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ABSTRACT

The Motion Imagery Standards Board (MISB) has created the Video National Imagery Interpretability Rating Scale (V-NIIRS). VNIIRS extends NIIRS to scene characterization from streaming video to include object recognition of various targets for a given size. To apply VNIIRs for target tracking, there is a need to understand the operating conditions of the sensor type, environmental phenomenon, and target behavior (SET). In this paper, we explore VNIIRS for target tracking given the sensor resolution to support the relative tracking performance using track success. The relative assessment can be used in relation to the absolute target size associated with the VNIIRS. In a notional analysis, we determine the issues and capabilities of using VNIIRS video quality ratings to determine track success. The outcome of the trade study is an experiment to understand how to use VNIIRS can support target tracking evaluation.

Keywords: VNIIRS, target tracking, performance modeling

1. INTRODUCTION

The MISB created the Video National Imagery Interpretability Rating Scale (V-NIIRS) [1] by extending the National Imagery Interpretability Rating Scale (NIIRS) [2, 3, 4] for static target discrimination to video. NIIRS is used for a variety of sensors including infrared [5, 6, 7, 8], synthetic aperture radar (SAR) [9, 10], hyperspectral [11, 12, 13, 14], and electro-optical systems [15, 16]. The NIIRS level is based on factors such as sensor resolution and related to the success of discrimination tasks such as detection, recognition, and identification.

The combinations of sensors and target scenarios are graphically depicted in Figure 1. The overlap in the center of Figure 1 of the sensors and target conditions demonstrates the need for both NIIRS and VNIIRS for stationary and moving target recognition. Examples include staring radar [17] and various platforms with EO/IR/SAR systems [18] depicted in Figure 2.

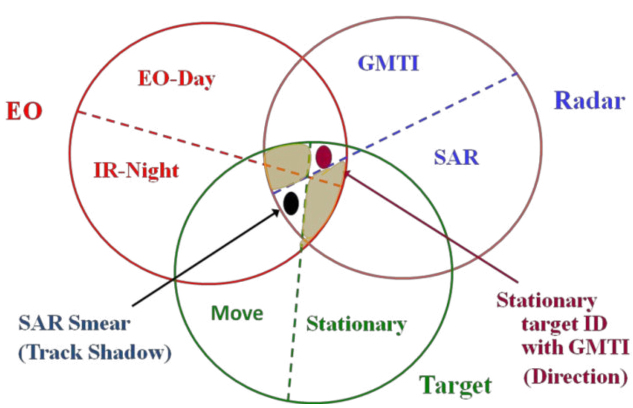

Figure 1 - Sensor-Scenario Combinations.

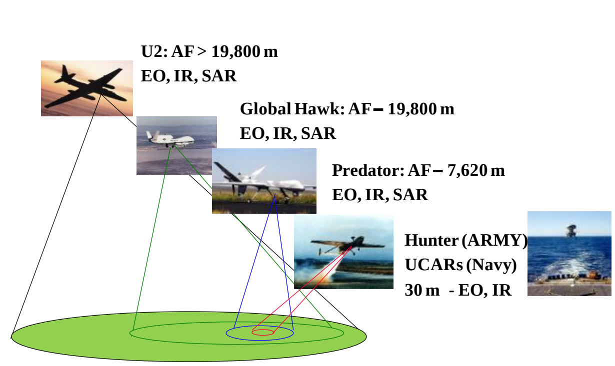

Figure 2 - Example platforms, sensors, and coverage area

1.1 Target Recognition

High credible combat identification (CID) is important to military operations to determine where friendly, enemy, and neutral combatants are located [19]. The goal of CID is to reduce fratricide and collateral damage to civilians while making it difficult for combatant targets to hide among friendly and neutral populations. Architectures employing

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cooperative and non-cooperative sensors have great potential to improve CID technologies and capabilities. However; sensors can be adversely affected by environmental factors such as weather and time of day, imaging geometries which obscure the target of interest, and counter measures. Operating conditions (sensor, target, and environmental variations) make robust CID difficult [20]. For CID, there is a need to understand the video quality as related to tracking performance.

