Fuzzy Landmark Detection in Simultaneous Localisation and Mapping for Agricultural Robots

B. S. Blackmore[1], S. Choudhury[2]

[1] University of Thessaly, Department of Crop Production, Volos, Greece
[2] Indian Institute of Technology, Kharagpur, India

simon@unibots.com
sanjiban.choudhury@gmail.com

ABSTRACT

This paper deals with the problem of landmark detection for application of Simultaneous Localization and Mapping (SLAM) for agricultural robots. A new method of using a fuzzy rule base for fast evaluation of landmarks based on its measurement error, amount of dynamic nature, need for a landmark and evaluation time has been proposed. The output of the fuzzy system is a multiplier which represents the degree of uncertainty of the landmark. High values of uncertainty results in landmarks being discarded, average values results in revaluation, and smaller values result in acceptance with the error covariance being a product of the multiplier and the measured covariance. Selected landmarks with corresponding error covariance are used to update the Kalman Filter. Simulations show the effectiveness of the fuzzy system in improving the relative position uncertainty.

Keywords: Autonomous vehicles, SLAM, Fuzzy Landmark Detection

1. Introduction

Simultaneous Localisation and Mapping (SLAM) is one of the major issues being researched in the world today. As the name suggest, for any robot to satisfy its usage in the day to day working environment, knowledge of the robot's position and information about the environment surrounding it is of the highest importance. Essentially, the process of SLAM comprises a twin fold technique – the identification of landmarks, i.e., points of reference on the map, and the alignment of sensor readings to find a best estimated location of the robot. Both these steps depend heavily on the type of environment in which the robot navigates. Wang, Thorpe and Thrun (2003) [10] solved the problem of SLAM on outdoor vehicles navigating in a relatively crowded area.

The case of an agricultural robot is different from the cases handled before because of several reasons. Primarily, the robot is designed to work in isolated outdoor areas, with mostly sparse landmarks. This implies that precision is not as key a factor as instalment cost, time and skills. Given such conditions, there are cases where landmarks are mostly static, while some being partially static. Most of the measurement errors of the landmarks are unknown and movement models of landmarks cannot be predicted either. Landmarks may range from stable rocks in the area to quasi-stable objects like a waving tree or beam. Uneven ground may cause abnormal disturbance to laser-scanners which may give false impressions of oscillating landmarks.

Subjected to these conditions, certain constraints arise. Normally, techniques eliminate dynamic characteristics in the observed environment, and rely solely on the static landmarks. Such a step in an already sparse environment would result in loss of relative accuracy. The existing methods do not consider any other factors into consideration – the present uncertainty in position of the robot, the time spent evaluating the nature of the landmark, the displacement of the landmark in the case of it being dynamic.

1

2. Related Work

Blackmore et al. (2002a) [2] argued that autonomous vehicles for agricultural operations should behave sensibly in a semi-natural environment, over long periods of time, unattended, whilst carrying out a useful task. This requirement demanded a robust system architecture which is compatible in a partial or unknown environment and capable of dealing with partial failure.

The dynamic nature of landmarks during the process of SLAM is a well researched topic and has various categories specific to certain conditions. The categories are as follows: objects which have move with every sensor update and objects which have known to have moved at least once. Objects that are oscillatory in motion and primarily have zero net displacement falls under the dynamic category in these papers and are consequently removed from the SLAM process.

Haehnel et al. (2002) [5] suggested a technique of determining dynamic nature on the basis of mismatch of sensor readings. Usage of Sample based Joint Probabilistic Data Association Filters have been applied to achieve the same. In Wang and Thorpe (2002) [9] a combination of SLAM and DTMO (Detection and Tracking of Moving Objects) is proposed, which performs dynamic nature elimination via scan matching algorithms. Moving objects in the robot's view is tracked and updated, improving the nature of the map. These techniques, primarily suited to rapidly changing dense environments, do not include changes happening outside the vision radar of the robot.

To account for changes occurring at all points of time, Biswas et al. (2002) [1] used a Bayesian approach to compare multiple maps taken at different points of time. By identifying the various temporal features, it removed elements that changed over time. Haehnel et al. (2002) [5] implemented the EM (Expected Maximization) that was an offline solution. During the Expectation step, it computed various measurements that might pertain to static landmarks, while in the maximization step, the position of the robot was found. Wolf and Sukhatme (2003) [11] presented an online mapping algorithm which differentiated between static and dynamic elements of the map, irrespective of the feature changing in the robots view. Thus in a controlled environment, this technique ensures that all objects in the robots history is accounted for.

The existing work shows that either the dynamic landmarks were treated as purely moving targets and tracked or as unnecessary distractions and ignored. However, both methods treat the outcome of a dynamic landmark in too definite a fashion. Presented in the next section is the framework of a new scheme for landmark selection, keeping scarcity of information and flexibility of outdoor systems in mind.

3. Fundamentals behind the proposed framework

As discussed in the previous section, dynamic landmarks need a systematic evaluation, which till now was purely based on an exclusive mathematical framework. However, specific to this application, a need to incorporate selectivity into the framework is required. Thus the spine of the framework is based on the underlying hybrid behaviour, consisting of deterministic and reactive behaviours.

Deterministic part of the behaviour ensures mapping and localisation to be dependent on a set of rules which govern landmark selection, landmark evaluation and landmark updating. Mathematically speaking these rules set the accepted values for covariance of measurement errors of robot position, time taken up by the SLAM process, frequency of localisation and other criteria. The rule base governing these factors is set based on current action undertaken by the robot. For example, the process of preliminary mapping of the ground would require relaxed techniques, while the process of moving in between rows would require much more accurate calculations. The word 'deterministic' is used since these fundamental laws are decided by the expert system of a farmer, specifically customized to his requirements. As a result these factors represent the demand the farmer requires from his side – be it speed of the system or accuracy of robot under different conditions.

