Simulation Framework for Research of "Intelligent" Reconnaissance Systems

Fredrik Näsström, Jonas Allvar, Viktor Deleskog
Swedish Defence Research Agency (FOI), SE-581 11, Linköping
SWEDEN

Email: firstname.lastname@foi.se

ABSTRACT

This paper describes a modular simulation framework that can be used for testing of "intelligent" reconnaissance sensor systems in various environments, weather conditions and time of day. The simulation framework is called MSSLab (Multi-Sensor Simulation Lab) and it allows for high fidelity sensor data simulation. One objective to develop this framework is to facilitate development, testing and evaluation of new signal processing algorithms in different scenarios. High quality sensor simulations require that all simulation models e.g. terrain models, target object, material classification, scene simulation and sensor models are of high quality. HLA (High Level Architecture) is used to integrate the different simulation models into a distributed and reconfigurable multi-sensor simulation framework.

1.0 INTRODUCTION

The war-fighters are now facing a broad spectrum of conflicts ranging from quasi-law enforcement operations to large-scale war against small groups of individuals to major state armies. At the Swedish Defence Research Agency (FOI) research has been conducted to make future sensor systems more "intelligent", thereby providing sensor operators with better situational awareness, higher system confidence, reduced risk of human errors and a reduced mental workload. Research has been conducted on algorithms for automatic detection, tracking, multi-sensor fusion, sensor management and positioning. To enhance the usability of signal processing algorithms they need to work in a broad spectrum of situations and applications.

Reconnaissance information can be collected with various reconnaissance systems such as UAVs, combat vehicles etc. To maximize the impact of the research, it is essential to understand how the Armed Forces would like to improve operations. Together with the Swedish Armed Forces, we have developed several scenarios to study the possibility of improving existing equipment and tactics. The developed scenarios can be used to determine what improvements are most important to study.

A modular sensor system simulation framework is developed at FOI that can simulate sensor systems in various environments, weather conditions and time periods. The simulation framework is called MSSLab (Multi-Sensor Simulation Lab). In order to perform accurate simulation of sensor systems in various environments high quality terrain models are required. A number of different objects are modeled in the infrared spectrum, including military vehicles, tanks, ships and helicopters. Also motor vehicles and humans in different type of clothing are modeled [1]. These objects are imported into high resolution terrains, using different approaches which will be described later in more detail. Verification of sensor simulations with real sensor data has been conducted for thermal IR.

This paper presents our method to simulate "intelligent" reconnaissance systems. Section 2 presents the MSSLab and the verification of sensor simulations that have been performed. In Section 3 the current signal processing algorithms are described, along with their performance in different reconnaissance scenarios. Finally, some conclusions are drawn together with a discussion of some future work in Section 4.

2.0 MSSLAB

2.1 The architecture

MSSLab enables high fidelity sensor simulations in different scenarios. To enable this in a cost effective manner, it is important to integrate different simulation models into MSSLab. We have therefore chosen to build MSSLab on the MOSART [2] simulation framework, which is based on High Level Architecture (HLA) [3]. This allows the simulations in MSSLab to be distributed, modular and flexible.

The computation units in an HLA simulation are called federates and these are distributed in the simulations. The advantage of this approach is that you can replace different computation units in the simulation (see Figure 1). Federates in the simulation exchange data through a so-called Federation Object Model (FOM). MSSLab has extended the existing standard with information necessary to connect the different parts of the sensor system into a sensor algorithm chain [4].

We have, as far as possible, focused on integrating COTS (Commercial off-the-shelf) non real-time simulation tools that produce sensor signals based on physically well-founded models. The existing COTS tools for high quality sensor data simulations are usually made to work separately for each type of sensor, e.g. radar or EO/IR (Electro optical/Infrared). Therefore, we have used HLA to integrate such "stand alone" sensor simulation tools, together with signal processing algorithms, detailed object and terrain models, atmospheric models, scenario engine etc. into a multi-sensor simulation framework.