Many recognition algorithms have been proposed and performance results published in the literature to address the CID problem for both moving and stationary targets [21]. The majority of the identification results have concentrated on single sensor measured electro-optical (EO) / infrared (IR) [22, 23, 24], high-range resolution radar (HRRR)/ synthetic aperture radar (SAR) [25, 26], and wide area motion imagery [27, 28, 29, 30, 31]. Much of this work focused on a single sensor look at an area of interest to produce CID decisions from one dimensional (1-D) signatures and two dimensional (2-D) images [32]. To improve upon single sensor look identification performance, CID algorithms fused multiple looks from the same sensor over different viewing geometries and times, exploiting additional target information gained from changes in the sensor-target geometry. Multi-look fusion can be accomplished a number of ways [33,34] such as using a decision-level fusion algorithm [35] to combine single look recognition results in a serial fashion or by averaging 1-D signatures from all looks to create a mean signature that is then run through an ATR algorithm [36]. Decision-level fusion among sensor outputs relies on the image quality assessment.

1.2 Moving Target Recognition

Airborne tracking and classification (target) [37, 38, 39], track and recognition (type) [40] and simultaneous tracking and identification (allegiance) [41, 42] of high value ground targets is a difficult task impacted by operating conditions. Layered sensing, using a combination of standoff and short-range sensors, maintains target track and classification in cluttered environments such as cities or densely vegetated areas through sensor diversity. Kinematic tracking aids target classification, recognition, and/or identification [43], as shown in Figure 3. Data, feature, decision, or information fusion is necessary for high confidence target classification to be achieved using multiple sensors and sensor modalities supporting moving target classification such as GMTI and HRR [44]. Confident target classification or identification performance is improved by exploiting the extra information gained from independent sensing modalities through information fusion for automatic target recognition (ATR). One common sensor type for tracking and classification is video. To determine the performance gain for tracking; there is a need to understand the video quality as presented to a user [45].

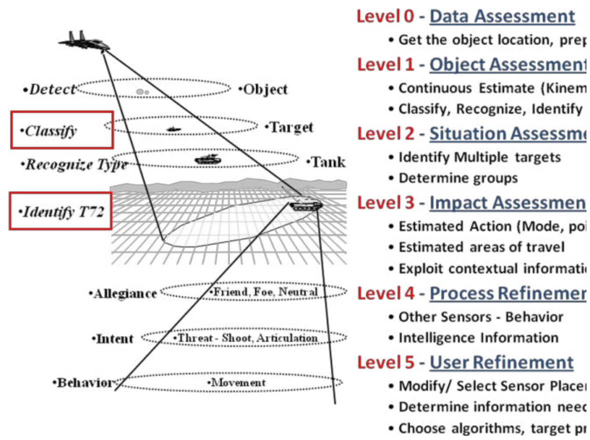

Figure 3 - Information Fusion Levels and tasks.

V-NIIRS includes movement analysis associated with the NIIRS categories of:

- **Detection:** Is the perceptibility of an object at a particular location from its surroundings (e.g., foreground vs. background).
- **Classification:** Is the determination of whether a detected object is a member of a particular set of possible targets or non-targets (e.g., wheeled versus tracked vehicles).
- **Recognition:** Is the determination that a target belongs to a particular functional category (e.g., a tank, a truck, or an armored personnel carrier).
- **Identification:** Whether friend, foe, or neutral as described from its object parts and behaviors.

1.3 VNIIRS

VNIIRS has many developments with a key focus of this paper using the work of Young, *et al*. [46, 47] and the Motion Imagery Quality Equation (MIQE). Initial derivations were done by Irvine *et al*. [48, 49, 50, 51] to lay a foundation for a motion imagery quality metric that utilized the NIIRS ground sampling distance. They looked at the varying frame rate [52], perceived interpretability [53], and eventually the interpretability scale [54]. The methods were used for performance modeling for target recognition [55, 56]. Given various applications, there was a need to assess the image quality against compression standards [57, 58, 59, 60]. Recent efforts included VNIIRS in support of event recognition [61, 62] and tracker performance [63, 64]. VNIIRS supports all levels of information fusion.

2. VNIIRS FOR INFORMATION FUSION

Information fusion includes functions of object assessment (Level 1 fusion) and situation assessment (Level 2 fusion) as detailed in the Data Fusion Information Group (DFIG) model [65] and shown in Figure 4. Figure 5 presents the related information modeling needed to support target tracking. To support high-level information fusion (L2-L6) [66], there is a need for information management [67] and context modeling [68] for which VNIIRS is applicable.

