RECONFIGURABLE SLAM UTILISING FUZZY REASONING

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ABSTRACT

The objective of this research work is to develop a software-based reconfigurable framework using top-down fuzzy logic reasoning for a Planetary Monocular-Simultaneous Localisation and Mapping (PM-SLAM) system potentially for application to the problem of autonomous rover navigation. PM-SLAM requires low-level monocular vision-based features for environmental perception and mapping, along with control inputs for rover pose estimation. The robustness of PM-SLAM is challenged when any of the input features become too noisy or computationally intensive. In order to maintain an acceptable degree of accumulated error in estimated pose and complexity of the visual feature inputs, a top-down fuzzy logic reasoning module is used to reconfigure the lower-level visual feature detection stage. The system autonomously switches from the more complex type of features to relatively sparser and accurate ones based on the confidence output of the fuzzy inference system. Quantitative analysis of the proposed method using simulated images generated with the Planet and Asteroid Natural scene Generation Utility (PANGU) shows that a reconfiguration is successfully performed, significantly reducing computation time and error.

Key words: Reconfigurable PM-SLAM, Fuzzy inference, Visual saliency.

1. INTRODUCTION

There is an increasing recognition that complex autonomous systems should follow a distributed systems architecture rather than isolated engineered approach. Systems that utilise generic and modular frameworks tend to have a higher potential for reconfigurability. Reconfigurability is the property of a complex system to autonomously generate system-wide hardware or software changes in response to any anomalous sensory feedback or external perturbations. These configurations can either be hardware-based, such as, physical sensors and manipulators, software-based, such as, computer vision algorithms for environmental perception, or agent-based, such as, reconfiguration of higher-level goals, actions and plans [7]. Within the range of potential applications of a reconfigurable system, planetary exploration rovers are considered to be one of the fundamental examples. Planetary rovers are complex autonomous systems that are designed to work in extremely harsh environments without any human intervention. The capability to reconfigure its functional and software components can provide great benefits in terms of success of its primary goals and mission objectives.

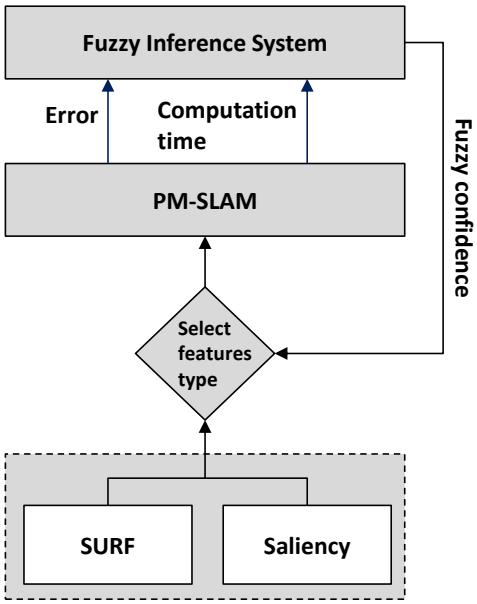


Figure 1: System diagram of the fuzzy inference-based reconfigurable PM-SLAM.

The objective of this research work is to develop a software-based reconfigurable Planetary Monocular-Simultaneous Localisation and Mapping (PM-SLAM) [10] system using top-down fuzzy logic reasoning potentially for application to the problem of autonomous planetary rover navigation (cf. Figure 1). PM-SLAM requires low-level monocular vision-based features for environmental perception and mapping, along with control inputs for rovers position estimation. The robustness of PM-SLAM is challenged when any of the input features become too noisy or computationally intensive. In order to maintain an acceptable degree of accumulated localisation error as well as complexity of the visual feature inputs, a top-down fuzzy logic reasoning module is