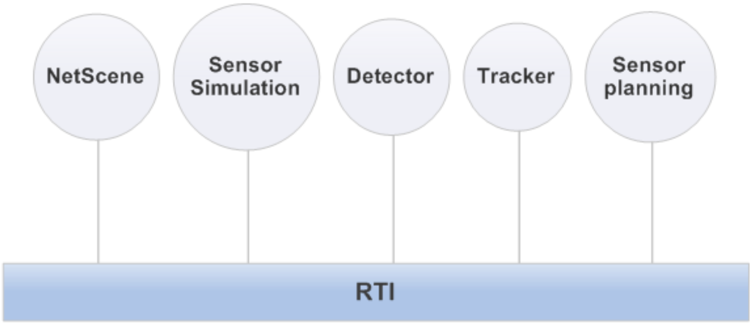

Figure 1: Example of a federation in MSSLab.

2.2 Terrain and objects

In order to perform accurate simulations of sensor systems in various environments, terrain models with high quality is required. The following terrain models are included today:

- A geospecific Swedish countryside model with forests and open fields,
- A geospecific Swedish city model with inner city, industrial areas, ports etc., and
- A geotypical Middle Eastern model with a city and a military camp.

Figure 2: Terrain models in MSSLab: a geospecific Swedish countryside model with forests and open fields, a geospecific Swedish city model with inner city, industrial areas, ports etc., and a geotypical Middle Eastern model with a city and a military camp.

For accurate simulations of IR sensors, it is also very important that the object models are of high quality. A 3D model library of objects and humans has been developed. Figure 3 shows some 3D models of ground vehicles and Figure 4 shows some results from the signature calculations using TAIThermIR [5]. With this tool, realistic IR signatures are calculated for different weather conditions, self-heating, configurations, etc. The IR signatures are then stored in a signature library.

Figure 3: Examples of ground vehicles with visual textures used in MSSLab.

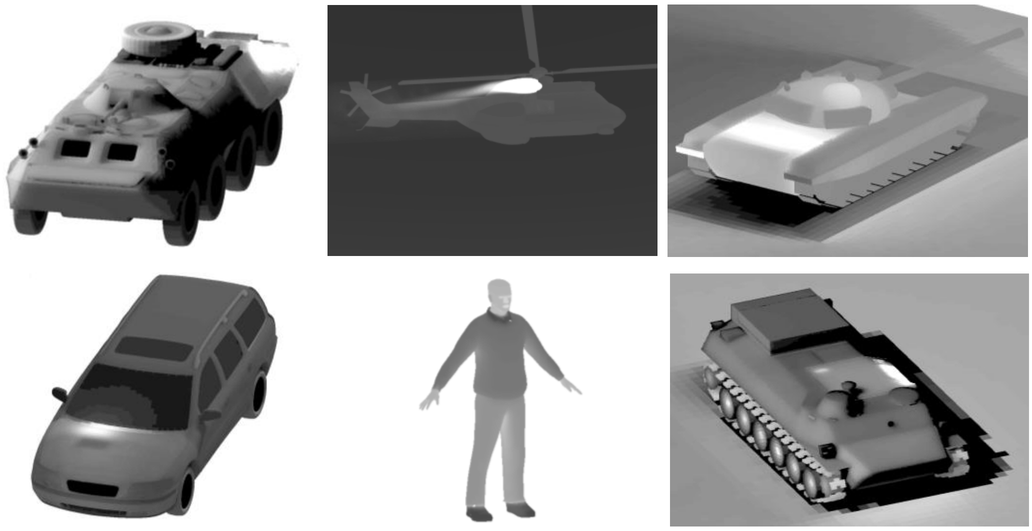

Figure 4: Examples of calculated infrared signatures using TAIThermIR. From left to right and top to bottom: BTR70, Airbus Helicopters H215, T-72, Volvo V70, human and MT-LB.

