Performance Prediction Modelling of Low SNR Tracking Algorithms

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Abstract—**The paper presents a Performance Prediction Model (PPM) for predicting the expected detection and tracking performance of a sequence of images based on collection parameters. The Detection PPM is similar to the GIQE but is designed to optimize probability of detection by maximizing peak Signal to Noise Ratio (SNR). Tracing performance can be modelled using binomial distributions related to number of positive detection vs number of collections. Theoretical analysis shows predicted defection performance with increasing SNR and number of collections. Such performance predictions will help tack the exposure and number of frames to meet a collection requirement.**

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1. INTRODUCTION

Performance prediction models are critical in satellite operations to help establish the optimal viewing geometry and imaging exposure for collections based on a variety of tasking parameters. The image quality of the collection can be adversely influenced by altitude, viewing geometry, solar lighting, atmosphere conditions, target requirements, and sensor capabilities. The General Image Quality Equation (GIQE) is used to predict collection performance for contextual imaging tasks with single frame images and provides an estimated quality based on the National Imagery Interpretation Rating Scale (NIIRS) scale[1]. In persistent imaging tasks a user is often more interested in detecting and tracking an object over a single high-quality picture. This paper proposes a performance prediction model for selection the best collection conditions for a sequence of images that is suitable for detection and tracking applications. The Tracking Performance Prediction Model helps operators establish the best collection conditions for a detection and tracking application. The tracking prediction model is based on optimizing probability of detection. The equation is provided here with comparisons to detection performance calculations from simulated images.

2. TARGET DETECTION PERFORMANCE AND GIQE

Satellite image quality has historically rated using the NIIRS scale which describes the ability of an image to perform a image interpretation task. It is a rating scale that instructs an image analyst if the image has sufficient resolution to perform an intelligence task. A low NIIRS might indicate the ability to count ships and object on the deck. A higher NIIRS will allow the user to perform tasks on smaller objects such as counting cars in a parking lot and identify the model. Although the NIIRS scale is subjective based primarily on human interpretation, there are engineering equations to approximate NIIRS based image collection parameters called the General Image Quality Equation (GIQE). The GIQE version 5 is as follows,

$$NIIRS = A_0 + A_1 \log(GSD) + A_2\left[1 - \exp\left(\frac{A_3}{SNR}\right)\right]\log RER + A_4 \log(RER)^4 + \frac{A_5}{SNR}$$

A0 = 9.57
A1 = -3.32
A2 = 3.32
A3 = -1.9
A4 = -2
A5 = -1.8

Where the Relative Edge Response (RER) is the maximum slope of the optical edge response function between two pixels, the Ground Sample Distance (GSD) is the spacing between pixels in inches, and Signal to Noise Ratio (SNR) is the ratio between target contrast and noise in detector counts.

Overhead imaging system need to take collect a high volume of images daily and still meet the image quality requirements of the end users. The overhead collection systems are functioning on two competing requirements. The first requirement is to maximize the number of collections that meet all users. This requires the operators to minimize the time spent on each collection. Yet each image must have sufficient quality to meet the user's needs. So, the images must have sufficient. signal level and resolution to perform the users imaging task.

Performance prediction models (PPM) provide a quality metric to assess the image quality based on the collection geometry and sensor exposure mode. Fig 1 shows the relationship between role of a PPM in mapping sensor collection parameters to user satisfaction metric.

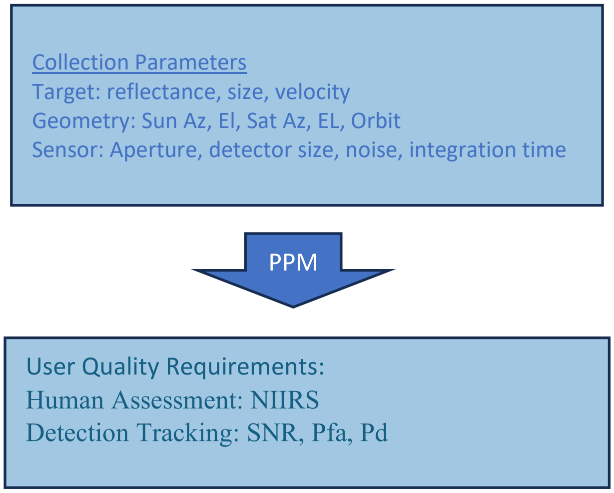

Fig. 1. Overview of PPM relationship between collection parameters and User quality metrics

For human assessment of single images, the NIIRS scale is often used. The original definition of the NIIRS scaled is based on a subjective assessment and it is essentially defined as a lookup table mapping a NIIRS number to an assessment task. The GIQE is an engineering approximation of the NIIRS scale that allows an estimate of the NIIRS value using an equation form based on imaging systems parameters like resolution and SNR.

This paper investigates a performance prediction model that applies to overhead detection systems. Detection and tracking systems will likely need a different assessment metric than NIIRS. Detection systems use multiple images instead of single images and rely on automated logic and tracking algorithms to perform the target detection.

The NIIRS equation is suitable for rating image quality for human interpretation, but the scale is not directly applicable to multi-frame detection tracking systems. A tracking system will rely on multiple frames to track moving objects. It is an automated process that relies on background suppression to remove the background, peak detection to extract the targets, data association to assign tracks to detections, and a Kalman filter to smooth the position measurements and extract velocity and acceleration. This paper investigates a set of equations to predict the performance of image systems that are used for detection and tracking missions. The detection system performance model will allow users to predict the quality of a set of frame collections for a detection mission. The performance prediction model is usually part of a satellite tasking and scheduling systems that ensures the images are collected efficiently to meet the user requirements.