Reactive behaviours are independent of processes and rather account for the ambient uncertainty. Unlike deterministic parameters, these factors are primarily local to a particular landmark being evaluated. For any given landmark, it has its own degree of dynamic nature, mathematically modelled by deviation of its median and deviation of its mean. These inputs represent the factors the farmer cannot be expected to determine like degree of uncertainty of a landmark.

The deterministic and reactive inputs are fed into a fuzzy rule base, which tries to find a fuzzified best fit solution matching the deterministic criteria as well as the reactive ones. A fuzzy system is very useful in this application because it lends the flexibility that a robust system requires. Certain deterministic criteria may be relaxed if a reactive criterion is being satisfied better, and thus the robot isn't unnecessarily cut off from vital information. Also cumulative failures in being able to satisfy deterministic as well as reactive criterion add up in such a system, and thus prevent partial failures in the localisation system. In this paper, it has been shown how the proposed system handles partial failures and is tolerant to dynamic nature to a certain extent.

3.1 Detection of Landmarks

This is the first stage of the SLAM process. Robots are equipped with sensors such as laser scanners, which detect the environment around and return proximity of obstacles. Many standard techniques are there to extract landmark depending on the environment. Spike landmark approach is one. [7].

In addition to using static and quasi-static obstacles as landmarks, predefined landmarks may be mentioned. For example, a field may have intentional cicular posts so that robot senses it as a landmark with a very high confidence rating. Ryde and Hu (2005) [8] suggested means of landmark detection by both Range Weighted Circular Hough Transform as well as a novel squared-residual voting strategy.

This detection stage is usually a decoupled process from localisation, since after approximating and computing, it generates the coordinates of landmarks which then is compared, accepted or rejected. However the framework requires much more information from the detection stage. The decision about the nature of landmark requires information like deviation of estimated centre of the pole.

3.2 Kalman Filters

In the interest of simplicity as well of ensuring robustness, a linear KF [6] will be used; however the robot model is not linear [14].

4. The Fuzzy Framework

Once a landmark is detected, certain key features are extracted from the landmark, which adequately represent all desirable properties of the landmark. These features are use to classify a landmark as either static, or dynamic, or quasi-static. They should also convey the measurement error associated with a landmark. These features clubbed together represent landmark specific variables.

Landmark specific variables are not enough to determine inclusion of it for calculation. Certain global factors play a huge role in determining if the landmark is needed or not, whether the current process in question requires more accuracy or less, how much of landmark evaluation time is in hand, the present position uncertainty of the robot. These variables together are called global variables.

These two sets of variables are fed into the fuzzy rule base. Each input variable consists of a fuzzy template – a set of membership functions with appropriate linguistic term – which converts crisp input to fuzzy input. The output has more than one variables containing crisp output [13]. These variables specify whether the landmark is accepted, in evaluation, or discarded, based on pre-programmed conditions. During the process of final acceptance, the fuzzy output specifies the measurement error covariance and the lifetime of the landmark.
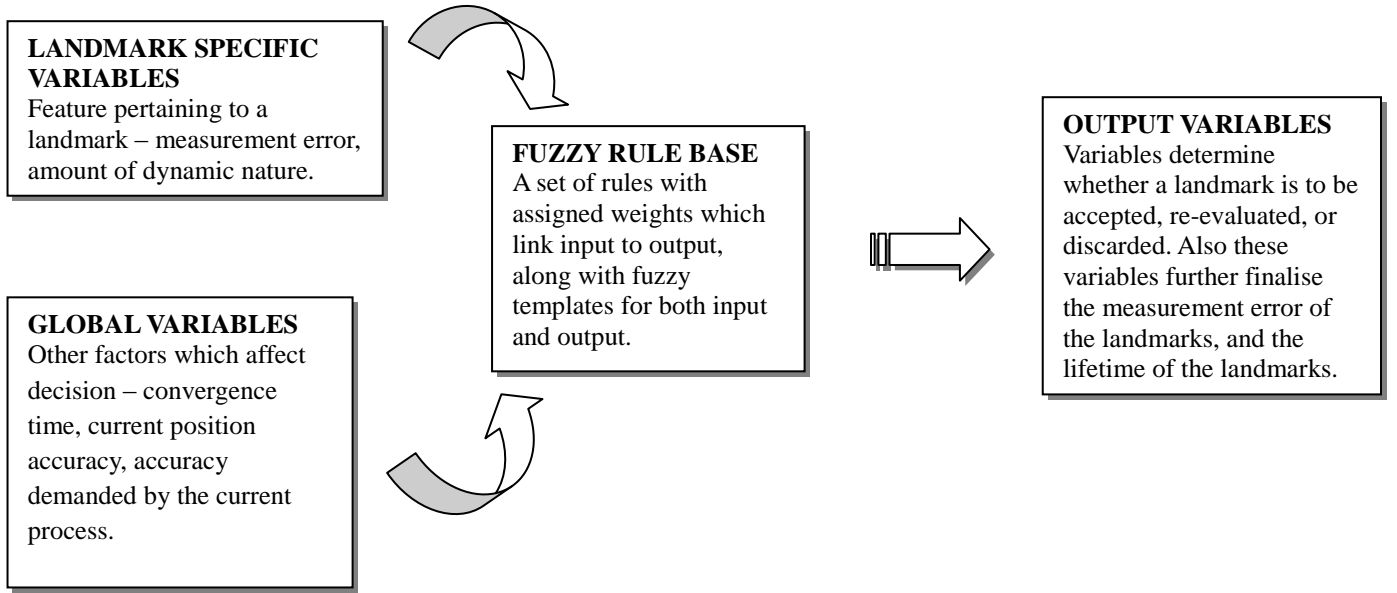
LANDMARK SPECIFIC VARIABLES Feature pertaining to a landmark – measurement error, amount of dynamic nature.		OUTPUT VARIABLES Variables determine whether a landmark is to be accepted, re-evaluated, or discarded. Also these variables further finalise the measurement error of the landmarks, and the lifetime of the landmarks.
	FUZZY RULE BASE A set of rules with assigned weights which link input to output, along with fuzzy templates for both input and output.	
GLOBAL VARIABLES Other factors which affect decision – convergence time, current position accuracy, accuracy demanded by the current process.		