2.3 Simulation of IR sensors

For simulation of infrared sensors, the simulation program SE-Workbench-EO [6] is used. The SE-Workbench-EO can simulate sensor systems in ultraviolet, visual and infrared domains. The program uses physics-based models for propagation, transmission, reflectance and absorption, and thermodynamic models for calculating the physical surface temperature. SE-Workbench-EO requires material classified terrain models and the object models can be obtained from TAIThermIR [7]. MODTRAN [8] is used to model the atmosphere in both software. Figure 3 shows two simulated LWIR (long-wave infrared) images using MSSLab. The left image shows a simulated LWIR image with three ground vehicles: a truck, a T-72 tank and a BMP-3 combat vehicle. The right image shows a simulated LWIR image with two animated persons.

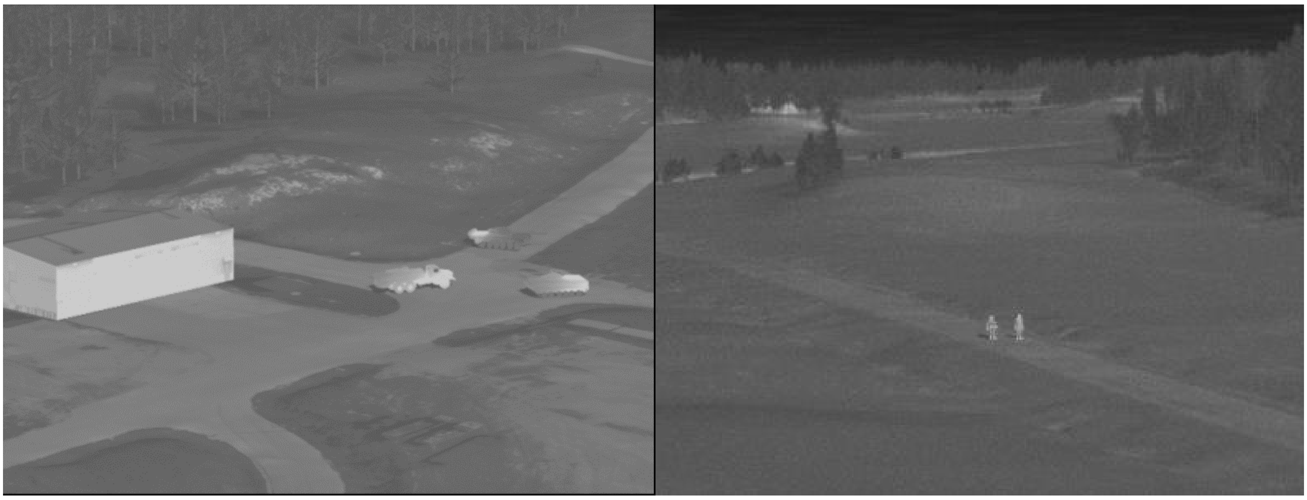

Figure 5: The left image shows a simulated LWIR image with three ground vehicles: a truck, a T-72 tank and a BMP-3 combat vehicle. The right image shows a simulated LWIR image with two animated persons.

2.4 Verification

To verify that the sensor simulations corresponds to real world sensor data, three approaches have been used:

- automatic detection of objects,
- quantitative analysis using the software TerrTex [9], and
- statistical analysis of apparent temperatures and gradient magnitudes in simulated and real sensor data.

Real data have been collected over the years. The data used in the verification was collected with an IR camera mounted on a helicopter to simulate reconnaissance from a UAV. The IR camera was equipped with a *Quantum Well Infrared Photodetector* (QWIP) LWIR detector with a resolution of 320×240 pixels. The helicopter flew over a field where different military vehicles driving, e.g. T-72 tanks and MT-LB armored vehicles. A 50 seconds long sequence was chosen to be used in the verification. Temperature and weather data was collected during the trial so the conditions could be recovered in the simulation environment, as described above. The IR images have been computed using the SE-Workbench-EO program. Both simulated and real images from the sequence used in verification can be seen in Figure 6.

In the first approach an object detector based on boosting technology is applied. The detector is trained on simulated LWIR data. Intuitively, the detection performance should be equivalent for real data and simulated data. Computed values for precision and recall is used to compare the results. The results show no big differences but false negatives are detected when the real images get highly detailed, e.g. when stones and bare rocks are visible. This is expected since the detail level of the terrain model is lower than that of the real data.

