Near Infrared Star Centroid Detection by Area Analysis of Multi-Scale Super Pixel Saliency Fusion Map

Xiaohu Yuan*, Shaojun Guo, Chunwen Li, Bin Lu, and Shuli Lou

Abstract: The centroid location of a near infrared star always deviates from the real center due to the effects of surrounding radiation. To determine a more accurate center of a near infrared star, this paper proposes a method to detect the star's saliency area and calculate the star's centroid via the pixels only in this area, which can greatly decrease the effect of the radiation. During saliency area detection, we calculated the boundary connectivity and gray similarity of every pixel to estimate how likely it was to be a background pixel. Aiming to simplify and speed up the calculation process, we divided the near infrared starry sky image into super pixel maps at multi-scale by Simple Linear Iterative Clustering (SLIC). Second, we detected the saliency map for every super pixel map of the image. Finally, we fused the saliency maps according to a weighted coefficient that is determined by the least square method. For the images used in our experiment, we set the multi-scale super pixel numbers to 100, 150, and 200. The results show that our method can obtain an offset variance of less than 0.27 for the center coordinates compared to the labelled centers.

Key words: near infrared; starry star; saliency; Simple Linear Iterative Clustering (SLIC)

1 Introduction

Celestial navigation uses “sights” or angular measurements taken between a celestial body (the sun, the moon, planets, and stars) and the visible horizon, and it is the art and science of using celestial bodies to determine an observer’s position on the earth.

In celestial navigation, a Charge-Coupled Device (CCD) is commonly used for visible light navigation. However, during the daytime, CCD imaging is easily influenced by strong light, which may make the CCD detector lose the star target. From a spectral analysis of daytime clouds and stars, we can find that the near infrared J (1.25 μm), H (1.65 μm), and Ks (2.15 μm) bands are ideal bands for exo-atmospheric target detection. However, thermal radiation telescopes can seriously affect the galaxies’ and stars’ detection sensitivities when the wavelength is greater than 2 μm. Otherwise, when the wavelength is \( \leq 1 \mu m \), the interstellar reddening and moonlight will seriously affect the optical sensing of the telescope. Therefore, to achieve celestial navigation, in general, using H bands for stellar detection can effectively obtain the stellar targets.

The star area’s extraction of a near infrared starry image is different from a CCD visible light image. A near infrared starry map obtained under gaze conditions has the characteristics of large targets, strong radiation interference, and no obvious center of masses. Zhang et al. estimated the starry image background first and enhanced a threshold to segment the stars and background. In addition, this method cannot meet the demands of near infrared star centroid extraction.

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because the hard threshold segmentation can easily bring many false star spots. Lu et al.\textsuperscript{[5]} suggested that the distribution of stellar targets on starry images has a Gaussian distribution. In addition, they proposed a method of interpolating the star areas by Gaussian interpolation, which can improve the accuracy of the star centroid. However, for the near infrared starry image, the star area fails to be obtained accurately due to the existence of a large amount of interference and noise. Wang and Guo\textsuperscript{[6]} proposed using a single super pixel map and saliency detection to obtain the star area, although the saliency result always came with many offset pixels, and may have, at times, lost too many stars. For large objects, the calculated center result is not accurate enough. According to the analysis of the gray characteristic of these near infrared images, the following problems must be solved when using the near infrared starry image for celestial navigation\textsuperscript{[6]}.

1. Efficiently segmenting the star regions and background regions and obtaining the complete star regions to calculate the centroid;
2. For each near infrared starry detector, there must be at least 3 star targets;
3. Matching the detecting stars in a star library.

During the recognition process, we often only use large stars to match the star library\textsuperscript{[6]} but we still need more accurate saliency star areas for the large star chosen. To obtain a more accurate centroid of the stars and keep more stars in the saliency map, we first converted a starry image into multi-scale super pixel maps. Then, we detected the saliency map of every super pixel map. Finally, we fused the saliency result maps by a weighted coefficient, which was determined by the least square method.

2 Image Saliency Computation

Our approach consisted of three main steps: multi-scale super pixel map detection that converted an image into a set of super pixel maps, super pixel saliency computation that calculated the saliency score for each super pixel in all of the maps, and multi-scale saliency fusion that combined the saliency maps over all the super pixel maps to get the final saliency map. The entire process is illustrated in Fig. 1.

2.1 Background connectivity

Figure 2 is a near infrared starry gray image captured by the gazing state. Through the feature analysis of the background, the central star target, and target radiation, we found that there were obvious differences among the three in the spatial layout.

