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A robust star identification algorithm with star shortlisting

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Abstract

A star tracker provides the most accurate attitude solution in terms of arc seconds compared to the other existing attitude sensors. When no prior attitude information is available, it operates in “Lost-In-Space (LIS)” mode. Star pattern recognition, also known as star identification algorithm, forms the most crucial part of a star tracker in the LIS mode. Recognition reliability and speed are the two most important parameters of a star pattern recognition technique. In this paper, a novel star identification algorithm with star ID shortlisting is proposed. Firstly, the star IDs are shortlisted based on worst-case patch mismatch, and later stars are identified in the image by an initial match confirmed with a running sequential angular match technique. The proposed idea is tested on 16200 simulated star images having magnitude uncertainty, noise stars, positional deviation, and varying size of the field of view. The proposed idea is also benchmarked with the state-of-the-art star pattern recognition techniques. Finally, the real-time performance of the proposed technique is tested on the 3104 real star images captured by a star tracker SST-20S currently mounted on a satellite. The proposed technique can achieve an identification accuracy of 98% and takes only 8.2 ms for identification on real images. Simulation and real-time results depict that the proposed technique is highly robust and achieves a high speed of identification suitable for actual space applications.

Keywords: Star tracker; Lost-in-space mode; Star pattern recognition; Star identification; Star shortlisting

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1. Introduction

Developing an autonomous and reliable attitude determination system is one of the most important requirement for satellite missions as these missions demand a high accuracy for determining their attitude in the space. Many attitude sensors such as the sun sensor, magnetometer, star tracker, and earth sensor have been developed for estimating the orientation. Of all above sensors, star trackers have become widely popular in the past two decades because they provide a highly accurate orientation information in terms of arc seconds (Wie, B., 2008; Wertz, J. R., 2012).

A star tracker is an optoelectronic device which utilizes the position of stars to determine the orientation of the satellite. When no prior attitude information is available, the star tracker operates in the “Lost-In-Space (LIS)” mode. The basic principle of operation of a star tracker in the LIS mode is based on firstly identifying the stars captured in the image and later calculating the attitude from the position measurements (stored in the star catalog) of the identified stars. The latter part of calculating the attitude can be easily accomplished by the existing QUEST or TRIAD methods (Shuster, Malcolm David, S. D. Oh, 1981). The challenging part is the correct identification of the stars in the image captured despite the problems of patch mismatch, magnitude uncertainty, and false stars in the image. Many star pattern recognition techniques have been proposed in the last two decades (Ho, K., 2012) for solving the problem of star identification.

The star pattern recognition techniques can be segregated into two parts – geometric based and pattern based. Geometric based techniques utilize the features such as the angles and distances formed by the star clusters for constructing the star pattern database (SPD) and identification purposes. Star clusters can range from a size of three (Liebe, C. C., 1993), four (Mortari, D., Junkins, J. L., Samaan, M., 2001) or can consists of all the stars which lie within the field of view (FOV) of the center star (Kolomenkin, M., Pollak, S., Shimshoni, I., Lindenbaum, M., 2008). Some geometric based techniques form features such as utilizing the area formed by all the possible star clusters for comparison purposes (Cole, C. L., Crassidis, J. L., 2006). Many variations of the geometric based approach have also been proposed in the recent years where different transformations (Delabie, T., Durt, T., Vandersteen, J., 2013; Roshanian Jafar, Shabnam Yazdani, Masoud Ebrahimi., 2016; Samirbhai, M. D., Chen, S., Low, K. S., 2016; Hernández, E.A., Alonso, M.A., Chávez, E., Covarrubias, D.H., Conte, R., 2017; Schiattarella, V., Spiller, D., Curti, F., 2017) are applied to the geometric features for pattern recognition. The grid algorithm (Padgett, C., Kreutz-Delgado, K., 1997) initiated the pattern-based approach, which develops a coded pattern of the stars for comparison and identification

purposes. The research community has widely adopted the pattern-based idea and many modified approaches of this idea have also been developed (Na, M., Zheng, D. N., Jia, P. F., 2009; Yoon, H., Paek, S. W., Lim, Y., Lee, B. H., Lee, H., 2013). Recently, an optimized grid algorithm (Aghaei, Mahdi, Hamid Abrishami Moghaddam, 2016) specifically for tackling false stars was proposed, which has significantly improved the performance of the initial grid approach. Some star pattern recognition techniques – low memory SPD (David D. N., James P. A., Peter C. L., Haytham M.E., 2010), optimized SPD (Pham, M. D., Low, K. S., Chen, S. S., 2013) were developed specifically for achieving a high speed of recognition. Apart from the above two general approaches, a multi-purpose panoramic camera based star pattern recognition was proposed recently in (Opromolla, R., Fasano, G., Rufino, G., Grassi, M., Pernechele, C., Dionisio, C., 2017). An exhaustive review of all the existing star pattern recognition approaches is provided in Star Identification (Guangjun Zhang, 2017).

A star pattern recognition technique is evaluated based on two parameters - the recognition reliability (identification accuracy) and the run time for identification. For achieving a high recognition reliability, more features are preferred to be extracted along with more combinations of star clusters and thus, more comparisons must be made. However, such an exhaustive process will increase the time required for feature extraction and comparison with the SPD. This will lead to a low speed of identification. On the other hand, if fewer features are used with only some selected combinations of star cluster then the number of comparisons to be made are reduced significantly which will lead to a high speed of identification. However, the accuracy of correct star identification may decrease because of the selected number of features used for extraction and comparison. Thus, there is a trade-off between recognition reliability and speed.

