Radar Antenna Detection and Analysis for Autonomous SEI Collection

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Abstract

The ability of an unmanned system to visually determine the direction a ship’s radar antenna is facing can significantly improve the SEI collection process and provide opportunities for autonomous collection. This paper investigates methods for detecting and analyzing periodic motion of spinning radars in the maritime domain. The methods include feature based tracking and periodic measurements using similarity matrices.

1. Introduction

SEI collection is an important asset for information dominance. “SEI provides a reliable, long-range, all-weather positive target identification capability against seaborne platforms and land-based systems that emit radar signals.”[1]

The process of SEI collection is to “find non-intentional modulations in the receiving signals”[2]. An illustration of the required components is shown in Figure 1.

The SEI collection procedure currently requires a human-in-the-loop. The operator (human-in-the-loop) is required to point the SEI collection antenna at a ship’s spinning radar using optics bore-sighted with the collection antenna. The operator (sometimes a second operator) configures the SEI collection tuning parameters while the optic system is manually positioned to follow the ship radar. An SEI collection occurs when the operator confirms the position (shown in Figure 2) of the radar antenna is directing its beam at the collection antenna when the SEI system signifies a signal has been received. The collection is complete after the operator reads the name of the ship, confirms the radar signal is indeed from the ship, and acquires other distinguishing features (color, hull type, etc.)

Figure 1 SEI Collection Cartoon [4]

Figure 2 The angular position of radar we want to detect

The procedure the operator employs is an important step for providing ground truth. One of the four key core concepts for an SEI system design is “Providing ground truth (the correct identification of the emitters being evaluated) for the naming of the clusters and evaluation of the clustering process.”[2]

This is a complex, error-prone, and time-consuming procedure which could be significantly optimized through automation. The automation is addressed by researching methods for radar angular position and periodicity verification. For most collection sites, this step alone will cut down the need of two operators down to one.

The efforts addressing this vision system concept can also be extended to provide cueing for ship detection, tracking, and identification.

Another reason for autonomy is collection in hostile environments. SEI collection using the current procedures is not a safe option because of the risk of placing human operators in hostile environments. This risk limits the ability to monitor vessels of interest (VOI). A VOI can avoid intelligence collections by staying within the hostile environments. An autonomous SEI collection system would best support this scenario and could be tremendously advantageous to the DoD mission of MDA.
1.1. Related Work

1.1.1 SEI Specific
There are a multitude of research journals that address the electromagnetic signal parameter realm of SEI. These methods employ pattern recognition, classification, and feature extraction of the received signals [2].

1.1.2 Computer Vision
At this point in time, there is no other research using a computer vision approach to detecting the period and angular position of a radar on a ship. Work that is closely related to this topic includes tracking and stabilization methods, and periodic motion estimation.

There exist many different video stabilization systems that are hardware and also software solutions. Some use affine transformation models as in the Motion2D software library from Inria.

There are feature based methods which we will explore in this paper provided by a Kanade-Lucas-Tomasi method.

There is a vast amount of literature focused on the aspect of detecting or recognizing the periodic nature of rigid and non-rigid moving objects. In general the objects of interest are biological such as humans, animals, and trees [5].

We will follow closely the work presented by Cutler and Davis [7] which uses a similarity matrix representation to measure periodicity.

2. Our Model

2.1. Assumptions

The primary object of interest is rotating radar mounted to a ship. Our model assumes the viewing distance is long enough that an affine transformation model can satisfy all dominating transformations. This has been verified by measuring corresponding points of a ship in sample video sequences.

In fact, the model has shown a dominant translation factor and very minimal rotation, scale, and skew factors.

It is also assumed the field-of-view (FOV) is narrow enough to be able to view the radar. If the rotation of radar is not distinguishable from other motion artifacts in the video sequence then this model will fail.

It is also assumed for this effort that the radar is mostly in the FOV during the whole video sequence. The length of time the radar must be in the FOV is dependent on the slowest periodic rate of rotating radar. A typical range of rotation speed is between 24rpm to 50rpm. This means the slowest period would require a 2.5 second window of time the radar must be in FOV. The radar may be partially occluded.

The number of radars that exist in the FOV is not limited. Typically multiple radars on a ship will have a different periodic rate and position.

This model relaxes the requirement of number of ships in the FOV. There are many reasonable scenarios where multiple ships exist in the same FOV. Most of which arise when ships are in the same shipping lanes. This is the primary reason for the need of analyzing the period of the radar and its angular position for SEI collection to distinguish between radars.