Figure 1. A schematic of the fuzzy system

4.1 Landmark specific variables

These variables sufficiently represent the desirable features being searched for in a landmark. In plain linguistic terms, it captures how static a landmark is, how reliable it is and the error statistics including bias. On the other hand, if landmark detection is not as simple as searching for spikes in the laser data, then the calculation complexities may be solved by the fuzzy evaluation. The variables used for landmark evaluation are -

1. *Standard Deviation* – At every interval t, the measurement data is sampled, and the standard deviation of the set is updated. A landmark is defined as (x,y) and the standard deviation are σ_x and σ_y respectively. This value gives a basis for choosing the corresponding values in the Kalman Filter measurement noise matrix as well as the covariance matrix. For dynamic landmarks, these values escalate slowly, while for oscillating landmarks, the standard deviations increase and then stabilize at a fixed limit. Thus the expression used is as follows:

$$\sigma = \sqrt{(\sigma_x^2 + \sigma_y^2)} \tag{1}$$

This, depending on its range, allows distinction between types of landmarks very effectively.

2. *Standard Deviation of Median* – Every interval t, the (x,y) values of the landmark is stored and its current median (mx,my) is updated. From the set of medians the current standard deviation of median, σ_{mx} and σ_{my} respectively is calculated. The expression used is:

$$\sigma_m = \sqrt{(\sigma_{mx}^2 + \sigma_{my}^2)} \tag{2}$$

Even though this quantity is higher initially, it has much more advantage than standard deviation of mean. The reason being extreme data points affect the value of the mean, and for an approximately static object, such data points tends to increase the standard deviation. This however is not the case for a median, and it is the ideal case of equal distribution of random points about a bias that stabilizes the median standard

deviation. In the case of a mean standard distribution, the equal distribution isn't the governing factor as long as the points don't deviate much, even if they happen to be biased.

For example, in the case of a slowly moving object in the field, like another human being, standard deviation of mean would be less since mean isn't affected much. However the median value in this case of a biased movement, will start to escalate constantly, and thus a dynamic object is correctly identified.

However, it is not necessary to be restricted to only these features. More features can be added to either make sure a landmark is desirably static or a landmark matches as many desired characteristics as possible.

4.2 Global Variables

These set of variables are specifically chosen to incorporate environmental intelligence in the robot. It is not sufficient that robots identify and associate itself with landmark without taking into consideration certain background details. These details, which are termed as global variables, help to improve speed of evaluation of landmark by demanding a certain level of accuracy depending on its current state or its previous experiences with such landmarks.

The variables that chosen are as follows –

1. *Error covariance of robot position* – This is the current estimate of location uncertainty of the robot which when very low affects the requirement of landmarks, and when high raises the tolerance for accepting landmarks.

2. *Evaluation time of a given landmark* – If too much time is spent on evaluating a landmark, it can be ascertained with sufficient accuracy that the landmark is unimportant.

3. *Accuracy level demanded by process* – This is a measure of how accurate localisation has to be and is indicated by a real variable.

$$accuracy = \alpha * \rho + f(v, \kappa, process) \qquad (3)$$

Where ρ is a density of current occupancy grid, i.e, within a circular radius equal to laser range, α is a multiplier, v is velocity, κ is curvature of route and *process* is an offset which biases accuracy by a discrete step. For example during precise tasks, this offset is given a higher value, while during mapping of a field for route calculation purposes, this value can be relaxed.

4.3 Output Variables

1. *Uncertainty* - This uncertainty acts as a hard limiter dividing the system into 3 modes:
    i) *Normal operation* – The landmark is accepted with variance σ * √(result)
    ii) *Rejection* – The landmark is discarded
    iii) *Re-evaluation* – The landmark is subjected to re-evaluating the mean and median till the value either improves, or time runs out and it is accepted or it gets worse and it is rejected.
2. *Lifetime* - This represents the lifespan of the landmark before it is subjected to re-evaluation. This variable protects and ensures that landmark retains its 'static' or 'quasi-static' nature periodically and never takes anything thing for granted.