In this paper, we propose a novel combination of star shortlisting and pattern recognition algorithm which excels at both the recognition reliability and speed. The first part of the proposed combination deals with shortlisting the stars based on worst-case patch mismatch, and the second part of the algorithm comprises of the pattern recognition technique which is based on an initial match confirmed by a running a sequential angular match. The former leads to achieving a low time complexity for identification and the latter leads to attaining a high recognition reliability. The proposed idea is benchmarked with the state-of-the-art star pattern recognition techniques on simulated images containing magnitude uncertainty, false stars, positional deviation and varying size of the FOV. Later, the proposed idea is also tested on the real images captured by a star tracker SST-20S. The paper is concluded by analyzing the results of the proposed combination of star shortlisting and pattern recognition algorithm.

2. Research Problem

Before explaining the proposed approach of robust and fast star identification, we will first concentrate on analyzing the problems faced in star pattern recognition in this section. In Fig. 1, we show an illustrative example to describe the major problems faced in star pattern recognition. Image captured by the star tracker is restricted by a defined FOV. The star pattern database (SPD) is constructed by taking the same FOV and utilizing the features extracted from the neighboring stars which lie within the FOV of the center star. In Fig. 1, the solid circle is the SPD of the center star A and the stars which lie in the FOV of the star A are labeled from 1 to 10. The dotted circle is the image captured by the star tracker, where I_c is the center of the image. Let us assume that the star A is the closest to I_c and needs to be identified. The major problem as can be seen from the example in Fig. 1 is that in the SPD of star A there are stars 1 to 10 as its neighboring stars, however, in the image captured by the star tracker the neighboring stars for the star A are the stars 1, 3, 8, 9 and 10 (common with the SPD). There is also one false star F (noise), which is captured by the star tracker in the image, but not a part of the SPD of star A .

Fig. 1 An illustrative example demonstrating the problems faced by star pattern recognition techniques.

The above-described scenario is a major problem faced by the star pattern recognition techniques, as the captured image need not coincide exactly with a patch of the SPD, and thus will cause a mismatch between the comparison of the features extracted from the image with that of the SPD. This problem is also elevated because of the *magnitude uncertainty* of the star tracker and brightness ambiguity of the stars, which results in missing to capture the low magnitude stars. Apart from this, there are many potential sources of confusion such as planets, comets, meteors, other nearby satellites, and space debris which can be wrongly recognized as stars while capturing

the image. These false stars are not present in the SPD but are present in the image. This will lead to an increase in difficulty of identifying the correct stars in the image.

The aim of a star pattern recognition technique is to select a reference star and identify it correctly despite the above-mentioned problems. Reference can be selected either based on the *distance* (star closest to the center of the image, as in Fig. 1) or on the *brightness* (the brightest star in the image). The techniques which utilize the brightness of stars (Delabie, T., Durt, T., Vandersteen, J., 2013; Sohrabi, S. H., Shirazi, A. B., 2010) for selection of reference star or for identification are more prone to failure because the order of brightness of the stars in the image and the database differs. The studies in (Accardo Domenico, Giancarlo Rufino, 2002; Padgett Curtis, Kenneth Kreutz-Delgado, Suraphol Udomkesmalee, 1997) also suggest that the brightness of the stars is an ambiguous feature for comparison and should be avoided.

Having analyzed the above problems, we propose a star identification algorithm based on the identification of the star nearest to the center of the image and do not rely on the ambiguous brightness of the stars. The proposed idea addresses both the problems of recognition reliability and speed. Our algorithm utilizes all the stars which lie in the FOV for feature extraction, however, we apply a shortlisting method for selecting only a part of the SPD before performing the star pattern recognition. The star pattern recognition process further comprises of an initial match followed by a running sequential angular match. The overall flow of the proposed algorithm is shown in Fig. 2.

Fig. 2 Proposed algorithm flow.

The rest of the paper is structured as follows. Section 3 deals with the feature extraction, construction of the look-up-table (LUT) based on worst-case patch mismatch, and the star pattern database generation for the proposed idea. In section 4, the shortlisting technique and the star pattern recognition technique are explained in detail. Later it is shown how the combination of shortlisting and pattern recognition technique is used for obtaining a high recognition reliability as well as a high speed of identification. Finally, section 5 compares the performance of the proposed idea with the state-of-the-art star pattern recognition techniques, and results are concluded in section 6.

3. Feature Extraction, Look-Up-Table and Star Pattern Database Construction

In this section, we will explain the process of feature extraction, look-up-table (LUT), and star pattern database (SPD) construction for the proposed idea.

3.1 Feature extraction

The proposed technique uses two rotation invariant features – radial distance of each neighboring star from the center star and the relative angle that the consecutive neighboring stars make with the center star, as shown in Fig. 3. Every star having a relative magnitude (M_v) of less than 6 in SAO J2000 catalog (Myers, J. R., Sande, C. B., Miller, A. C., Warren Jr, W. H., Tracewell, D. A., 1997) is considered at the center of the FOV and all the stars which lie within the FOV of the center are taken into account in an anti-clockwise increasing angle which forms a pattern vector as shown in Fig. 3. The above mentioned two features are then extracted and given by Eq. (1) and Eq. (2) respectively.

