Autonomous Cooperative Visual Navigation for Planetary Exploration Robots*

Masoud S. Bahraini, Abdelhafid Zenati, and Nabil Aouf

Abstract— **Planetary robotics navigation has attracted the great attention of many researchers in recent years. Localization is one of the most important problems for robots on another planet in the lack of GPS. The robots need to be able to know their location and the surrounding map in the environment concurrently, to work and communicate together on another planet. In the current work, a novel algorithm is designed to cooperatively localize a team of robots on another planet. Consequently, a robust algorithm is developed for cooperative Visual Odometry (VO) to localize each robot in a planetary environment while detecting both intra-loop closure and inter-loop closures using previously observed area by the robot and shared area from other robots, respectively. To validate the proposed algorithm, a comparison is provided between the proposed cooperative VO and the single version of VO. Accordingly, a planetary analogue real dataset is employed to investigate the accuracy of the proposed algorithm. The results promise the concept of cooperative VO to significantly increase the accuracy of localization.**

I. Introduction

For the last few decades, mobile robots and autonomous systems have become a hot research topic resulting in major advances and innovations. Nowadays, mobile robots can perform complex tasks autonomously in various domains including military, medical, space, and commercial applications that can operate on the ground, at sea and in space. Deploying a team of robotics to lunar for construction purposes in the next few years is one of the main plans for planetary and space application [1], [2]. In those applications, mobile robotic platforms should perform complicated tasks including navigation in complex dynamic environments [3], [4]. A robotic platform needs to be self-localized if it is designed to autonomously navigate itself in its environment without any human intervention or even in the absence of the Global Navigation Satellite System (GNSS). Visual Odometry (VO) has been used for space applications where there is no Global Positioning System (GPS) signal. Visual cameras are the most used sensors due to low power requirements, availability, and highly physical compactness, which can be used for space application to perform visual navigation [5]–[7]. Readers may refer to papers that outline recent developments in VO [8]–[13] and Simultaneous Localization And Mapping (SLAM) [14]–[18]. Independently from the mounted sensor on the robotic platform, VO can be implemented either on a single platform basis, i.e., each robot performs independently self-localization, or cooperatively, i.e., self-localization for each robot is obtained from data fusion between at least two robots.

For the single version of VO, an omnidirectional VO approach was investigated by [19] to estimate the motion of a planetary rover. In addition, a localization technique was proposed in [20] using augmented unscented Kalman filter for planetary rovers to estimate the slippage ratio and enhance the accuracy of VO estimation. Also, a stereovision based VO algorithm was proposed by [21] for a lunar rover in sandy terrains. Mouats et al. [22] proposed a method to improve the accuracy of VO when there are illumination and contrast variations in stereo images. They also investigated a performance analysis of the most commonly used feature detectors and descriptors in the challenging environment with poor lighting conditions [23]. A relative navigation scheme for uncooperative and unknown space platforms has been proposed in [24] which combines local feature matching based on the histogram of distances descriptor [25] and pose estimation based on an adaptive H_∞ recursive filter.

To improve the accuracy of single platform visual navigation, the literature examines the cases of cooperative visual navigation in centralized [26], [27] and decentralized [28], [29] manners in which whether all platforms send their information to a central visual navigation algorithm (centralized) or visual navigation is computed on multiple platforms (de-centralized). Thrun and Liu [30] used sparse extended information filters and homography to solve the multi-vehicle SLAM problem. Nemra and Aouf [31] investigated a centralized stereo-vision SLAM technique for cooperative Unmanned Aerial Vehicles (UAV) using a non-linear H_∞ filtering scheme. They extended their works in [26], where the employed features were an adaptive variant of the SIFT features. Additionally, Li and Aouf in [32] proposed the stereo vision cooperative SLAM method for UAVs where the collaborative estimation was implemented with an information filter and covariance intersection technique. Nemra and Aouf [28] suggested an adaptive de-centralized cooperative visual SLAM that was based on a stereovision system. With the proposed solution, a group of UAVs can construct a large reliable map and localize themselves in this map without any user intervention. Also, Boulekchour *et al.* [7] proposed a system for real-time cooperative monocular visual SLAM that involves multiple

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unmanned aerial vehicles. A brief survey on cooperative SLAM/VO can be found in [29]. Despite the extensive field experiments and research in visual navigation, there has been no attempt to tackle cooperative visual navigation in the space environment where a long-duration mission is needed in a challenging environment. Moreover, to perform VO, it has been usually assumed that the operating environment has sufficient illumination, enough texture to be extracted and sufficient scene overlap between the stream of images, while these assumptions are not accepted in the real planetary environments. This paper aims to propose a robust algorithm to cooperatively navigate two mobile robots during a long mission in a challenging planetary environment.