3. DESCRIPTION OF IMAGE SEQUENCES

Overhead imagery in a detection and tracking application has a sequence of frames from a fixed vantage point. The image sequences and be described as follows,

$$I_{ijk} = B(i + \Delta i_k, j + \Delta j_k) + n_{ijk} + T_k \delta(x_k, y_k)$$

The target is a point sequence with intensity T_k and position x_k, y_k and the background scene is $B(i,j)$. Images can contain sensor platform jitter: $\Delta i_k, \Delta j_k$. Image has additive noise from the detector element over the sequence: n_{ijk}. In each frame, small targets can move across the image. Fig. 2a shows a typical background scene. Assume there is a sequence of frames with slight jitter in the horizontal and directions. Assume these scenes have an additive noise shown in Fig 2b. The scene also has the target motion as described in Fig 2c.

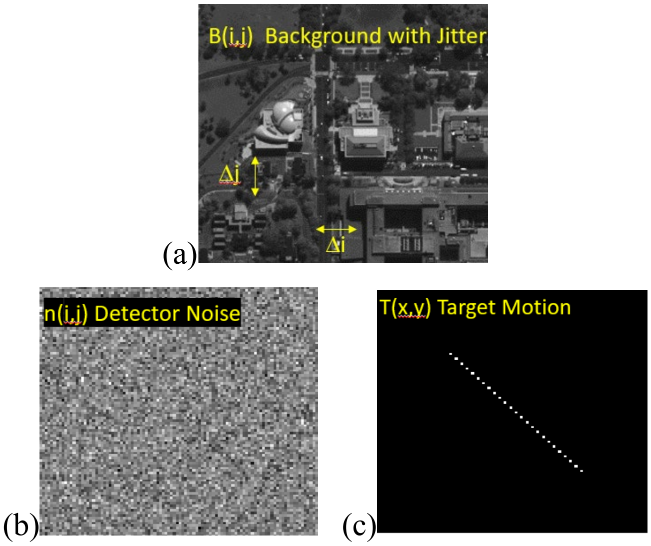

Fig. 2. (a) A image sequence dwells on a fixed scene with possible jitter motion (b) The contains additive white noise (c) the target in a continuous trajectory from frame to frame

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4. MOVING TARGET DETECTION

In a persistent imaging system, the target is a small object that moves on a relatively fixed background. Usually, an image registration technique like normalized cross correlation is applied as a first step. Then a background subtraction technique is applied to separate the stationary scene from the moving targets. A simple technique could be to subtract a mean image from each frame. Robust Principal Component Analysis is a stronger technique to remove background since it is effective where there is sub-pixel jitter and give consistent results with bright targets. What is left after background subtraction is a sparse image that has only the moving targets and the additive noise. A scene, background, and sparse image are shown in figure 2.

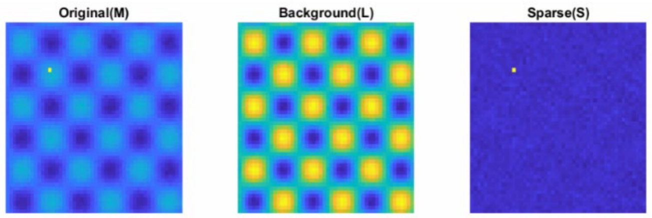


Fig. 3. Example of background and target extraction from an image

5. PEAK DETECTION THRESHOLD

The resulting sparse matrix image contains detection regions and additive noise. A detection occurs when the measured signal peak is above a threshold. In a Continuous False Alarm Rate detector (CFAR) the detect level can be set to a single threshold for an expected false alarm rate.

The detection threshold is an SNR multiplier β above the noise level to set a false alarm rate. In testing an image pixel for detection, a beta of 4.75 has pfa ~ 1e-6. Same as 1 fa per 1kx1k image region

$$p_n(x) = \frac{1}{\sqrt{2\pi}\sigma_n} e^{-x^2/2\sigma_n^2}$$

$$p_{fa} = \frac{1}{2}\operatorname{erfc}\left(\frac{x_T}{\sqrt{2}\sigma_n}\right)$$

Let $x_T = \beta\sigma_n$. The detection threshold is an SNR multiplier B above the noise level to set a false alarm rate. In testing an image pixel for detection, a beta of 4.75 has pfa ~ 1e-6. Same as 1 fa per 1kx1k image region. Figure 4 shows how the number of false alarms increases for SNR thresholds of 4.5, 4.75, and 5.

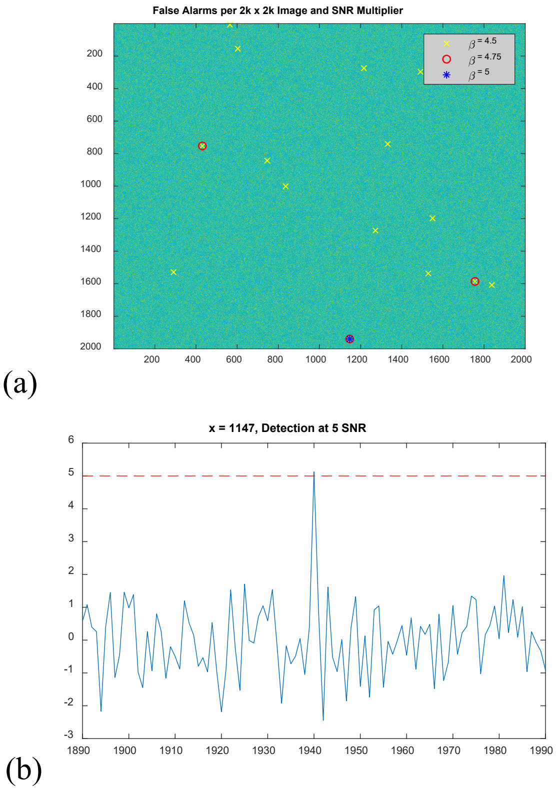
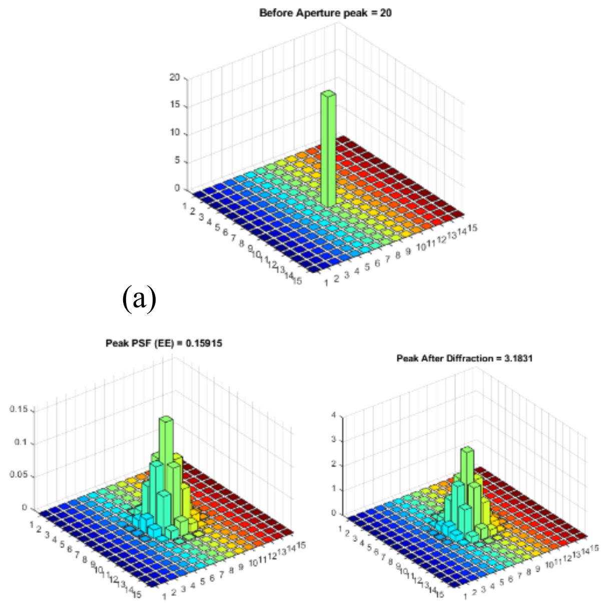


