EVALUATION OF FEATURE DETECTORS FOR INFRARED IMAGING IN VIEW OF ACTIVE DEBRIS REMOVAL

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ABSTRACT

Active Debris Removal (ADR) is a type of rendezvous missions in which the target is uncooperative. Since there are more unknowns, importance of continuous measurement updates becomes clear where infrared cameras could fill this gap at low cost. Despite the theoretical advantages, the question still remains; can they practically work in ADR scenarios? In this paper, we focused on fundamentals of object detection, recognition and tracking "features" in the way they are influenced by the characteristics of these thermal-imaging systems and how the thermodynamics of the scene could affect their traceability. We evaluated some of the point and edge based feature extraction methods for their performances in ADR scenarios and to be used in a relative navigation sensor. Various spatial and frequency based feature detection algorithms were investigated and deeply evaluated in order to cover a wider perspective.

Key words: Active Debris Removal; infrared imaging; thermal imaging; feature detectors.

1. INTRODUCTION

Since the Space Debris problem has been a growing threat to vulnerable space assets, the sustainability of space has been questioned more by the community. The studies [14][13], showed that the current process will only increase the number of Space Junk if there is no means of remediation action like Active Debris Removal (ADR) Missions. The ADR missions can be considered as a variant of Rendezvous and Docking (RvD) missions where the target is uncooperative meaning that there are no fiducial markers on target and target cannot keep a certain attitude respect to chaser or is even tumbling [12]. Therefore more advanced technologies have to be developed for ADR targets that are with many more unknown parameters [19].

In RvD, LIDAR, RADAR and Visual Cameras are generally the main source of information for the relative pose of the chaser during the Far and the Close Range operations of Rendezvous and Docking (RvD) missions [5] and therefore are also possible sensors for ADR missions. The RADAR is an active system that provides the target distance and direction (angle) information mainly during the long and medium range operations by evaluating the echo of emitted RF signals [3]. As part of being an active sensor, they require significant power from hosting spacecraft and therefore are not favourable. Although they can also operate in very short range, achieving the required performance is relatively more difficult therefore are not preferred in close proximity operations (final part of Close-Range Rendezvous Phase which is also known as close proximity) [5]. LIDAR is also used for retrieving the range and the target structure information based on reflection of laser pulses from target. Like RADAR, it is an active sensor and the accuracy at very close range is considered to be limited [4]. Moreover, they have moving parts in the system for scaning purposes and it is not favoured by the Attitude and Orbit Control System (AOCS) of the hosting spacecraft. In the case of demonstrated RvD missions, the target is generally cooperative and has few retroreflectors to increase the visibility by reflecting most of the signal that was emitted enabling quicker processing and identification [5]. Some recent experimental studies showed that the operation range of LIDAR systems for Space Rendezvous against non-cooperative targets can go up to 260m [8]. Visual systems are the passive sensor alternative of the LIDAR and RADAR approaches and are used heavily in close proximity operations. Their working principle is based on reflected Sun light from the target. Studies like [15] showed that their measurement accuracy can go down to two cm or better in relative range and 0.05 degree or better in terms of relative orientation. However, the visual systems also have some drawbacks like being unoperational under eclipse or being affected by the solar glare. In the case of a debris in Low Earth Orbit (LEO) where the target would be in eclipse for nearly one third of its orbit, such limitation can result in divergence of the navigation filter from solution due to lack of measurement. In current RvD demonstrations, this situation is avoided by mission design like different approaches to client spacecraft or planning the manoeuvres such that Sun would not be in the field of view or avoiding certain geome-

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tries that would cause specular reflections. Besides the fact that these additional constraints have somehow impact on Guidance Navigation and Control system design in a negative way in terms of limiting the solutions, such constraint might even not be applicable or infeasible for ADR scenarios due to the number of unknowns. During the final approach, the chaser's relative attitude and the position information is quite important for the success of the mission, especially if the target is uncooperative and tumbling like in ADR. A small error in the navigation filter could cause a catastrophic failure in the overall mission.