In this paper, a new algorithm is proposed to localize a team of robots in planetary applications. In the proposed cooperative VO algorithm, two main blocks are triggered concurrently on each robot including VO and Loop Closure Detection (LCD) algorithms. The former obtains the pose of the robot using a robust motion estimation algorithm. The latter compares the current view of the robot obtained from the stereo camera with the shared key-images to detect the loop closures in the challenging planetary environment. LCD is one of the main challenges in the planetary environment due to poor knowledge about existing features, brightness variations across the environment and illumination. To tackle this problem, a robust visual loop closure module is deployed to detect any overlapping fields of view for two or more vehicles. In the current work, instead of using conventional keyframes to retrieve the previously observed area, a set of key-images is shared between the robots to detect the loop closures. Once the positive feedback is received from the LCD building block, the collaborative optimization process will be triggered between any robots involved in the loop closure. The proposed cooperative visual navigation is relying on the shared views that collaborative and cooperative robots might have when conducting their respective tasks. The areas are shared at an instant time *T* between the robots, besides the views that have been seen at different times by the robots. The proposed approach for cooperative VO is validated using an analogue planetary dataset named the Erfoud dataset [33]. The rest of this paper is organised as follows. Section II provides the details of the proposed cooperative VO approach. The obtained experimental results using a real dataset in an analogue planetary environment are reported in Section III, followed by conclusions and the scope of future works in Section IV.

II. Cooperative VO Algorithm

In this section, the main building blocks of the proposed algorithm for cooperative VO is described in detail. It is assumed that the robots are equipped with a stereo camera as the main observation sensor. An overall scheme of the proposed algorithm is illustrated in Fig. 1.

In the proposed algorithm, a robust stereo-temporal matching approach is designed to prevent losing feature points during the motion estimation process. Optical flow, Kanade-Lucas-Tomasi (KLT) feature tracker is employed to track feature points in the stream of stereo images. Also, Perspective-n-Point (PnP) algorithm is applied for 2D-3D matching in motion estimation. Additionally, the M-estimator SAmple Consensus (MSAC) algorithm [34] is used to eliminate spurious correspondences in this algorithm. One of the main contributions of the proposed algorithm is the sharing of the key-images between the robots to detect loop closures. The selected key-images including feature points and their descriptors along with their 3D position are stored on the robots and can be shared between the robots to detect any overlapping fields of view for two robots. The optimisation process triggers after finding several shared areas between any robots involved in the loop closure (inter-loop closure) and any previously seen area by the robot itself (intra-loop closure). The cooperative navigation as described above relies on the shared views that cooperative robots might have when conducting their respective tasks. The shares to be exploited are not limited to the ones that are shared at an instant time *T*, but also the views that have been seen at different times by the robots. The blocks of the proposed algorithm shown in Fig. 1, can be summarized as the following stages to estimate the pose of the robots from the stream of stereo images.

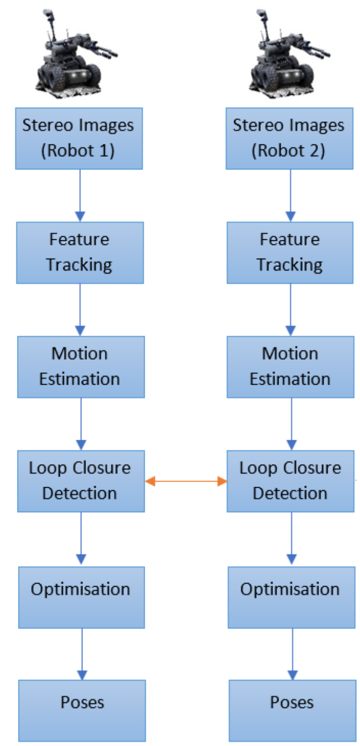

Fig. 1. Overall scheme for the proposed cooperative VO algorithm.