Fig. 4. (a) line plot showing a noisy background causing false alarm (b) A 2k x 2k image with Gaussian noise σ = 1 averages 1 false alarm at threshold of SNR=5

The peak of an imaging system is usually blurred by the optical and detector components. When the target is a point source, the energy is spread by the system point spread function and the strongest part of the signal is at the peak in the center. This is the strongest part of a point detection that will register a signal. The strongest pixel in the point spread function is the Ensquared Energy (EE) is the peak of the Point Spread Function (PSF). The EE is used to calculate the signal peak after optical diffraction. The resulting signal peak is EE time the signal from the point target.

Fig. 5 shows the concept of Ensquared Energy. Fig 5a shows the original point source energy at 20 units. Fig 5b



(a)

(b)

(c)

Fig. 5. (a) total signal before aperture (b) Ensquared Energy is Peak of point spread function (c) Peak of signal after passing through the optics is the total signal times the Ensquared Energy (20 x 1.59 = 3.18)

Essentially, the EE is the fractional loss of signal due to optical and system blur. The next section will describe a method to estimate the SNR of a single target peak in a detection system.

6. PEAK SIGNAL OF A SUB PIXEL TARGET

To predict the detection performance, we need to predict a peak SNR based on collection parameters. We would like a peak SNR of 5, 6 or more for straight detection. Other tasks like classification might require higher peak SNR. Signal (electrons) of a target that is smaller than a pixel.

$$S_{peak} = (L_{100}\Delta\rho_t)(A_{target})\left(\frac{A_0}{R_{slant}^2}\right)(t_{int})(EE)(\tau_0 QE)$$

EE is a fraction of energy in the center pixel of system PSF. The signal is in units of electrons at a detector element. The peak signal is the maximum contrast between the measured target peak and the background. The signal of a target is smaller than a pixel. Noise is from the background shot noise, read noise, and dark current.

$$N_e = \sqrt{N_{re}^2 + S_b + I_{dark}t_{int}}$$

The background signal in electrons for this calculation is

$$S_b = (L_{100}\rho_b + L_0)\left(\frac{R_{slant}^2 pitch^2}{fl^2}\right)\left(\frac{A_0}{R_{slant}^2}\right)(t_{int})(\tau_0 QE)$$

The resulting peak signal SNR is

$$SNR_{peak} = \frac{S_{peak}}{N_e}$$

The combined Peak SNR equation:

$$SNR_{peak} = \frac{S_{peak}}{N_e} = \frac{(S_{100}\Delta\rho_t)(A_{target})\left(\frac{A_0}{R_{slant}^2}\right)(t_{int})(EE)(\tau_o QE)}{\sqrt{N_{re}^2 + (L_{100}\rho_b + L_0)\left(\frac{R_{slant}^2 pitch^2}{fl^2}\right)\left(\frac{A_0}{R_{slant}^2}\right)(t_{int})(\tau_0 QE) + I_{dark}t_{int}}}$$

Some geometry parameters vary with Sun Elevation, target elevation, altitude such as - Signal 100% reflector (S_{100}), haze (H), slant range (S_{range}), background reflectance (ρ_b). Some user target parameters such as - Area Target (A_{target}), Target Reflectance Contrast ($\Delta\rho_t$). Some constant sensor parameters such as - Optic Area (A_0), Ensquared Energy (EE), optical transmission (τ_0), quantum efficiency (QE), read noise (N_{re}), dark current(I_{dark}).

7. ROC CURVE FROM SINGLE IMAGE DETECTION

A Receiver Operator Characteristic (ROC) is a curve that describes the statistical performance of a detection system. It is generated by varying β and calculating detect and false alarm probability at that value. Plotting the detection probability vs false alarm rate produces the ROC curve. Fig. 6 shows how a ROC curve is calculated for a signal of SNR 3 and a β of 1.5. Probably of detection is the area under the detection distribution past 1.5. The false alarm probability is the area under the false alarm distribution past 1.5.

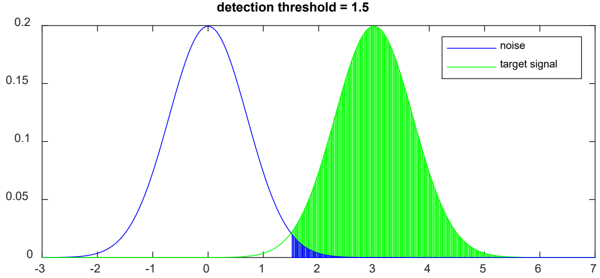


Fig. 6. ROC curve for detection with a single image shows detection and false alarm performance as SNR increases.

If detections are required in a low SNR environment, the detection threshold is lowered to allow more detections with increased false alarms. Assuming a Gaussian detector noise model and a fixed SNR on the target, the ROC curves showing Probability of detection to false alarm rate are shown in Fig 7. These curves show improved performance as target SNR improve. The goal of the detection system is to have the largest detection probability with the smallest false alarm rate.