On the other hand, Infrared Imaging systems could overcome the weakness of these systems quite effectively since it is a passive sensor which does not require target to be actively illuminated like LIDAR or RADAR, and can operate under eclipse conditions unlike Visual Systems. These systems are based on the principle (also known as Planck's Law) that all objects with a temperature greater than absolute zero emits thermal radiation. Therefore, if Space Debris is not in absolute zero and Infrared sensor is sensitive enough, the Infrared Imaging system shall be able to detect. For performance concerns, Infrared Imager has to be selected specific to the application and it is based on the target temperature range since it is linked to power spectrum of the radiation. Depending where is the debris on the orbit respect to Sun, thermal environment in space could change drastically. However the peak of radiated energy goes towards the higher wavelength for lower temperature therefore Longwave Infrared (Thermal) band would most likely serve for this approach. On the other hand, infrared based relative navigation for ADR is a concept and the performance of image processing algorithms had not yet been analysed to proceed forward.

Even though there have been studies like [17] providing a good insight in performance of feature detection algorithms in thermal imagery, the datasets were not representative for our purposes. Therefore in our study, we aim to evaluate the effect of the thermally dynamic environment of space that ADR target would experience in Long-Wavelength Infrared (LWIR) imageries from the Image Processing/Computer Vision perspective. The goal is to evaluate the performance of existing feature detection algorithms which were developed for and also tested with Visual data, in the context of Infrared Imagery under space environment which would be representing an ADR mission.

The paper organisation is as the following. At first we provided the facts about the thermal imaging to explain the challenges of the modality itself as well as the brief description of the interest point and edge extraction methods that were evaluated in the study. Following the evaluation methods used in this study would be given. The result of our analysis for each feature detector in our simulated ADR scenario would be given. At last, we discussed about the impact of these results on navigation algorithm design and possible challenges of thermal imagery within the context of ADR.

2. INFRARED IMAGING FACTS

Depending on the temperature, all objects above absolute zero temperature emit electromagnetic radiation in their corresponding spectrum and infrared imagers converts this radiation to image intensity values.

There are two major types of sensing tools for thermal/infrared radiation: thermal detectors and photodetectors. In the case of thermal detectors, responsive elements are sensitive to temperature changes to measure the radiative fluctuations (e.g. bolometers, thermocouples ... etc) whereas photodetectors respond to variations in the number of incident photons (e.g. InSb photovoltaic detector) [18]. Among all, uncooled microbolometers which measure the resistive changes due to thermal radiation are known to be widely used in terrestrial applications since they could provide sufficient sensitivity at low-cost [11]. By considering the cost effectiveness and its promising use in space applications, this study focuses on performance of feature detection algorithms in infrared imagery captured by uncooled microbolometer technology.

For infrared imagery, [7] defined four main challenges for working with Infrared images such as "Low SNR-Low Resolution", "Infrared Reflection", "Halo Effect/Saturation" and "History Effects". As it is described "Halo Effect/Saturation" occurs around the objects with high contrast and could be difficult not to associate with the object for ferroelectric sensors. The other most important challenge is the "History Effects" which disqualify the use of brightness constancy concept used in optical flow algorithm.

In the context of ADR applications, Infrared imageries also encounter different scene structure compared to their terrestrial counterparts. The targets *Space Debris* change their temperature profile over an orbit (with duration down to 90 minutes) as their geometry with Sun varies over time. Moreover, the man-made materials covering the Debris surface also show different response characteristics throughout these quasi-cyclic thermal profiles which makes the thermal scene quite dynamic and unique. We have identified one fact unique to Infrared Based tracking systems in Space: thermal dynamic nature of the target therefore the scene. The described case had been simulated statically by a Synthetic Infrared Image Generator [1] considering this fact and shown in Figure 1. The top scenes are simulating the Space Background and the below scenes the Earth Background. The left scenes are representing the Space Debris during a favourable configuration with respect to Sun for heating up *hot case* whereas the right scenes are representing the same target cooled down during the eclipse *cold case*.

