Analysis of Electro-Optical Sensor Performance Using a 3D Synthetic Environment

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ABSTRACT

The Canadian Forces rely on electro-optical sensors for their intelligence surveillance reconnaissance (ISR) missions. In the last decade, sensor performances have tremendously improved and their use has been diversified. The Forces want to know about the performances they can get with their new sensor suites under a large diversity of operational conditions. Performance assessment in the field are time and money consuming. It can also be difficult to perform tests under conditions similar to those encountered in real theatre of operations. We think that Modelling and Simulation (M&S) can provide a valid alternative. In the last decades, DRDC Valcartier has developed Karma, a simulation tool that can generate 3D synthetic wartime scenes. However, in its current version, images generated by Karma may be far from reality as they do not fully reflect the sensor limitations. To overcome the limitations, detection, recognition and identification range (DRI) estimators are being integrated in Karma, exploiting the advanced atmospheric models used at DRDC for the development of EO/IR sensor Tactical Decision Aid along with revised sensor detection models. Future work is planned to deal with complex scenarios containing both surface and aerial targets in inhomogeneous backgrounds.

1.0 INTRODUCTION

Performances of sensing technologies have been tremendously improved during the last decades. Catching up with it, the Canadian Forces (CF) exploit an increasing number of electro-optical (EO) sensors in various spectral wavebands to fulfil their intelligence surveillance reconnaissance (ISR) role. The cost of maintenance and training of the various systems has led to diversification of sensors applications. However, the adaptation of sensors to new tasks may come with limitations that the Forces must be aware of. To determine the performances of sensors in their various tasks, the CF often rely on DRDC to conduct tests and evaluation under a variety of conditions. For performances assessment, preference is generally given to field trials wherein one attempts to replicate operational conditions as much as possible. However, many conditions of interest are difficult to reproduce. Furthermore, field trials take time to plan and come at a significant cost. An alternative is to address sensor performances using Modelling and Simulation (M&S).

1.1 Karma

DRDC Valcartier has developed a 3D synthetic scene generator, called Karma, capable of mimicking realistically theatres of operations under various wartime environments (e.g. desert, urban, maritime, and rural). The simulation allows one to create scenarios that include a large number of platform types, weapon systems and sensors. A key feature of Karma is its capability to deploy a large variety of countermeasures.

The Karma scene generator is based on Unreal Engine 4 (UE4) and Open Scene Graph. Work is still in progress to adapt the functionality of UE4 in the thermal bands. UE4 is a commercial game engine which can deal with a large diversity of scenes, objects with astonished realism. **Figure 1** shows an example of a scene generated using UE4. The images illustrate the scene complexity Karma can deal with; buildings, vegetation, terrain types, vehicles (ground or aerial) and individuals (armed or not) can be included in the scenes.

Karma provides the flexibility to define sensors operating in dissimilar spectral bands. Sensor specifications are provided as inputs. Atmospheric conditions including sun/moon illumination, cloud coverage and precipitation (rain, snow), are taken into account to alter the radiance captured by the sensors. However, in the current official version, Karma scene images remain unaffected by the sensors limitation (e.g. MTF, noise).

1.2 EO/IR sensor Tactical Decision Aid

Concurrently, a significant amount of effort has been devoted at DRDC for the development of computer models aimed at making trustful in-situ predictions based on weather forecasts. The laboratory prediction software, called Predictor, exploits a suite of advanced models of atmospheric effects developed over many decades at DRDC, and contained in the EOSPEC (EO Sensor Performance Evaluation Codes) library [1]. Calculations use sensor specifications provided as inputs and build up on custom numerical weather prediction (NWP) products developed by the Department of Environment & Climate Change Canada. Figure 2 shows examples of Predictor outputs. The Detection, Reconnaissance and Identification (DRI) capacity of the sensor is described in space and time using a green-yellow-red code familiar to the military.

Sensor performance TDA’s require high-fidelity models that are optimized in computation time. It was decided to exploit as much as possible the TDA models for the integration in Karma of the DRI range estimator (DRIRE).

Section 2.0 introduces the physical approach used for the calculation of the DRI and Section 3.0 shows how the integration into Karma is performed. Examples of calculations are presented in Section 4.0. Furthermore, efforts are devoted to the scene rendering enhancement accounting for the sensor characteristics. This is discussed in Section 5.0.

