Sensor Analysis for Satellite Rendezvous

Sydney I. Dolan*
Purdue University, West Lafayette, IN, 47907

Passively safe satellite rendezvous is critical to future mission design, an enabling technology for satellite formation flying, docking with the space station, and satellite servicing. To properly assess the spacecraft's relative location to its target, computer vision is required. This paper will cover historical examples of computer vision, the basics behind image processing, the proposed image processing methodology, and future research required for this sensor analysis.

I. Introduction

The purpose of this research is to develop an algorithm that can determine the range of a target spacecraft and provide a probability estimate of confidence in the range number. The algorithm should be able to quantitatively estimate noise, and identify distinctive features in the image. Additionally, it should robust enough so that if the spacecraft is approaching its target from a variety of angles, the algorithm can still pick up similar features in different photos. Developing sensor architecture is a process that typically requires a team of engineers with a background in image processing or in electrical engineering, so any simplifying assumptions or areas that require further work will be discussed in the Future Work section.

II. Literature Review

A. Historical Missions

A literature review was performed to determine common sensors on similar missions. A list of relevant missions, their purpose, and relevant sensors, can be found in greater detail within this section.

1. Cubesat Proximity Operations Demonstration (CPOD)

The purpose of CPOD was to demonstrate rendezvous, proximity operations and docking using CubeSats. The mission was novel because it required very little power for proximity operations, and the scale of the spacecraft made the technology accessible. For proximity operations, CPOD used a narrow angle visibility camera, a wide angle visibility camera, IR, star sensors, and sun sensors [1].

2. Orbital Express

The purpose of Orbital Express was to utilize autonomous robotic technology to refuel and reconfigure a satellite. As a result of this mission, DARPA was able to establish the feasibility of on-orbit servicing. Through this mission, DARPA found that if enough about the chief spacecraft was known, then the servicing spacecraft can dock and refuel it. For this mission, Orbital Express used a narrow angle visibility camera, a wide angle visibility camera, IR, a video guidance sensor, and a laser range finder[2]. Orbital Express contains a unique tracking system, Vis-STAR. This system determines the relative range and attitude of the target through image processing. A real-time image correlation algorithm takes advantage of a priori knowledge, enabling relative navigation with respect to a target that is holding its position. The algorithm used a centroid tracker as an additional tool for estimating target position [3].

3. PRISMA

Shifting towards the international stage, the Swedish Space Corporation developed PRISMA to test autonomous formation flying. Consisting of two satellites, Mango and Tango, they relied on a video guidance system, a narrow angle visibility camera, and a wide angle camera [4]. While PRISMA was not directly docking, relative state knowledge was still required.

*Student, School of Aeronautics and Astronautics, 701 West Stadium Avenue, West Lafayette Indiana 47907, AIAA Student member

4. Dragon

Another important historical example of satellite rendezvous is capsules docking with the International Space Station (ISS). SpaceX's Dragon vehicle was designed to deliver cargo, and eventually people, to orbiting destinations. One of its most notable accomplishments was when it became the first commercial spacecraft in history to deliver cargo to the ISS and safely return cargo to Earth. To aid in this historic feat, it used a combined IR and LIDAR known as DragonEye for docking [5].

5. Cygnus

Northrop Grumman's Cygnus Spacecraft was developed to launch cargo to space, particularly the International Space Station. It uses IR and LIDAR for docking. These two capabilities were combined into TriDAR, which is an ongoing algorithm developed for thermal IR imaging. Four computer vision techniques were used: basic blob centroiding, oriented BRIF, template matching, and speed up robust features (SURF)[6] . SURF was implemented in the final algorithm developed this semester, and will be discussed in greater detail in later sections.

6. Automated Transfer Vehicle (ATV)

The ATV was a spacecraft developed by the European Space Agency, for cargo transport. It utilized LIDAR, a video guidance sensor, and a laser range finder. On board the ATV is a functional unit, the GNC Measurements (GMS). The GMS predicts the angular rate with respect to the inertial frame to determine the ATV's inertial attitude. Additionally it uses star-tracker based measurements to predict the ATV three-axis attitude with respect to the inertial reference frame. Lastly, using the GMS, the ATV can estimate the ATV position and velocity [7]. The ATV is a limited example, because it requires retroreflectors on the chief spacecraft to be able to assess its range.