5. Simulation and Results

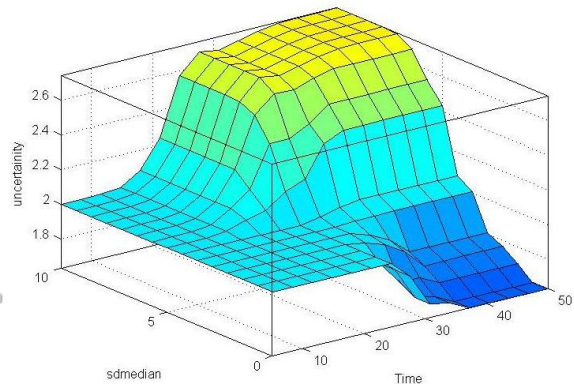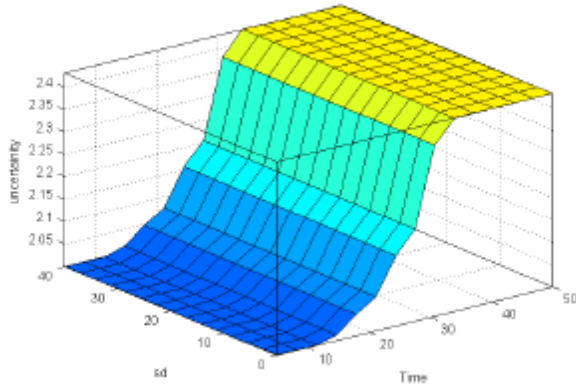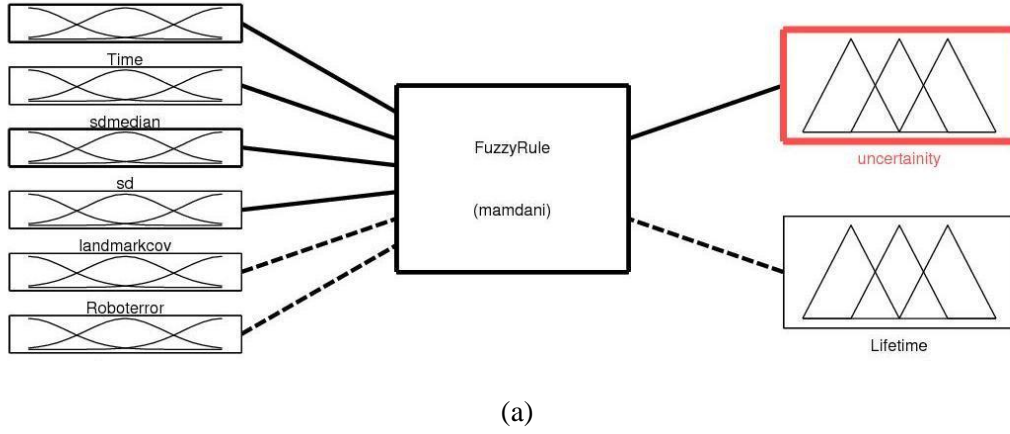(a)

(b)   (c)

Figure 2. (a) The fuzzy inference system. (b) The surface plot of output (uncertainty) v/s input (Time and standard deviation of mean). (c) The surface plot of output (uncertainty) v/s input (Time and standard deviation of median).

The FIS is coupled with standard KF and is then tested over some hypothetical scenarios to examine the performance of the filter. For all test cases a 2D plot of ground will be used, with some landmarks of varying accuracy, and the robot having to traverse from one point to another.

Case I: Standard Kalman Filter versus Fuzzy Rule Base – Linear Stretch
As explained in figure 3, the robot is required to trace the trajectory shown in green in figure 3.(a). The robot has a restricted sensor rang of <20 m in this case so it cannot see all landmarks at all times. Whenever a landmark is seen it is re-entered into KF calculations. Initially the robot sees two landmarks, then three, then reduces to none and then it sees the final landmark.
When the prediction error graph in figure 3.(c) is observed, it is seen that when the robot sees all 3 landmarks, i.e. at around t=150, its error is greatly reduced. Its error stays low at t=300 even when its sees nothing as the dead reckoning error hasn't built up a lot yet. At t=380 when it sees landmark 4, which is quasi static (robot is unaware), the error builds up due to confidence in a varying value. Figure 3.(b)

shows the covariance varying over the track. It can be seen how spread out landmark 4 is and how it affects the covariance of the robot as well as landmark at the end of the track.
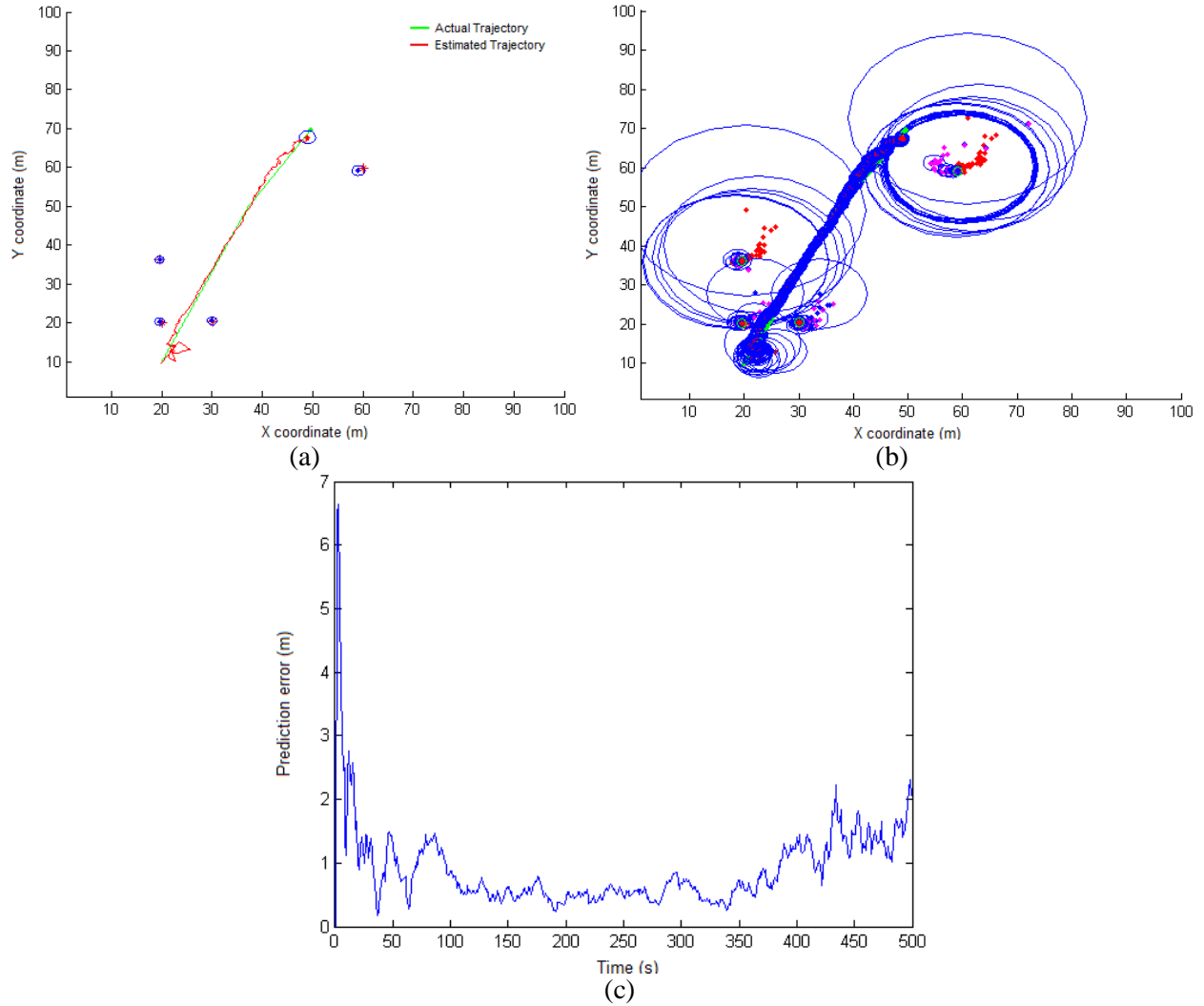