The most obvious feature was that the connecting length between a target area and the border pixels was much smaller than a background area. In addition, the spatial difference between the diffuse spot and the background was far larger than the target area. Therefore, we first calculated the correlation of the background and the boundary to obtain stable background pixels, then calculated the correlation between star regions or halo diffusion regions and the background to effectively eliminate the effect of diffusion spots.

We used a measure to quantify how likely it is that a super pixel region $R$ was connected to the near infrared image boundary super pixel, which can be called “boundary connectivity”. It is expressed in the following form:

$$\text{BondCon}(p) = \frac{|\{p|p \in R, p \in \text{Bond}\}|}{\sqrt{|\{p|p \in R\}|}}$$ (1)

![Fig. 1 Framework of our proposed star saliency areas detection approach.](image)

![Fig. 2 An infrared starry image.](image)
where Bond is a set of super pixel patches from the edge image and \( p \) is any image super pixel patch. From Fig. 2, we can find that the perimeter of a target region is much larger than the length connecting it to the boundary patches. In addition, the BondCon is the value of the ratio. To calculate the BondCon value more efficiently, we replaced the perimeter of the target region with the square root of the image patch area.

### 2.2 Background consistent

A reliable background estimation can ensure the accuracy of star target saliency detection. A more reliable background estimation is known to make the consistent background value of an unknown image patch more accurate, which is useful to distinguish a star target from its background.

In saliency detection, the saliency value of a pixel is determined by calculating the contrast between the pixel and its surroundings. In Refs. [7–11], the authors set the surrounding pixels as the saliency cues, then computed the appearance distance of the center pixel to all the cues. At the same time, they also computed the color distance in Commission Internationale de L’Eclairage (CIE) space. The two types of distance were used to weight the saliency of the center pixel. In this fashion, a super pixel’s contrast in our work can be written as in Eq. (2):

\[
\text{Contrast}(p) = \sum_{k=1}^{N} d_{\text{app}}(p, p_k) w_{\text{spa}}(p, p_k) \tag{2}
\]

\[
w_{\text{spa}}(p, p_k) = \exp \left( -\frac{d_{\text{spa}}^2(p, p_k)}{2\sigma_{\text{spa}}^2} \right) \tag{3}
\]

where \( d_{\text{app}}(p, p_k) \) is the Euclidean distance between the gray values of super pixels \( p \) and \( p_k \). \( d_{\text{spa}}(p, p_k) \) is the distance between the centers of super pixels \( p \) and \( p_k \), and \( \sigma_{\text{spa}} = 0.25 \) in Ref. [11]. To describe the consistent background of super pixel, we used \( w_{\text{bg}}^k \) to estimate the probability that a super pixel was a background super pixel. The probability \( w_{\text{bg}}^k \) was mapped from the boundary connectivity value of super pixel \( p_k \). When the boundary connectivity value of \( p_k \) was large, the value of \( w_{\text{bg}}^k \) was close to 1, and when the value was small, \( w_{\text{bg}}^k \) was close to 0. We define \( w_{\text{bg}}^k \) as

\[
w_{\text{bg}}^k = 1 - \exp \left( -\frac{\text{BondCon}^2}{2\sigma_{\text{BondCon}}^2} \right) \tag{4}
\]

Empirically, we set \( \sigma_{\text{BondCon}} = 1 \) in the process of the infrared star target saliency detection process. In addition, the saliency results were very insensitive to the value of \( \text{BondCon} \) between 0.5 and 2.5. To enhance the contrast between the target area and background, we combined Eqs. (2)–(4) to get Eq. (5):

\[
w_{\text{Contrast}}(p) = \sum_{k=1}^{N} d_{\text{app}}(p, p_k) w_{\text{spa}}(p, p_k) w_{\text{bg}}^k \tag{5}
\]

According to Eq. (5), some object regions (weak stars) with high \( w_{\text{bg}}^k \) values from the background regions will have more contrasted with the background. In addition, the contrast of the background (spanning spot area) with small \( w_{\text{bg}}^k \) will be attenuated. Although the equation can enhance the saliency value of the weak stars and attenuate the values of diffusing spot areas, there were still noise and bumps, and we needed to optimize the saliency results.