2.2. Noise

There exist artifacts that must be accounted for that are considered to be noise with regard to measuring periodicity of a rigid object.

2.2.1 Maritime Weather
The maritime domain always introduces weather effects that can cause imagery to degrade to the point of uselessness. The contrast is affected by the attenuation of light travelling through a medium such as haze, fog, and rain as well as an additive light that carries no information [8].

There are many methods of dehazing imagery. The simple approach of using histogram equalization fails due to the spatial dependence of the weather effects [9]. Our approach will assume no video image enhancement was employed beforehand.

2.2.2 Nuisance Artifacts
There are also many other artifacts on a ship that may mask itself as a useful periodic signal such as humans walking on the bridge near a rotating radar. Birds flying across the FOV are also a common occurrence.

Our approach must be able to discriminate a radar from all other nuisance artifacts.

3. Generalized Approach

The system design approach for analyzing periodicity can be generally described by two modules: Tracking/Stabilization and Periodicity Analysis. The
system diagram of this approach is shown in Figure 3.

![Periodic Analysis System Diagram](image)

Figure 3 Periodic Analysis System Diagram

There are many methods that solve the stabilization and tracking module. Any method can suffice and feed into the periodic analysis module.

Likewise, there are many methods of analyzing periodicity which are in general independent of the previous video tracking step.

Methods do exist that are independent of tracking and segmentation [5]. However these methods depend on feature extraction from the periodic moving object itself. The motion of the ship alone dwarfs the motion of the radar and is a crap shoot hoping for a feature point to land on the spinning radar which may be partially occluded.

### 3.1. Video Tracking and Stabilization

The dominant motion in the video sequence arises from the motion of the ship in the foreground. The background is typically the sky. In some cases, mountains, cityscapes, and additional ships can also exist in the background.

A direct method can be employed for stabilizing the image. A feature based method shall also do well because of the large corner count due to the highly rigid structural design of a ship. We will avoid the direct method and feature based method debate [6] by ultimately exploring both methods.

We investigated stabilizing the video sequence using a feature based method. The features were generated from the Kanade-Lucas-Tomasi (KLT) method [10],[11].

In future work we will explore using direct methods to employ stabilization.

#### 3.1.1 KLT Feature Extraction

Ideally we want know the translation between the first frame and any frame afterwards. This method requires that features must be extracted for every frame. See Figure 4 for an example of extracted features using KLT.

![Features Extracted from Frame 1](image)

Figure 4 Features Extracted from Frame 1

#### 3.1.2 Translation Estimation with LLS

Initially a linear-least-squares approach was employed for estimating the affine transformation matrix. Comparing six different frame displacements, the rotation matrix was identity with a variance of 4.4E-05. This confirmed the dominant transformation in the video sequences was translation.

The linear-least-squares approach is not a dependable estimate as the displacement between frames increase or if noise begins to dominate the feature space. Indeed, the LLS method failed after feature points were lost in sample video sequences.

KLT feature extraction does not guarantee the same features are extracted for each frame in a video sequence. For example, there is a feature point in Figure 4 at the (x,y) position (312,76) on the ship’s mast. Sixty frames later this feature point doesn’t exist in Figure 5. The same is seen at the location (157,280).

There are also new feature points that arise in later frames which cause LLS estimations to fail. For example, feature points (151,419) and (275,173) in Figure 5 don’t exist in Figure 4.

![Features Extracted from Frame 60](image)

Figure 5 Features Extracted from Frame 60

#### 3.1.3 Translation Estimation with Centroid

It is desirable to estimate the translation for every frame at a rapid rate in order to be near real-time with estimating
the periodicity of the radar. We also need to account for the gross changes in features selected for each frame.

We investigated a method loosely based off of a trajectory conditioning method by Rabaud and Belongie [12]. The main idea is to create a new feature point located at the centroid of a cluster of feature points.

A large percentage of the features extracted are features from the ship therefore the translation of the centroid of these feature points should also be the translation of the ship in the video sequence. This relaxes the need to find feature point correspondences for translation estimation. See Figure 6 for an illustration.

![Figure 6 Centroid creation between two frames](image)

This method works well if there is small amount of feature dying and re-spawning between frames. Video sequences were stabilized with this method to research periodic measurements.

However this method still suffers from the same effects as LLS. For example, if there were no translation between two frames but a feature point was lost (or gained) from one frame to the next, a false translation would be induced by the centroid method.