Fig. 3 Feature extraction for the proposed technique.

$$r_n = \sqrt{(x_n - x_c)^2 + (y_n - y_c)^2} \quad (1)$$

$$A_n = \tan^{-1} \frac{(y_{n+1} - y_c)}{(x_{n+1} - x_c)} - \tan^{-1} \frac{(y_n - y_c)}{(x_n - x_c)} ; \text{ if } n \neq N$$

$$A_n = 360 - (A_1 + A_2 \dots + A_{N-1}) ; \text{ if } n = N \quad (2)$$

where x_n and y_n are the pixel co-ordinates of the n^{th} neighboring star, N is the total number of neighboring stars in the FOV of the reference star, and x_c and y_c are the co-ordinates of the reference star A . For shortlisting the star entries, only radial distances $\{r_1, r_2 \dots r_N\}$ are utilized whereas, both the radial distances and relative angles $\{A_1, A_2 \dots A_N\}$ are used for the generation of SPD, which is explained later in this section.

3.2 Worst-case patch mismatch calculation and LUT construction

1. Worst-case patch mismatch calculation

As mentioned earlier, the major problem that the star pattern recognition techniques face is the patch mismatch between the SPD and the image captured. So, we propose to first compute the worst-case patch mismatch that can occur for a center star. We understood that the patch mismatch occurs because of the displacement and the rotation of the image captured when compared to the SPD (as was shown in Fig. 1). By worst case, we mean the *maximum difference* (d_{max}) that can occur in the number of stars between the SPD and the image captured solely because of the patch mismatch. For calculating the d_{max} , a unique simulation approach is adopted which is explained in Fig. 4.

Fig. 4 Worst-case patch mismatch simulation.

For every center star ID, the following steps are performed in a sequence:

- 1) Every star which lies in the FOV of the center star (star ID selected) and the center star itself is shifted by a step of 1 pixel in the x-direction as shown in Fig. 4.
- 2) Every star, after shifting, is rotated by a step of 1 degree in the counterclockwise direction.
- 3) The distance of each star from the center of the image is calculated.
- 4) If the star nearest to the center of the image is still the same as the star ID (star A, in the example in Fig. 4) for which this operation is performed, then step 2, step 3, and step 4 are repeated. These steps are repeated

until the nearest star to the center of the image is different from the center star ID or when the degree of rotation reaches 360^0 .

- 5) If the degree of rotation reaches 360^0 , then we shift to step 1 and the whole process is repeated until the point when the star nearest to the center of the image is no longer the same center star ID (star *A* in Fig. 4).

Fig. 5 Flowchart for worst-case patch mismatch simulation.

When the star nearest to the center of the image changes, the *maximum difference* occurs between the number of stars in the SPD of the center star ID and the number of stars currently in the image. For example, in Fig. 4, if any of the neighboring stars 1 to 7, during the above simulation process becomes the closest to the center of the image, then the worst-case patch mismatch has occurred for star *A* and d_{max} for star *A* is given by Eq. (3).

$$d_{max} = N_{SPD} - N_{image} \quad (3)$$

where N_{SPD} is the initial number of stars in the SPD of the center star (7, in the example in Fig. 4) before the operation of worst-case patch mismatch began and N_{image} is the number of stars which lie within the FOV of the

center of the image when the worst-case patch mismatch situation has reached. The quantity d_{max} is calculated for every star having a magnitude threshold (M_v) of less than 6 from the SAO J2000 (Myers, J. R., Sande, C. B., Miller, A. C., Warren Jr, W. H., Tracewell, D. A., 1997) star catalog. This entire process of calculating the worst-case patch mismatch is explained in detail in the flowchart in Fig. 5. We will now explain the construction of the LUT based on the worst-case patch mismatch.

2. LUT construction based on worst-case patch mismatch

We only use the radial distances of the neighboring stars for constructing the LUT. The LUT consists of four threshold levels for each center star, which are calculated as follows:

- 1) Thresh 1: This threshold level represents the scenario when none of the stars are missed in the FOV of the center star. Thus, without missing any stars in the FOV of the center star, the summation of the radial distances of all the neighboring stars (N_{SPD}) from the center star is calculated for this threshold level. This threshold level is given by Eq. (4). It should be noted that this is the maximum value of all the threshold levels, as it considers all the neighboring stars.

$$Thresh1 = \sum_{i=1}^{N_{SPD}} r_i \quad (4)$$

- 2) Thresh 2: This threshold level is calculated to consider the stars missed due to the patch mismatch. It is essential to understand from the process of worst-case patch mismatch simulation that the neighboring stars which are *farther* away from the center star have a *high probability* of been missed compared to that of the stars which are nearer to the center star. This is because of the displacement of the image captured when compared to the SPD.

As mentioned earlier, the maximum number of stars that can be missed due to patch mismatch is d_{max} . Thus, for calculating this threshold level, we miss d_{max} number of neighboring stars starting from the *farthest* star from the center star. The summation of radial distance is calculated after missing those *farthest* d_{max} stars. This threshold level is given by Eq. (5). Having calculated Thresh 1 and Thresh 2, it should be clear that the summation of radial distances of the neighboring stars in the image captured (having *only* patch mismatch) will fall between Thresh 1 and Thresh 2 of the reference star ID in the LUT.

$$Thresh\ 2 = \sum_{i=1}^{N_{SPD}-d_{max}} r_i \quad (5)$$

- 3) Thresh 3: The levels Thresh 3 and Thresh 4 are calculated for considering the low magnitude missing stars in the image. As described earlier in section 2, magnitude uncertainty adds more missing stars to the problem of patch mismatch. We already considered the *farther* away missing stars due to patch mismatch by calculating the Thresh 2 level. The *nearest* stars to the center star have a less chance of getting missed due to patch mismatch, however, they may get missed because of low magnitude. Thus, we need to consider these low-magnitude nearest stars which may get missed in addition to the missed stars due to patch mismatch.