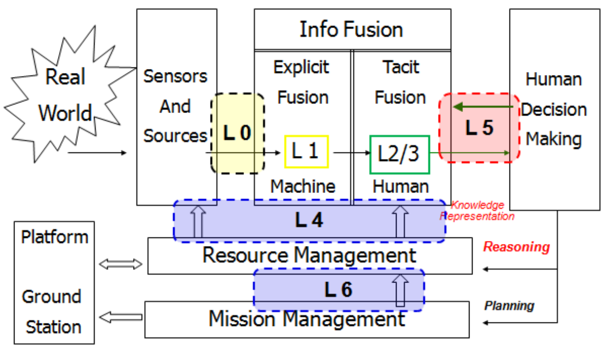

Figure 4 - Data Fusion Information Group Model (L = Level)

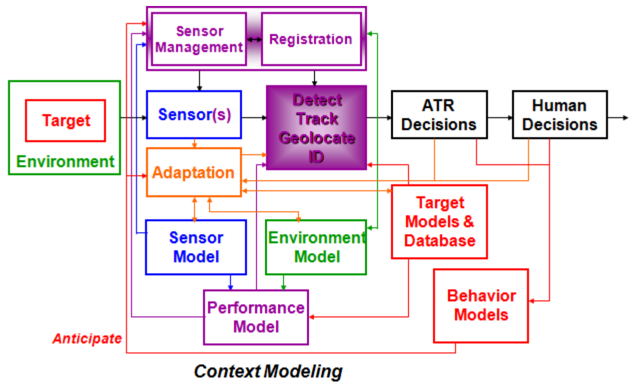

Figure 5 - Models in support of target tracking.

Three elements are highlighted relevant to VNIIRS:

- *Sub-object assessment (Level 0)*: Relevant information, databases, and interconnectivity are typically performed on a sensor by sensor basis such as measurement, signal processing, and filtering. Data quality is thus a sensor data analysis that is inherent to information fusion.
- *Low-level Information Fusion (Level 1)*: Low Level Information Fusion (LLIF) object assessment determines when, where, and what an object is through data alignment, association, tracking, and identification. Alignment projects the data into a common reference frame where data for an object of interest is associated via sorting or correlating observations so that estimating position and velocity is possible and object identification may occur. The types of level 1 fusion are image fusion [69, 70], feature fusion, and decision fusion as well as target tracking [71, 72]. Using both object tracking and target recognition methods can support instances with occlusions [73,74], but needs model updating [75]. A summary of methods for object assessment of tracking and identification is presented in [76].
- *High-level Information Fusion (Level 2 – Level 6)*: High level information fusion (HLIF) tasks include mission planning, sensor placement, and algorithm selection [77]. Level 2 focuses on situation assessment [78, 79], while Level 3 is impact assessment. Level 4 includes sensor resource management [80, 81] for the collection and optimal placement of sensors to increase the positional accuracy of the target [82, 83]. Finally, Level 5 includes the user [84] which demands methods of assessment [85] that includes qualitative and quantitative approaches [86] against the Level 6 mission requirements.

Using these three concepts, VNIIRS can support the data quality as sub-object data assessment that feeds the fusion process of both LLIF tracking and recognition as well as HLIF sensor management, mission performance, and user analysis.

3. NIIRS MODELING

An EO/IR/SAR fusion performance model was created to examine the impact of feature fusion to combat identification (CID) decisions and to assess the fusion gain potential for the modeled sensors. Determining the data that supports target tracking is dependent on the image quality.

3.1 NIIRS Quality

Tracking algorithms need to account for data quality. The data quality affects the value and number of available features that can be extracted for CID applications. For example, target features in poor quality imagery are increasingly merged together or obscured as quality degrades, rendering feature extraction difficult and adversely impacting CID decisions. An image quality model was developed using the *national imagery interpretability rating scale* (NIIRS) to assess the quality of EO/IR/SAR data. A description of the NIIRS rating scale is found in Table 1 with estimated resolutions included.