used to reconfigure the lower-level visual feature detection stage. The system autonomously switches from more complex saturated feature detection method (e.g., SURF [11]) to relatively sparser and accurate blob-based features (e.g., visual saliency [25]) based on the decision of a fuzzy inference system. The fuzzy inference system comprises a combination of membership functions and a fuzzy rule-base that maps the accumulated error and time complexity to a degree of confidence (for any specific lower-level feature detection method used). Based on a-priori defined confidence threshold, a decision is taken to reconfigure the lower-level feature detection stage in order to reduce the accumulated error and computation time in order to maintain system-wide stability. The current work involves quantitative analysis of the developed framework performed on simulated images generated using the Planet and Asteroid Natural scene Generation Utility (PANGU). The analysis performed here show that the framework successfully triggers a reconfiguration routine that significantly improves PM-SLAM system performance.

2. BACKGROUND

2.1. Reconfiguration in Complex Systems

Intelligent systems designed to operate in remote and sometimes hostile environments are subject to a number constraints that require long durations of autonomous operation with resilience to subtle environmental, technical and physical perturbation. Intelligent systems based on reconfigurable frameworks can prove to be useful in such situations. Reconfiguration can be carried out in terms of hardware components, in case one of the peripheral components is either lost, damaged or subject to malfunction [7]. In other cases, reconfiguration can take place due to anomalies or imperfections in controllers, based on some type of performance metrics. This is usually managed by higher-level system providing rational decisions, e.g., a rational agent. This is commonly known as Plug & Play Control in literature [27]. Software-based reconfiguration usually takes place in one or more of the functional components of an autonomous system architecture. Functional components in planetary rovers constitute a significant degree of the Guidance, Navigation and Control (GNC) architecture, e.g., *rover perception system* [18]. A reconfiguration may be required if the low-level visual feature detection stage within the perception system becomes erroneous or computationally inefficient.

2.2. SLAM Systems

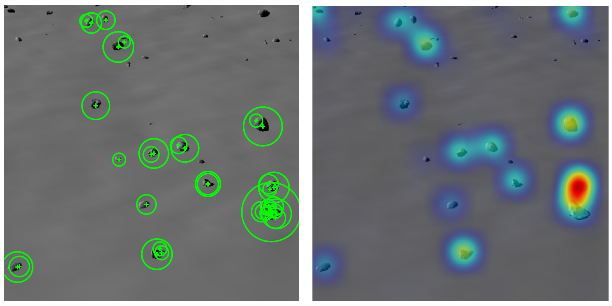
Simultaneous Localisation And Mapping (SLAM) is a probabilistic technique for estimating the position of a mobile agent in an unknown environment while concurrently creating a map of local features. This is achieved using a combination of control data, model of the vehicle dynamics together with environmental observations. Both the control data and the environmental observations are assumed to be inherently noisy. A margin of error exists in the accuracy of the control data (e.g., due to wheel-slip), where as accuracy of the environmental observations depends upon the sensors used. Combining the sources of information can minimise the associated errors [8, 15]. Within the last decade, cameras have remained the dominant exteroceptive sensors in the majority of SLAM systems [22, 6, 14, 23]. The performance of vision-based SLAM systems therefore depends upon the lower-level feature detection step to a significant degree. Although multiple techniques for improving individual parts of SLAM systems exist in literature, this paper will focus on improving SLAM performance via system reconfiguration within the feature detection stage.

2.3. Visual Feature Detection

Various types of feature detection techniques are available in literature for visual SLAM applications. Most popular methods are based on shape analysis and detection, edge-detection operators, interest-point detectors (e.g., SIFT (Scale-Invariant Feature Transform) [28, 16], SURF (Speeded Up Robust Features) [2, 29]), and Haar-like features (e.g., [1]). For more than a decade, there has been an effort to develop machine vision techniques that can define regions of interest (ROIs) in terms of their global and local conspicuity characteristics, known as *visual saliency models* [3]. To date, one such method, i.e., [13], has been used for the detection of planetary rocks [25]. These models are mostly inspired by the information selection property of biological visual systems, and their underlying paradigms are motivated by cognitive research. Such methods can offer great potential for planetary monocular visual SLAM applications. Within the context of this paper, two techniques; *SURF* and *saliency*, will be used for visual feature detection within the proposed reconfigurable SLAM architecture.