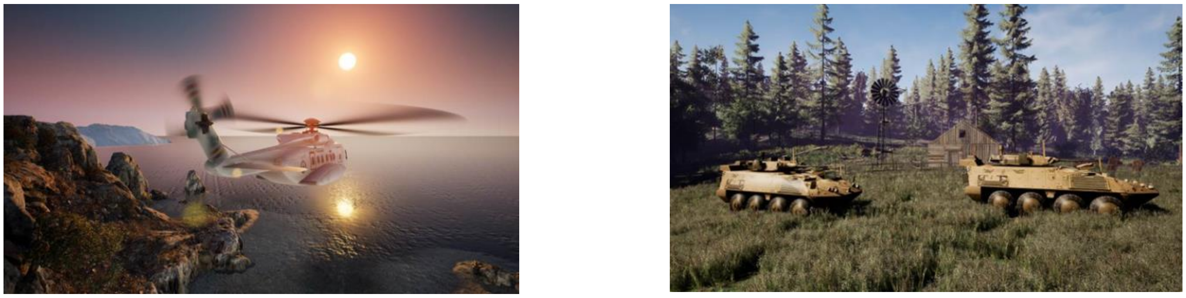


Figure 1: Example of a scene created in the simulation environment.

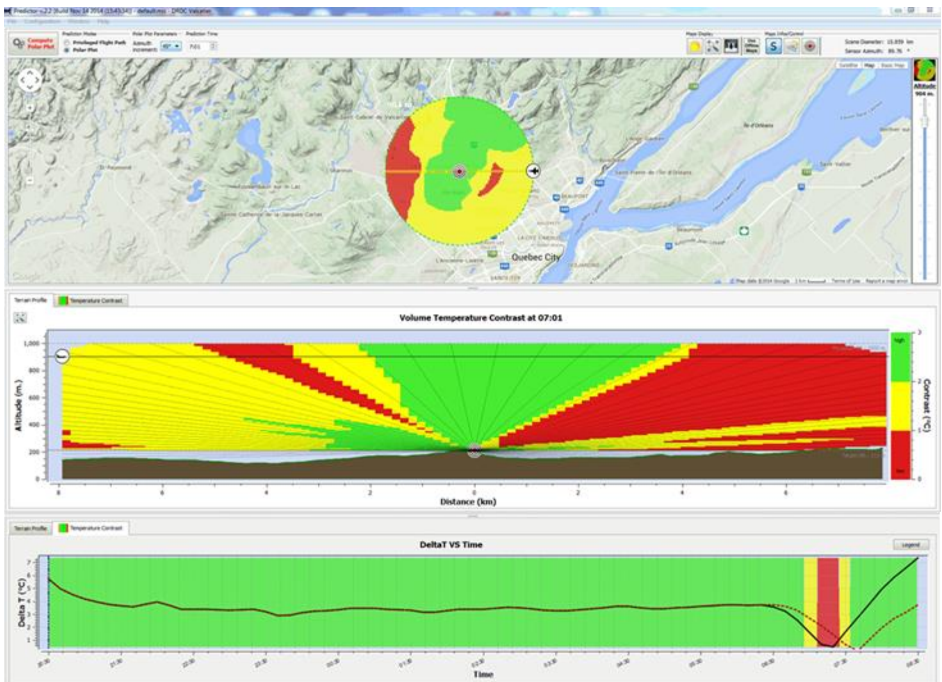


Figure 2: Example of the *Predictor* outputs.

2.0 MODELLING OF SENSOR DETECTION PERFORMANCE

The objective is to provide realistic estimates of sensor DRI ranges as sensors and targets move into the Karma scene. At given time steps, calculations of the perceived radiance contrast between the target and background signals are performed:

$$C_I = |I_t - I_B|, \tag{1}$$

where I_t is the apparent target radiance and I_B is the radiance of the background (e.g. what is behind the target). Both are calculated taking into account the reflectivity and emissivity defined as inputs for all scene elements. Radiance of all entities is assumed uniform (standard variation $\sigma_{It} = 0$). Should a target include special features (like hotspots), they would be considered as different elements.