The existing approaches such as Pyramid (Mortari, D., Junkins, J. L., Samaan, M., 2001), *k*-nearest neighbors (Roshanian Jafar, Shabnam Yazdani, Masoud Ebrahimi., 2016) rely on the *nearest four* stars for star pattern recognition. Thus, we select *four* stars as a worst case of the number of nearest stars missed due to magnitude uncertainty. For the sake of not making the window of qualification between the threshold levels big, we split the four low magnitude stars into two halves. Thus, for calculating Thresh 3, we will only consider missing two more stars in addition to the d_{max} stars missed for Thresh 2. Hence the *farthest* ($d_{max} + 2$) stars are missed for calculating this threshold level and the summation of the radial distances of the remaining stars from the center star is calculated. This threshold level is given by Eq. (6). Having calculated Thresh 3, it should be clear that the summation of the radial distances of the neighboring stars in the image captured (containing missed stars due to patch mismatch and less than three missed stars due to magnitude uncertainty) will fall between Thresh 1 and Thresh 3.

$$Thresh\ 3 = \sum_{i=1}^{N_{SPD}-d_{max}-2} r_i \quad (6)$$

- 4) Thresh 4: As explained earlier while calculating the Thresh 3 level, the consideration of low magnitude missing stars is divided into two halves. This level is the final level of all the thresholds and considers the second half of the low magnitude missing stars. Thus, for calculating this level, the *farthest* ($d_{max} + 4$) stars are missed and summation of the radial distances of the remaining stars from the center star is calculated. This threshold level is given by Eq. (7).

$$Thresh\ 4 = \sum_{i=1}^{N_{SPD}-d_{max}-4} r_i \quad (7)$$

From the above calculation of the threshold levels, it should be noted that for each star ID, Thresh 1 > Thresh 2 > Thresh 3 > Thresh 4.

A Look-Up-Table (LUT) shown in Fig. 6 is then prepared offline with all the four thresholds calculated for each star entry as described earlier. We consider the star entries having a M_v of less than 6 from the SAO J2000 star catalog for constructing the LUT. The total number of star entries is 4956. For a particular center star, a circular field of view (FOV) of 15° is considered for the above operations. There is one more parameter in the LUT, called the check bit, which is initially 0 for every star ID. The purpose of the check bit is explained later in part 4.3 of section 4 of this paper. Having constructed the LUT, we will now describe the process of generating the SPD.

3.3 Star pattern database (SPD) generation

The SPD is first prepared offline and loaded into the star tracker on-board memory along with the LUT. For constructing the SPD, the same parameters of M_v and FOV are adopted as considered for constructing the LUT. We will now describe the SPD construction for star A (in Fig. 3).

Referring to Fig. 3, we have nine neighboring stars to star A at the center. Both the radial distances and relative angles are considered for constructing the SPD. Hence, the feature vector for star A is constituted as a sequence - $\{r_1, A_1, r_2, A_2, r_3, A_3, \dots, r_9, A_9\}$. If a star at the center has N number of neighboring stars within its FOV, its feature vector would look like $\{r_1, A_1, r_2, A_2, r_3, A_3, \dots, r_N, A_N\}$, where the features r_n and A_n are calculated as was described in part 3.1 of this section. The LUT and SPD constructed for the proposed technique are shown in Fig. 6.

Look-Up-Table						Star Pattern Database			
Index	Check bit	Thresh 1	Thresh 2	Thresh 3	Thresh 4	$\{r_1, A_1\}$	$\{r_2, A_2\}$	...	$\{r_N, A_N\}$
0	0	4563	2696	1866	1176	{103.7, 51.3}	{434.8, 19.4}	...	{268.5, 6.27}
1	0	3580	2331	1551	849	{378.1, 39.2}	{347.7, 4.7}	...	{165.5, 73.9}
2	0	4596	1742	1056	499	{351.9, 20.6}	{485.3, 45.6}	...	{347.6, 4.7}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
4955	0	4637	3263	2435	1729	{400.2, 9.9}	{306.0, 3.2}	...	{423.9, 6.1}

Fig. 6 Look-Up-Table and Star Pattern Database for the proposed technique.

4. Shortlisting and Star Pattern Recognition

In this section, we will explain the proposed idea of star shortlisting and star pattern recognition.

4.1 Shortlisting

The process of shortlisting using the LUT is shown in Fig. 7. As can be seen in Fig. 7, there are three slabs (windows) allotted to the LUT. Slab 1 is between Thresh 1 and Thresh 2, Slab 2 is between Thresh 1 and Thresh 3, and Slab 3 is between Thresh 1 and Thresh 4. Once the image is acquired, the summation of the radial distances of all the neighboring stars which lie in the FOV of the star nearest to the center of the image (reference star) is calculated by Eq. (8), which is used for shortlisting the star entries.

$$R_{sum}^I = \sum_{i=1}^N r_i \quad (8)$$

where N is the total number of neighboring stars which lie in the FOV of the reference star in the image captured.

Fig. 7 Shortlisting technique.