3. FEATURE DETECTORS

A wide variety of feature detectors exist in literature for visual camera applications. Among these interest point

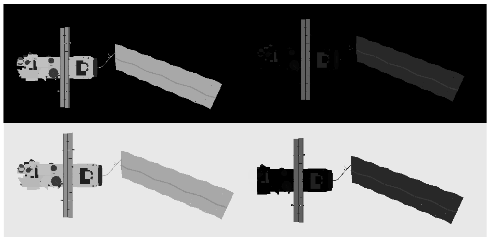

Figure 1. Possible Scenes with different background and eclipse conditions

and edge based methods are quite commonly used in target detection and tracking applications. This section briefly describes some of these extractors that were used in our analysis. The selection was based on the information that the feature extraction method uses such as frequency or spatial cues. Since the formation of thermal images is different than visual modalities and the feature detectors in the field have been developed from visual applications, by selecting extractors with different approaches (frequency or intensity based) we aimed to perform a more informative evaluation in the sense that it should be possible to extrapolate our results to other extraction methods using similar approaches.

3.1. Interest Point Detectors

Good Feature to Track (GFTT) [16] is a corner detector based on first derivative of the image. Intensity variations around point $\mathbf{x}(u, v)$ are searched in a neighbourhood window of $w(u, v)$ by using an autocorrelation function $E(x, y)$ (Equ-1) which had been approximated by [6] as Equ-2 by using Taylor expansion.

$$E(x,y) = \sum w(u,v)\,[I(u+x,v+y)-I(u,v)]^2 \tag{1}$$

In the case of GFTT, a point $\mathbf{x}(u, v)$ is selected as a corner whenever the minimum eigenvalue of search window image gradient (Equ-2) is above a given threshold.

$$E(x,y) \approx \sum_{u,v} w(u,v) \begin{bmatrix} I_u^2 & I_uI_v \\ I_uI_v & I_v^2 \end{bmatrix} \tag{2}$$

Speeded-Up Robust Features (SURF) [2] is a blob detector which is based on Hessian matrix approximation. The detection is performed at different scales and the Hessian matrix $H(\mathbf{x}, \sigma)$ at point $\mathbf{x}(u, v)$ with scale σ in image I is defined as Equ-3 where $L_{xx}(\mathbf{x}, \sigma)$ is the convolution of the image I with second order derivative approximation of the Gaussian function. The SURF features are detected when the determinant of Hessian is maximum.

$$H(\mathbf{x},\sigma) = \begin{bmatrix} L_{xx}(\mathbf{x},\sigma) & L_{xy}(\mathbf{x},\sigma) \\ L_{xy}(\mathbf{x},\sigma) & L_{yy}(\mathbf{x},\sigma) \end{bmatrix} \tag{3}$$

Phase Congruency Point (PC-P) [9] [10] detection algorithm is based on the fact that edges are formed when the image Fourier components are in phase. Phase Congruency (PC) claims that it can handle long sequence of images with the same threshold value and have better localisation performance as it is not using Gaussian smoothing for noise reduction. Phase Congruency (PC) measure at point $\mathbf{x}(u, v)$ is defined as:

$$PC(x) = \frac{\sum_n W(x)\lfloor A_n(x)\Delta\Phi_n(x) - T\rfloor}{\sum_n A_n(x) + \varepsilon} \tag{4}$$

where $\Delta\Phi_n(x) = \cos(\phi_n(x) - \overline{\phi}(x)) - |\sin(\phi_n(x) - \overline{\phi}(x))|$ in which $A_n(x)$, $\phi_n(x)$ and $\overline{\phi}$ represent respectively the amplitude, phase of the n^{th} component at position $\mathbf{x}$ and mean of the phase components that were considered, $W(x)$ is the weighting function of frequencies, T is estimated noise threshold and ε is a small constant to avoid zero division. $\lfloor\ \rfloor$ is the operator which returns the value for positive and 0 for negative. Based on the fact that PC moments vary with the orientation, PC-P is defined when the maximum and minimum moments of point $\mathbf{x}(u, v)$ are large indicating a corner like sharp variation in the image.