2.4. Fuzzy Inference Systems

Fuzzy inference systems (FIS) utilise fuzzy set theory in order to map the input space (such as low-level feature inputs) to outputs (such as fuzzy decisions based on confidence values). Fuzzy inference systems are used for logical decision-making and discerning patterns within inputs (e.g., from low-level sensors) [12]. Inputs and outputs of FIS are associated with fuzzy confidence values using class membership functions (fuzzy sets). Definition and optimisation of membership functions within FIS is mostly carried out using learning-based methods (e.g., *neural networks*), however such techniques rely heavily on the scale of training data as well as amount of adjusted parameters [5]. Alternatively, membership definitions as well as parameter setting can also be carried using empirical knowledge of the underlying sensory system. Top-down fuzzy inference systems have been successfully applied in the field of automated control [20], data classification [19], expert systems [26] and computer vision



(a) (b)

Figure 2: SURF (2a) and Saliency features (2b) on PANGU test image.

[24]. In this paper, the model based on Mamdani FIS [17] is used due to its simple structure of *min-max* operations and high degree of successes in other complex control architectures, making it appropriate for PM-SLAM.

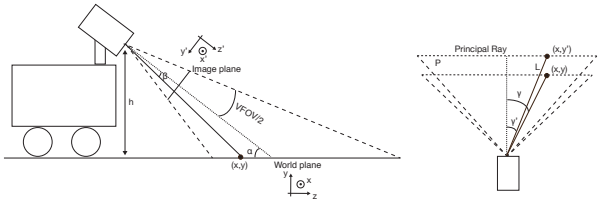
3. RECONFIGURABLE SLAM

The proposed system uses top-down feedback from a fuzzy inference system in order to reconfigure the low-leve vision-based feature detection stage. The two types of features used in this paper are SURF and visual saliency. Saliency-based feature detection is adopted from [25]. The FIS generates confidence values, which quantify the performance of the PM-SLAM system based on the posterior error and computation time. A pre-set threshold value is used to perform reconfiguration.

3.1. PM-SLAM

The Planetary Monocular vision-based Simultaneous Localisation and Mapping (PM-SLAM) technique has been designed for autonomous rover navigation on extra-terrestrial planets. It is a modular localisation and mapping technique, which uses monocular images to identify and track visual features [9] in order to determine a pose. The basic layout of PM-SLAM includes: a feature tracker in 2D, a module that provides depths perception, a SLAM filter, i.e., Extended Kalman filter (EKF) in the current case. Different types visual feature detection and tracking techniques have been implemented in PM-SLAM, e.g., a SURF feature tracker, semantic blob-based (visual saliency) features, or a hybrid of multiple feature types, each with distinct performance characteristics. This allows for optimal performance via reconfiguration based on top-down fuzzy confidence values.

The Speeded Up Robust Features (SURF) identify points of interest within each image, producing a set of descriptors, which are used to perform matching over subsequent images (cf. Figure 2a). Outlier rejection is performed using a Euclidean distance-based threshold criterion between feature descriptors over multiple image frames.



(a) (b)

Figure 3: Mapping of camera coordinates to the ground plane: side view (3a) and top view (3b).

Saliency features generate blob-based regions of interest as mentioned in [25] (cf. Figure 2b). Saliency blobs are much sparser as compared to SURF points. Tracking is performed over subsequent images using k-NN method similar to [25].

PM-SLAM uses a *geometric method* (known as, ***'Direct Depth'***) in order to achieve depth perception from monocular images within the current framework, and is an extension of the method employed in [4].