A. Feature Tracking

After receiving the stream of stereo images, detecting and matching feature points across different images are essential for both camera tracking and mapping tasks. To obtain more stable feature extraction and tracking results, each image is divided into buckets to propagate the feature points through the whole image. A border is also set around the image to avoid the generation of feature points in this region which are not reliable due to the movement of the mobile robot. ORB feature descriptor is used to match the corresponding feature points across different viewpoints, which is robust to large viewpoint change. The KLT feature tracker is employed to track the binary feature points between the frames. It should be noted that a successive stream of stereo images needs to be capture to track the feature points by using optical flow feature tracking.

B. Motion Estimation

After successful feature tracking, motion estimation is triggered to obtain the relative pose between two frames. By concatenation of every relative pose estimation, the full trajectory of the robots can be retrieved. A 2D-3D matching approach is employed to calculate the pose of the robot from 3D points on the previous image and their corresponding 2D reprojections on the current image. The PnP algorithm is applied to obtain the camera pose of one frame with respect to the 3D points from the other frame. The relative pose from the 2D-3D approach is fully determined as a constraint for the next pose graph optimization. The outliers in the set of point correspondences result in errors in the PnP algorithm. Thus, the RANSAC (RANdom SAmple Consensus) methods can be employed to reduce the outliers and consequently make the final solution for the camera pose more robust. Herein, the MSAC algorithm is used to perform this task.

C. Loop Closure Detection (LCD)

One of the main challenging problems in cooperative VO is to correctly manage the perceived information from the environment. The performance of cooperative VO algorithms highly relies on the LCD mechanism, which entails the correct identification of previously observed areas. The loop closure can be either intra-loop closure when the robot detects a loop from its previously observed area, or inter-loop closure when the robot detects a loop from the shared images from the other robots. If the robot is moving in a long loop, the pose estimate error is growing while in reality, the vehicle is likely in an already mapped area. If we use traditional methods for data association, e.g. gating area, we would not be able to detect the loop closure. A robust LCD scheme is needed to build a consistent map by adding constraints to the map generation process. Although different types of sensors can be used to detect loop closure, the visual solutions have been frontier, especially motivated by ubiquitous and the low cost of cameras, the increase in processing power and the richness of the sensor data. The LCD problem can be converted into an online image retrieval task to determine if the current image has been taken from a known location.

In this paper, instead of using keyframes to retrieve the previously observed area, a set of key-images is shared between the robots to find the loop closure. Applying this approach leads to reducing the computational time significantly while the robots don’t need to generate and save the map of the environment. If it is the case to generate the map of the environment, obtained point clouds by either stereo camera or LiDAR can be registered to the poses as well. Therefore, vehicle-to-vehicle relative pose estimates can be recovered with a robust registration solution in a global optimisation framework that can construct a large reliable map and localize themselves in this map without any user intervention.

The proposed LCD is based on binary descriptors to retrieve previously seen similar images. A simple but effective mechanism can be used to group images close to the pose of the robot in a gating area and search within them, which reduces the computational efforts.

D. Optimisation

Herein, a pose graph approach is used to store information for a 3D pose representation. A pose graph contains nodes connected by edges, with edge constraints that define the relative pose between nodes and the uncertainty on that measurement. An optimisation algorithm modifies the nodes to account for the uncertainty and improve the overall graph. We represent pose at each time instant with a graph node which are unoptimized poses of each node represented in the world coordinate system. Once a loop closure has been detected, the algorithm uses the graph optimization method (i.e. nonlinear least-squares error minimization via the Gauss-Newton or Levenberg-Marquardt algorithm) to find a configuration of the nodes that is maximally consistent with all the constraints.

The main challenge of the space environment is the high similarity of the images in the space environment acquired from different views of the robots involved in the cooperation. Outlier LCDs result in incorrect relative pose constraints and consequently ruin the pose graph optimisation. False LCD may happen in high similarity environment including space environments even if the descriptor is perfectly designed. It is more challenging in the space environment where there is a lack of knowledge about the existing features, brightness variations across the environment and illumination. To improve the robustness of pose graph optimization, we may increase the level of confidence for similarity matching by setting a high matching threshold but this will significantly reduce the number of accepted loop closures.

III. Results and Discussion

There are many challenges in space environments in terms of existing features, brightness, and illumination. To validate the proposed approach and compare the results with available existing methods in the literature, a planetary analogue real dataset is used [33]. The planetary analogue dataset was obtained by two mobile robots shown in Fig. 2. This dataset was collected by the two mobile robots on three different planetary analogue sites in the Tafilalet region of Morocco [33].

Fig. 2. mobile robots in the planetary analogue real dataset [33].