Program	Narrow Angle Vis	Wide Angle Vis	IR	LIDAR	Video Guidance Sensor	Laser Range Finder	Radio Frequency Crosslink	Kurs Russian Radar System
CPOD	X	X	X					
Orbital Express	X	X	X		X	X	X	
PRISMA	X	X			X		X	
ATV			X	X	X	X		X
Cygnus			X	X				
Dragon			X	X				

Table 1 Rendezvous Sensors

Ultimately, this research led to the following hardware selected for sensor analysis: wide angle and narrow angle visibility cameras, as well as a laser range finder. A summarizing table of relevant missions is shown in the table. As shown in table 1, most of the missions either used a camera, or laser ranging of some sort. In the case that the chief spacecraft does not have retroreflectors, or there is no information known about the chief, the laser will be too computationally intensive and expensive. The algorithms used for vision processing will be discussed at length in this paper. While other sensors can be added on to add further confidence in the estimates, the current scope of research is only for the cameras and laser range finder.

B. Image Processing Examples

The fundamental theory behind range assessments in image processing is rooted in the concept of parallax. Parallax is defined as a displacement or difference in apparent position of an object viewed along two different lines of sight. Differences in the size due to the object's location in the foreground or the background are key indicators to the objects relative location to the camera [8] The premise behind determining range in this research is utilizing the concept of parallax by comparing two different images of a target spacecraft.

Sensor analysis on the spacecraft is required to estimate the range of its target, as well as provide a covariance matrix to assess the probabilistic accuracy of these numbers over time. Mader and Reese and investigated this topic for the field of transportation analytics [9] They developed a method to distinguish between cars and trucks based off of a video feed of a highway. The method itself was based upon previous work in the field using covariance matrices as an accurate descriptor for regions. To determine the number of cars and trucks in the image, the paper used the following steps:

1) Image acquisition
2) Image preprocessing
3) Background subtraction
4) Image cleaning
5) Conversion to binary image
6) Segmentation
7) Development of the covariance matrices.

In the acquisition and preprocessing step, the image from the camera is converted to the proper data format, then rotated and cropped to the proper orientation for the analysis to work properly. Then, in the background subtraction step, the algorithm converts the image to grayscale and removes pixel values that are within the certain range. The range of acceptable values is determined by the content of the image itself. For example, if the image is one a mainly white background, then the appropriate range would exclude values that are in the white pixel range. The image cleaning step introduces a common problem in image processing, which is the process of identifying objects and vehicles from the image, but not blurring background noise into desired object. In this paper, they create a cleaned up version of the image using a median filter with a 5 x 5 neighborhood. After that, the algorithm removes all low value pixels. In images, pixel numbers represent the brightness in the image on a scale of 0 to 255, with 255 taken to be white. In this algorithm subtracting 20 from the pixel numbers and removing all the negative numbers removes shadow or black areas in the photo. Following the image cleaning, the image is converted into binary. In the segmentation step, the objects are detected by finding all pixels that form contiguous groups more than 60 pixels each. A 'k-means algorithm' was applied to help with separating different objects. Lastly, covariance matrices were built depending on the relative size of the selected object, (in this case if it was a car or truck) [9].

Analysis of the algorithm found that there were several shortcomings. When images had several cars, or regions that contained portions of cars, then the algorithm had a difficult time properly recognizing the object. Therefore, conditions such as bumper to bumper traffic would give a poor average image and a significant amount of image overlap[9].

While this algorithm is effective in analyzing cars and trucks in the intended video feed, the code is very hard to adapt to other areas. One of the benefits of transportation analytics is that the backgrounds are very still, so the filtering process can be standardized because the general orientation will not change. Furthermore, unlike space, the relative orientation of the camera is fixed, so it will be easier to estimate range without additional attitude dynamics. The fundamental process applied to develop this algorithm was a useful base for developing the required steps to determine range for our applications.