The position in the world frame in y is calculated from (u,v) in the image frame. Where the axes are defined as in Figure 3a. The angle β (around the x axis with the origin at the camera) is calculated:

$$\tan(\beta) = (\frac{2v}{V} - 1)tan(\frac{VFOV}{2}) \tag{1}$$

using geometry:

$$y = \frac{H}{\tan(\alpha + \beta)} \tag{2}$$

To calculate x in the world frame, the angle γ' is used (defined as the angle at the camera origin and around the normal to the plane P, and parallel to both the x axis and the line L between the camera origin and the feature in camera frame) (cf. Figure 3b).

$$\tan(\gamma') = \frac{(u - \frac{U}{2})}{\sqrt{(\frac{U}{2\tan(\frac{HFOV}{2})})^2 + v^2}} \tag{3}$$

Using right-angled triangle formed on the plane P with the shared camera origin, the feature on the world frame and point on both P and the world frame, x can be calculated:

$$x = (\sqrt{H^2 + y^2})\tan(\gamma') \tag{4}$$

State estimation is performed using EKF. The control signal given to the filter's predict step is the perfectly planned path of the rover, designed to represent a *'command'* to move the rover (i.e., rover's odometry measurements). The update and augment steps are performed using features extracted from images taken from placing a virtual camera in PANGU simulation. The poses at which the images are captured have deviations from the control signal, to simulate the rover's true position due to wheel slip and other environmental factors. The detected features are used by the filter in the form of a local x,y and z co-ordinate in the rover's local 3D plane.

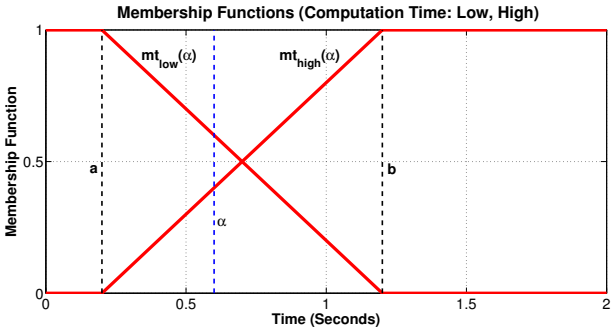


Figure 4: Fuzzy membership functions $\text{mf}_{\text{low}}(\alpha)$ and $\text{mf}_{\text{high}}(\alpha)$ associate a confidence value based on computation time.

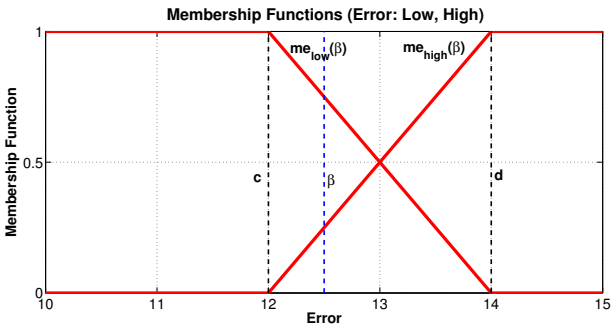


Figure 5: Fuzzy membership functions $\text{me}_{\text{low}}(\beta)$ and $\text{me}_{\text{high}}(\beta)$ associate a confidence value based on error.

3.2. Fuzzy Inference System

The fuzzy logic inference system incorporates two input fuzzy variables, *computation time* and *error* in order to infer decisions for maintaining optimal performance within the PM-SLAM system. If α is the computation time required for each iteration within PM-SLAM, the associated fuzzy membership functions, i.e., '$\text{mt}_{\text{low}}(\alpha)$' and '$\text{mt}_{\text{high}}(\alpha)$' are defined as:

$$\text{mt}_{\text{low}}(\alpha) = max\left(min\left(1, \frac{b-\alpha}{b-a}\right), 0\right) \tag{5}$$

$$\text{mt}_{\text{high}}(\alpha) = max\left(min\left(\frac{\alpha-a}{b-a}, 1\right), 0\right) \tag{6}$$

where, the parameters a and b are experimentally defined thresholds. These membership functions associate the fuzzy values *"low"* and *"high"* with the input computation time respectively. The functions are illustrated in Figure 4.