To verify the simulations in more quantitative terms the software TerrTex [10] is used, which is developed by FOI. The software is specialized in texture analysis in digital images, such as spatial properties of targets in a natural background. Spatial properties are important when applying detection, classification and identification methods. Simulated target textures are of good quality so the spatial properties are similar in simulations and real data. Background properties differ between simulation and real world since the dynamics in the background are lower in simulated images caused by lower detail level in the simulated terrain.

The last approach in the verification analysis is to compare statistical properties of simulated and real images. Properties are computed from the distributions of: apparent temperature and gradient magnitudes in simulated and real images, see Figure 7 and Figure 8. These two features are common in detection algorithms to distinguish a target from background. *Earth Mover's Distance* (EMD) [11] and $\chi 2$-statistics are used to compute the divergences of gradient magnitudes and apparent temperature distributions from real and simulated sensor images. When comparing the divergences, over time we see that the distributions of gradient magnitudes and apparent temperature are almost equal but starting diverge after 40 seconds when higher details in the real image are visible, see Figure 9 and Figure 10. This is expected since the terrain model currently have too few details as described above for the other two methods.

Figure 6: Top: Comparison of an IR-image from a real (left) and simulated (right) QWIP-sensor. Bottom: Same scene but with a visual sensor (left: real, right: simulated).

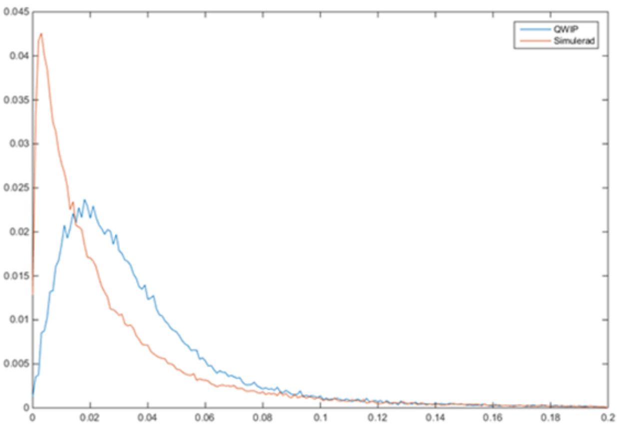

Figure 7: Computed distribution of gradient magnitudes in simulated (orange) and real image (blue).

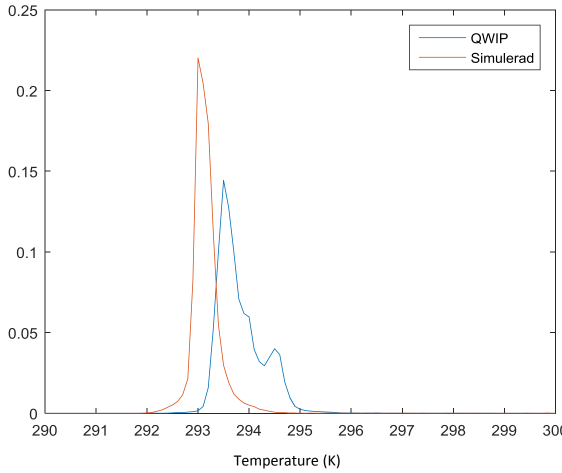

Figure 8: Computed distribution of apparent temperature (Kelvin) in simulated (orange) and real image (blue).