3.2. Edge Detectors

Sobel operator computes an approximation of image gradients and fires edges when the gradient of image I is higher than a threshold. In terms of computation, it is considered to be relatively inexpensive which makes the method very attractive besides the artifact related to selected kernel sizes.

Laplacian of Gaussian (LoG) which is also known as blob detector, is an approximation of filter to compute image second derivative by using a Gaussian Kernel (Equ-5). Edges are defined at the zero-crossings of the filter applied images.

$$g(u,v,\sigma) = \frac{1}{2\pi\sigma^2} \exp^{-\dfrac{u^2+v^2}{2\sigma^2}} \tag{5}$$

Phase Congruency Edge (PC-E) [9] [10] is also based on phase components of the image in Fourier domain and the measure is same as given in Equ-4. However, in this case the point $\mathbf{x}(u, v)$ considered to be part of an edge as long as maximum moment at that point sufficiently large enough.

4. REPEATABILITY AND SIMILARITY

The ability of detector to extract the same feature under different conditions are evaluated under repeatability measure. A detector with high repeatability implies that it is invariant to the environment/condition in which the extractor is tested.

For our study, the repeatability measure R for interest point detectors is defined as the ratio between the number of matched points $\sum X_{ij}$ and the number of extracted features $\sum X_i$ of the reference frame (Equ-6). In order to eliminate the effect of interest points matching algorithms, we considered features matched when the euclidean distance between two features was less than one pixel. Since the observed scenery is fixed during the time of retrieval, extraction methods shall only observe a thermally dynamic environment which justify our approach.

$$R_{ij} = 100 \cdot \frac{\sum X_{ij}}{\sum X_i} \tag{6}$$

In terms of edge matching algorithm, we had followed a similar approach as interest point detectors. In order to eliminate the effect of edge matching algorithms in our evaluation, each extracted edge image was brutally compared with edges of others features by using a similarity measure S_{ij}:

$$S_{ij} = 100 \cdot \frac{\sum C_{ij}}{\sum I_i} \tag{7}$$

where $C_{ij} = I_i \cap I_{j,j \neq i}$ and I_i, I_j are the reference edge image, the compared edge image respectively. The edge images were considered to be preprocessed before by performing non-maximal suppression and constant thresholding over the sequence. Since such pre-processing would also be expected to be performed before any computer vision algorithm that would use lines to improve the precision of the algorithm, the results and conclusions of this approach shall provide more meaningful information.

5. COMPUTATION TIME

Navigation algorithms are chain of processes in which the feature extraction algorithms are the very first step of it. Considering the limited computational power for space applications, it is important to minimise the required computational power as much as possible while sustaining a decent level of performance. Therefore computational time of extraction methods play significant role for the algorithm development.

In our study, we had defined the computational time for point detectors per extracted interest point by dividing the processing time of image by number of features extracted to have a normalised merit. In the case of edge extractors, we had followed a slightly different approach due to the fact that edge images are often post-process depending on the algorithmic approach. Therefore the computation time of edge extractors are not normalised by number of edges as interest point detectors.

Table 1. Camera properties.

Property	Value
Detector	Uncooled microbolometer
Resolution	384x288
HFOV	29.9°
Focal length	18mm
Aperture	f/1
Pixel size	$25\mu m$
Spectral range	$8\mu m$ - $14\mu m$
NETD	$\approx 50mK@30°C$