### 2.3 Multi-scale super pixel saliency map fusion

After conducting the super pixel region saliency computation, each region had a saliency value. For each level, we assigned the saliency value of each region to its contained pixels. As a result, we generated \( M \) super pixel saliency maps \( \{S_1, S_2, \ldots, S_M\} \), then, fused them together and obtained the final super pixel saliency map

\[
S = g(S_1, S_2, \ldots, S_M).
\]

For multi-scale super pixel saliency maps, we discovered a multi-scale super pixel saliency map fusor. Given the multi-scale super pixel saliency maps \( \{S_1, S_2, \ldots, S_M\} \) for an image, our aim was to learn a combinator \( S = g(S_1, S_2, \ldots, S_M) \) to fuse the maps together to form the final saliency map \( S \). In our implementation, we found that a linear combinator \( A = \sum_{m=1}^{M} w_{m} S_m \) can perform well by learning the weight using a least square estimator, i.e., minimizing the sum of the losses as shown in Eq. (6) over all the labelled star areas. The labelled star areas can be labelled by hand.

\[
\text{loss} = \min \left( \| A - \sum_{m=1}^{M} w_{m} S_m \|_F^2 \right) \tag{6}
\]

### 3 Multi-Scale Super Pixel Detection

In Section 2, we indicated that our proposed method requires Simple Linear Iterative Clustering (SLIC)\(^{12}\) to detect the multi-scale super pixel maps for an image before we could detect the saliency map. The aim was to avoid the calculation of pixels and speed up the computing process. One single super pixel map may still keep some diffusion pixels in the target regions, but if we detected the saliency maps of super pixel maps and fused the saliency results for centroid computation,
the centroid accuracy would not have been affected. There are a large number of small and weak stars in a near infrared starry image and to extract more near infrared stars, one can set the size of a super pixel to be small, which means one image will contain more super pixels. If one super pixel contains fewer pixels, the detection will take more time, and more noise may be left in. Therefore, we introduced the multi-scale super pixel detection method. Maps containing larger numbers super pixel may reduce the noise, and those containing fewer may keep the small star areas. For a larger Field Of View (FOV) near an infrared starry image (1024×1024), the numbers of pixels one super pixel contains may be 150, 200, 250, or 300. The top images of Fig. 3 show the super pixel results of a near infrared image obtained under the condition of gazing, and the bottom images are the result of a larger FOV image.

Saliency detection was performed by connecting all adjacent super pixels \((p, q)\) and assigning their weight, \(d_{app}(p, q)\), as the Euclidean distance between their gray values. Then, an undirected weighted graph was constructed. The geodesic distance between any two super pixels \(d_{geo}(p, q)\) is defined as the accumulated edge weights along their shortest path on the graph \([13]\).

\[
d_{geo}(p, q) = \min_{p_1=p, p_2, \ldots, p_n=q} \sum_{k=1}^{n-1} d_{app}(p_k, p_{k+1})
\]

\[
d_{app}(p, q) = \frac{1}{n_p} \sum_{p_i \in p} \text{gray}(p_i) - \frac{1}{n_q} \sum_{q_i \in q} \text{gray}(q_i)
\]

where \(n_p\) is the number of pixels in super pixel \(p\), \(n_q\) is the number of pixels in super pixel \(q\), and \(\text{gray}(\cdot)\) is the gray value of one pixel in the super pixel. We defined the geodesic distance of \((p, p)\) as 0 for convenience. Then, the “spanning area” of a super pixel was defined as in Eq. (9). The “spanning area” was used to describe the relative effects among super pixels.

\[
\text{Area}(p) = \sum_{k=1}^{N} \exp \left( -\frac{d_{geo}^2(p, p_k)}{2\sigma^2_{clr}} \right) = \sum_{k=1}^{N} S(p, p_k)
\]

where \(N\) is the number of super pixels. Equation (9) computes a soft area of super pixel \(p\). We noted the operand \(S(p, p_k) \in (0, 1]\), which was used to characterize how much super pixel \(p_k\) contributes to \(p\). The closer the value was to 1, the more \(p_k\) contributed to \(p\). For two super pixels \(q\) and \(p\), if they were in a flat region, we could set \(d_{geo}(p, q) = 0\) and \(S(p, q) = 1\). Therefore, we could ensure that \(q\) adds a unit area to the area of \(p\) (the unit of \(q\) may be some pixels of the diffusion spot). If \(q\) and \(p\) were in different regions, there must be one or more strong edges between them \((d_{app}(p, q) \gg 3\sigma_{clr} \text{ and } S(p, q) \approx 0\)). Experiments showed us that \(\sigma_{clr} \in [5, 15]\) made the result more stable so we set \(\sigma_{clr} = 10\).