Table 1. NIIRS Definitions

NIIRS Level	EO	IR	SAR	Resolution
0	Uninterpretable Image	Uninterpretable Image	-	-
1	Distinguish between taxiways & runways @ large airfield	Detect large cleared areas	Detect lines of transportation	> 9m
2	Detect military training areas	Distinguish level of vegetation	Detect very large defensive berm	4.5 to 9 m
3	Detect helipad based on configuration/markings	Detect driver training track	ID areas based on building pattern	2.5 to 4.5 m
4	Recognize by general type (tracked/wheeled)	Detect individual thermally active vehicles	Detect a convoy	1.2 to 2.5
5	ID by type large targets	Detect vehicles in revetment	Detect battery of towed artillery	0.75 to 1.2 m
6	ID spare tire on medium sized truck	Distinguish between thermally active APC & tank	Distinguish between wheeled & tracked	0.4 to 0.75 m
7	ID missile mount	ID missile transfer crane on transloader	Distinguish between medium tank & APC	0.2 to 0.4 m
8	ID handheld SAM	Detect closed hatches	Distinguish between guns by overall configuration	0.1 to 0.2 m
9	ID vehicle registration numbers	ID turret hatch hinges on armored vehicle.	Detect gun tubes on SPAA gun.	< 0.1 m

3.2 NIIRS Equations

General image quality equations (GIQE) were developed to predict NIIRS values based on sensor parameters. The general image quality equations for EO and IR sensors were implemented and related to a SAR sensor. The equation for an EO sensor is given by

$$\mathrm{NIIRS}_{EO} = 10.251 - a \log_{10}(GSD) + b \log_{10}(RER) - 0.656\,H - [0.344(G/SNR)] \tag{1}$$

where GSD is the geometric mean of the ground sample distance, H is the geometric mean height due to edge overshoot, RER is the geometric mean of the normalized relative edge response, G is the noise gain, SNR is the signal to noise ratio, a is constant (3.32 if RER = 0.9, 3.16 if RER < 0.9), and b is constant (1.559 if RER = 0.9, 2.817 if RER < 0.9). The variables and constant values remain the same for the infrared GIQE [9] given by the following expression

$$\mathrm{NIIRS}_{IR} = 10.751 - a \log_{10}(GSD) + b \log_{10}(RER) - 0.656\,H - [0.344(G/SNR)] \tag{2}$$

The SAR NIIRS is related to the IR NIIRS using the following equation developed in [9].

$$\mathrm{NIIRS}_{IR} = 1.14 + 0.18\mathrm{NIIRS}_{SAR} + 0.08\mathrm{NIIRS}^2_{SAR}. \tag{3}$$

The SAR ground sampling distance (GSD) resolution [9] is then determined by

$$GSD = 10^{[(10.751-\mathrm{NIIRS}_{IR})/a]} \tag{4}$$

where a is the constant value from the GIQE and NIIRS_{IR} is determined by Eq. 3. The number of cycles across the target of interest is then given by

$$\mathrm{N} = Dc\,/\,(2 \bullet GSD) \tag{5}$$

where Dc is the critical target dimension given by

$$Dc = (l \bullet w \bullet h)^{(1/3)} \tag{6}$$

and l is target length, w is target width, and h is target height. The image quality results are related to the target discrimination tasks using the *target transfer probability function* [9, 87] given as:

$$P(N) = \left[\frac{(N / N_{50})^{a+b(N/N_{50})}}{1 + (N/N_{50})^{a+b(N/N_{50})}} \right] \tag{7}$$

where a and b are constants respectively and N_{50} is the N value for 50% probability of success for a given discrimination task (detection, recognition, identification). The probability of task success (detection, recognition, and identification) for EO, IR, and SAR sensors for a 6 x 3 x 3.4 meter sized target based on image quality are found in Figure 6. The curves illustrate the unique sensitivities of each sensor based on the various NIIRS levels necessary for successful task discrimination.

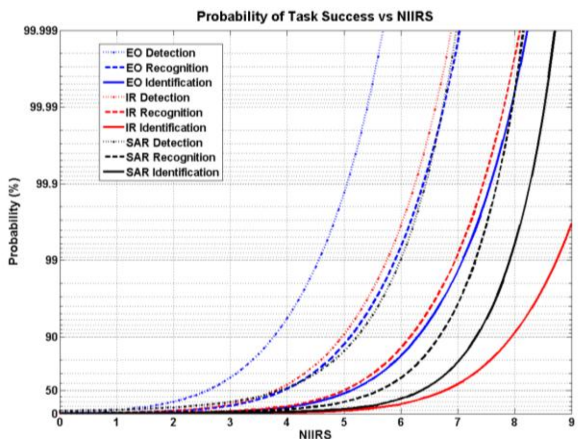

Figure 6 - Sensor task discrimination vs. image quality

3.3 NIIRS Resolution and Range

Next we relate the NIIRS values to sensor resolution by using Eq. (1-4) and varying the NIIRS values between 0 and 9 to determine the *GSD*. The results are shown in Figure 7.