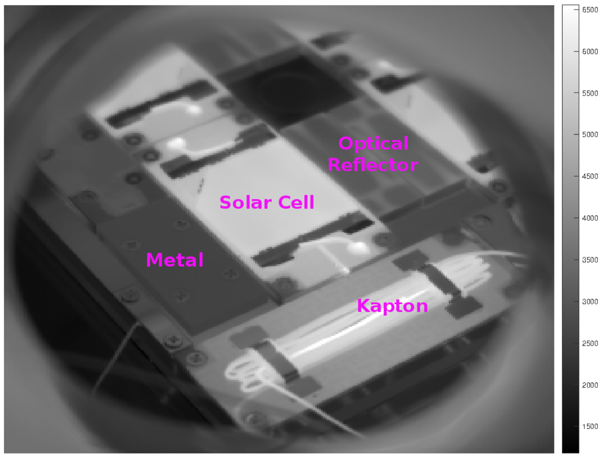

Figure 2. Infrared image of the target plate (Frame-20)

6. EXPERIMENTAL WORK

In order to evaluate the performance of feature detector in thermal imaging for ADR applications, it is important to have a representative environment on ground. Therefore, a unique dataset was captured to simulate thermally variant environment of space with real materials for this purposes. We have tested the selected point and edge detectors for their long term and short term performances to understand their reliability as it is an important measure of quality for navigation algorithms. We had performed our tests with Intel(R) Core(TM) i7-6700HQ CPU at 2.60 GHz.

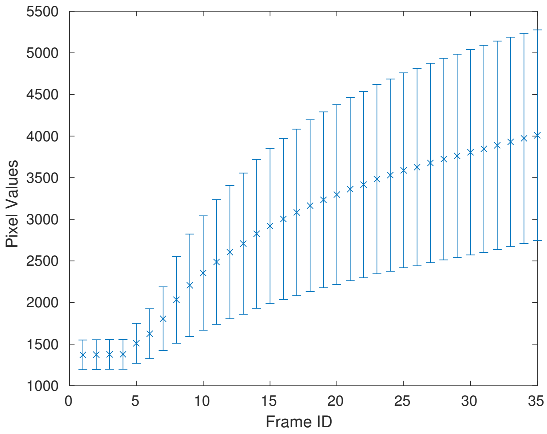

Figure 3. Variation of frame dynamic ranges while the target was heated

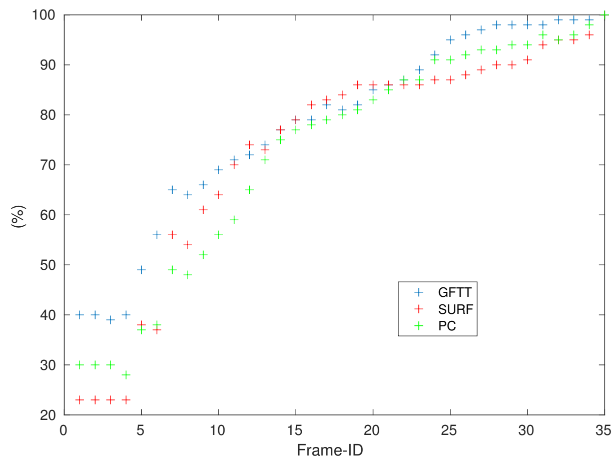

Figure 4. Repeatability measure R between the hottest scene (Frame-35) and the given frame

6.1. The Infrared Imaging Dataset

Thermodynamics in space is different from that on Earth due to the fact that the convective heat transfer cannot exist in vacuum. Therefore, terrestrial infrared datasets could be misleading for the sake of our study. On the other hand, there is no Infrared Dataset representing ADR scenarios and creating one is very difficult since access to space is not straight forward.

Our experimental set-up consists of a thermal vacuum chamber with an observation window transparent in LWIR band, a representative target with a thermal control, a LWIR camera (Table 1) and a laptop to store our data. Our representative target was a plate with collection of different spacecraft surface coatings (Figure 2) selected among typical materials and thermal control capability. The sample plate had been heated homogeneously from $40°C$ to $100°C$ in 10 minutes with reasonably constant rate to simulate the transition from eclipse to solar illumination of the target. The effect of this warm up on the dynamic range of the frames can be seen in Figure 3. During the experiment LWIR camera captured the scene with the constant frame rate of 1Hz.