Many background super pixels are not directly connected to the boundary pixels. To more commonly describe the boundary connectivity, we defined the length of a super pixel along the boundary as in Eq. (10).

\[
\text{len}_{\text{Bond}}(p) = \sum_{k=1}^{N} S(p, p_k) \cdot \delta(p_k)
\]

\[
\delta(p_k) = \begin{cases} 1, & p_k \in \text{Bond}; \\ 0, & \text{others} \end{cases}
\]

Combining Eqs. (9) and (10), we change Eq. (1) to Eq. (12) to describe boundary connectivity more conveniently.

\[
\text{BondCon}(p) = \frac{\text{len}_{\text{Bond}}(p)}{\sqrt{\text{Area}(p)}}
\]

**Fig. 3**  Multi-scale super pixel maps. Top: Maps of gazing infrared image; Bottom: Maps of larger FOV image.
4 Saliency Result Optimization and Star Centroid Computation

4.1 Saliency optimization
To combine multiple saliency cues of measures, previous works always simply used weighted summation or multiplication. This is a heuristic and is difficult to generalize. In the near infrared star detection process, the goal is to segment the stars from the background. In addition, simply using weighted summation is not enough to achieve this goal. It always segments the diffusion spot as a target, and the result is sensitive to noise. In this section, we propose computing the boundary connectivity of the super pixels and generating many background cues. Then, for an unknown super pixel, we computed the consistent background value to determine how likely it is to be a background one. This method computed centroids for stars very accurately. For more accurate centroids, we first computed multi-scale super pixel maps for an image and then computed their saliency maps. In addition, we fused all the saliency maps together and formed a more accurate saliency map for the image to detect star areas. Our method obtained more accurate centroids than the method of single super pixel saliency map in our experiment. When computing the objective cost function, the value of an object region was set as 1, and the background region value was set as 0. The optimal saliency map was then obtained by minimizing the cost function. Letting the saliency values of \( N \) super pixels be \( \{ s_i \}_{i=1}^N \), the objective cost function can be written as in Eq. (13):

\[
\begin{align*}
\min & \left( \sum_{i=1}^{N} w_{i,b}^b s_i^2 + \sum_{i=1}^{N} w_{i,f}^g (s_i - 1)^2 + \sum_{i,j} w_{i,j} (s_i - s_j)^2 \right) \\
\text{Background} & \quad \text{Star regions} \\
\text{Spanning spot regions} & \quad \text{Spinning spot regions}
\end{align*}
\tag{13}
\]

From Eq. (13), the constraint weights of the star target, background, and diffusing spot area are different. If super pixel \( p_i \) belongs to the background, then \( w_{i,b}^b \) will become large, and \( s_i \) will be close to 0. In addition, if \( p_i \) belongs to the star target, then \( w_{i,f}^g \) will become large, and \( s_i \) will be close to 1. For spanning area super pixels \((p_i, p_j)\), the weight \( w_{ij} \) can be calculated by Eq. (14):

\[
w_{ij} = \exp \left( -\frac{d_{\text{app}}^2(p_i, p_j)}{2\sigma_{clr}^2} \right) + u
\tag{14}
\]

where \( u \) is a constant used to optimize the noise, and it was set as 0.1 in the experiment. The three terms are all squared by errors, and the optimal saliency map is computed by the least-square method.

4.2 Star centroid computation
On the final near infrared starry image fused saliency map, we set the mean value of the saliency values as the threshold to segment the stars from the background. The segment resulted with little noise and the star target regions showed good connectivity. The good connectivity almost eliminated false alarms, and the false alarm rate was high when the original near infrared starry image was segmented by a hard threshold.

On the other hand, the optimized saliency map effectively decreases the spanning areas and determines the centroids of the stars more accurately. We computed the centroids of the stars in the corresponding saliency connective regions by Eqs. (15) and (16):

\[
x_0 = \frac{\sum x \cdot \text{gray}(x)}{\sum \text{gray}(x)} \tag{15}
\]

\[
y_0 = \frac{\sum y \cdot \text{gray}(y)}{\sum \text{gray}(y)} \tag{16}
\]

where \( x_0 \) and \( y_0 \) are the centroid coordinates of \( X \) and \( Y \) in the image of a star, respectively. \( \text{gray}(x) \) is the gray value of \((x, :)\) and \( \text{gray}(y) \) is the gray value of \((: y)\).

5 Experiment and Analysis

5.1 Dataset
In our experiment, we used the near infrared starry image shown in Table 1. We compared our method with state-of-the-art methods such as Saliency Filter (SF), Manifold Ranking (MR), Geodesic Saliency (GS), Saliency region detection with Image Abstraction (SIA), Hierarchical Saliency (HS),...
and Starry Super Pixel Saliency (SSPS)\(^6\). For all the methods, a Precision-Recall (PR) curve was used to estimate the performance. To obtain the PR curve, we first normalized the saliency maps and then compared them with the ground truth maps. The PR can be written as Eqs. (17) and (18).

\[
\text{precision} = \frac{SN_{\text{target}}}{SN_{\text{saligency}}} \quad (17)
\]

\[
\text{recall} = \frac{SN_{\text{target}}}{N_{\text{target}}} \quad (18)
\]

where \(SN_{\text{target}}\) is the number of pixels in the target saliency regions, \(SN_{\text{saligency}}\) is the number of all the saliency regions, and \(N_{\text{target}}\) is the number of ground truth pixels.