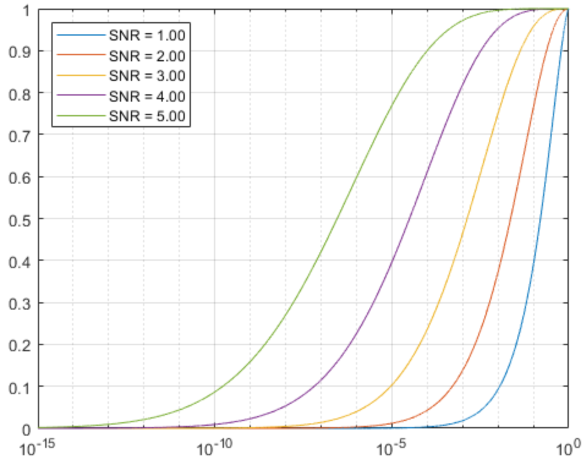


Fig. 7. ROC curve for detection with a single image shows detection and false alarm performance as SNR increases.

8. TRACKING PERFORMANCE FOR A STATIONARY TARGET

The single detection ROC curve is based on a fixed threshold on one sparse image that results from the background subtraction. The modelling approach used here will consider correlation of multiple images to improve the detection probability of lower SNR targets. The false alarms are removed by correlating the detections in multiple images based on a "K of N" rule. The assumes a verified detection needs to correlate K times in N total images.

To mathematically model the detection logic, it is assumed the correlations will occur within a small region or gate between the successive images. To correlate a detection between two images, assume that a detection in the first image is near the location in the second image but some movement is allowed. The second detection must be within a gate of n pixels around the location of the first image. N_{gate} is the number of pixels in the gate of the second neighborhood, The detection probability and false alarm probability when testing within the gate region is as follows,

$$p_{d\,gate} = p_{d1}$$
$$p_{fa\,gate} = 1 - \left(1 - p_{fa1}\right)^{N_{gate}}$$

Now the detection probability is the same since there is assumed to be one detection at that point between the images so, it will only appear once in each image at most. Multiple false alarms are potentially possible since each pixel has independent noise and any individual false alarm in the N_{gate} region will trigger a verified detection false alarm.

This logic can be further extended using a "K out of N" rule. The false alarms can be lowered by requiring the target be present in "K out of N" images which is evaluated using a modified binomial distribution. The lower threshold allows improved detection, correlation, and results in fewer false alarms. It is modelled by taking the single image Probability of Detection (PD) and False Alarm Rate (FA) and applying the modified binomial equation to provide an updated PD and FAR for "K out of N" rule.

The approach is to model the contributions of each frame to the detection probability. Refer to Fig. 8 below. In this example it is assumed that the target signal is stationary, and the gate does not move. So, a single fixed gate size is adequate. Now there are *N* total frames, and the first detection can occur on the *i*th frame. The first (*i*-1) frames have no detections. There is detection at the *i*th frame. The remaining frames are correlated to the *i*th frame using the correlation gate. This portion will have binomial statistics with *K-1* events in *N-i* trials. This totals to *N* frames and the overall probability is the multiplication of these individual probabilities.

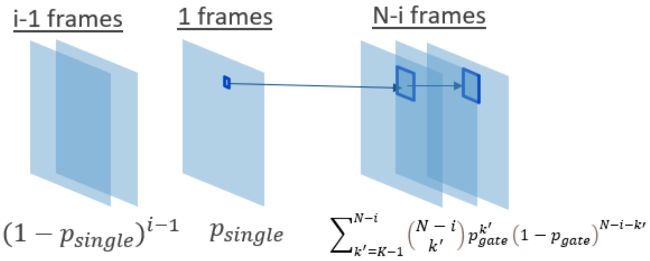


Fig. 8. Contribution of each frame to the total probability

The final detection and false alarm probability result from the sum of *i* from 1 to *N*,

$$p_{dK|N} = \sum_{i=1}^{N-K+1} (1 - p_{d1})^{i-1} (p_{d1}) \sum_{k'=K-1}^{N-i} \binom{N-i}{k'} p_{d\,gate}^{k'} (1 - p_{d\,gate})^{N-i-k'}$$
$$p_{faK|N} = \sum_{i=1}^{N-K+1} \left(1 - p_{fa1}\right)^{i-1} (p_{fa1}) \sum_{k'=K-1}^{N-i} \binom{N-i}{k'} p_{fa\,gate}^{k'} \left(1 - p_{fa\,gate}\right)^{N-i-k'}$$

Fig 9 shows a comparison of ROC curves generated from single image detection logic and "K of N" logic. This assumes Gaussian noise and the signal is present with an SNR of 3.5.