Once the R_{sum}^I is calculated, *firstly* it is checked whether it falls in Slab 1 for each star ID i.e. it should fall between Thresh 1 and Thresh 2, satisfying the following condition:

$$Thresh\ 2 < R_{sum}^I < Thresh\ 1 \quad (9)$$

Only those star IDs are shortlisted for which the above condition is true, and the check bit of those star IDs is *toggled* from 0 to 1. Later only those shortlisted star IDs are checked for the star pattern recognition process described in part 4.2 of this section. In the case that the correct star ID *does not get shortlisted* in Slab 1, the window is increased and is checked for Slab 2 and later if required for Slab 3. The condition for increasing the window size and shifting to Slab 2 and Slab 3 is dependent upon the result of the star pattern recognition technique. This

combination of the shortlisting technique and the star pattern recognition technique is explained later in part 4.3 of this section.

4.2 Star pattern recognition

1. Initial match

We will explain the proposed star pattern recognition technique and how it tackles the problems of mismatch, magnitude uncertainty, and false stars concurrently with the help of two examples in Fig. 8 and Fig. 9. The example in Fig. 8 depicts two circles (of the same FOV) – the solid circle is the pattern vector (SPD) of the star A , which is the same as was shown in Fig. 3 and the dashed circle is the image captured by the star tracker. Point I_c is the center of the image captured in Fig. 8. Let us assume that star A is closest to the point I_c and thus, is selected as the reference star to be identified. It should be noted from Fig. 8 that stars 1, 3, 4 and 9 are not a part of the image captured while they are present in the SPD of star A . Also, the star F (noise) is present in the image but not a part of the SPD of star A . Thus, the example in Fig. 8 contains the problem of patch mismatch and false stars. Hence the task of the proposed technique is to identify the star A despite the above problems.

Fig. 8 First example to explain the initial match and running sequential angular match.

The proposed technique extracts both the radial and relative angular features from the image captured and arranges them in a sequence in a similar fashion as was explained during the construction of the SPD. Both the features are used for finding the match in the SPD. Firstly, we will find an initial match in the SPD of star A . In Fig.

8, it can be clearly seen that the radial distances r_2 , r_5 , r_6 , r_7 , and r_8 in the image will match exactly with the radial distances stored in the SPD of star A . We can also note that the angles A_5 , A_6 , and A_7 in the image will match exactly with the angles contained in the SPD of star A . But the angles A_1 , A_2 , A_3 , A_4 , A_{F1} , and A_{F2} in the image will not get matched with the angles stored in the SPD of star A . For explanation of the initial match step of the proposed technique, let us assume that the angle A_5 is the smallest angle in the image.

Then the initial match will be checked by finding the match of the *smallest angle* in the image (A_5 in this example) with the angle present in the SPD of the star ID. In this example, A_5 will get matched with the angle A_5 stored in the SPD of star A . This angle match is then confirmed by finding the match of the radial distances of the stars containing that angle. In Fig. 8, angle A_5 is made by the stars 5 and 6. Thus, their corresponding radial distances r_5 and r_6 are checked for finding the match with the corresponding radial distances stored in the SPD of star A . Both the radial distances will find the match which makes sure that the angle matched is correct. Thus, only those star IDs are said to have an initial match which confirms *both* the angular match confirmed by radial distance match. We will now explain the second part of the proposed star pattern recognition technique.

2. Running sequential angular match

The first step of our proposed technique is to find the initial match. Later, to confirm that the initial match a star ID is indeed correct, a running sequential angular match is performed. The running sequential angular match starts from the angle after the initial match. For the example in Fig. 8, after the initial match of angle A_5 , angle A_6 and angle A_7 will get correctly matched with the angles stored in the SPD of star A . However, when it comes to the angle between the star 8 and star F, it does not get match with the SPD sequence of star A . Whenever the angle in the sequence does not match, the proposed technique shifts to check the radial distance match in the sequence. In this example, r_8 will find the match, however, r_F will not find the match. So, the next radial distance r_2 in the image sequence is checked, which will find the match in the SPD of star A . After any two radial matches in the sequence are confirmed, the angle contained in between those matches is compared. In the image, the angle between star 8 and star 2 is the summation of A_{F1} and A_{F2} . In the SPD of star A , the angle between star 8 and star 2 is the summation of the angles A_8 , A_9 , and A_1 . As can be seen from Fig. 8, the summation of the angles in the image matches with that of the SPD. Thus, the radial match is confirmed by this angular match. For any other star ID, when this process does not find a match anywhere in the sequence, it will break from checking further sequence of the angles and distances. Later, for this example, when we focus on the angle between star 2 and star 5, it is the

summation of angles A_2 , A_3 , and A_4 . After applying the same process of matching the radial distances first and confirming with the angle summation, angle in the image between star 2 and star 5 will get matched with that in the SPD of star A . We can note that for this star A , we started from angle A_5 as the initial match and are back to angle A_5 after completing the running sequential angular match. Thus, a perfect sequential angular match is obtained for a single cycle of 360 degrees for the star A . Hence star A is correctly identified as the reference star even if there are missing stars due to patch mismatch and false stars in the image.

Fig. 9 Second example involving brightness ambiguous missing stars to explain the proposed star pattern recognition technique.

In Fig. 9, we show another example when some nearest stars to the reference star A are missed because of magnitude uncertainty. In this example, let us assume that the stars 6 and 7 in Fig. 8 are also missed to be captured by the star tracker due to their low brightness, and the image does not contain the false star F for this example. Thus, the captured image is the dotted green circle shown in Fig. 9 which contains only stars 2, 5, and 8 as the neighboring stars to star A . Hence only three radial distances and relative angles are extracted as the features from the image captured in the example in Fig. 9.