Figure 3. (Simple KF) (a) Trajectory robot forced to follow is shown in green, estimate in red. The red dots are 4 landmarks, and blue dots are the estimates of where the landmark is, while the blue radius is the uncertainty. (b) The progressive change of covariance of robot as well as all landmarks along the track with time (Circles show error bound for location). (c) The prediction error of robot position with time.

The same scenario is now tested with Fuzzy rule base KF. Figure 4.(a) shows that the robot has traversed the route, like in previous case however the change can be seen in the covariance radius of the 4th landmark, i.e., it is substantially larger than others.

The first three landmarks are accepted rather quickly due to their accuracy, and one can see from figure 4(c) that error reduces till t = 250 when it can see no landmark. Following that the dead reckoning is an accumulative error and the error graph increases.

At t=350, the robot starts evaluating the 4th landmark, and accepts it with a very less confidence which is enough to remove the bias from dead reckoning and bring the error down. Thus the 4th landmark in this case helps the robot while in the previous case made things worse.
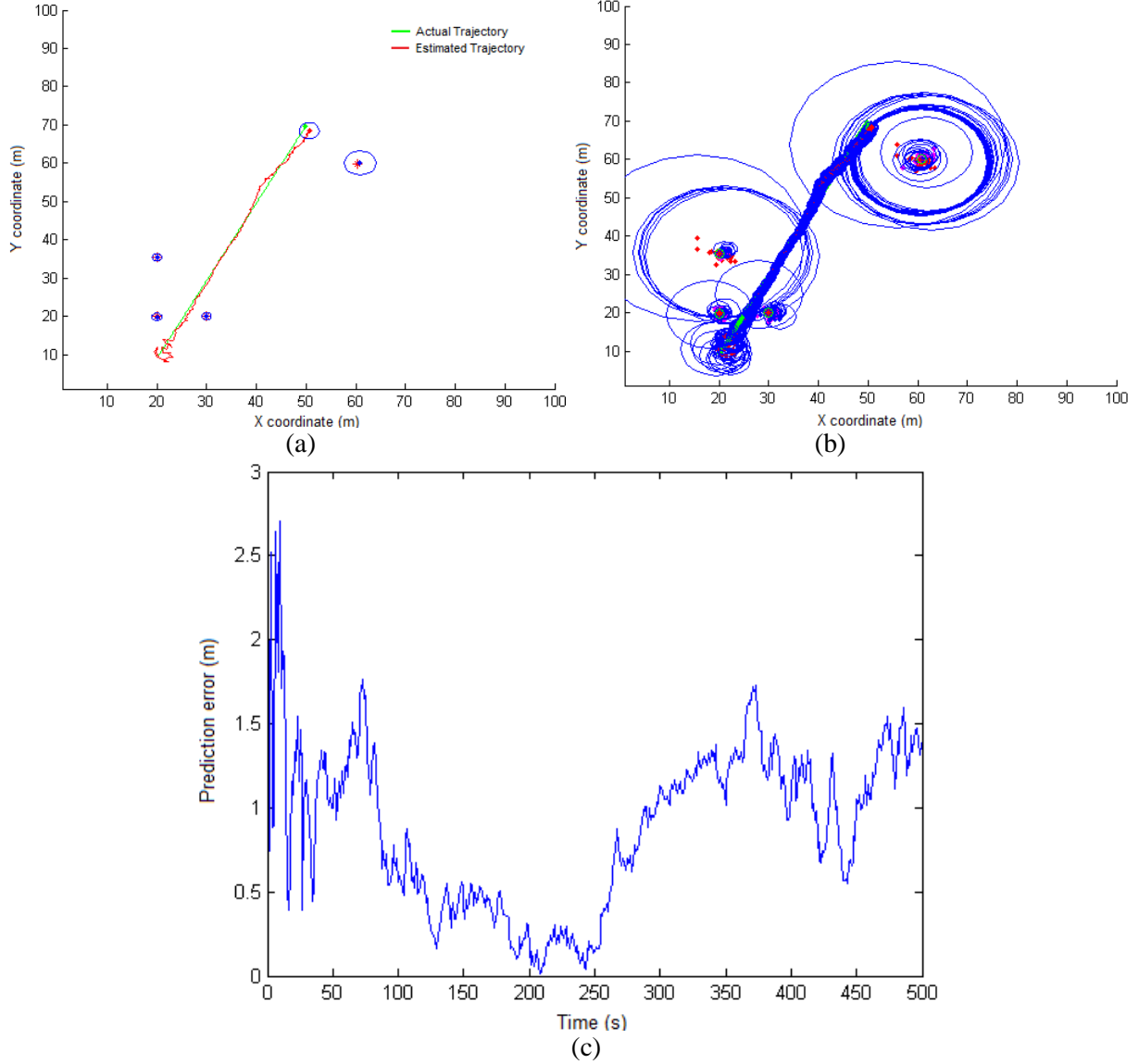
7