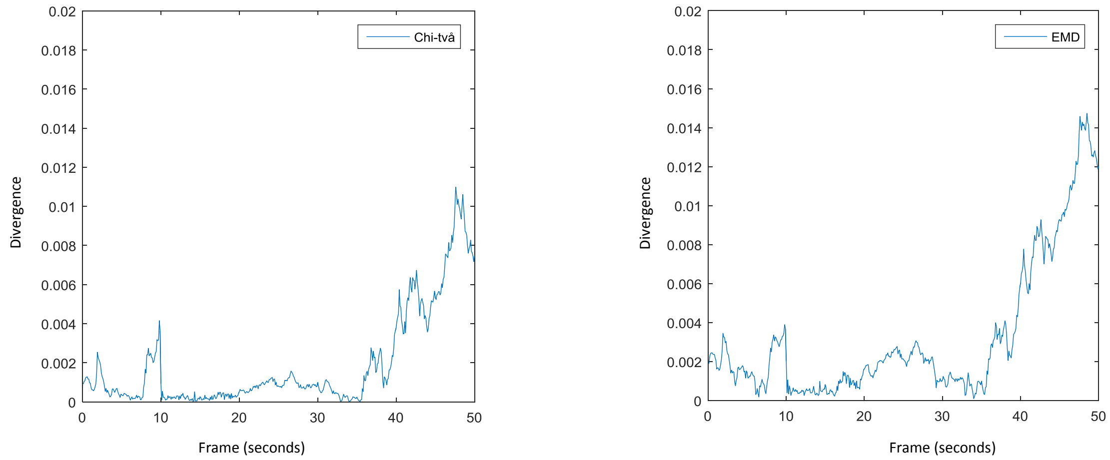

Figure 9: Statistical divergence (left: $\chi 2$, right: EMD) between distributions of gradient magnitudes in simulated and real image over a 50 seconds long sequence of images.

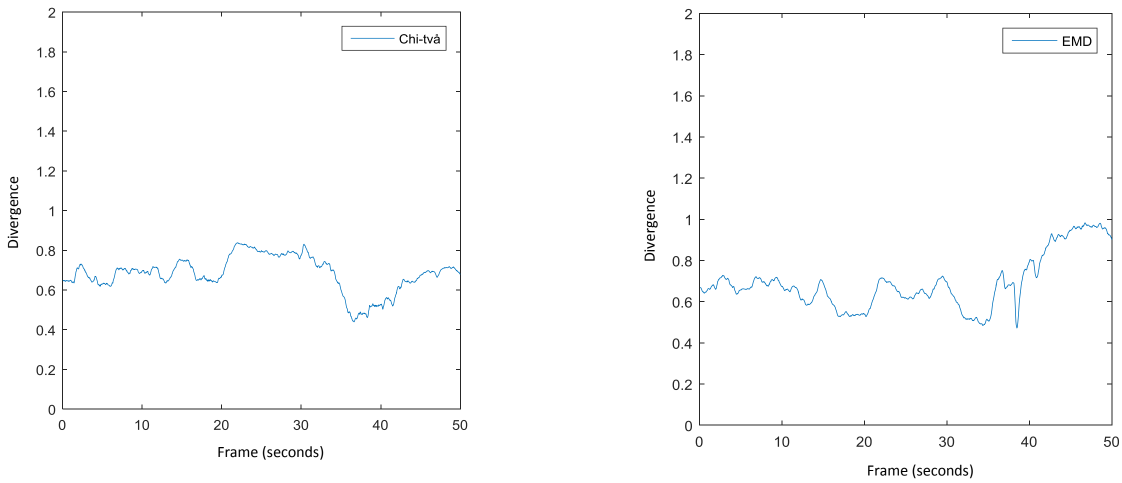

Figure 10: Statistical distance (left: $\chi 2$, right: EMD) between distributions of apparent temperature in simulated and real image over 50 s long sequence of images.

3.0 THE SIGNAL PROCESSING CHAIN

FOI develops algorithms for automatic detection, tracking, sensor fusion and sensor management etc. with the aim to make future sensor systems more intelligent. These algorithms are implemented in MSSLab, see Figure 1, as well with real sensors on experimentation platforms.

3.1 Automatic target detection

FOI has developed both shape and motion detection algorithms to detect different types of targets [12]. The currently used detector in MSSLab is the shape aware variant, which based on LogitBoost boosting technique [13, 14, 15]. It divides the image into regions and scans over them to find parts of target-specific shapes. Because the range is uncertain, the detector searches for targets in different scales. Each image is applied individually so it can be used even when the sensor platform is moving, for example in a UAV or a combat vehicle.