For explaining the working of the proposed technique for the example in Fig. 9, let us assume that the angle between the star 5 and star 8 is the smallest angle in the image. As described earlier, the initial match for the proposed technique will start with matching the smallest angle and the corresponding radial distances of the stars containing the smallest angle. Thus, the angle between star 5 and star 8 in the image - $A_5 + A_6 + A_7$ will get matched

with the corresponding sequential summation of the angles in the SPD of star A . This angular match will also get confirmed by the radial distances of star 5 and star 8. Hence the initial match is fixed in the SPD of star A .

The latter process of the running sequential angular match technique will remain the same as was described for the example in Fig. 8. Thus, star A will be correctly identified in Fig. 9 even if there are low magnitude missing stars. Hence according to the proposed star pattern recognition technique, a star will be correctly identified if and only if it satisfies both the initial match and the running sequential angular match for the *single cycle* of 360 degrees.

4.3 Combination of shortlisting and star pattern recognition technique

Fig. 10 Final algorithm flow – Combination of star shortlisting and star pattern recognition technique.

The star pattern recognition technique, consisting of the initial match and the running sequential angular match is applied only to the star IDs that get shortlisted. Initially, the shortlisted star IDs are the ones which qualify for the window under the Slab 1 of the LUT as was explained in part 4.1 of this section. However, there might arise a situation in which the correct star ID gets *failed* to be shortlisted by the technique i.e. it does not qualify for the window under Slab 1 of the LUT. This situation will arise when there is a high magnitude uncertainty along with the existing problem of patch mismatch. This problem is taken care of by the proposed combination of shortlisting and star pattern recognition technique. It is important to note that the proposed star pattern recognition technique identifies the reference star correctly if and only if any of the shortlisted star IDs satisfies the *perfect single cycle match*. So, in the case, when the correct star ID is not shortlisted, none of the shortlisted star IDs will qualify for the perfect match by the star pattern recognition technique. Thus, we will *increase the window* for the qualification of shortlisting. This process of increasing the window, and thus shifting to Slab 2 and later if required to Slab 3 is explained in Fig. 10.

If the star pattern recognition technique is not able to find the perfect match from the initial list of shortlisted star IDs (under Slab 1), the summation of radial distances in the image (R_{sum}^I) that was calculated is now checked if it

falls under Slab 2 i.e. between the Thresh 1 and Thresh 3 as was shown in Fig. 7. Only those star IDs are checked whose check bit is 0 because the star IDs for whom the check bit is 1 are already tested for the perfect match by the star pattern recognition technique. If R'_{sum} falls under Slab 2 for that star ID, it is shortlisted and the check bit for that star ID is toggled from 0 to 1. This will create a new list of shortlisted star IDs that will further go through the same process of the star pattern recognition. If still after checking for Slab 2, the perfect match is not found, it is tried later for Slab 3, keeping in mind to shortlist only those star IDs for which the check bit is still 0. Eventually, if the perfect match is still not found after checking for Slab 3, all the remaining star IDs will be shortlisted and checked by the star pattern recognition technique.

Whenever a perfect match is found for the image, the corresponding star ID in the SPD is allotted to the reference star in the image. Later, the neighboring stars to the reference star in the image can be easily identified from the sequence of the SPD of the reference star ID. Two to three correctly identified stars in the image are enough for attitude calculation, which can be accomplished by the existing QUEST method (Shuster, Malcolm David, S. D. Oh, 1981).

5. Results – Performance and Benchmarking

The performance of the star pattern recognition techniques was evaluated on the simulated images generated from the sky map of the SAO J2000 star catalog. At a particular ascension angle (α) and declination angle (δ), the stars having a M_v of less than 6 and which lie within 15° circular FOV were considered to be captured in the image. The images were generated by varying the ascension angle (α) from 0° to 360° and the declination angle (δ) from -90° to $+90^\circ$ at an interval of every two degrees increment. Totally 16200 images were generated by the MATLAB software with the resolution being 1024×1024 and pixel size equal to $13 \mu\text{m}$. This operation covers the *full sky scan* from the star catalog SAO J2000. The simulations were performed on a PC with specifications - Intel core i7, 3.4 GHz processor, and 8GB RAM.

State-of-the-art star pattern recognition techniques which claim to provide high robustness and fast identification were implemented. We compare a high identification accuracy technique based on shortest distance transform (SDT) (Delabie, T., Durt, T., Vandersteen, J., 2013), a high speed technique based on search tree with optimized database (STOD) (Pham, M. D., Low, K. S., Chen, S. S., 2013), and a highly robust geometric voting algorithm (GMV) (Kolomenkin, M., Pollak, S., Shimshoni, I., Lindenbaum, M., 2008) with our proposed combination of star shortlisting and pattern recognition technique. The testing was initiated with an ideal image having only patch

mismatch. Later magnitude uncertainty, false stars, and positional deviation was added to the ideal image to check the robustness of the star pattern recognition techniques. The star pattern recognition techniques were also tested for varying values of the FOV.

Firstly, the benchmarking of the proposed idea with the above-mentioned star pattern recognition techniques in different scenarios is shown in this section. Later, the performance of the *proposed shortlisting technique* is described. Finally, the results of the testing of the proposed combination of star shortlisting and pattern recognition technique on the real images captured by a star tracker SST-20S are shown.

5.1 Ideal case

In an ideal case scenario, the image will solely have the problem of patch mismatch. Table 1 summarizes the performance of the star pattern recognition techniques in the ideal case scenario.