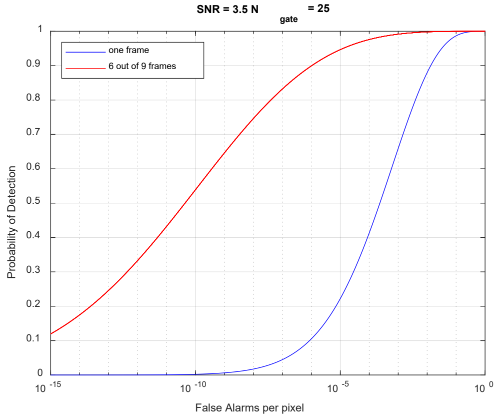


Fig. 9. Predicted detection performance when the SNR is 3.5 and Ngate = 25

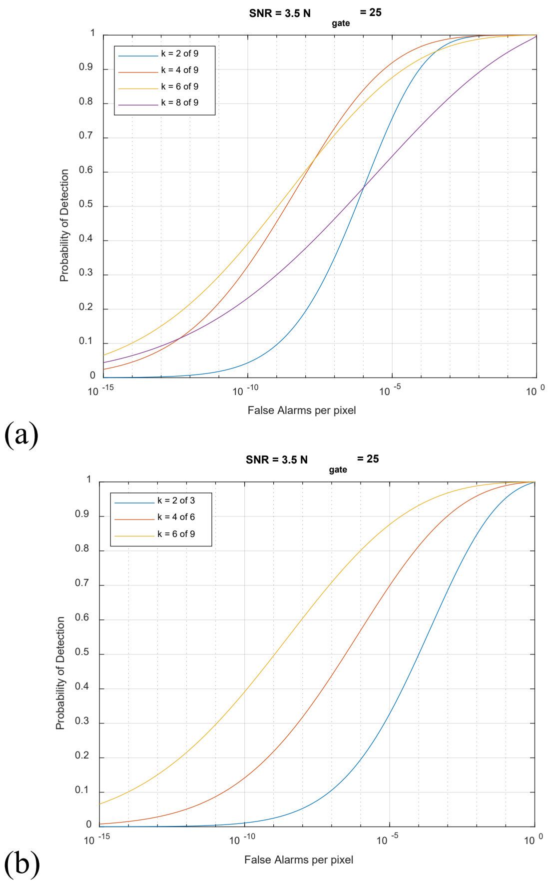


Fig. 10. Predicted detection performance at SNR = 3.5

The equation allows us to find the detection performance variation as K changes when the number of images is fixed. Here there are 9 image to correlate the detections. Fig 10(a) show plots of how performance varies with K for a signal with SNR of 4. What is interesting is that best performance is when K is about 60% of N. High values of K near 8 and 9 are too restrictive and prevent detection. Low values of K near 1, 2 and 3 cause too many false alarms causing the ROC curve to move to the right. The best performance is when is neither extremely high nor low but closer to 60%.

We can compare detection performance as the number of image collections vary. Fig 10(b) show 3 cases with number of collections as 3, 6, and 9. Here K is 66% of the N for 2 of 3, 4 of 6, and 6 of 9 detection rules. As expected, detection performance improves as the number images increase which is an expected result.

9. Comparison ROC Curves from MATLAB Simulation with Stationary Target

For a more realistic scenario, a simple tracking logic will be used to associate the detections between the images. The tracks are updated by associating current detections to current tracks if they are within the correlation gate. Global Nearest Neighbour (GNN) association means that closest detection is automatically associated with closest tracks without multi-hypothesis logic to create extra tracks for other nearby detections in the gate. After association the track position is updated as the mean location of the detections. A false alarm is only counted if there are no valid detections within the track. There is no track deletion logic.

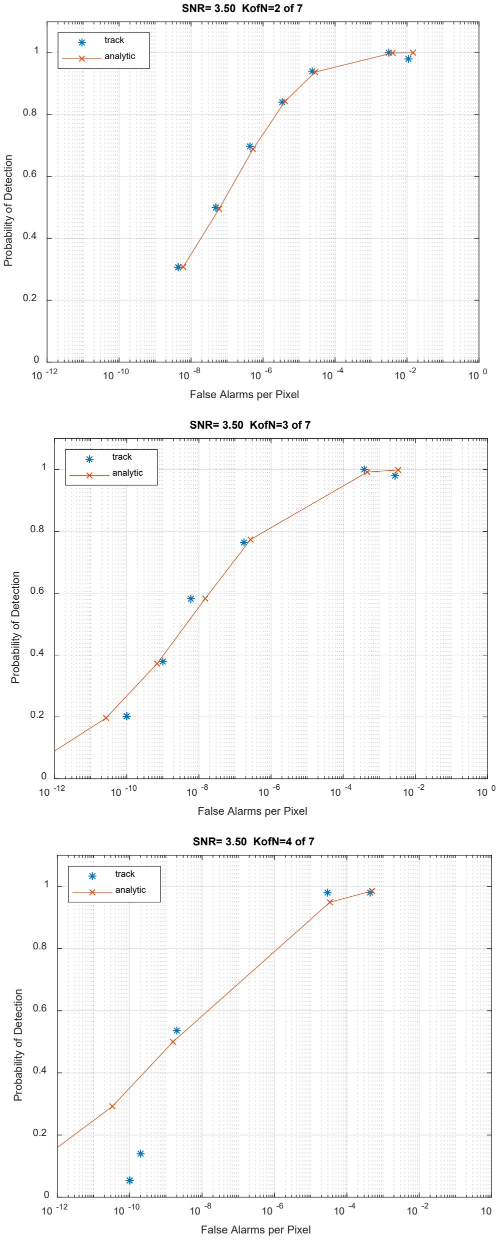


Fig. 11. Comparing modelled "K of N" ROC curves with MATLAB simulation and GNN tracker

There are 7 images in a sequence and the tracker will need to use a "K of N" association rule to verify the detection. The images have a has dimensions 1000x1000 and normally distributed noise with zero mean and standard deviation of one, n_i (x,y)=N(0,1). The image has a target inserted with an SNR of 3.5 and additive gaussian noise. The correlation gate is a 5x5 pixel region with Ngate=25 total pixels. Fig. 11 shows the results with a simple tracker, and they agree well with the analytic ROC curves.

10. TRACKING PERFORMANCE FROM A MOVING TARGET

The previous section modelled the detection performance of a tracking system that is identifying a stationary target. This section will make an update to the method to consider a moving target. In this approach it is assume that after the first detection the tracking will have a position estimate, but the velocity is unknown. That means the next detection gate will have to be larger since the motion could be in any direction.

The previous section modelled the detection performance of a tracking system that is identifying a stationary target. This section will make an update to the method to consider a moving target. In this approach it is assumed that after the first detection the tracking will have a position estimate, but the velocity is unknown. That means the next detection gate will have to be larger since the motion could be in any direction.

When the second detection occurs, the tracker can provide a velocity estimate and a steady state gate will be applied for the remainder of the frames.