3.1.4 Translation Estimation with RANSAC

We explored the spatial-temporal volume produced by the features extracted from the video sequences. Overall, there is a consensus of translation between features points. Figure 7 demonstrate this behavior.

What is also evident in Figure 7 is the dying and re-spawning of features which can be seen as holes within the “snake” lines. These holes cause the translation estimations with LLS and the centroid methods to fail.

We explored estimating translations based on a randomized sample consensus (RANSAC) method presented by Fischler and Bolles [13]. This will exploit the strong translation consensus of features and minimize the damage induced by features dying and re-spawning.

![Figure 7 (a) Features displayed in spatial-temporal volume for a video sequence. Notice the ”snakey” lines caused by the translation of the ship. (b) The same type of “snakey” lines appear in a different video sequence. (c) The same features from (a) with a different viewpoint. There is a strong consensus of motion between these “snake” lines.](image)
We created a delta matrix that contains all possible translations for each frame in a video sequence. Therefore the first row of the matrix would contain all translations with respect to frame 1. The second row of the matrix would contain all translations with respect to frame 2, etc. Ideally this would generate a skew-symmetric matrix. However since RANSAC is a randomized algorithm, it is expected the delta matrices will not be exactly skew-symmetric.

We also populated the delta matrix with an indicator value whenever the RANSAC algorithm presented a large error. This normally occurs when there is in fact no consensus in features between two frames. This causes the delta matrices to appear to have a peppered noise artifact.

The results for the translation in the x-direction are shown in Figure 8.

![Figure 8 (a) Delta matrix for x-direction (b) Selective median filtered delta matrix](image)

We have found the delta matrices do support our hypothesis that the matrices are skew-symmetric. There is a strong spatial dependence between translations.

Differing from conventional noise, the location of the peppered noise in these matrices is known. We took advantage of this by running a selective median filter only on the points that were labeled noise. We ran a larger median filter window after each iteration until all the noise was removed. The results are shown in Figure 8(b).

This exploration demonstrates we can estimate a translation based off of previous translation values. For example, the translation from Frame 1 to Frame 60 may be (6, -7). The translation from Frame 1 to Frame 61 should be close to the same value of (6, -7) and not (0,0) or the opposite (-6,7). This is something we should consider in future work.

### 3.2. Periodic Signal Analysis

A robust method for detecting periodic motion and motion symmetry was outlined by Cutler and Davis [7]. We will explore their method and then propose a simpler method that is afforded from the special case of periodic motion from rotating radars.

#### 3.2.1 Cutler and Davis Method

Suppose a pixel located at the region the radar is spinning is observed. The pixel will match itself a period of time $p$ translated by pixel positions $\delta_x$ and $\delta_y$.

$$I(x, y, t) = I(x + \delta_x, y + \delta_y, t + p) \quad (1)$$

The translation vector parameters, $\delta_x(t)$ and $\delta_y(t)$, are known from the previous stabilization step. Or these values are zero if the video sequence is stabilized.

The unknown parameter is the period, $p$. What we do know is the minimum and maximum values of $p$. The typical range is 2.08 to 2.5 seconds. This is a key factor in developing a robust periodic analysis method.

A simple SAD match is used to measure similarity of pixels parameterized by two time values, $m$ and $n$.

$$S(m, n) = \sum_{(x,y) \in \Omega} |I(x, y, m) - I(x, y, n)| \quad (2)$$

$\Omega$ is the region of pixels that is selected for detecting periodicity.

Cutler and Davis point out that this similarity matrix, $S(m, n)$, is in fact a recurrence matrix without time-delayed embedded dimensions. The usefulness comes from the plot encoding the projection of the objects spatiotemporal dynamics [3].

We can explore this method by setting the region of interest, $\Omega$, to be a horizontal scan line that overlaps the location of the radar. This is shown in Figure 9. The horizontal lines indicate the location a scan line is positioned. The position of this scan line is updated according to the stabilization vector, $[\delta_x(t) \ \delta_y(t)]^T$.

![Figure 9 Scan Line in Video Frame](image)
Figure 10 illustrates a similarity matrix generated from a stabilized scan line positioned over a rotating radar. The units of time for this plot is in frames. Each frame was approximately 33ms in duration. The main diagonal running from the top-left down to the bottom-right is the self-symmetry match at times $m=n$. Besides the main diagonal it is evident that there are other symmetry matches at approximately (25, 95) and (95, 25). By inspection this equates to a 70 frame period which is 2.31 seconds. The true period of the radar is 2.44 seconds which is 74 frames.