Table 1 Benchmarking of star pattern recognition methods – Ideal case

Technique	Identification accuracy (%)	Cases of multiple star IDs matched for the reference star (%)	Run-time (sec)	SPD size (MB)
GMV	94.3	13.11	0.567	1.31
STOD	90.3	21.01	0.21	1.4
SDT	95.78	10.97	0.337	4.7
Proposed technique	99.57	0.1	0.22	1.7

As can be seen from the results in Table 1, the identification accuracy of the proposed technique outperforms those of the compared star pattern recognition techniques. One more important advantage of the proposed technique is there are only 0.1% cases when multiple star IDs are matched for the reference star. This is because the proposed technique employs a perfect match of 360 degrees or 2π radians. The run-time listed in Table 1 is measured by the MATLAB software with the PC specs of Intel core i7, 3.4 GHz processor and 8 GB RAM. As can be seen from Table 1, the proposed technique gives almost comparable run-time to STOD (fastest), only a slight 0.01 sec more. It reaches almost the same performance as STOD in terms of run-time because of the shortlisting of star IDs adopted. SPD size (including LUT) of our technique is 0.4 MB more than that of GMV and 0.3 MB more than that of STOD.

However, storing up to 5 MB is not a problem in the on-chip memory of current on-board computers when the focus is on identification accuracy, robustness, and run-time of the algorithm.

5.2 Magnitude uncertainty of stars

Whenever the star tracker captures the image of the stars, there are always some low magnitude stars which do not get captured by the sensor. We simulate such a scenario by applying a relative magnitude (M_v) uncertainty. For example, if the M_v uncertainty is 0.2, it will imply that the stars captured in the image which has a M_v of greater than 5.8 will be missed by the image sensor (M_v threshold is 6.0). M_v uncertainty was varied from 0.0 to 0.4 in steps of 0.05. This method of simulation is adopted from the one described in GMV.

Fig. 11 Performance of star pattern recognition techniques in the scenario of magnitude uncertainty.

The performance of the star pattern recognition techniques for the case of magnitude uncertainty is shown in Fig. 11. In this scenario, GMV, which is based on voting of the euclidean distances of the neighboring stars from the reference star fails because the vote count for the reference star reduces due to the missed neighboring stars. STOD fails as well because it searches the tree database with the number of neighboring stars as the parameter. SDT also fails because one of its feature extracted is the brightness of the stars. The proposed technique maintains a high robustness in this case due to the running sequential angular match technique as was explained in the example in Fig. 9.

5.3 False stars

As was described in section 2 of this paper, there are many potential sources of confusion which can be wrongly recognized as stars. To simulate such a scenario, the number of false stars (with random position and brightness) per image were varied from 1 to 5. This simulation approach for the scenario of false stars is adopted from the one described in STOD. The performance of the star pattern recognition techniques for the case of false stars per image is shown in Fig. 12. In the case of false stars added to the image, GMV and STOD will fail drastically because of the same reason for which they failed during the magnitude uncertainty of stars. In this scenario, however, SDT maintains a decent accuracy of identification. The robustness of the proposed technique in this case was explained in the example in Fig. 8.

Fig. 12 Performance of star pattern recognition techniques in the scenario of false stars.

5.4 Deviation in star positions

A spacecraft usually undergoes vibrations, unexpected velocity, and acceleration changes. Due to this, the image captured by the star tracker is distorted which eventually leads to positional deviation of stars. Thus, apart from the three major problems of patch mismatch, magnitude uncertainty, and false stars, a star pattern recognition technique also faces the problem of deviation in star positions (euclidean distances will be the most affected feature). It was studied in (Jun, Z., Yuncai, H., Li, W., Da, L., 2015) that the maximum positional deviation of a star is usually around 1.0 pixel. Thus, to simulate such a scenario, the positional deviation was introduced in ideal images from 0.1 pixels

to 1.0 pixels in the steps of 0.1. The performance of the star pattern recognition techniques in the case of positional deviation is shown in Fig. 13.

For the scenario of positional deviation, the proposed technique and SDT are quite robust to the distortions caused in the image whereas the identification accuracy of GMV and STOD decreases drastically. This is because GMV and STOD extract only the distance as the feature for recognition while the proposed technique utilizes relative angle and SDT utilizes brightness in addition to the distance for feature extraction.

Fig. 13 Performance of star pattern recognition techniques in the scenario of positional deviation.

5.5 Varying values of Field of View (FOV)

Star trackers have varying values of field of view (FOV). The performance of a star pattern recognition technique varies with different values of FOV. This is because different FOVs will have a different number of stars captured in the image for a satellite having the same orientation. As the number of stars captured varies, the number of features extracted will also vary. The performance of the star pattern recognition technique becomes critical when the FOV value is low as the number of stars captured will be less, which makes the task of reliable star identification challenging. Thus, to simulate the above scenario and test the performance of the star pattern recognition techniques, we vary the FOV value from $20^\circ \times 20^\circ$ to $8^\circ \times 8^\circ$ as shown in Fig. 14. These values of FOV adopted for testing are usually the FOV values for star trackers (Guangjun Zhang, 2017).

It can be seen from Fig. 14 that all the star pattern recognition techniques have a high performance when the FOV is large, and the identification accuracy decreases as the FOV keeps getting smaller. In terms of performance, STOD is the most affected technique by variation in FOV as it considers the number of neighboring stars as one of the features for comparison. The identification accuracy of GMV and SDT techniques do not fall drastically in this case because they employ voting and brightness as the additional features respectively. As can be seen from Fig. 14, the proposed technique is the least affected by the variation in FOV because of the full cycle of running sequential angular match adopted.