The robots were traversed on large scale motion trajectories from a few hundreds of meters up to one kilometre. Although the dataset was recorded for single-agent application, it can be applicable for cooperative planetary purposes by dividing one of the obtained datasets into two parts and assumed that two robots are moving in the planetary environment at the same time.

The ground truth (GT) of the robots in the selected dataset (Minnie in Merzouga, Trajectory 22, Replay 1)[1] and their initial position are shown in Fig. 3. It is assumed that the robots are starting to move at the same time from the shown initial positions quite far away from each other (~170 m). During the motion of Robot 1, it is expected to observe part of the trajectory of Robot 2 as inter-loop closure at Zone 3 and a part of the previously observed area by itself at Zone 2. Since both robots are starting at the same time by the same speed, Robot 2 is expected to observe the previously seen area by Robot 1 at Zone 1. It should be noted that since robots are moving in the opposite direction at Zone 4, it was not expected to detect the loop closure at this zone. Additionally, since Robot 2 is passing through Zone 3 earlier than Robot 1, it was not expected to detect the loop closure at this zone by Robot 2. The motion direction of the robots is marked in Fig. 3 by the arrows.

Some of the detected loop closures and the corresponding matched images using the LCD algorithm are shown in Figs. 4-9. The matched feature points are illustrated by the red circle marker and green plus marker in the left and right images, respectively. The corresponding feature points are connected by the yellow lines.

It can be seen that, although the shape of the terrain has been changed in the environment due to the movement of the robots, the LCD algorithm is robust to match the similar images and identify the previously observed areas.

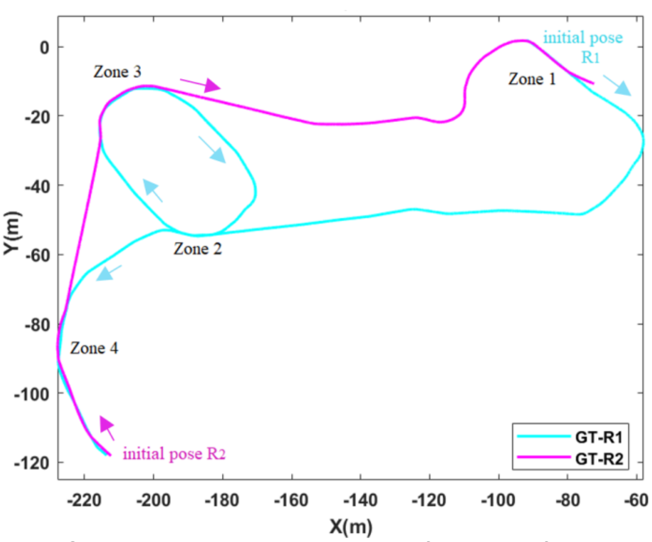

Fig. 3. Ground truth and the initial position of the robots for selected trajectory from the Erfoud dataset along with loop closures zones.

[1]https://www.laas.fr/projects/erfoud-dataset/minnie-merzouga-trajectory-22-replay-1

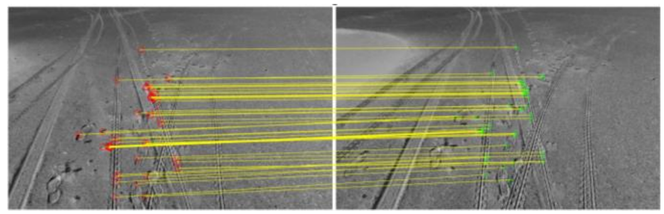
Fig. 4. Corresponded images and matched feature points using the LCD algorithm (images: 0013 vs 1974).

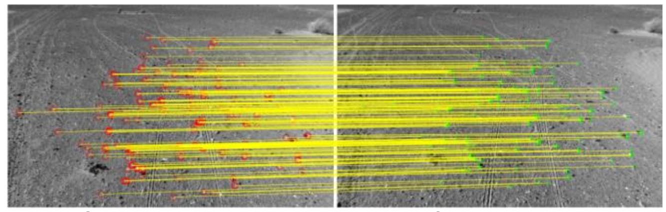
Fig. 5. Corresponded images and matched feature points using the LCD algorithm (images: 2862 vs 3712).

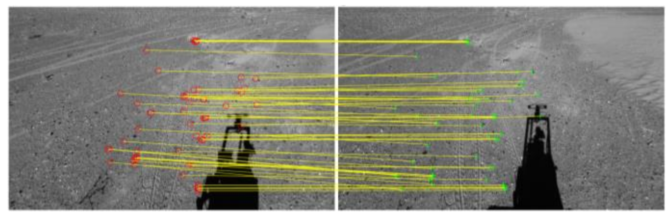
Fig. 6. Corresponded images and matched feature points using the LCD algorithm (images: 3104 vs 6359).