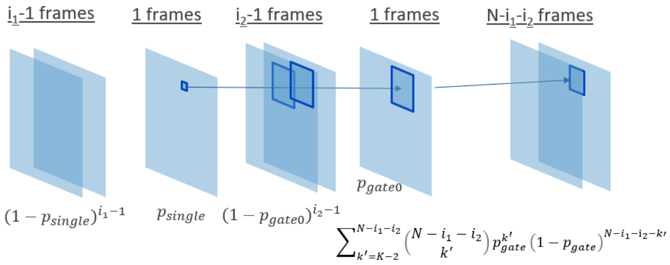


Fig. 12. Contribution of each frame for constant velocity tracing. An initial larger gate for second detection and a steady state gate for remaining frames

Fig. 12 illustrates the probabilities applied to each frame to update the ROC curve model to include the initial larger gate for the second association to compensate for a moving target. For any remaining frames, the tracker is testing 3 or more associations and the smaller steady state gate. In the model the first detection is at the i_1 frame and the second detection is at i_2 frames after the first.

The resulting equation is as follows.

$$p_{dK|N} = \sum_{i_1=1}^{N-K+1}(1-p_{d1})^{i_1-1}(p_{d1})\left[\sum_{i_2=1}^{N-K-i_1+1}(1-p_{dgate0})^{i_2-1}(pdgate0)\cdot\sum_{k'=K-2}^{N-i_1-i_2}\binom{N-i_1-i_2}{k'}p_{d\,gate}^{k'}\left(1-p_{d\,gate}\right)^{N-i_1-i_2-k\prime}\right]$$

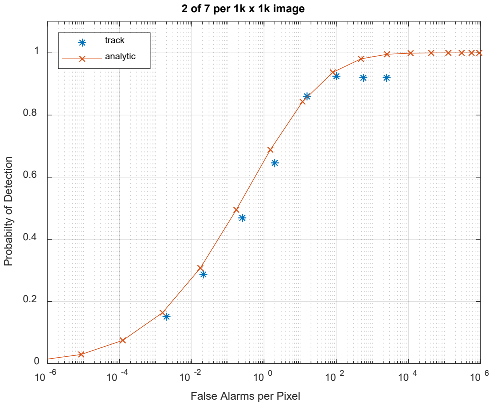
$$p_{faK|N} = \sum_{i_1=1}^{N-K+1}\left(1-p_{fa1}\right)^{i_1-1}\left(p_{fa1}\right)\left[\sum_{i_2=1}^{N-K-i_1+1}\left(1-p_{fagate0}\right)^{i_2-1}(pfagate0)\cdot\sum_{k'=K-2}^{N-i_1-i_2}\binom{N-i_1-i_2}{k'}p_{fa\,gate}^{k'}\left(1-p_{fa\,gate}\right)^{N-i_1-i_2-k\prime}\right]$$

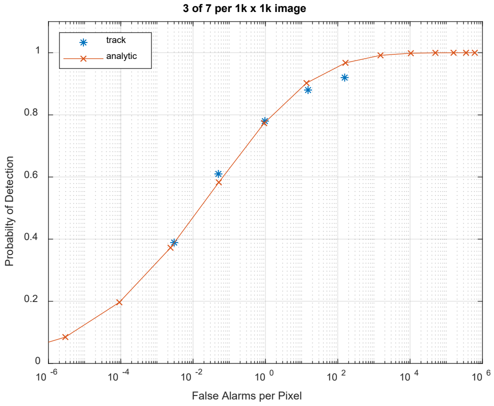
with

$$p_{d\,gate0} = p_{d1}$$
$$p_{fa\,gate0} = 1-\left(1-p_{fa1}\right)^{N_{gate0}}$$

11. ROC CURVES FROM CONSTANT VELOCITY TARGETS

This simulation is similar to case stationary target example in the previous section except that the target is moving with a constant velocity of 1 pixel per second and the initial gate for the second detection is 10 pixels per side or 100 pixels. The steady state gate is 25 pixels after 2 associations and a velocity estimate is available. There are 7 images in a sequence and the tracker will need to use a “K of N” association rule to verify the detection. The images have a has dimensions 1000x1000 and normally distributed noise with zero mean and standard deviation of one, n_i (x,y)=N(0,1). The image has a target inserted with an SNR of 3.5 and additive gaussian noise. The steady state correlation gate is a 5x5 pixel region with Ngate=25 total pixels. Fig. 13 shows the results with a simple tracker, and they agree well with the analytic ROC curves.





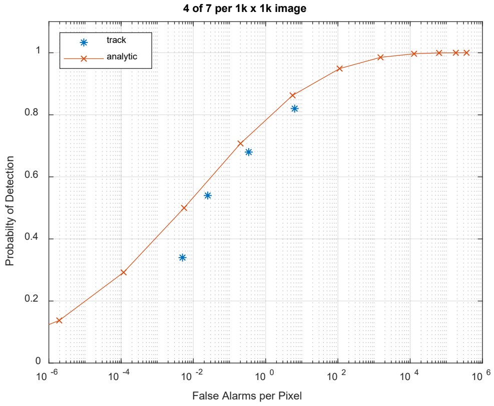


Fig 13. The resulting equation is as follows.

The results show the 2 of 7, 3 of 8 and 4 of 7 cases. Here the analytic ROC curves agree well with the simulated curves. There is some missed detection in the upper right of the curves near 90% for the simulations this is because a GNN association rule was used and for low β there were occasions that false alarms caused a miss correlation on the proper detection and the track was corrupted. This resulted in some missed detections. As β got larger the false alarms were fewer and this missed associations did not occur as frequently. Still a multi hypothesis association rule would likely prevent some of these missed detections since it is not immediately thrown out. Overall, the ROC analytic model agreed well with the MATLAB simulations.

The previous section describes a background that is uniform, with no extra content, essentially a clear background with additive Gaussian noise. This section will consider the detection performance modeling for a scene with a realistic scene as background that will create non-gaussian noise.