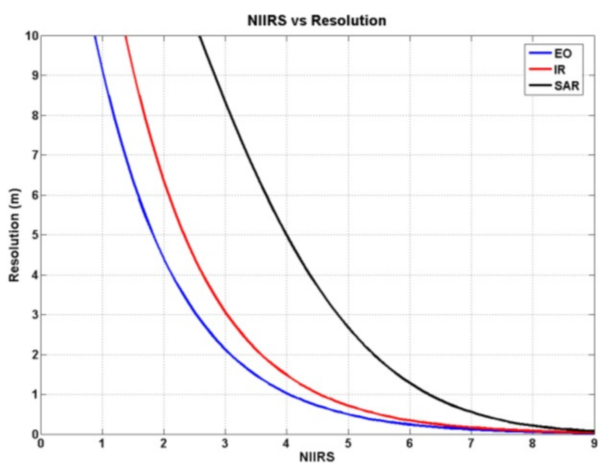

Figure 7 - Image quality vs. sensor resolution

Then the sensor resolution is related to range for each sensor modality. Optical sensor resolution can be related to operational range by writing the *GSD* in terms of sensor parameters as

$$GSD = (FOV / P)\, R \tag{8}$$

where FOV is the sensor field of view in degrees, P is the number of pixels in the largest sensor dimension, and R is the sensor range to target in meters. The range sensitivity for optical sensors expressed in Eq. 8 indicates that resolution improves at closer ranges and degrades at standoff sensing ranges.

SAR resolution is a function of sensor parameters only and is therefore independent of range. The SAR cross range resolution is given by

$$\text{Cross Range Resolution} = \lambda / 2L \tag{9}$$

and the range resolution is

$$\text{Range Resolution} = c / 2BW \tag{10}$$

where λ is the wavelength in meters, L is the synthetic aperture extent, BW is the radar bandwidth in Hz, and c is the speed of light in meters per second.

4. VNIIRS MODEL

4.1 VNIIRS Definitions

VNIIRS definitions extend from NIIRS as shown by Young, *et al.* [46]. Table 2 lists some of the relations between the NIIRS and VNIIRS levels. While there are many inherent relations between NIIRS and VNIIRS, context provides some external information [88, 89]. The first is *roads* that provide information [90, 91] as discuss in NIIRS-3 and VNIIRS-3. The second is group tracking which assesses multiple moving targets [92, 93] in NIIRS-4 and VNIIRS-4. VNIIRS Levels 5 and 6 relate to tracking and classification. However, VNIIRS Level 7 would provide enough information to discern the pose of a vehicle so as to infer direction [94] which is a key parameter for a user [95, 96].

Table 2 Comparison of Selected NIIRS Criteria to V-NIIRS

NIIRS	NIIRS Criteria Task and Object	NIIRS Criteria Context	VNIIRS	VNIIRS Criteria Task and Object	VNIIRS Criteria Context
0	Not useful	Obscuration	-		
1	Detect area	Port, Road	-		
2	Detect building	Warehouse	2	Lacks enough detail for dynamic content	
3	Recognize a large Truck by type.	Roads	3	Visually track the movement of convoy	on an improved road near location
4	Recognize tracked vehicles, field artillery	when in groups	4	Visually track the movement of vehicles	On a typical road
5	Distinguish between different vehicles such as support vans	in a known support base, when not obscured	5	Visually confirm the rotation of parts	Connected parts (Turret on a tank)
6	Classify automobiles as sedans or station wagons	In a parking area	6	Visually track classified vehicle	on roadways in medium traffic
7	Classify individual Road markings	Railroad ties, lane markers	7	Visually confirm the movement of objects	Something thrown from vehicle
8	Classify a handheld gun	Linked with person	8	Visually confirm the movement of person	Walking, running
9	Classify equipment (e.g. shovels, rakes, ladders)	in a open-bed, light-duty truck.	9	Visually confirm the movement of body parts	Arms and legs
-			10	Visually confirm the movement of hands	Person signaling
-			11	Visually confirm the movement of fingers	Tactical positions