Similarly two piecewise fuzzy membership functions, i.e., '$\text{me}_{\text{low}}(\beta)$' and '$\text{me}_{\text{high}}(\beta)$', are associated with the posterior error from the EKF within PM-SLAM,

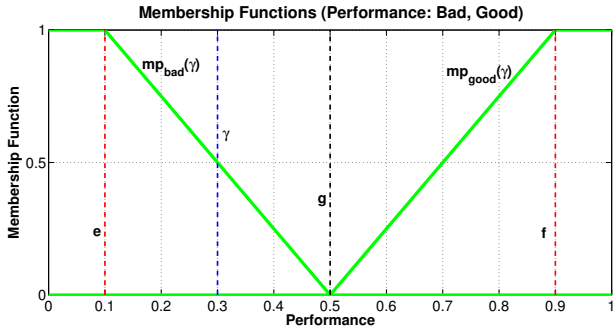


Figure 6: Fuzzy membership functions $\text{mp}_{\text{bad}}(\gamma)$ and $\text{mp}_{\text{good}}(\gamma)$ associate a confidence value on system performance.

$$\text{me}_{\text{low}}(\beta) = max\left(min\left(1, \frac{d-\beta}{d-c}\right), 0\right) \tag{7}$$

$$\text{me}_{\text{high}}(\beta) = max\left(min\left(\frac{\beta-c}{d-c}, 1\right), 0\right) \tag{8}$$

where, the parameters c and d are experimentally defined thresholds. These functions associate the fuzzy values *"low"* and *"high"* respectively, with the input error. Refer to Figure 5.

The output variable defines the performance of the PM-SLAM system based on the *aggregated* confidence value computed using fuzzy inference. Two fuzzy membership functions, i.e., '$\text{mp}_{\text{bad}}(\gamma)$' and '$\text{mp}_{\text{good}}(\gamma)$' associated with the system performance output define a confidence measure on how "*good*" or "*bad*" the PM-SLAM system is performing:

$$\text{mp}_{\text{bad}}(\gamma) = max\left(min\left(1, \frac{g-\gamma}{g-e}\right), 0\right) \tag{9}$$

$$\text{mp}_{\text{good}}(\gamma) = max\left(min\left(\frac{\gamma-g}{f-g}, 1\right), 0\right) \tag{10}$$

The parameters e, f, and g are experimentally defined thresholds. These functions associate the fuzzy values *"bad"* and *"good"* respectively with the consequence of the fuzzy inference technique. Figure 6 illustrates these functions in detail.

Mamdani's technique is applied to the input variables to perform fuzzy inference. A fuzzy rule-base combines the input variables to compute the rule strength. The antecedents within the fuzzy rule-base use the fuzzy operators *AND* as t-norm and *OR* as t-conorm to compute a single membership value. For this paper, the AND method is set to *min*, OR method is set to *max* and implication is set to *min*. The implication operator truncates the consequent's membership function output. The *max* operator is used to aggregate the outputs from multiple rules into

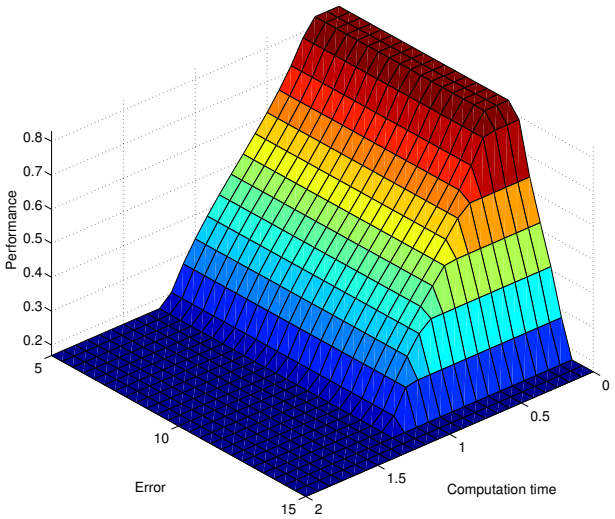


Figure 7: Plot of the output surface of the proposed FIS using the inputs variables.