Radiative quantities collected by a given sensor are calculated using the DRDC EOSPEC library [1] considering atmospheric conditions defined as input. The Electro-Optical Sensor Performance Evaluation Codes (EOSPEC) library allows one to take into account efficiently, and with fair accuracy, all impacting atmospheric effects. The scene illumination is governed by the sun/moon radiation as a function of the time of the day and the location in the world, and atmospheric transmission and radiance are calculated along propagation paths based on the physics of atmospheric radiative transfer. EOSPEC contains a selection of land and sea aerosol models. Furthermore, the EOSPEC models allow one to finely account for refraction (ray bending) and turbulence in the surface layer. Accounting for all these effects in the Karma 3-D environment is made workable for wideband systems owing to the fast correlated-K radiative transfer algorithm featured in EOSPEC. This is done through an advance interface to MODTRAN. Running MODTRAN in the usual way could necessitate unacceptable computation times, especially when multiple scattering must be taken into account. EOSPEC, developed at DRDC, is a key component of a tactical decision aid (TDA), aimed at providing trustable in-situ DRI predictions based on daily weather forecasts.

In EOSPEC, a plane-parallel atmosphere is considered. One of the six MODTRAN standard profiles can be selected, or a user-defined atmosphere can be used. A typical EOSPEC atmosphere comprises three dominant super layers characterizing respectively the surface layers, upper-air layers and high-altitude layers. A blending technique can be invoked to ensure a smart connection of aerodynamic profiles between the surface and upper-air layers.

Sensors are mainly characterized by their spectral response and sensitivity. The latter is described using Minimum Resolvable Contrast (MRC) functions, which give the contrast requirement as a function of the spatial frequency (in cycle/mrad). The current version of Karma uses measured MRC functions. Regular sensor characterization procedures include measurements of MRC. This is carried out following a set of standard rules. Measured MRC functions can be assumed optimal, as throughout the procedure, the testers can adjust the sensor gain (as they wish) to maximize performances.

For the MRC calculations, a target critical length, l_c, must be defined by the user. The critical length is, from the perspective of the user, the length that the system must resolve to fulfil a given mission. In detection models, the critical length is normally chosen somewhat smaller than the apparent physical critical dimension. As described in Section 3.0, the critical length is determined by Karma taking into account overlapping of targets, as scene objects intersect against each other in the scene. At a given range, R, the angle subtended by l_c is θ_c (mrad) = $1000\,(\frac{l_c}{R})$. The critical spatial frequency to be resolved by the sensor is then: $f_c\,(\mathrm{cycle/mrad}) = \frac{1}{2000} \cdot \frac{R}{l_c}$. Following the classical Johnson approach, the MRC value at f_c is assumed to give the required contrast for a 50% probability of success. In the Johnson formalism, this corresponds to N50 = 1. Depending on the scenarios and missions, one may choose to apply a difficulty factor to f_c: $f_c' = f_c \cdot F_{diff}$. Published detection experiments with the Johnson approach show that F_{diff} normally range between 0.7 and 1.3.

In Karma, detection is declared whenever:

$$C_I > MRC(f_c') + C_{thr}, \tag{2}$$

where C_{thr} is an user-defined detection threshold. We believe that this formulation is more convenient than the usual approach which incorporates a calculation of probability (known as the Target Transform Probability

Function), as the latter depends upon arbitrary-defined coefficients[1].

3.0 IMPLEMENTATION IN KARMA OF THE DETECTION PERFORMANCE COMPUTATION

For the integration in Karma, three key models were created: SegmentedImagingSensor, ContrastAnalyzer and DetectionRecognitionIdentification [3] [4].

The ContrastAnalyzer analyzes the segmented images provided by the SegmentedImagingSensor and calculates the effective angular size of the scene entities and their respective effective contrast. DRI ranges are calculated using these parameters by DetectionRecognitionIdentification.