RemoveDEBRIS, is a revolutionary UK satellite designed to test how to remove space junk. RemoveDEBRIS performed several trials to evaluate viable methods for removing unwanted objects in orbit. One technology demonstration that RemoveDEBRIS is performing is using a vision-based navigation system that uses cameras and LiDar technology to analyze and observe potential pieces of debris and then subsequently harpoon them [10]. A paper on the visual navigation system by Keyvan Kanani explained the architecture and process of the technology. First the silhouette of the target is extracted in the image. Then, the selected target is compared to a database of prototype views whose contours correspond the most to the extracted silhouette. The algorithm utilizes a similarity metric that is based off of silhouette matching, which considers both the distances and the orientation of the edges. Once the closest prototype view is found, its associated attitude is considered as initialization of the target attitude. When the target has been detected and matched with an attitude, a frame to frame tracking can be performed. While the true effectiveness of this methodology will not be known until the RemoveDEBRIS mission has been completed, the results of the synthetic ground testing are publicly available. Testing has shown good performance, with an error on position of only about 1 percent of the distance to target at ranges of 5 meters to 100 meters and error on attitudes less than 1 degree [11].

The processing methodology from RemoveDEBRIS inspired some of the aspects of my proposed sensor analysis. The concept of having a database of stored images at different angles is highly appealing as an additional way to validate the range. Furthermore, this approach is useful because it does not require additional hardware on the target spacecraft.

III. Semester Progress

The suggested architecture for sensor analysis is shown in the diagram below. The technical descriptions of each of the main steps will be discussed within this section. 1. Compare new image to a "good image" to get image noise levels (SSIM) 2. Filter noise 3. Identify features in the image (SURF) and compare to previous images 4. Generate a range and attitude estimate in pixels based on the comparison and filter features that are not similar. (RANSAC) 5. Convert (5) to physical measurements through scale factor