5.2 Star saliency region detection and centroid computation

Figure 4 shows the saliency map of all the methods in Section 5.1. Here, we only show the results of three near infrared starry images obtained from stable gazing. From the results in Fig. 4, we found that our method could effectively separate the radiation spot region caused by the near infrared star diffusion. However, there are still many residuals of the diffusion spot in single scale super pixel saliency maps. In addition, in the multi-scale super pixel saliency maps, the residual of the diffusion spot is much lower. After computing the centroid by Eqs. (15) and (16), we may find that the error caused by the residual was reduced compared with that of the single scale super pixel one\(^6\). The PR curves of the five methods are shown in Fig. 5. Our method had the best shape in the saliency map. While it maintained a high callback rate, it could also reach high accuracy for the positions of the saliency pixels. The methods closest to ours are MR and SSPS, although they keep more diffusion spot pixels in the result. GS and SF also have the same problem of keeping too many diffusing pixels. Although our method still had some diffusing pixels, it had significantly fewer than other compared methods, and our method had the best PR curve.

Figure 6 shows the Mean Absolute Error (MAE) of the compared methods and the proposed method, and our method had the least MAE of all the compared methods. If one wants to maintain a high callback rate, then the accuracy will decrease quickly. To better express the accuracy of the centroid of our method, in Fig. 7 we draw the computed centroids of the stars to
5.3 Algorithm adaptability analysis

In the experiment described in this paper, the near infrared starry images were all obtained by gazing at one star. All the star target regions included many diffusing spot pixels that affected the accuracy of star centroid computation. In addition, the saliency maps more or less included some diffusing spot pixels because the star saliency region was really too large in contrast the real coordinates.
the hull image. For this reason, we raised the following question: if a star becomes small and has less diffuse area, can our method achieve the same good results with high accuracy? On the other hand, when a platform obtains a near infrared starry image, it cannot gaze at the star continuously. More often, the starry images obtained are more similar to the images shown in Fig. 8 (Row 1). The three images are the 1st, 2nd, and 6th frames of an image set. To prove the universality of our method, we detected the stars of the near infrared starry images. The results are shown in Row 2 of Fig. 8. The saliency star target regions were all larger than 15 pixels. This constraint can greatly eliminate noise and weak stars and saving time for star match and recognition. Figure 8 shows that our method for the near infrared starry star saliency detection may obtain more accurate regions because the spanning spots caused by the diffusion are weak. The normal starry images in Fig. 8 prove the adaptability of our method for centroid computation of near infrared starry images. The centroid comparison of our method and the labelled coordinate is shown in Fig. 9. To show the advantage of the multi-scale super pixel-fused saliency map for star centroid detection, Fig. 10 shows the comparison of \( \sigma \) value curve between SSPS and our method. From Fig. 10, it is easy to find that the fusion of multi-scale super pixel saliency maps may detect more accurate star areas, making the star centroid computation more accurate than the single super pixel saliency map method for centroid computation.

6 Conclusion

This work proposes using boundary connectivity to value how likely it is that a pixel belongs in the background. To simplify the calculation process, we introduced SLIC to compute the super pixels of a near infrared starry image, then, we chose the boundary super pixels as original cues to calculate the boundary connectivity of other super pixels and to find more background super pixels. All the background super pixels would be set as background cues for consistent background value computation. If the value of an unknown super pixel was computed, we could decide whether it is a background super pixel. Single super pixel saliency maps always leave many diffusing spot pixels, which may affect the accuracy of centroid computation. This work detects the saliency map on a multi-scale super pixel and then fuses the saliency results to form a final saliency map for each image. The fused saliency map makes the PR and the centroid more accurate. From the results of the experiment, we found that for a set of stars obtained by a gazing state, the
standard variance was less than 0.23. For stars obtained by a normal state with a larger FOV, the bias standard variance was even less than that of the gazing state, and the value was less than 0.13. Moreover, our method can easily eliminate the effects of noise and avert many false alarms; such false alarms can easily occur when segmenting star targets from the background by a hard threshold.

Fig. 9 Center position comparison of stars in a large FOV image set.

Fig. 10 Deviation variance comparison of SSPS and our method.

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