6.2. Comparison of Interest Point Detectors

The point features are one of the most accurate cues that are used in object tracking through which good navigation solutions could be achieved. One of the challenges of ADR scenarios for infrared based applications is that the target temperature variations are quite fast respect to terrestrial application and the invariance of the feature detectors in this environment is unknown. Therefore, our experimental approach will concentrate to evaluate the performance of feature detectors under this scope.

In the first test, point features were extracted from the last frame which had the highest contrast, were compared with the point features of all frames in the sequence of selected frames. The amount of matches provided the information on how long the features extracted in Sunlight conditions can be kept during the eclipse transitions. The analyses were performed on the strongest 100 feature points of each frame also in order to evaluate the effect of ranking in tracking. By this way, we would observe the shift in the ranking of the features.

Figure 4 shows that the repeatability of all feature detectors decreases as the overall temperature of the scene decreases. In general, the repeatability of GFTT is higher than the other interest point detectors. The repeatability of the trackable points had a steep decrease between fourth and ninth frame due to sudden thermal signature variation of very low thermal inertia material *Kapton* and low thermal inertia material *Solar Cell*. However, the repeatability of the feature detectors had been more than 60 % until the sudden change in thermal signatures in Frame-9. Besides its general good performance, GFTT provided much better repeatability measure when the scene was cooler.

Second experiment evaluated the performance of detectors in short term variations. Figure 5 shows the repeatability between the frame and its consecutive frame. In general, repeatability measure stayed above 90 %. However, between the Frame-5 and Frame-10, the repeatability measure dropped below 90 %. In Frame-5, GFTT started to extract feature points around the boundaries of very low thermal inertia materials (Kapton coated temperature sensors) and low thermal inertia material (Solar Cells). In the case of SURF, the location of detected features had been significantly changed since structure of Infrared Imagery changed in terms of blobs. New features from higher octaves/scales had started to be detected. In PC-P, the distribution of point features in Frame-5 followed a different pattern which could be related to an increase in the magnitude of frequencies selected by PC-P calculations (Log filter used in PC-P only allows parts of frequency spectrum to be computed for high speed pur-

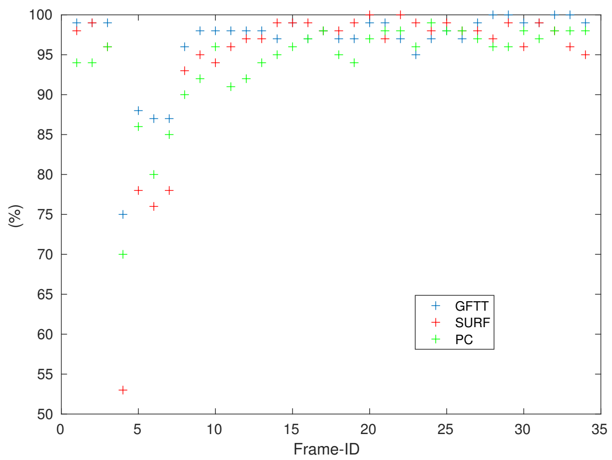

Figure 5. Repeatibility measure R between the frame and its following frame

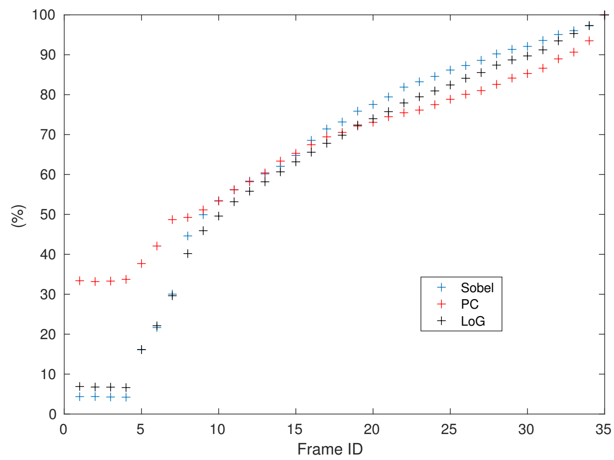

Figure 6. Similarity measure S between the hottest scene (Frame-35) and the given frame