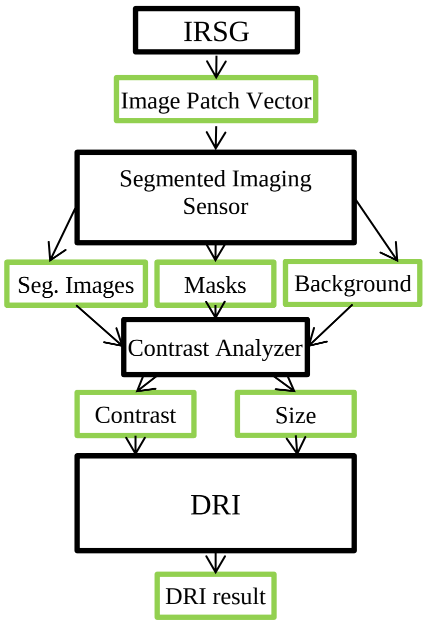


Figure 3: Model architecture implementation [4].

The Segmented Imaging Sensor deals with the overlapping of targets as they intersect with each other. Partial images are stores in a partial image vector (PIV), at each time step (frame) for each and every element of the scene. The partial images contain the radiance information of the element when considered isolated, and a target opacity coefficient defined as input and characterizing the transparency of the object. (The opacity coefficients are averaged over the spectral response and the atmospheric transmission.) In the partial image Vector (PIV), the images are stored from the farthest to the closest entities. In addition, the true background image (e.g. sky, land), containing no object, is saved in the PIV at each time step. When an object (or part of it) gets behind another one, a mask is defined on the front target image over the hidden portion of the target behind. **Figure 4** shows an example of segmented image results. In this case, a small static cube is masked by a bigger cube moving from the right to the left. The first row shows the scene radiance images and the second the mask for the far static cube (visible part from the observer).

Figure 4: Segmented image results for a given scenario [3].

The radiance of a front object covering another one is given by: $I_f = (1-\alpha)I_b + I_t$, where α is the opacity factor of the front target (a number between 0 and 1); I_b is the radiance of the object behind; and I_t is the radiance of the target when considered independently. When several objects overlapped, the procedure has got to be applied recursively for all objects, going from back to front.

Radiance contrast was defined in equation (1). This definition had to be adapted to work in the scene generation. The contrast was defined for each pixel and is given by:

$$C_I = I_f - I_b. \tag{3}$$

By combining this equation by the equation (1), the contrast can be written:

$$C_I = I_t - \alpha I_b. \tag{4}$$

For the targets of interest in the simulation, an effective apparent subtended angle, θ_{eff}, is determined for each frame considering the intensity captured by all pixels. The apparent effective angle (θ_{eff}) is calculated by weighting the visible and masked portions of the true target.

The apparent effective angle, θ_{eff}, is used in Eq.(5) for the calculation of the critical frequency, f_c.

$$f_c\ (\text{cycle/mrad}) = \frac{1}{2000} \cdot \frac{R}{l_c} = \frac{1}{2\theta_{eff}}. \tag{5}$$

As mentioned in Section 2, the critical frequency will depend on the mission (e.g. detection, reconnaissance or identification) and a difficulty factor can optionally be applied:

$$l_{ca} = \frac{l_c}{F_{diff}}. \tag{6}$$

Where l_{ca}, would be actual critical length. Note that the difficulty factor, F_{diff}, can be interpreted as an effective N50 value in the Johnson formalism.

4.0 RESULTS FROM RANGE ESTIMATOR

This section compares DRI calculation in Karma using the newly integrated (DRIRE) module with results obtained by running the DRDC TDA model.

In the test study, we consider a scenario wherein a 5 m-square plate lies on a background target which itself lies on a grass background. The sensor, a MWIR camera with a fixed 15 degree FOV is located above the target and moves towards it. The sensor starts at a given altitude and moves downward towards the target. This way, the sensor crosses the detection, reconnaissance and identification ranges on its way to the target. The camera specifications, including its MRC, are taken into account. Uniform spectral emissivity was considered for the target.

Table 1 shows results obtained using Karma and the TDA models. Results are in good agreement. The difference is larger for the detection distance, but the values are reasonably close to the recognition and identification distances. Recent tests conducted with varying FOVs reveal somewhat larger discrepancies. Further tests need to be carried out.

Table 1: Comparison of the results obtained in the TDA and Karma environment [4]

Camera	DRI Flag	Distance (km)	
		Karma	EOSPEC
1	D	3.978	3.12
	R	1.128	1.05
	I	0.558	0.58

Yet, this example shows the potential of DRIRE calculations in Karma for range performance prediction. This preliminary test can be extended to more complex ones to consider, for instance, scenarios that include vehicles and humans in complex background. A nice thing with Karma is that the sensor aiming can be varied in the course of the simulation to play search and rescue scenarios. We think that this tool can greatly help support mission planning.