A realistic scene is assumed to collected with multiple frames. There will be a moving target in each scene, along with noise. The background scene may experience jitter, causing slight variations in motion and shifts in the scene. The problem is to identify the moving target within the scene and determine which targets are the same object.

Fig 14 shows the steps performed to detect potential targets in the image. The detection logic will be used to evaluate the probability of false alarm and detection probability for a single frame. The process starts with a number of collected frames that are dwelling on a fixed location. The second step is the take the average of the images along each pixel to create a mean background image. This mean image is subtracted from each frame to form a background suppressed image of sparse image. The background-suppressed image is thresholded to highlight the signal peaks that can represent potential target. These peak regions are clustered so that connected pixels are assumed to be part of the same target.

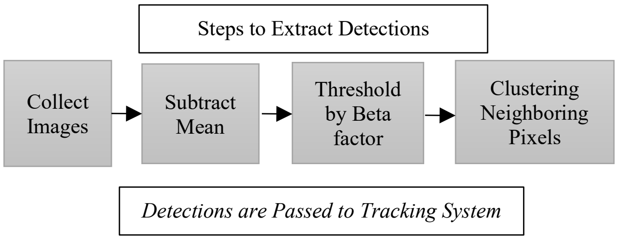


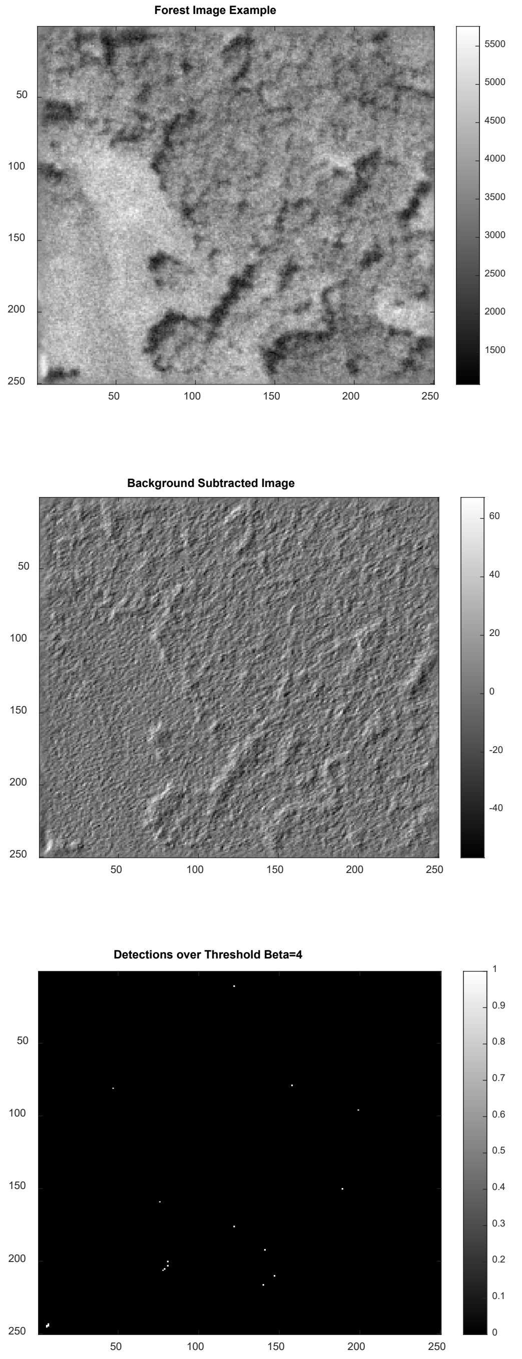
Fig 14: Steps performed to extract targets with a realistic background

A forest scene is used as an example. Figure 15a shows the forest scene with a single target. There are 5 frames in the sequence. The mean of the 5 frames is subtracted from each other frames to create a sparse image. The sparse image contains clutter noise and the moving target.

The clutter noise is a result of the slight misregistration between the frames. The clutter noise is essentially highest at the areas where there are strong image gradients or where the image intensity is changing quickly. Figure 15b shows an example sparse frame after background subtraction. The noise is more structured than gaussian noise. The noise is strongest in the frame at the same locations where the edges are changing the are aligned with the strong gradients in the image. Figure 15c shows the extracted detections after applying a threshold. The threshold is a value, β, that is a SNR level for the threshold.

Equation 12a shows the analytic approach to predicting the detection and tracking performance based on the various input parameters. The key parameter describing the background noise is the background probability noise distributions pd1 and pfa1. The statistics are based on the distribution of the clutter noise after the background subtraction process.

The distributions can be estimated by evaluating the number of detections based on varying thresholds. Probability of detection is calculated when there is the presence of a target signal. Probability of false alarm is evaluated from detections when no signal is present. Fig 16 shows the evaluated probability of detection and false alarm probability for this scene under an SNR of 5.



(a)

(b)

(c)

Fig 15 (a) Example Forest Scene with a target. (h) Background Subtracted Image (c) Thresholded image showing peak regions that identify detections.

These distributions are put in the detection performance modeling equations to predict the ROC curves for different K of N detection rules.

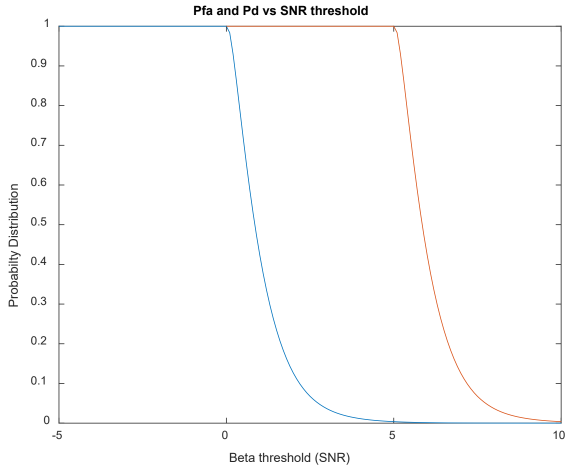


Fig 16. Detection and false alarm probabilities for the forest scene when SNR is 5