Figure 4. (Fuzzy & KF) (a) Trajectory robot forced to follow. (b) The progressive change of covariance of robot as well as all landmarks over time. (c) The prediction error of robot position with time.

Case II: Fuzzy Rule Base –Non Linear Stretch

Even though a couple KF is being used, it is desirable to test against non linear stretches. Though EKF may have considerably reduced the error, the purpose of using linear KF with non linear routes is to check how the κ parameter in the global variable accuracy demanded affects the choice of landmarks.

When the robot makes a turn, at around t=310, it can be seen in Figure 5.(c) that error explodes up since no landmark is being used for reference and dead reckoning error increases. However the robot only senses the fact that it made a turn, which is indicated through the global variable accuracy. As landmark 4 is being evaluated, it becomes essential given the circumstances and as soon as it is accepted, the error comes down. However this landmark will be subjected to re-evaluation and will be taken into less confidence during the second time. This will prevent the high uncertainty of readings making the prediction error worse.
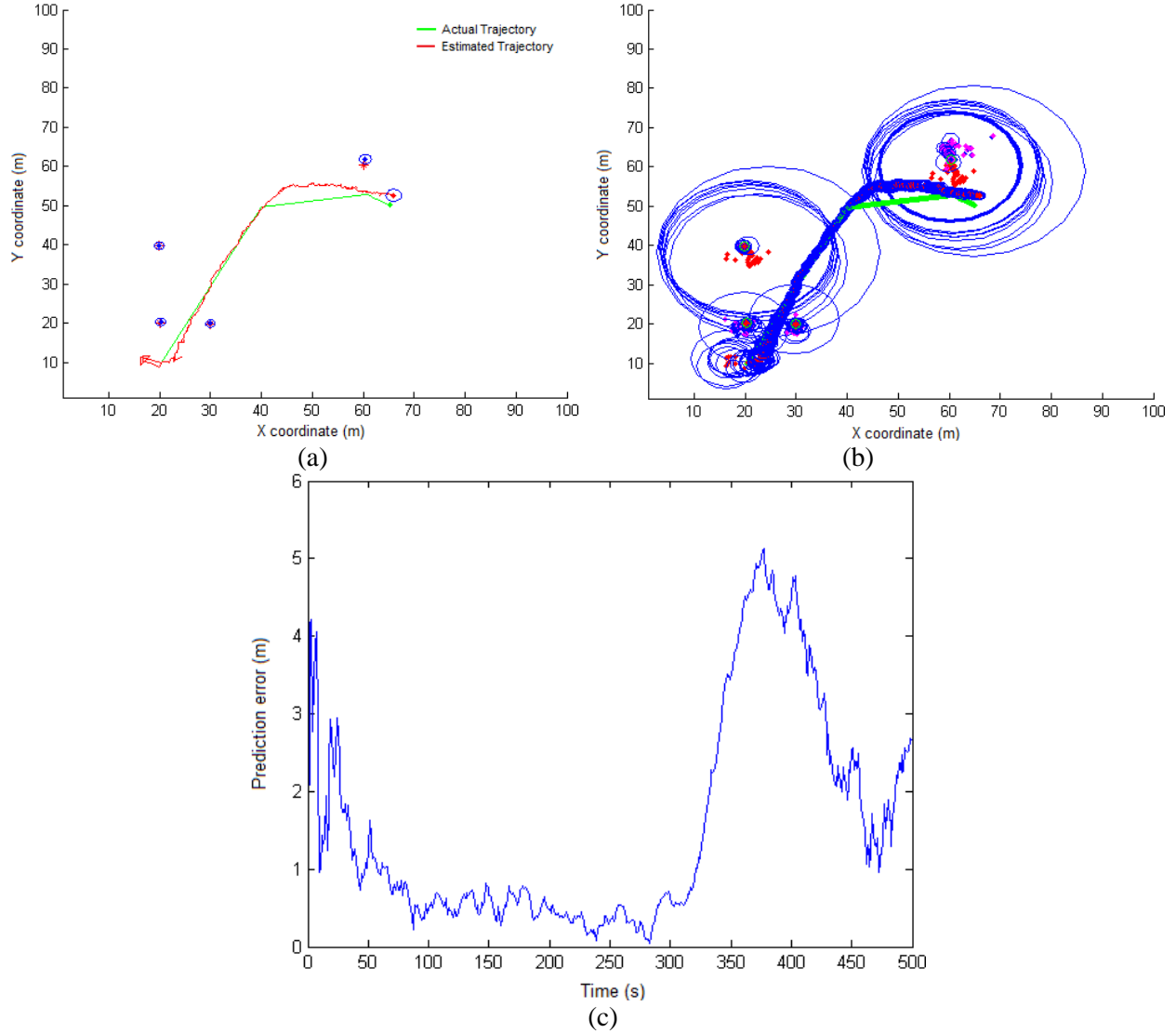
Figure 5. (Fuzzy & KF) (a) Trajectory robot forced to follow. (b) The progressive change of covariance of robot as well as all landmarks over time. (c) The prediction error of robot position with time.