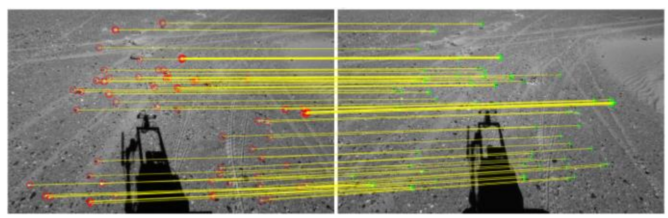
Fig. 7. Corresponded images and matched feature points using the LCD algorithm (image 3161 vs 6415).

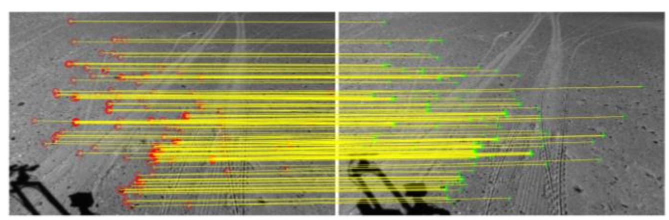
Fig. 8. Corresponded images and matched feature points using the LCD algorithm (images: 3229 vs 6482).

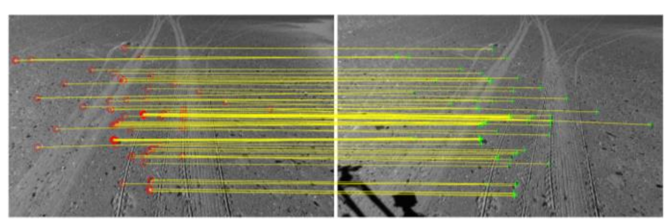
Fig. 9. Corresponded images and matched feature points using the LCD algorithm (images: 3239 vs 6493).

In the following, the accuracy of the single version of the VO algorithm is investigated in Fig. 10 where the trajectory of the robots is plotted and compared with the GT. In this figure, the obtained trajectory by applying the proposed CVO algorithm is also compared with the GT.

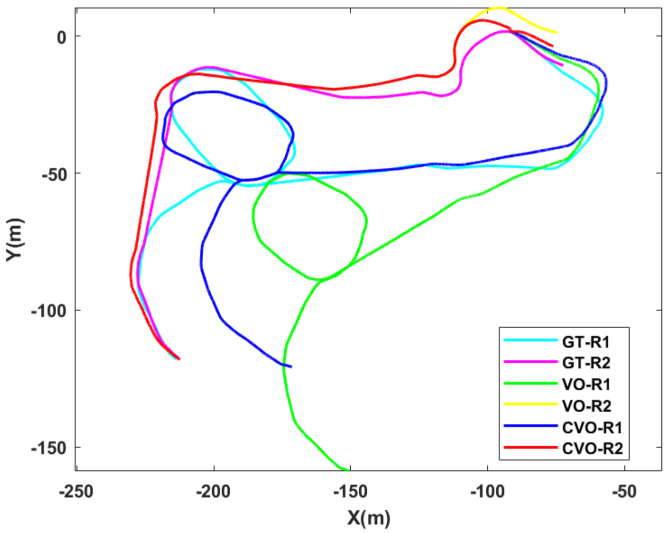

Fig. 10. Comparison of the estimated trajectory of the robots by cooperative VO (CVO) and the single VO.

It can be seen that the single version of the VO algorithm has a high drift for Robot 2 during its motion in the environment which is shown by the green line. Since Robot 1 has detected part of the observed environment by Robot 2 at Zone 3, the optimisation process triggers for Robot 1 after detecting the inter-loop closures. It can be seen that by exploiting the proposed method a significant improvement happens in the accuracy of the trajectory of Robot 1 which is shown by dark blue in Fig. 10. It should be noted that the intra-loop closure at Zone 2 is also taken into account when the optimisation process for Robot 1 is triggered. Moreover, Robot 2 has detected part of the observed environment by Robot 1 at Zone 1 as the inter-loop closure. The impact of the optimisation process on improving the trajectory of the robot in the area close to the GT can be observed at this zone. Furthermore, the error of the estimated trajectory by a single and cooperative system is investigated. Figures 11 and 12 show the error between the estimated trajectory of the GT for Robot 1 and Robot 2, respectively. The detection of a previously seen area by Robot 2 results in a high impact on the estimated trajectory of Robot 1. From Fig. 11, the accuracy of localization is drastically improved in both X and Y directions by applying the proposed algorithm where the improvement is not limited to the loop closure area and is distributed through the whole trajectory. From Fig. 12, an improvement in the accuracy of the estimated trajectory can be also observed where a previously seen area from Robot 1, has been detected by Robot 2.