Table 2. Computational times for interest point detectors

Interest Point Method	Speed$_{Mean}(\mu s)$
GFTT	97.4
SURF	71.0
PC-P	1180.4

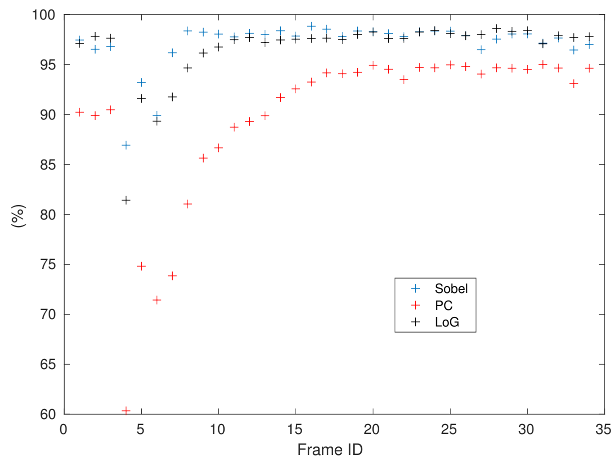

Figure 7. Similarity measure S between the frame and its following frame

poses).

The last test on interest point detectors was to compare their computational time as it was described previously. Table 2) shows the mean of computation times over the sequence of our dataset where SURF had the minimum mean computation time and GFTT had comparable timing. Among all, PC-P showed the worse performance as expected.

6.3. Comparison of Edge Detectors

Edge features provide less accurate information for tracking algorithms however they are much easier to extract in quasi-textureless imageries like one captured by infrared modalities. When there is not enough interest points, tracking algorithms can still proceed by using the edge information.

The first evaluation on edge extraction methods was to examine how long the edge features extracted in a favourable condition (when the object was hot) can be kept as the target passes through the eclipse transition. Longer traceability provides the robustness to recover from lost in Space scenarios where the algorithm fails to track the object or tracked object disappear for number of frames. Figure 6 shows that the similarity of all edge detectors decreased significantly for all detection methods towards the first frame. This was as expected due to variation in thermal response to heat flux for different types of surface coatings over time. As the scene got cooler where the noise became dominant in low contrast images PC-E outperformed Sobel and LoG edge detectors.

Second experiment evaluated the performance of detectors in short term variations. Figure 7 shows the similarity between the frame and its consecutive frame. Although Sobel and LoG had again shown better performance over PC in high temperature where the contrast of within the scene was high, this had been linked to the large amount of edges extracted by PC method which had been found out to be more sensitive to low contrast therefore provided more features than others. However, comparing to repeatability measure of interest points edge detectors had overall better similarity merit.

The last test on edge detectors was to compare their computational time as it was described previously. Table 3) shows the mean of computation times over the sequence of our dataset where Sobel had the minimum mean and PC-E had worst performance.

Table 3. Computational times for edge detectors

Edge Detection Method	$\text{Speed}_{Mean}(ms)$
Sobel	0.72
LoG	3.76
PC-E	119.90

7. DISCUSSIONS

Most of the navigation solutions rely on the feature based information for their estimations where stable and accurate features become important. Since the detectors in the field are designed for visual imagery and at most tested for terrestrial thermal imagery applications, their performance in ADR like scenarios is unknown. The unique challenge of thermal based applications in ADR is the rapid variations of the thermal environment in which the target signatures change overtime. Briefly, the behaviour of the spacecraft surface coatings to thermal environment is different as they are used for different purposes in spacecraft thermal control such as to cool down the internal heat of an equipment or to reflect the solar thermal flux to prevent an equipment getting hotter. In our experiment, we had evaluated this fact.