Adapted from: Young, D., *et al*., "Video National Imagery Interpretability Rating Scale criteria survey results," Proc SPIE, (2009) [46]

4.2 Target Tracking Model

Since the selected scenarios include target tracking, a probability of tracking success model was developed and included in the modeling process [13]. Driggers, Aghera, *et al*. [13] postulate that for an EO sensor tracking a single target, the probability of correct vehicle track is

$$EO\_P_{track} = [2.2 - 0.835\, e^{-R_V}]\, [0.5 - 0.03 GSD^2] \quad (11)$$

where resolution in meters is given by GSD and sensor revisit rate is R_v in Hz.

To determine the probability of track success for an IR sensor, where the variables are the same:

$$IR\_P_{track} = [1.04 - 0.835\, e^{-R_V}]\, [1.14 - 0.03 GSD^2] \quad (12)$$

Using a similar format to Eqs. 11 and 12, the authors infer that the SAR probability of correct track is provided as:

$$SAR\_P_{track} = [0.65 - 0.835\, e^{-R_V}]\, [2.85 - 0.04 GSD^2] \quad (13)$$

A plot of the probability of track success for a one second revisit rate is shown in Figure 8 for EO/IR/SAR sensors with respect to the sensor resolution. EO video tracking is slightly more sensitive to resolution than IR video tracking. Thermally active targets in lower resolution can be detected and tracked with IR sensors while loss of target detail from poor resolution adversely impacts EO tracking performance. Expected SAR tracking performance is much better at lower resolutions in comparison. The tracking probability can be related to image quality using the sensor resolution.

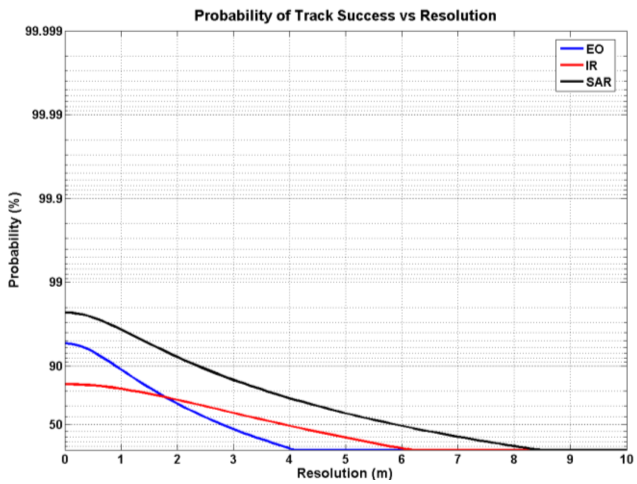

Figure 8 - Target track probability versus resolution

4.3 Motion Imagery Quality Equation (MIQE)

The Motion Imagery Quality Equation (MIQE) provides a method to predict the Video National Imagery Interpretability Rating Scale (V-NIIRS) given system technical parameters. MIQE can be used for VNIIRS assessment given imagery quality and metadata information. Using the performance modeling approach, computation of the probability of task success uses the motion imagery quality for multi-intelligence dependence processing chains. Finally, the MIQE provides a method to convert technical parameters into V-NIIRS equivalents which are more easily used by analysts for mission driven data collection and assessment. The MIQE is modeled as:

$$MIQE = M - a \log_{10}(GSD_{GM}) + 2 \operatorname{Log}_{10}(Q) + b \operatorname{Log}_{10}(RER_{GM}) - 0.656\,(H) - (0.344)[G/\min(SNR, \beta)] \quad (14)$$

where M is constant, GSD is the ground-sample distance [0.75 cm – 220 cm], Q is the quality factor [1 - 2], H is the height [0.9 – 1.9], G is the noise gain [1 – 19], SNR is the signal-to-noise ratio [2 – 130], β is the SNR to contrast ratio [100 – 130], and for

RER ≥ 0.9, $M = 11.6$, $a = 3.32$, $b = 1.559$

RER < 0.9 $M = 11.53$, $a = 3.16$, $b = 2.817$

Movement criteria analysis such as making a turn, changing lanes, and getting into a car requires the assessment of the GSD, object length, field-of view, and resolution for different types of imagery.