The detection algorithm is trained to detect both people and vehicles. To detect people, a large dataset is produced with real IR images on people and background. For detection of vehicles, simulated IR images is used during training.

The probability of detection is high, particularly over several consecutive video frames. Detectors for different objects may run in parallel and the detector works for a range of pixel scales. Figure 11 shows two simulated LWIR images where the algorithm has detected a human (left) and three vehicles (right).

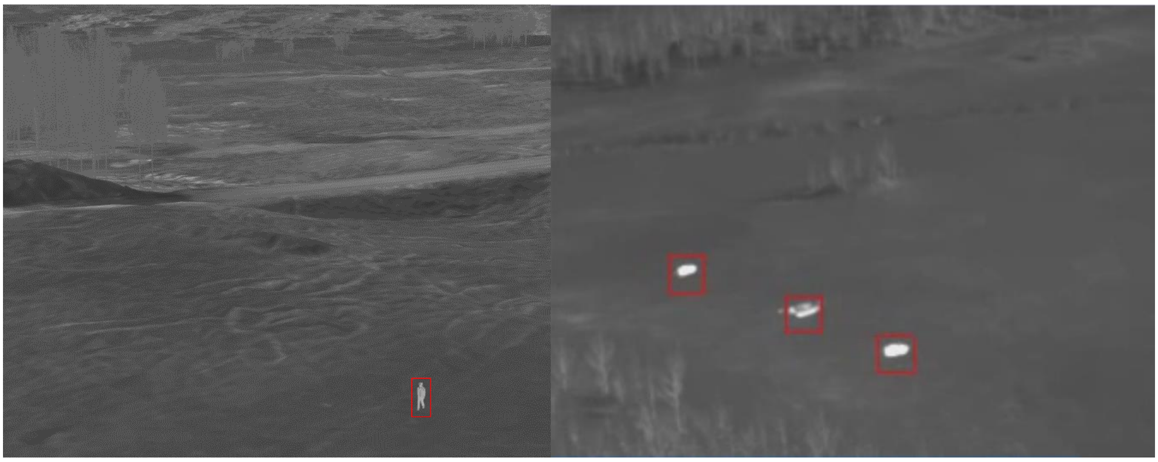

Figure 11: The left image shows a simulated LWIR images where the detection algorithm has detected a human and the right image shows three vehicles which has been detected. The detections are illustrated with red bounding boxes.

3.2 Target tracking

The concept of target tracking is to enhance the information value of the acquired target detections by connecting them over time to generate target tracks. Each target track describes how an object has altered its states over time, such as position and velocity which are the most basic states to be tracked of a target. The implemented target tracking algorithm used in MSSLab is based on a state of the art *Multiple Hypotheses Tracking* (MHT) framework [16, 17] where all modern tracking filters are supported, e.g.:

- Kalman filter (KF) and Extended Kalman filter (EKF)
- Unscented Kalman filter (UKF)
- Information filter (IF) and Extended information filter (EIF)
- Particle filter (PF)
- Probability hypothesis density (PHD)

The tracking algorithm is developed as a general framework to support high customization of observation models, e.g. radar, sonars, and cameras, and target models. Since the framework is generalized it can easily be applied to different applications. In [18] tracking of humans is done using real world IR detections, using the shape detector, from two platforms: a ground vehicle and an UAV. Because that buildings were in the scene, they needed to be modeled as obstacles in the tracking framework. If the buildings are not taken into account, target tracks will be deleted if they are behind a building since the tracker has then no knowledge that a track can be hided. This scenario proves the extensibility of the tracker algorithm.

3.3 Sensor Management

Real world scenarios may cover large areas, they may be cluttered with moving objects, or contain occluding obstacles like hills, buildings or vegetation. If available, an aerial view may bring more information that can be combined with the land-based sensors. To get the best situation awareness possible, good sensor management is required. The sensor management problem, in the context of this paper, is to actively direct sensor resources to survey unknown areas and follow targets while maximizing sensor area coverage.