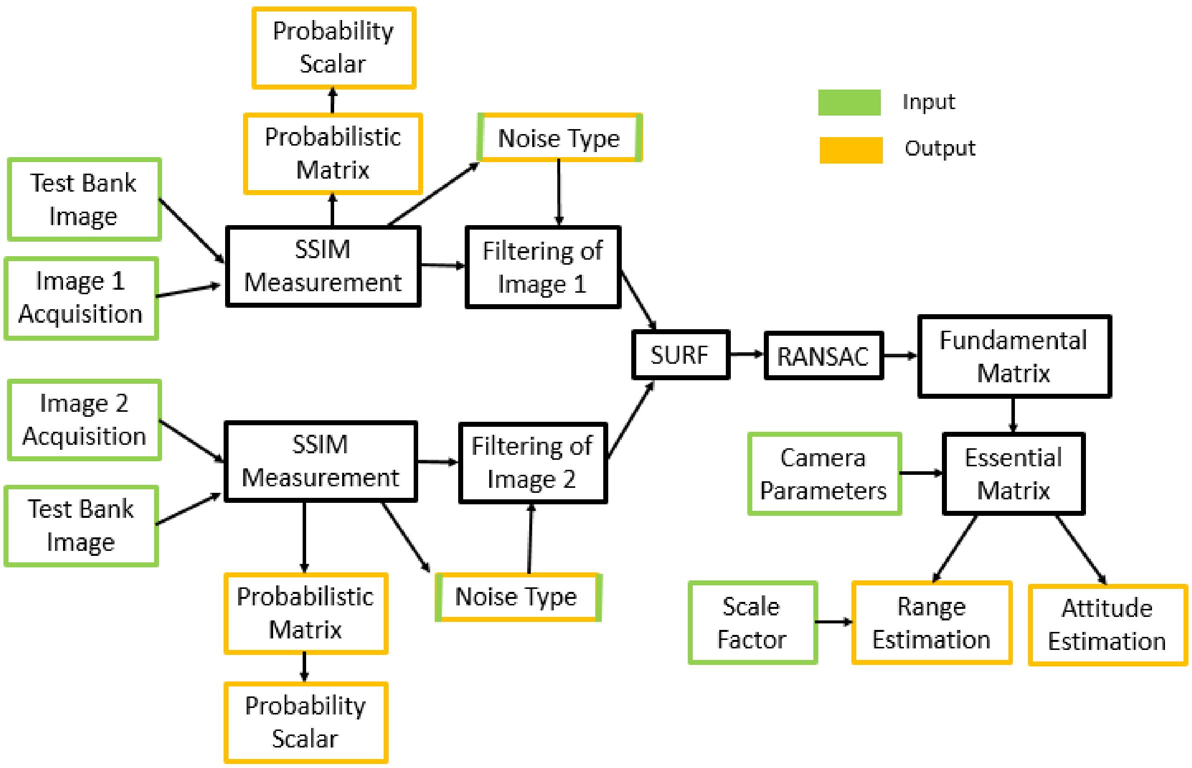

Fig. 1. Sensor Analysis Architecture

A. SSIM Measurement

After completing a literature review, I determined the first step in the process of sensor algorithm development was removing the noise from the image, much like the image preprocessing step. Following research into the field, one of the most established techniques to assess noise and image quality is a method called the Structural Similarity Index.

Unlike quantitative fields where performance can be objectively measured, images are a qualitative field, where the 'best image' is largely dependent on the viewer. One field within the larger realm of image processing is the niche field that focuses on developing a system that can objectively measure image quality through quantitative measures. Objective image quality metrics can be classified according to the availability of an distortion-free image. When there is a complete reference image, then the approach is known as full-reference, with nothing, it is a no-reference. When a reference image is only partially available, this is referred to as reduced-reference quality assessment [12]. For our purposes, we are assuming that the system is a full-reference system. Similar to the RemoveDEBRIS system, the sensor analysis will compare the image to a test bank of images of the target which can serve as the reference figure.

One of the simplest and most widely used methods for full-reference quality is mean square error (MSE). This method is computed by averaging the squared intensity differences of distorted and reference image pixels, along with the relevant quality of peak signal to noise (PSNR). This method is popular because it is not computationally intensive, and it has a clear physical meaning. However, this method is not a perfect system like human vision, which can immediately tell when there is significant noise in an image, and further optimization in the field is required.

Structural Similarity Index (SSI) was based off the premise that natural image signals are highly structured. By structured, this means that pixels have dependencies on each other, and these relationships can be used to understand the larger scene. The motivation of SSI is to find a more direct way to compare structures of the reference and distorted signals. A useful analog would be the spot the difference pictures in the newspaper. When humans look at those two images, they focus on identifying what is different by analyzing how the images have shifted from the original.

The philosophy behind SSI can be best understood through comparison with the error sensitivity philosophy. Traditional error sensitivity approaches estimate perceived errors to quantify image degradations, while the new philosophy considers image degradations as perceived changes in structural information. The error sensitivity is also a top-down approach. This avoids errors experienced by author, because the algorithm does not have to quantify every single distortion.

The structural similarity quality measure first begins with assessing the luminance of the surface. Luminance is the product of illumination and reflectance. Structures in the scene are there regardless of the illumination. Consequently, to properly explore the structural information in an image, the illumination within the image must be separated. Since luminance and contrast can vary across an image, local luminance is used. The overall similarity is dependent on the local luminance, the difference in projections of each of the main features, and the signal contrast. These metrics were chosen because they remain relatively independent.

Overall, for image quality assessment, it is useful to apply SSI locally rather than as an indicator for the entire image. As mentioned previously, image distortions may or may not be dependent on local image statistics. Thus, for the algorithm to be useful, the SSI is applied repeatedly over the entire image, developing a matrix, or structural similarity indicator matrix (SSIM). Then, the mean SSIM can be used to assess the quality of the entire image as a percentage of the reference image. [10]

This algorithm was chosen because it is an accurate way to assess the quality of the image when noise is involved. When compared to other methods, SSIM is able to assess noise in the image at a quantitatively higher rate. Furthermore, unlike other popular methods, SSIM is effective for the type of noise that is expected in the space environment. Analysis has shown that SSIM can properly assess stretched images, blurred images, salt-pepper impulsive noise, and mean shifted noise. SSIM is commonly used in satellite industries as well, and can be considered a dominant method of measuring video quality [12].

The output of the SSIM function is a mean number to assess the quality of the image when compared to the original, as a matrix of the local structural similarity. In this research, the difference between the original and the final is the major factor when developing the probabilistic accuracy of the estimations.