A *single sensor*, *single look*, *task discrimination model* was created using the target transfer probability function determines a baseline tracking and classification performance versus range for each sensor selected for a common target. The N_{50} values of a given sensor for target detection support the tracking performance assessment:

$$N_{50} = 0.75\, C\, [(C/\Delta t)^2 + 1] \tag{15}$$

where C represents the image complexity of the data: 1 – low, 1.5 – medium low, 2 – medium, and 2.7- high. Δt is a constant ranging from 1 to 10.

5. V-NIIRS ASSESSMENT

Using the MIQE, we are interested in modeling the quality of the information from high-resolution full motion video or low-resolution wide area motion imagery [97,98,99] as depicted in Figure 9.

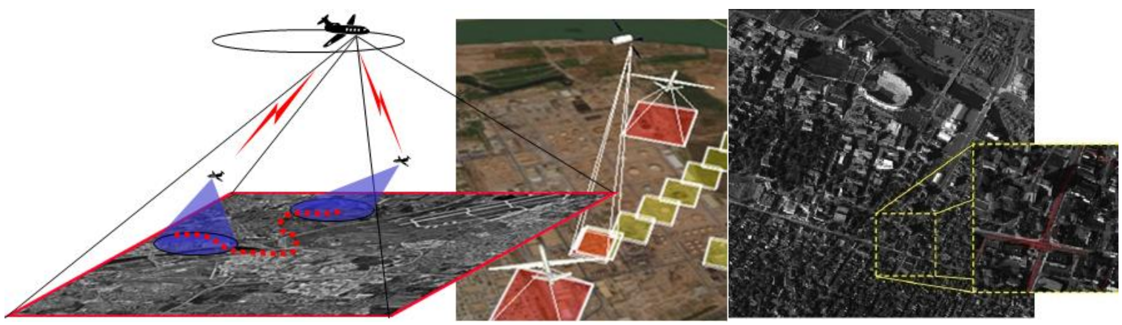

Figure 9 - Wide Area Motion Imagery (WAMI) data

Using the MIQE, the goal was to look at the differences between NIIRS and V-NIIRS for a target tracking scenario. Using the GIEQ, we extend the analysis to the MIEQ. Figure 10 and Figure 11 plot the (V)-NIIRS versus the ground sampling distance and the N_{50} value which demonstrates similar performance for EO and video sensors.

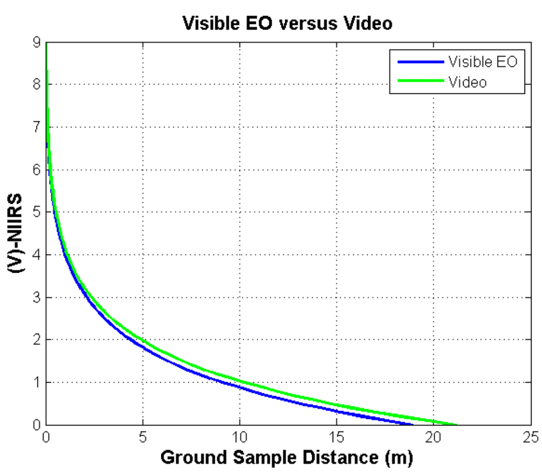

Figure 10 – (V)-NIIRS versus ground sampling distance

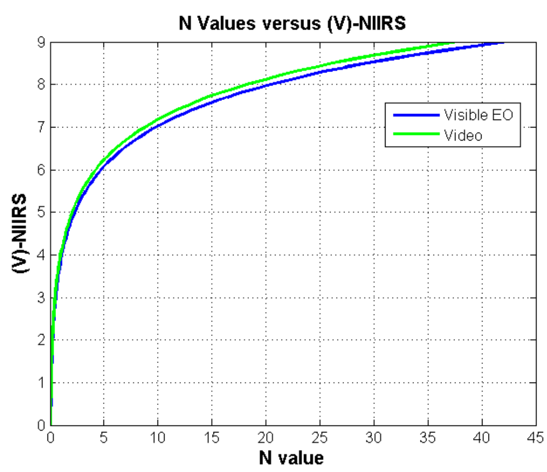

Figure 11 – (V)-NIIRS versus N_{50} Value

Figure 12 (and expanded in Figure 13) show resolution versus (V)-NIIRS which illustrate that EO quality and the video quality have similar effects on the track performance. The results demonstrate that the video and image quality are related and since frame-by-frame image analysis is completed to support tracking, that the VNIIRS rating (even of a standard image) could be used to characterize the track performance.