Case III: Standard Kalman Filter versus Fuzzy Rule Base – Quasi Static among static landmarks

The following scenario will first be tried with normal KF. 3 of the 4 landmarks shown in figure 6.(a) has lower variance than 4th one as it is quasi-static. Since the robot assumes equal variance for all landmarks in simple KF approach, these readings disturb the otherwise accurate readings.

The initial steady prediction error was 1.5 m when all 4 landmarks were being considered. As time progresses, the Kalman Gain corresponding to 4th landmark decreases and filter error comes down to 0.5 – 1 m. The point behind this scenario is that, there was no definite need for the 4th landmark to be taken into calculations, as the remaining 3 was already satisfying requirements.
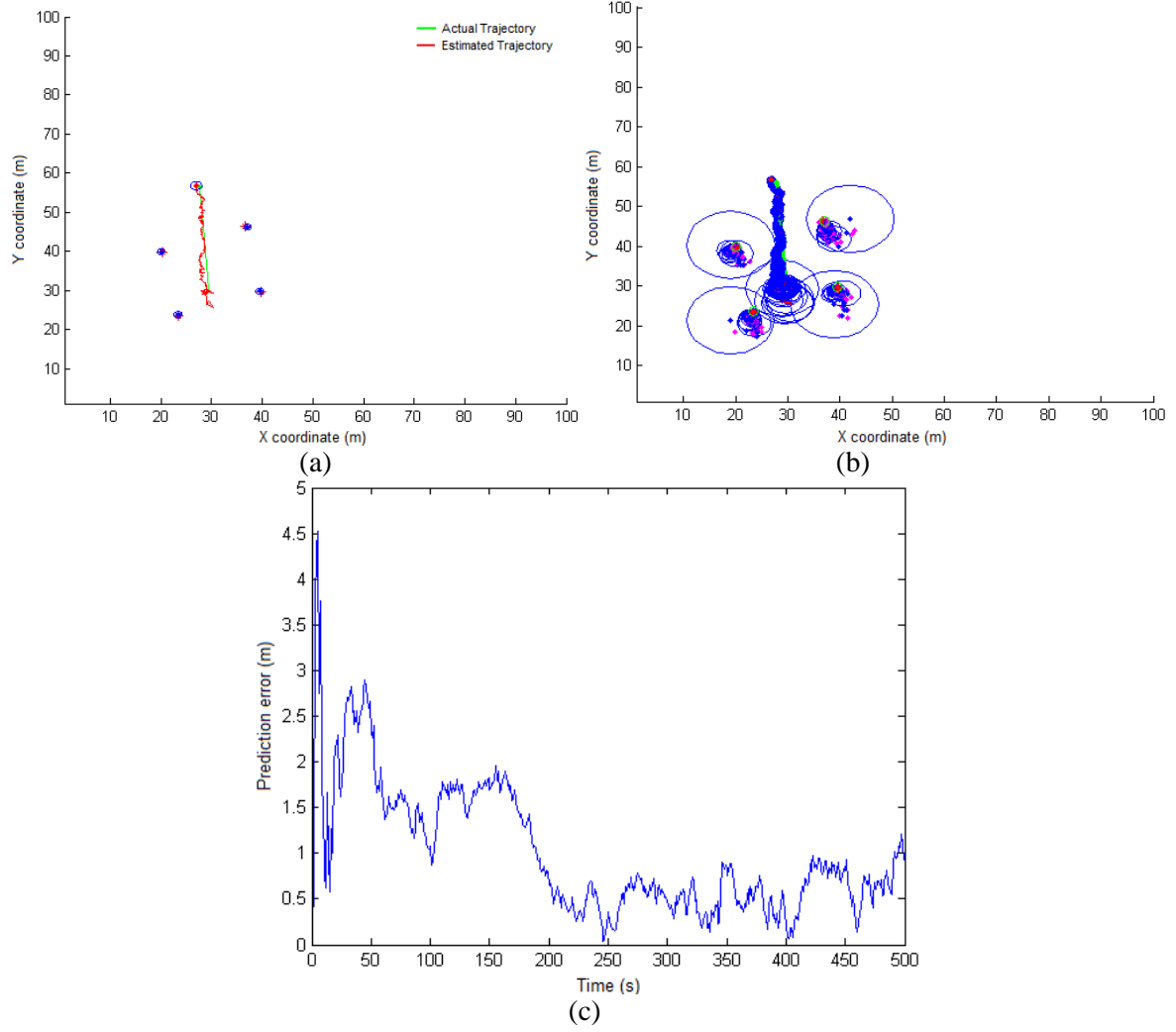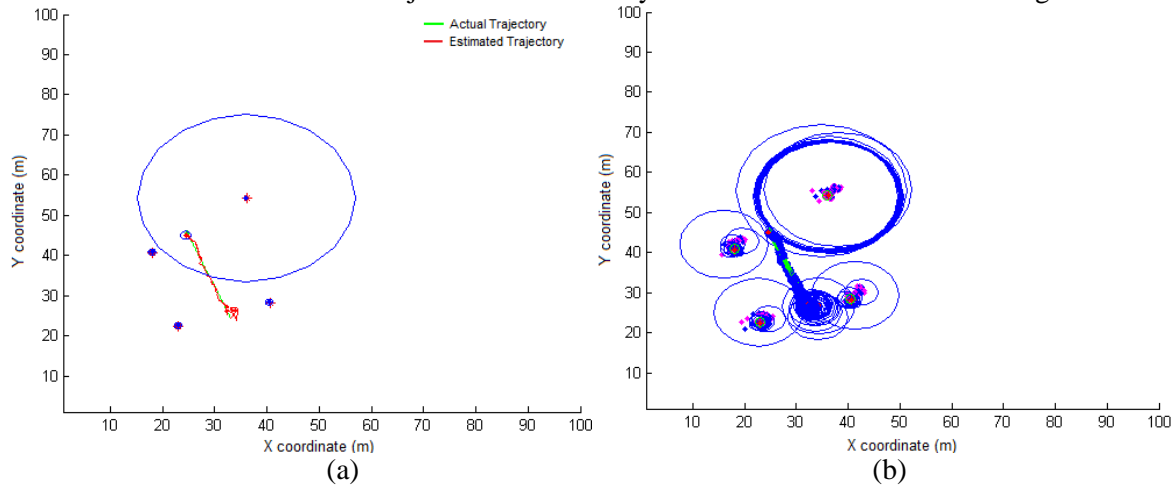
(a)   (b)