Our experiments showed that the responses of spacecraft surface finishes to thermal variations in the environment significantly differ. We have observed that the lower and the closer the temperature between materials the more difficult it is to distinguish them. At low temperatures, the contrast due to emissivity difference became invisible as the contrast differences became lower than the camera sensitivity. In order to estimate the thermal signature of the target precisely, very accurate information on surface coatings and the orbital information (to perform detailed thermal analysis) at the moment of the mission is required. However, ADR mission does not allow such detailed predictions for use by the chaser or on ground. Therefore, our study suggests that appearance based initialisation for thermal based ADR navigation solution would be prone to failures.

In terms of interest point detectors GFTT, SURF and PC-P methods were evaluated as example of first, second derivative spatial and frequency approaches. Interestingly, GFTT provided slightly better results than the other two. This could be due to the fact that the extracted feature had better localization. In cooler images where the noise plays a significant role, the performance of GFTT had been the best among the all which is also the computationally the least heavy approach. The evaluation of the repeatability measure R in long term suggested that thermal variations create a challenging environment for signature based loop closure type algorithms in which the features shall be detected after a period of time. The short term repeatability figures suggest that even relatively small thermal variations has significant impact on repeatability of the interest point features. Computation time wise, detector based on spatial information SURF was the fastest. However GFTT also showed similar pattern. This could be due to the fact that both filters require single stage computation in which a kernel scans the image. As expected PC-P had the worst computation time linked to complexity of Fourier analysis within the algorithm. Our experiments suggest that GFTT or similar kind of feature detector would suit best for the infrared based relative navigation algorithms in ADR.

In terms of edge detectors Sobel, LoG and PC-E methods were evaluated as example of first, second derivative spatial and frequency approaches. In general, edge features also got affected from the decrease in average scene temperature like interest points. PC-E outperformed in cooler scenes where the noise was more dominant. However, the slope of decrease was steeper than the interest point detectors. This was mainly due to low Signal-to-Noise-Ratio (SNR) as noise also created line like patterns. Even though in long term feature tracking PC-E out performed over other methods, this approach performed the worst in short term tracking. Overall edge features had similar performance over interest point feature extractors in our ADR simulated environment. Computation time wise, edge detectors based on spatial information Sobel performed the fastest due to the fact of simplistic nature of window based method. As expected PC-P had the worst computation time linked to complexity of Fourier analysis within the algorithm. Despite the performance in traceability in the sequence, speed performance penalised PC-E algorithm to be used in infrared based relative navigation algorithms.

Our experiments also showed that during the eclipse transition, the features extracted around the regions between very low inertia and high inertia materials would not be good features to track. Moreover, the use of such features should be carefully handled since they might mislead the tracking and therefore the navigation algorithm of ADR.

8. CONCLUSIONS

For space applications, thermal imagery has advantages over visual sensors. It can provide continuous information without getting affected by the illumination conditions like eclipse and solar glare. Infrared imagery acquires information about thermal appearance of the target. This is very beneficial for cases especially like in ADR where there are more unknowns then many different types of rendezvous.

In space, thermal environment changes very fast and depends on many parameters which we cannot know perfectly for ADR targets. Even though ADR target exact thermal signature cannot be known, simple calculations suggest that we can observe them by infrared cameras. However, we have to keep in mind the environmental challenges to design a proper navigation system.

Our study showed that thermal variations together with material properties of ADR targets can cause significant variations in their infrared signatures. These temperature variations shall not be considered like illumination variations in visual cameras as in some cases they could be observed as inverted colors for a gray scale image. We had shown that both interest point and edge detectors would suffer from thermal variations during the eclipse transitions.

We had also shown that the interest points are the least affected features and the edges were prone to noise when the scene was cooler or in other words image contrast was lower. In terms of computational time, we had seen methods based on spatial information performed quite fast. Our study showed that feature detection methods based on spatial information similar to GFTT could provide the optimum solution in terms of traceability and computation time for infrared based relative navigation algorithms. However, depending on the available memory and computation power in the system the solution could be adjusted for different modes/phases of the mission.

9. ACKNOWLEDGEMENT

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