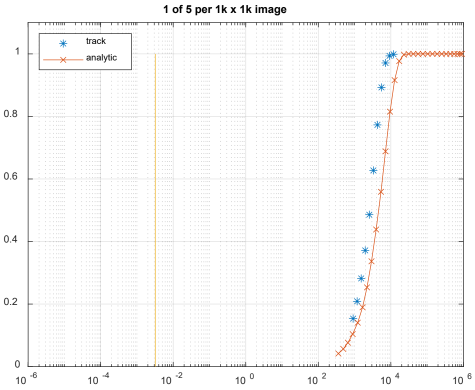
4. PREDICTION MODEL COMPARED WITH MONTE CARLO SIMULATION

The prediction model is based on the development outlined in section 3. A MATLAB based Monte Carlo Simulation of the tracking system is used to compare to the predicted results.

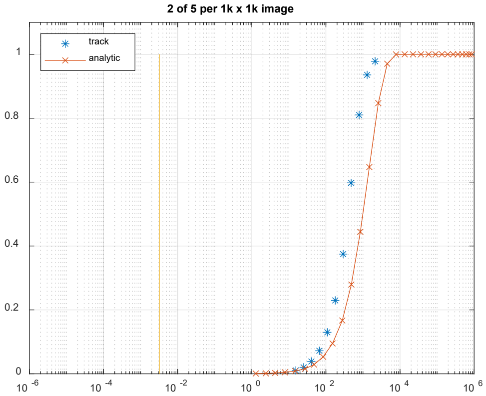
This simulation implements the background suppression detection logic described in Fig. 12. The detections are associated into tracks using the two-gate logic described in Fig 12. The first detection gate is a 7x7 pixel rectangle. The gate size for 2 or more detections is 5x5 pixels.

A simple tracking logic will be used to associate the detections between the images. The tracks are updated by associating current detections to current tracks if they are within the correlation gate. Global Nearest Neighbor (GNN) association means that closest detection is automatically associated with closest tracks without multi-hypothesis logic to create extra tracks for other nearby detections in the gate[5].

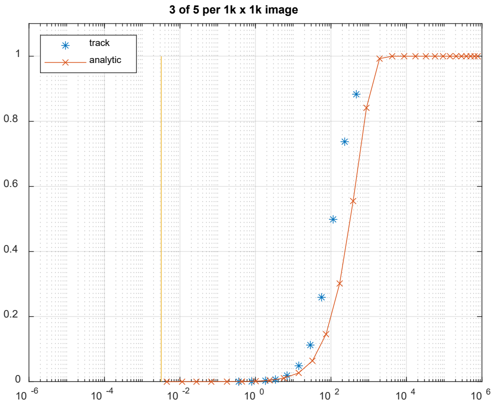
There are 5 images in a sequence of the same aimpoint. The background is the forest scene in Fig 15a. There is a line-of-sight jitter of 0.1 pixels between the frames. The targets are moving in the frame with a velocity of 2 pixels per frame. The target has an SNR of 4 over the expected clutter noise. The background suppression is based on the mean of the image set subtracted from each image. The target detections are based on finding where the background suppressed image is above the detection threshold. Neighboring pixels in a region are clustered together so that each connected set forms a potential detection. The detections are passed through the association logic and 2 state Kalman filter. Results are shown in Fig 15 comparing the prediction model to the MATLAB simulated results.



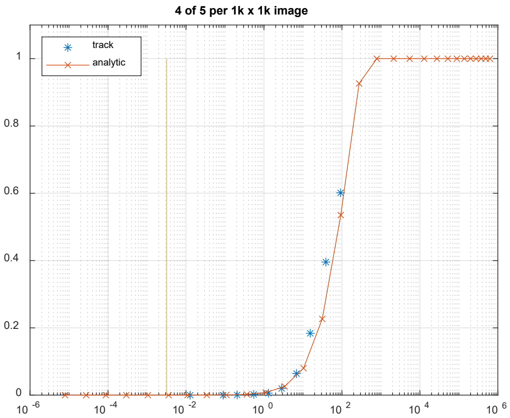
(a)



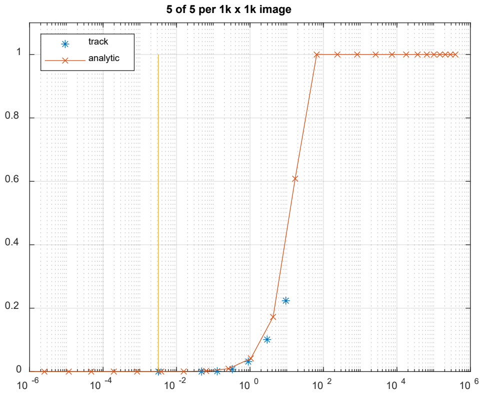
(b)



(c)



(d)



(e)

Fig 17. Comparison of prediction model and Monte Carlo Simulation using (a) 1 of 5 detection logic (b) 2 of 5 detection logic (c) 3 of 5 detection logic and (d) 4 of 5 detection logic (e) 5 of 5 detection logic

12. CONCLUSIONS

This paper has shown a performance prediction model that is applicable for low SNR tracking and detection collections. A single image detection performance is based on the SNR of the processed image after background suppression which is typical of detection algorithms. A peak SNR equation is provided that can predict peak SNR and subsequently probability of detection in a single frame using CFAR detection analysis. This paper showed that by using a modified binomial equation model it was possible to describe the improved performance of ROC curve in K of N rules for low SNR tracking. This will allow the predicting of improved performance with increased number of collections. This modified binomial ROC model was improved for constant velocity cases which require a large initial gate. The results were verified with Monte Carlo Simulations

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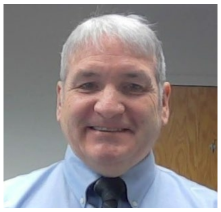

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