(c)

Figure 6. (Simple KF) (a) Trajectory robot forced to follow. (b) The progressive change of covariance of robot as well as all landmarks over time. (c) The prediction error of robot position with time.

Now if the same situation is applied to the fuzzy rule base with KF system, it is seen that the 4th landmark is rejected after evaluation since it is not needed. Figure 7(c) shows the error is below 0.5m most of the time and since 4th landmark was rejected its uncertainty circle shown in blue remains large.
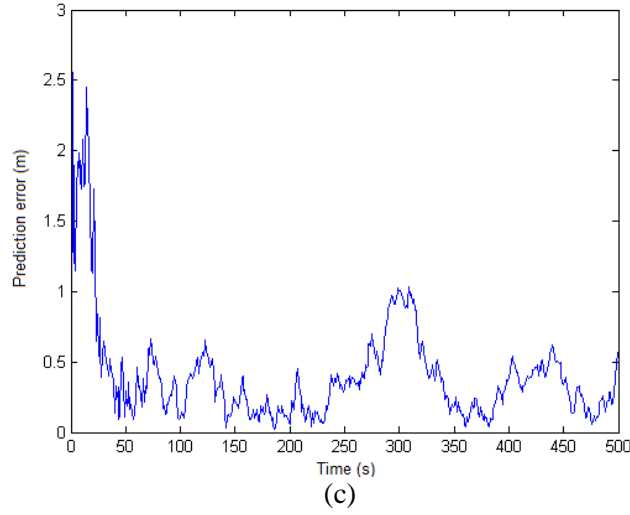

(a)   (b)

10

(c)

Figure 7. (Fuzzy & KF) (a) Trajectory robot forced to follow. (b) The progressive change of covariance of robot as well as all landmarks over time. (c) The prediction error of robot position with time.

To demonstrate how process and accuracy comes into play, the process of mapping with a SICK laser sensor over a farm area is further simulated. The figure 8 shows the farm and the result of the mapping. Mapping is done using occupancy grid method [4] over an area with wide open plain as well as closely spaced obstacles. During this process, the global variable 'accuracy' changes because ρ, the density of the laser scanner hit changes. This directly affects the velocity of the robot which increases as robot rushes to map the area. The crowded areas are more accurately mapped while the open spaces are allowed to have tolerance. The mapping algorithm used is a frontier search algorithm [12], which gives more straight line linear paths in open spaces and more convoluted paths in corners. Hence naturally in open spaces rather than relying on distant landmarks, the robot follows dead reckoning more accurately and in more crowded areas it corrects its estimate using several landmarks.
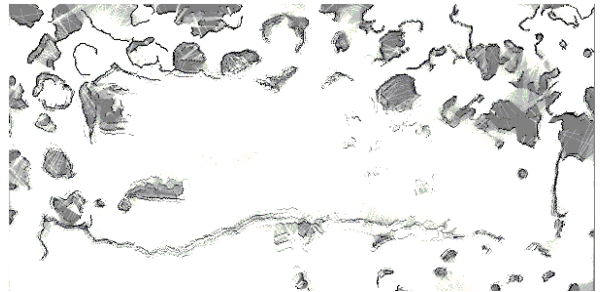
(a)   (b)

Figure 8. (a) The original map used as a basis for simulation. (b) Mapping done by simulated laser scanner over the field.

5. Conclusion

A new extension to the Kalman filter has been presented, which is very specific to outdoor robots. Having a fuzzy rule base sitting on top of the Kalman Filter structure, allows one to fault proof a robust system from mathematical anomalies, poor assumptions and unknowns. The fuzzy part of the decision chain helps to intuitively write a set of pre-defined known rules and the fuzzy function approximation can fill in the middle.

11

Some variables that have been parameterized are considered necessary when it comes to robots moving in uncontrolled environments, for example, complexity of path, speed, level of accuracy demanded, nature of landmarks, and the nature of readings. Besides the external factors, the local variables are based on intuition. For example, in a wide open field, an animal standing in a distance can be observed and used for some amount of time as a guide to a straight path, while on the other hand when in an area with trees on either side, the animal is a mere distraction.

All the possibilities of mapping with the fuzzy rule base have not been explored. Mapping is affected severely if localization error is considerable and may lead to sever distortions of the map. Hence for straightening the map back to normal form, regions of the map need to be selected which are invariant to transformation and regions which will be compressed or expanded.

There are several other parameters that can be used to expand the rule base – history of previous movements or history of a region. Such parameters can help in the introduction of a "premonition" about landmarks even before they are re-discovered.

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