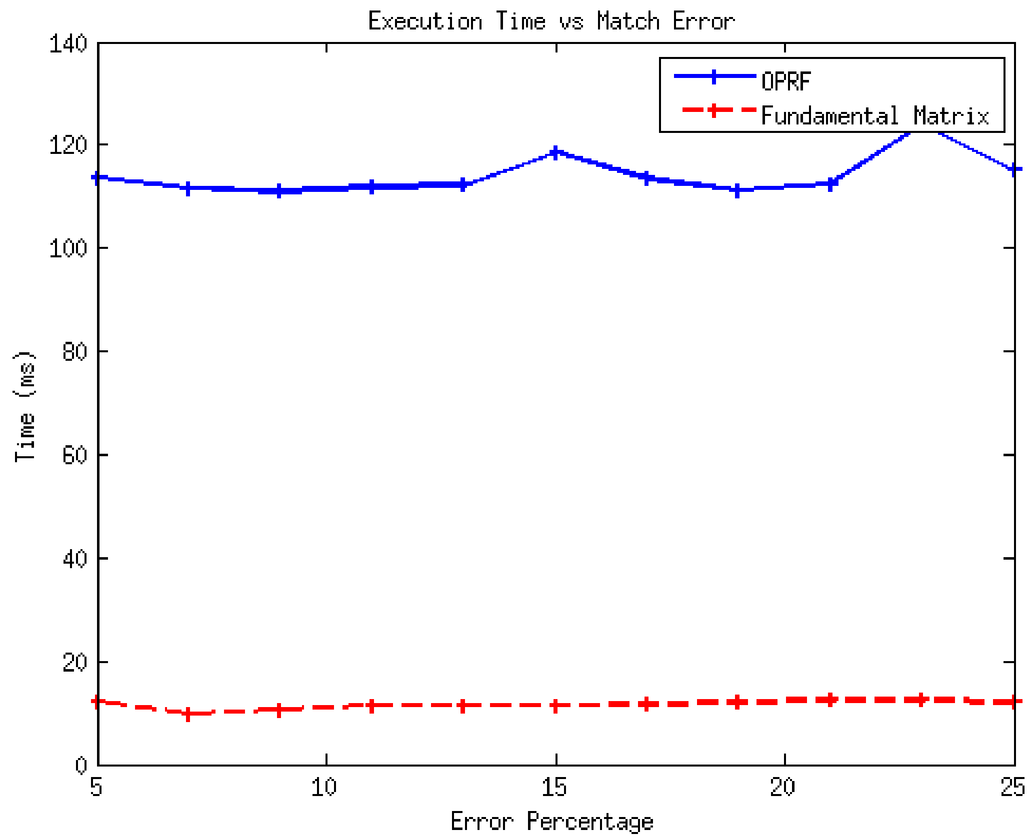

Figure 8: Time change according to matching error.

In the above figure it seems that different noise feature match error levels almost has no effect on times.

The next figure shows the effect of noise of matchings on result correctness of suggested(OPRF) and fundamental matrix data association algorithms and no data association.