Following the assessment of image quality, the image will be filtered, unless the image is below a given number, and would be statistically useless to perform analysis on. While filtering the image, it is possible to acquire the noise in the image through the MATLAB Image Filtering Toolbox. Further analysis will be required on the filtering needs of the mission, and this work will be discussed in the Future Work section.

B. Filtering

Following the assessment of image quality, the image will be filtered, unless the image is too poor in quality to be worth assessing, and would be statistically useless to perform analysis on. While filtering the image, it is possible to acquire the noise in the image through the MATLAB Image Filtering Toolbox. Further analysis will be required on the filtering needs of the mission, and will be discussed in the Future Work section.

C. Speeded Up Robust Features

Fig. 2. Feature Detection in Separate Images

With a filtered image, it is possible to begin the assessment of the range. To do this, the chosen algorithm relies on the concept of speeded up robust features (SURF). SURF is a local feature detector and descriptor. It is primarily used for object recognition [18]. The methodology used for this research was taken from the process in Peter Corke's Robotics, Vision and Control - Fundamental Algorithms in MATLAB textbook. In the textbook, Corke begins with an image that has already been filtered and preprocessed. The first step in estimating range is to run a SURF algorithm on the picture, which identifies potential features in the image. Then, the SURF Algorithm is run on a second image. It should be noted that this image would be another image taken from the spacecraft, not one from the test bank. This image can be from a different angle, or closer to the intended object. The SURF algorithm was built to identify which features are the same in two images, as shown in figure 2.

D. RANSAC and Fundamental Matrix

When the list of similar features in both images has been created, the subsequent step is to find a set of corresponding points that best fit a plane in the world. To do this, a RANSAC algorithm is used. RANSAC, random sample consensus, is an iterative method to estimate parameters of a mathematical model from a set of data that contains outliers, when outliers are to be accorded no influence on the values of the estimates. Hence, RANSAC is considered as an outlier detection method [13]. RANSAC is also extremely useful because it is able to quantitatively determine the number of outliers and number of inlier points in the set. As testing in this research continues, the RANSAC method can verify the quality of data, and if the current approach is the optimal approach going forward. The RANSAC method is also used to build a fundamental matrix, which captures the relative geometry of the two views.

E. Essential Matrix

Following the analysis of the image set, the next step is to input the camera parameters. For this project, the focal length, pixel size, and image dimension must be known. A camera object is built and it contains these characteristics as well as the principal point (location of the camera in the image plane), number of pixels and pose. If the principal point is not known, it is automatically assumed to be the center of the image. Recommended cameras for future testing are discussed in the Hardware Recommendations section. Then, the essential matrix is obtained by applying the camera intrinsic parameters to the fundamental matrix. Essential matrix is a 3x3 matrix that has additional properties so that it relates points in stereo images. A stereo camera is not formally required, as long as there are two cameras which are triggered simultaneously. The essential matrix is useful because it incorporates effects that alter the camera's image, such as focal length. The essential matrix is important to develop, because it can be decomposed into the cameras motion, both translational and rotational. To decompose the essential matrix, it is inverted along a given test point. The test point will have to be determined in future iterations, or a function of the camera's orientation. However, as a sanity check for results, if the camera orientation is to be kept fairly constant, the rotational part of the transformation is expected to be close to the identity matrix.

When decomposing the essential matrix into translational motion, one of the dependent relationships is that the translational motion has to be scaled. The estimated translation has the correct direction, but the magnitude will be off. Additional ways to address this issue will be discussed in the Future Work section. Scaling the translation matrix creates an estimate of the relative pose of the camera with respect to the first pose of the camera, represented as a homogeneous transformation.

Each point in the image can be considered as a ray in space. The points are based around the principal point in the camera, as well as a unit vector in the direction of the ray. The rays can be analyzed in each of the respective images, using the MATLAB move method, as well as the intersect method. These methods will return a z coordinate which is the depth of the point. If the rays do not intersect in each image, the closest point will be returned instead. The example in Corke's book, subsection 14.3.1, produces remarkably accurate results considering the magnitude knowledge was approximated. In the book, it is recommended to only use the inlier points from RANSAC for depth estimates. For each inlier, the ray is computed for each image. Then their relative intersections are calculated. The z-coordinate is the depth estimate, which is displayed. A sample display is shown in figure 3.