a single fuzzy set (i.e., defuzzification). This step is performed using the *centroid* method, which calculates the centre of the area under the fuzzy set. The final output from the FIS is used by the system to trigger a reconfiguration of the feature detection stage. A generated plot of the output surface of the proposed fuzzy inference system is shown in Figure 7.

4. EXPERIMENTAL ANALYSIS

4.1. Setup

The aim of these experiments is to test the ability of the proposed system to reconfigure the lower-level feature detection stage using confidence values from the FIS and a pre-defined minimum confidence threshold. PM-SLAM is susceptible to increasing state estimation error within EKF filter as well as computation time over multiple iterations. The fuzzy inference system output will be used to maintain an optimal level of computational load and error over the course of operation via reconfiguration of the feature detection stage from SURF to Saliency features.

4.2. Dataset

The dataset used in this paper is generated using a combination of the Planet and Asteroid Natural scene Generation Utility (PANGU) [21], (developed at the University of Dundee) and image capture software from the PM-SLAM. PANGU simulates planetary environments using parameters such as the levelness of the terrain and the number, size and distribution of craters and boulders. The dataset comprises 145 frames, with per frame monocular image size of 512×512 pixels recorded using a virtual

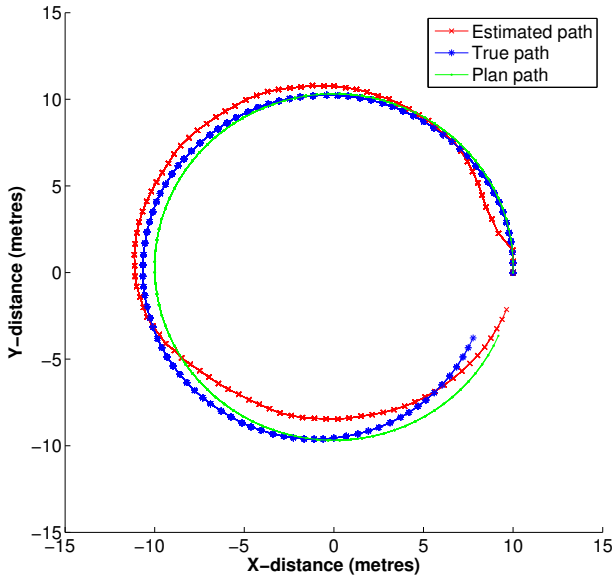


Figure 8: Pose estimation by PM-SLAM against *truth* and *planned* path using PANGU data.

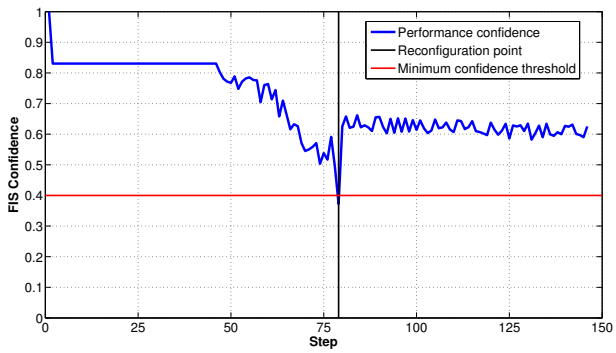


Figure 9: FIS performance-based confidence output for the proposed SLAM system.

camera 2 metres high from the surface, 30 degrees horizontal and vertical field of views (FOV) and 30 degrees pitch, covering a circular path trajectory (cf. Figure 8).