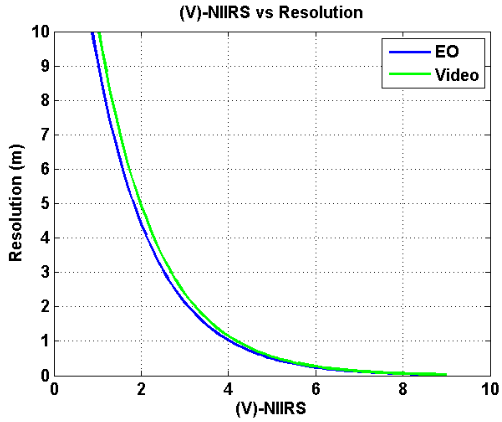

Figure 12 – Resolution versus (V)-NIIRS

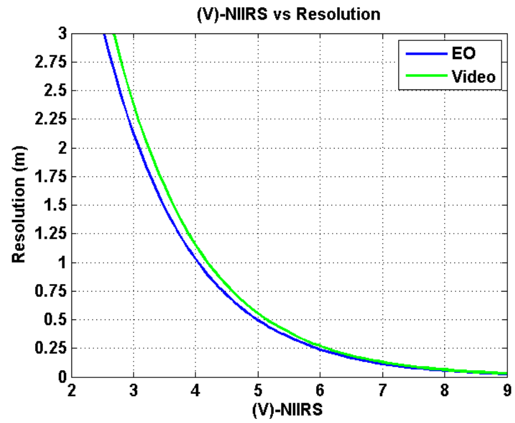

Figure 13 – Resolution versus (V)-NIIRS (expanded)

Building on the previous outlined developments, the probability of task success (detection, recognition, and identification) was desired for tracking. The VNIIRS supports the notional analysis in that a lower VNIIRS is needed for detection, while a higher VNIIRS is needed for tracking. A relative breakpoint is that for 90%, VNIIRS of 5 is needed for *P*(detection), VNIIRS of 6 for *P*(recognition), and VNIIRS of 7 is needed for *P*(identification).

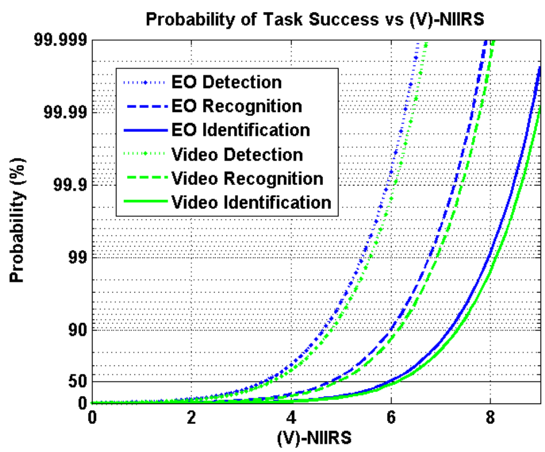

Figure 14 – Probability of EO/Video Detection, Recognition, and Classification versus (V)-NIIRS

It is thus noted that the definitions in Table 2 need to be slightly updated to correspond to the mathematical analysis. Note that the results presented in Figures 12 – 14 are for a fixed target size of 3 x 2.3 x 1.7 meters. A larger or smaller target would likely alter the curves slightly for the discrimination tasks.

6. CONCLUSIONS

In this paper, we focused on the developments from the NIIRS to the VNIIRS with an emphasis on data quality assessment for tracking and classification performance analysis. Using the Motion Imagery Quality Equation (MIQE), we reproduced the results for integration and assessment for tracking detection, recognition and identification task performance. The notional results require some updating to the VNIIRS definitions as to the required VNIIRS related to performance, which assumes that video is inherently used for tracking. User evaluation of video could include taking an individual frame which resorts back to the NIIRS (which was shown in the paper). Future efforts include using the analysis for compressed and uncompressed video, different imagery types, and realistic effects using various tracking techniques. The modifications would determine updates the MIQE that can be used as parameter choices for operators during collections and analysts exploiting the video content for various tasks such as target detection, classification, recognition (type), and untimely identification (allegiance of a known vehicle against behaviors). Future delineations would be made for different types of targets including persons and vehicles of other categories which would then require further refinement of the VNIIRS qualitative definitions.

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