To provide a statistical sense regarding the estimated error by applying the proposed algorithm, a quantity comparison is also reported in Table 1. Herein, the average error of the estimated trajectories by the single version of VO is compared with CVO. It can be observed that by applying the proposed algorithm for CVO, the average error of the estimated trajectory is considerably decreased from 20.32m to 6.75m in the X direction for Robot 1. Similar behaviour happens in the Y direction where the average error is drastically decreased from 21.63m to 5.60m for Robot 1. Also, the average error of the estimated trajectory is reduced from 3.66m and 3.98m to 3.43m and 3.29m in the X and Y direction, respectively, for Robot 2.

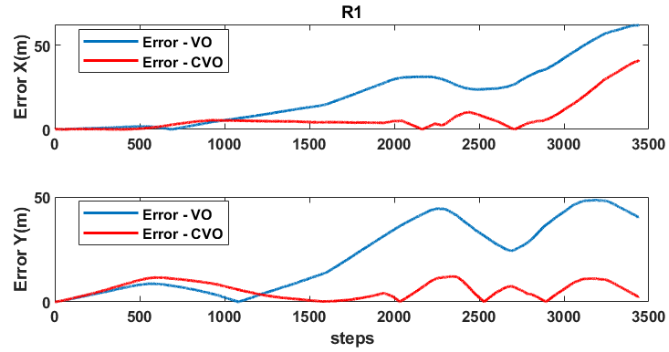

Fig. 11. Comparison of estimation error between single VO and cooperative VO (CVO) for Robot 1.

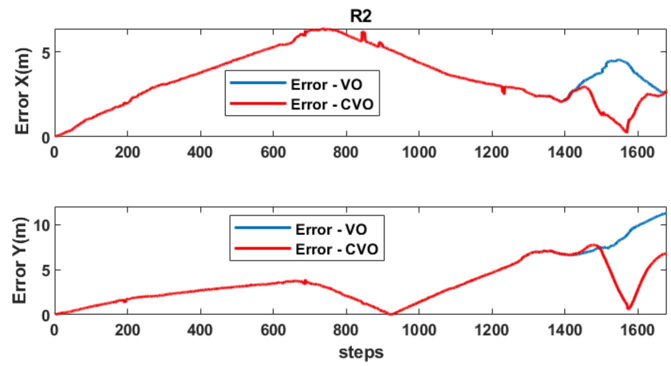

Fig. 12. Comparison of estimation error between single VO and cooperative VO (CVO) for Robot 2.

TABLE I. THE AVERAGE ERROR OF THE ESTIMATION TRAJECTORIES FOR COOPERATIVE VO (CVO) AND SINGLE VERSION OF VO

Direction	The Average Error			
	Robot 1 - CVO	***Robot 2 - CVO***	***Robot 1 - VO***	***Robot 2 - VO***
X (m)	6.7580	3.4321	20.3292	3.6682
Y (m)	5.6038	3.2993	21.6346	3.9856

IV. CONCLUSION

This article develops a novel cooperative VO algorithm to collaboratively localize a team of robots by only checking the key-images on other planets. The building blocks of the proposed cooperative VO algorithm was described in detail. VO and LCD blocks were deployed concurrently to localize the robots and detect any overlapping fields of view for any possible loop closure. The proposed cooperative VO algorithm was tested on the planetary analogue Erfoud dataset to investigate the accuracy of the estimated trajectories. After describing the possible shared area between the robots in the environment, some of the detected loop closures and the corresponding matched images using the LCD block were shown. Feeding the detected loop closures into the optimisation process by checking the shared key-images, significantly improved the accuracy of the estimated trajectory of the robots. It can be concluded that by applying the proposed cooperative algorithm in conjunction with successful LCD, promising results are achievable. Future directions for this work include, not limited to, investigation of the effectiveness of the proposed algorithms corroborated through the representative experimental dataset and extension to cooperative visual SLAM.

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