Two key behaviours are identified during reconnaissance: search for new targets and to follow tracked targets. To search for new targets, the sensor sweeps over a predefined sector so that all sensors together cover the area around. When a new target is detected it is added to the collection of targets. For a period of time, each target is assigned to be followed by one sensor. The choice of which sensor that is assigned is based on some basic, but sufficient, conditions: ability to increase precision of estimated target position, ability to classify target as hostile or friendly, or defeat a hostile target. When information about the environment, e.g. terrain and vegetation, is available it can be used by the management framework to choose the best sensor with respect to time and location [19].

In Figure 12 a scenario of a sensor management problem is illustrated [19]. A reconnaissance group of four vehicles advances along a road in an unknown enviroment. Each vehicle is equipped with a steerable IR-sensor to be utilized by the sensor management framework. All targets are detected while the surroundings of the group are reguarly updated to detect new potential targets.

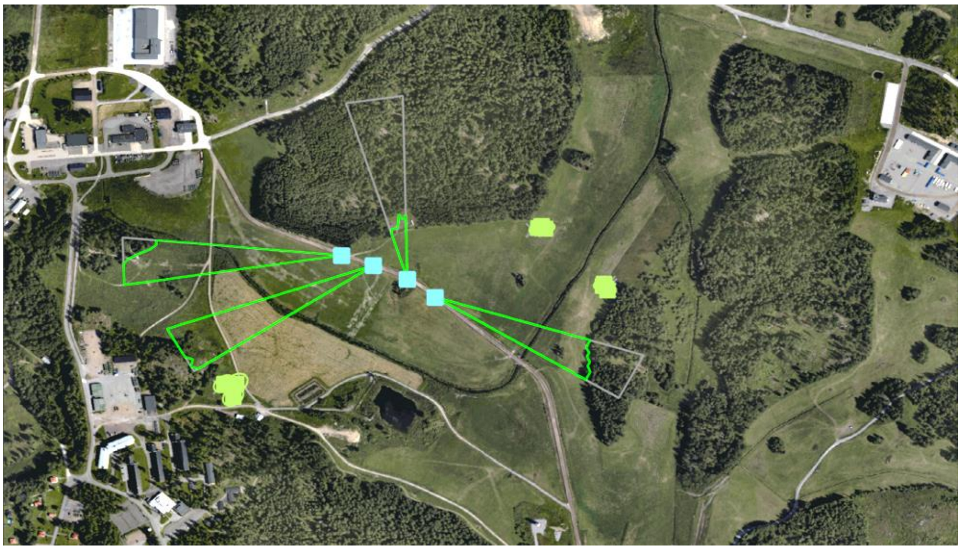

Figure 12: A sensor management example of a reconnaissance group of four vehicles (blue) advances along a road. The current field-of-view of each sensor is illustrated with green lines. Three groups of targets (green), classified as neutral, have been detected.

4.0 DISCUSSION AND FUTURE WORK

This paper describes the current status of the work on simulation of sensors in MSSLab and examples of signal processing that is integrated to the simulation framework. The verifications of sensor simulations show that the dynamic range of the simulations is a bit too low. Tests was made with bump mapping of the textures on the ground. This means that the normal on the surface is varied using a height map, which results in a bumpy surface and the surface is perceived as more varied. Initial results seem promising, but more analysis is needed.

A detection algorithm has been tested with both measured and simulated data and it is shown that the detector gives approximately the same result. The terrain models in MSSLab have today too few details, such as stones and bare rocks, and more work is needed to add that kind of details to the terrain model. More work is also necessary to verify that the sensor simulations in all weather conditions have high quality.

Algorithms for target detection, target tracking and sensor planning are used to study reconnaissance from both combat vehicles and UAVs. The detection algorithm and target tracking algorithms work well, but more information is needed of the target so we are currently working on automatic target recognition with deep learning algorithms. The sensor planning we use today works well for simple scenarios, but it takes too long to build scenarios with collaborative sensor platforms that will coordinate their reconnaissance. More work is therefore needed to enable the sensor planning to work properly in complex scenarios.

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