Fig. 14. Performance of star pattern recognition techniques for varying values of FOV.

5.6 Performance of the proposed shortlisting technique

The main purpose of the proposed shortlisting technique is reducing the overall time required for identification of the stars in the image. It accomplishes this task by giving a shortlisted list of star IDs for pattern recognition. The performance of the shortlisting technique is measured in terms of the number of shortlisted entries (N_{sh}) out of 4956 star IDs and the probability that the shortlisted entries contain the correct star ID (p_{sh}). As the number of shortlisted entries will vary for every slab, the performance of the shortlisting technique must be evaluated for every slab.

As can be seen from Fig. 15, the performance for Slab 1 gives the least N_{sh} followed by Slab 2 and later Slab 3. This is because the window of Slab 1 is narrow compared to a wider window of Slab 2 and the widest window of Slab 3. Thus, the p_{sh} is highest in Slab 3 followed by Slab 2 and later Slab 1. In Fig. 15, the number of missing stars

are due to the *magnitude uncertainty* in addition to the patch mismatch. Hence the p_{sh} of the Slab 1 decreases drastically when the number of missing stars increases. Whereas for Slab 3, which has a wider window for shortlisting, the p_{sh} does not fall that drastically. This is because the lower threshold (Thresh 4) of Slab 3 is calculated by missing four more stars adding to the worst-case patch mismatch. Whereas, for Slab 1, the lower threshold (Thresh 2) is calculated by missing only the worst-case patch mismatch number of stars. It is evident from the results in Fig. 15 that the shortlisting technique provides only *one-third* (1544 / 4956) of the SPD to the pattern recognition technique in case of Slab 1 and a *worst case of half* (2440 / 4956) of the SPD in the case of Slab 3. This makes the proposed combination of star shortlisting and pattern recognition technique fast as was depicted in the results shown in Table 1.

Fig. 15 Performance of the proposed star shortlisting technique.

5.7 Performance of the proposed idea on real images captured by a star tracker

The proposed combination of the star shortlisting and pattern recognition technique was implemented on the real images captured by a star tracker SST-20S currently mounted on a Low Earth Orbit (LEO) satellite, namely, VELOX-C1 (VELOX-CI Satellite. 2015). The specifications of the SST-20S star tracker are shown in Table 2. As the M_v of SST-20S star tracker is 6.3, the LUT and the SPD of the proposed technique were prepared accordingly with the M_v of 6.3 for the real-time testing of the proposed idea.

For the real-time environment testing, the proposed technique was implemented on Linux-based C platform with PC specifications i7 – 3.4 GHz and 8 GB RAM. It was tested on 3104 continuous images captured by the star tracker. The total number of sets of images are 102 with approximately 30 images in each set.

Table 2 Specifications of SST-20S star tracker

Parameter	Value
Field of View (FOV)	$15^0 \times 15^0$
Sensitivity	$M_v 6.3$
Star catalog	SAO J2000
Number of star entries	6903 star IDs
Resolution	1024 x 1024 pixels
Pixel size	13 μm
Focal length	50 mm
Boresight accuracy	<40 arcsec

By comparing the attitude obtained by the star tracker SST-20S and the attitude calculated after applying QUEST (Shuster, Malcolm David, S. D. Oh, 1981) on the star IDs identified by the proposed technique, the identification accuracy was calculated. If the difference between the calculated attitude and the real attitude was less than 40 arc seconds, it was considered as a correct identification.

The proposed technique was able to identify 3043 images correctly out of the 3104 images, thus giving an identification accuracy of 98%. The technique failed to identify the stars correctly in 2 out of 102 sets. It failed as it was unable to find an initial match in these two sets of images. The proposed technique took 73.2 ms on an average to identify the stars of which reading the image data, pre-processing and centroiding operation took 65 ms. Implementation of the proposed idea and to output the identified star IDs occupied only 8.2 ms. One of the identified real images by the proposed technique is shown in Fig. 16 where the center of the image is marked with purple (I_c). The star nearest to I_c i.e. the reference star is marked with orange and is identified by the star ID 4908 from the SPD. From the sequence of the star ID 4908 stored in the SPD, the rest of the identified neighboring stars are marked with yellow.

Fig. 16 An identified real image by the proposed technique.

6. Conclusion

A novel combination of star shortlisting and pattern recognition technique has been proposed for the Lost-In-Space mode star tracker. Firstly, the shortlisting technique provides the star pattern recognition technique a *shortlisted list of star IDs* (almost one-third to half of the total number of star IDs). Later, the star pattern recognition technique uses an initial match confirmed by a running sequential angular match for a *single cycle of 360 degrees* for identifying a unique star ID for the reference star in the image. It is evident from the simulation results that the proposed algorithm is *highly robust* to the cases of patch mismatch, magnitude uncertainty, positional deviation, and even false stars (maintaining identification accuracy above 97%). This performance is also justified by the experimental results obtained after testing the proposed technique on the real images. Moreover, the proposed technique provides a *fast identification* by occupying only 8.2 ms in real time. Thus, a highly recognition reliable and fast star identification algorithm with star shortlisting is developed. Real-time testing of the proposed idea also justifies that it can be employed for actual space applications.

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Highlights

- A novel combination of star shortlisting and pattern recognition technique is proposed.
- The proposed idea is highly robust achieving an identification accuracy of 98% on real images.
- The proposed idea is also fast occupying only 8.2 *ms* for identifying stars in the real images.