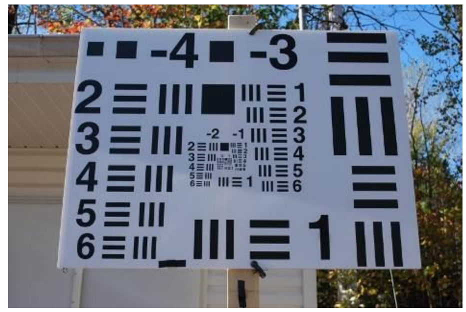
5.0 APPROACHING REALITY WITH KARMA

Unreal Engine 4 used in Karma offers the possibility to create environments containing a great deal of details. Nonetheless, up to recently, as sensor properties were not taken into account in the image generation process, the output images were always cleaner than reality. A new M&S tool, called FPAImager, has recently been developed and integrated into Karma to tackle the issue. The tool can among else incorporate effects such as optical blur or aberration, motion blur and noise.

The Scene generator in Karma generates images calibrated in radiance. The images are then communicated to the FPAImager module which applies image degradations. FPAimager includes models for calculating sensor high-level parameters (e.g. MTF, NETD, etc) using the sensor specifications given as input. Alternatively, a recent option allows one to use laboratory measurements of the needed parameters. Use of the second option is thought to produce more reliable results.

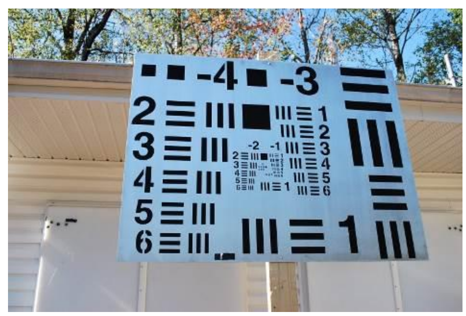
Examples of output presented herewith were obtained using calculated MTFs using sensor specifications. An experimental campaign was conducted to collect sensor images at various ranges and determine the DRI ranges under the prevailing conditions, with the aim of validating and hopefully improving the theoretical model used for the estimation of range performances. Measurements were carried out on a range located at DRDC Valcartier. Reference targets (resolution bar charts of different types) were installed in the scene as shown in **Figure 5**. The heated chart is made of a heated back panel with an aluminum mask in front of it.

Heated target (front view)



Coroplast target

Heated target (side view)

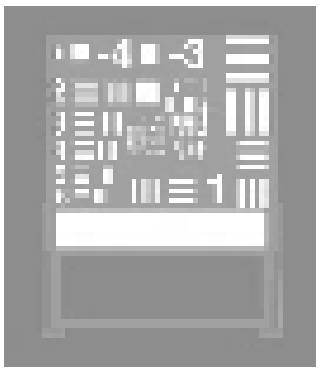


Aluminum target

Figure 5: Reference targets photography used during the experimental campaign.

Figure 6 shows an example of the Karma simulated IR image of the heated target at close range. Good similarity between the simulated and the captured image was obtained, both images exhibiting a slight loss of resolution. Note that in this example a simplified background was used for the test.

Original Image



Simulated

Original

Figure 6: Heated target simulated compared to the original image.

6.0 CONCLUSION

Evaluation of sensor performances and effectiveness are routinely conducted using field trials wherein it is attempted to replicate operational conditions. However, performance field trials come at a significant cost. A M&S-based method is presented in this paper as an alternative for the evaluation of electro-optical sensors performances.

In Karma, a 3D scene generator developed at DRDC, advanced physical models were incorporated with the aim of evaluating with a high-degree of confidence sensor performances in various tasks and under a variety of environments. The computational approach for the DRI range performances was introduced and calculation examples were shown. We think that the developed M&S tool can provide helpful support to mission planning.

The FPAImager module newly incorporated in Karma allows one to reproduce with realism image degradation caused by sensor limitations. This tool is efficient to quickly assess system upgrades.

Improvement of the M&S tools will be pushed forward to deal with complex environments, and considered scenarios that include multiple vehicle types and humans.

7.0 REFERENCES

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