We have found that using a weighting term can amplify the periodicity in the similarity plot. The result is shown in Figure 11.

Figure 11 Similarity Plot of Stabilized Scan line with Weight Term

The weight function used was a Hanning window:

$$w(x) = \frac{1}{2} \left(1 - \cos \left(\frac{2\pi x}{|\Omega_s|}\right) \right) \quad (3)$$

Where $|\Omega_s|$ is the length of the scan line. This takes advantage of the fact that the radar is in general located near the center of the image.

The new similarity matrix with the weighted function is:

$$S(m, n) = \sum_{(x,y)\in \Omega} |I(x, y, m) - I(x, y, n)| \cdot w(x) \quad (4)$$

The next step after creating a similarity matrix is to generate a new matrix, $A$, that is the normalized autocorrelation of the similarity matrix, $S(m, n)$.

Figure 12 and Figure 13 are autocorrelation plots of the scan line similarity matrix and weighted scan line similarity matrix respectively. The peaks in the autocorrelation matrices arise from the periodicity of the rotating radar. The distance between these peaks are measured to determine the period of the rotating radar. A non-maximal suppression method is used to find the peaks, $P_t$, from the autocorrelation matrix. The peaks are then matched to two different synthetic lattices parameterized by a pixel distance term, $d$. A square lattice
and a 45 degree rotated square lattice (quincunx shape) are used in the match metric process.

Each lattice is generated according to the $d$ parameter and matched to the peaks, $p_i$. The search may be limited by choosing a minimum and maximum value $d$ which corresponds to the range of periods radars have. Figure 14 and Figure 15 demonstrate these synthetic lattices overlapping the autocorrelation matrix.

Figure 14 Square Lattice

Figure 15 Quincunx Lattice

The distance parameter, $d$, is chosen from the lattice that best matches the non-maximal suppressed peaks from the autocorrelation matrix. This distance is measured in frames which then can be converted into time. This method reasonably measures the period to be 2.4 seconds for this particular demonstration.

### 3.2.2 Simpler Method

The Cutler Davis method has been proven to be robust and resilient to amplitude modulations. However it is an involved process requirement many steps.

We suggest a method that is afforded by the specific and simplicity of the periodic motion of radars.

Suppose we contain a buffer of scan line images and stack them frame by frame. This image is shown in Figure 16.

The vertical helix shape is from the radar rotation. Time begins at the top horizontal line and progresses in time downward frame-by-frame.

Knowing the minimum and maximum time periods ($p_{\text{min}}$ and $p_{\text{max}}$ respectively), we can use a SAD match metric very similar to Equation (2) only the time parameters are much more rigid. Instead of matching all possible pixels forward and backward in time for each scan line, we employ a match starting at the minimum time period and end with the maximum allowed period. For example; a scan line at time $t$, Scanline$(t, \Omega_z)$ is compared to all scan lines in the range Scanline$(t + p_{\text{min}}, \Omega_z)$ to Scanline$(t + p_{\text{max}}, \Omega_z)$ where the horizontal pixels of the scan line are represented by $\Omega_z$. This generates a modified similarity plot shown in Figure 17.

Figure 16 Scan Line Buffer

Figure 17 Modified Similarity Plot

Notice that this modified similarity plot is a 45 degree clock-wise rotated subsection of the full similarity plot in Figure 11. (See Figure 18)
Ideally, the lowest error value in the subset-rotated similarity matrix should exist in the same column position for every row. This is easier to demonstrate using a mesh plot of the same subset-rotated similarity matrix shown in Figure 19.

Measuring the period is simplified by summing the errors for each column and selecting the period that corresponds to the column with minimal error. The estimated period for this method was 2.4 seconds which was the same as the Cutler-Davis method.

4. Conclusion

We addressed the need of stabilization for analyzing periodicity of rotating radar on ships. We explored methods using LLS, centroids and RANSAC. We demonstrated the time-dependence of translation which may prove to be useful in future work.

We explored an existing method of robust periodic motion analysis. We also proposed a simplified method of measuring periodicity based on methods proposed by Cutler and Davis.

Future work entails researching methods for detecting the angular position of the radar. We need to explore methods in detecting the spatial location of the radar in a video sequence. In addition to this we need to run our periodic measurement methods to more video sequences to verify the methods are robust for this particular application.

References

[5] Ivan Laptev, Serge Belongie, Patrick Pérez, and Josh Wills, Periodic Motion Detection and Segmentation via Approximate Sequence Alignment, ICCV 2005