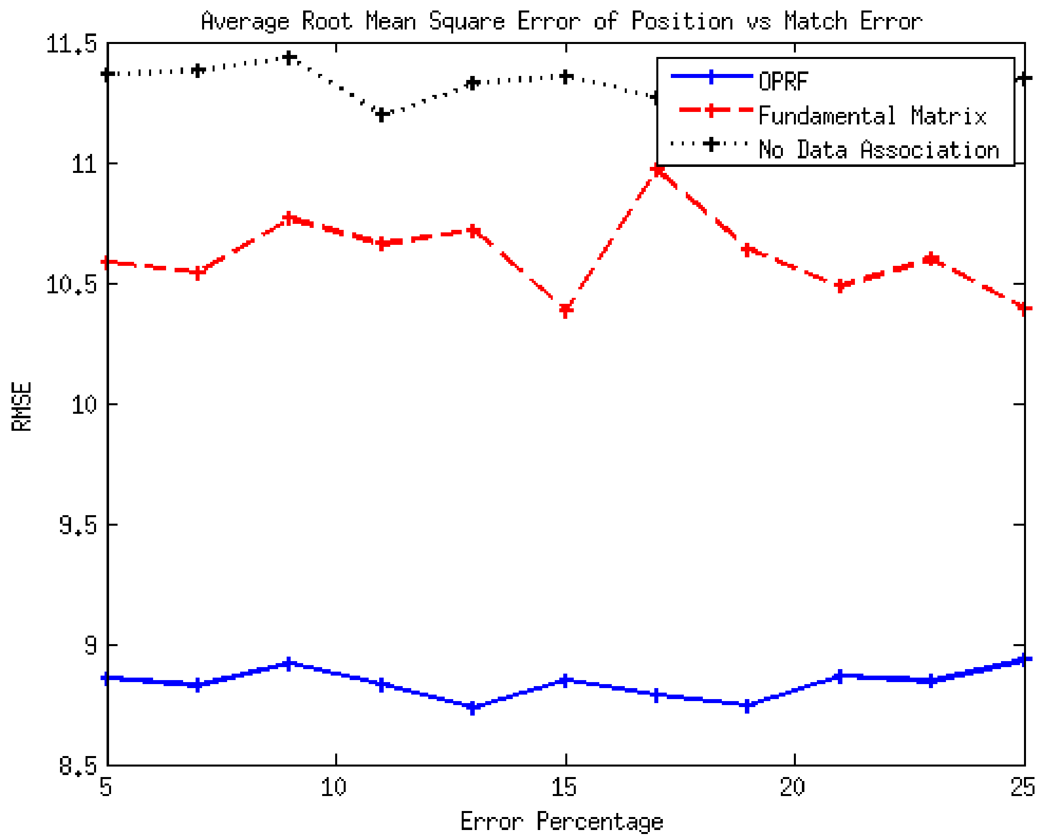

Figure 9: Error in position according to matching error.

In the above figure it seems that different feature match error levels has linear but little effect on RMSE. Also it can be noted that OPRF has a very good quality

The results show that OPRF has superior quality in the presence of measurement noise and match error. It is still better in the presence of noise on control input, but the error increases almost linearly with noise. It is caused by mis-projection of all the landmarks. To overcome this error it is recommended to use Particle Filter instead of EKF in the main loop. However times are not as good as fundamental matrix data association algorithm because of projection all teh measured landmarks fr each selected subset.

Chapter V

CONCLUSION

This thesis attempts to create a reliable and robust localization application in the existence of natural human movements. To overcome error propagation failures caused by erratic movements, mostly seen in deterministic data association algorithms, probabilistic ones are introduced. However they have also difficulties

- Reliable data association given large uncertainties in the vehicle position.
- The representation of landmarks that are not suited to simple geometric classification.
- The reliable detection of cycles (loops) in the map and consistent map update on loop closure.

This thesis presents solution to data association problems and verifies practical utility through experimental applications in outdoor environments (i.e., hand held camera, natural human movements ...). This chapter summaries the contribution of this thesis and proposes a set of future direction for completing and extending this work.

5.1 Contributions of the thesis

This thesis is concerned with the robustness and tractability issues for practical stochastic localisation in large-scale, particularly outdoor, environments. Specific contributions are made towards reliable data association within an Extended Kalman Filtering framework.

This thesis presents the following contribution for localization. A batch data association method called one point ransac with epipolar correspondence (ORPF) is developed, which permits robust association in cluttered environments with high performance.

The theoretical contributions of this thesis contain comparison of main data association methods in literature and also introduction of a new one.

5.2 Future work

In the described method linearization is used. That can cause to mismatches. For this reason model generation step can be changed if the performance of result is satisfactory.

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