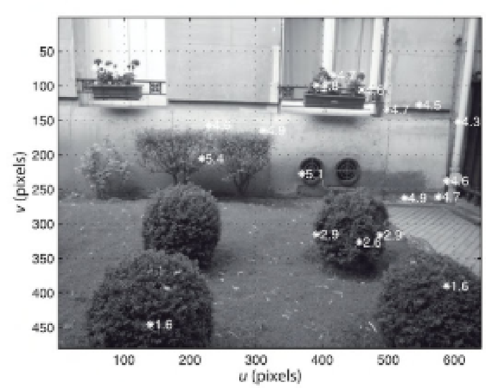

Fig. 3. Depth Estimates from Algorithm

IV. Testing

To test the Structural Similarity Method, sample easier photos were required. The difficulty in finding stock photos for the testing relates to the fact that future testing would require information about the camera characteristics. After researching proper photo banks, the Kodak Lossless True Color Image Suite was chosen. This database has information about the camera, photographer, and all the photos are in lossless PNG format rather than jpeg [14].

The other main database used was the Tampere Image Database. The database is intended for evaluation of full-reference image visual quality metrics. The database itself has supplementary software to help calculate the correlation between chosen metrics and the mean opinion score, as well as the general value for the metric. Similar to the Kodak Lossless True Color Image Suite, the technical characteristics of each image are publicly available as well. This resource was particularly valuable for algorithm testing because the website has a listing of the SSIM for each photo. Thus, it was possible to evaluate SSIM's effectiveness for different types of noise, as well as validate if the algorithm was working properly. Additionally, the website validated that SSIM is one of the more robust ways to analyze the quality of images.

The Tampere Image Database contains 25 reference images and 1700 distorted images. The images themselves were obtained from the Kodak Lossless True Color Image Suite, but they have been manipulated to be more suitable for our application. The database is a huge resource to those in the image processing field, over 838 observers have performed 256428 comparison of visual quality of distorted images of 512856 evaluations of relative visual quality in image pairs [15].

A. Hardware Recommendations

If more formal testing is required, my research has shown that a Nikon F4 camera is an optimal choice for this system. The Nikon F4 was one of the first fully digital cameras. Most of the electronics were designed and built by NASA at the Johnson Space Center [16] . Unlike other cameras the Nikon F4 has actually been space-rated, and have been used on multiple EVAs. In the event that the Nikon F4 cannot be acquired, NASA also uses the Kodak DCS 460, DCS 760, Nikon D1, D2X, D2Xs, D3X, D3S, D4, and D800E [17]. These cameras have accessible specifications sheets, both through the companies themselves, as well as reports from professional and amateur photographers [18].

Determining a laser range finder was considered to be out of the scope of this research. If formal hardware selection is required, it can be completed in subsequent semesters.

V. Future Work

Filtering images from the space environment was decided to be out of the scope of this project. However, for future iterations of the project, a filtering method should be selected. One reason that filtering was avoided was because camera noise is different in a space environment than in an Earth environment. This is largely due to the exposure time for cameras in space. One possible method to use is a medium filter. Medium filter was the suggested filtering method for SURF, as one of its distinctive characteristics is that is preserves edges while removing noise.

Currently, the range estimate relies on a scale factor. The current algorithm will be able to assess change over time, but a scale factor, at least at the start, will be required to evaluate the change in translational distance. One way that this number can be provided is creating an estimate based off the spacecraft's relative locations in each of their orbits. The more accurate this scale factor is, the more accurate the image processing will be. Another option would be to state that the laser range finder can provide the distance, or at least the proper magnitude between the spacecraft and its target. This aspect of the research is primarily theoretical, so the design consideration is mainly a factor in developing the robustness of larger architecture.

One resource on Purdue's Campus is Professor Bouman, in the School of Electrical Engineering. Bouman teaches a course, EE637, Digital Image Processing I. The course notes are online, as well as the lectures are all posted online. The course objectives are to learn and apply analytical methods of image and 2-D signal processing, learn techniques commonly used in image processing, and develop experience using computers to process images. The recommended text is Handbook of Image and Video Processing by Al Bovik, which is another potential future resource [16].

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