4.3. Results and Discussion

The proposed PM-SLAM setup (refer to Figure 1 for system diagram) takes two distinct configurations. System is initialised with SURF-based feature detection and tracking. Overtime the computation time and error increases to a level that triggers the reconfiguration of the feature detection stage since the confidence (generated by the FIS) has drops below a pre-defined threshold. The new configuration utilises saliency-based features.

Figure 9 shows the FIS confidence based on system performance. It continues to decrease over time for the proposed SLAM system until it reaches the pre-set threshold. A reconfiguration of the low-level feature detection stage is triggered as soon as the performance confidence

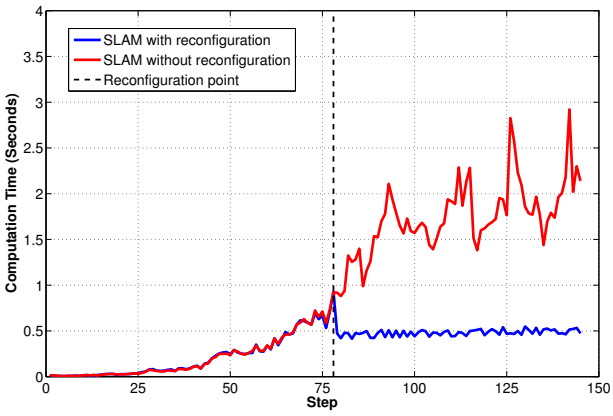


Figure 10: Plot shows the computation time for the proposed reconfigurable SLAM system against a system without reconfiguration.

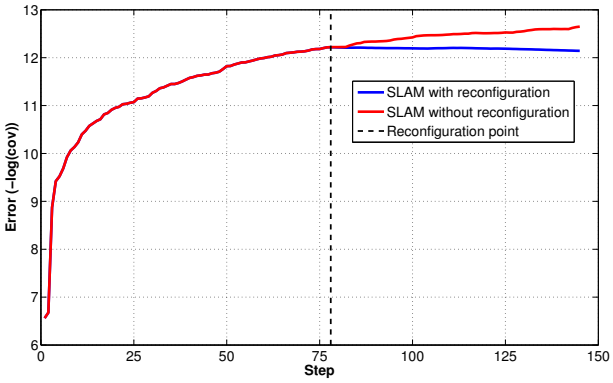


Figure 11: Plot shows the posterior error generated by the EKF for the proposed reconfigurable SLAM against a system without reconfiguration.

falls below this threshold. An increase in performance is observed following this reconfiguration, both in terms of computation time and error. Referring to Figure 10, a significant reduction in the computation time is observed for the proposed system following this reconfiguration. On the contrary, the it continues to increase for the same PM-SLAM system without any reconfiguration. Similarly, Figure 11 presents the behaviour of the error over multiple iterations, which stop increasing further following this reconfiguration, while it continues to increase for the system without any the FIS. Note that the FIS confidence increases back to an optimal level as well (cf. Figure 9).

5. CONCLUSION AND FUTURE WORK

This paper introduced a reconfigurable framework for Planetary Monocular-Simultaneous Localisation and Mapping (PM-SLAM) system potentially for application to the problem of autonomous rover navigation. The system used a higher level fuzzy inference system to generate system performance-based confidence measures based on the EKF posterior error and computation time. The proposed framework performs reconfiguration within the low-level feature detection stage in order to improve the performance of PM-SLAM. Using dataset generated from Planet and Asteroid Natural scene Generation Utility (PANGU), quantitative analysis of the proposed system were carried out in order to test the performance of the proposed framework. These experiments showed that the proposed system was able to maintain optimal PM-SLAM performance, which is crucial for systems designed for extraterrestrial planetary environments. Furthermore, FIS has been proven to be successful in quantising system performance in terms of confidence measures which are intuitive for human operators monitoring the system.

In future this system can be extended to other types of SLAM filters as well as feature detection techniques. Furthermore, the higher level FIS system can be replaced with more complex rational agent-based architectures that are generic and highly flexible in terms of physical and functional capabilities.

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