Synthetic Environment Experimentation for the Detection of IEDs using Mini-UAS High Resolution Imaging

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ABSTRACT

In the present work, we discuss some of the required elements for the detection of IEDs using mini-unmanned aerial systems (UAS). Target detection, classification and identification standards along with a neural-algorithm based automatic target detection and identification system are evaluated. A genetic-algorithm based autonomous mission management system has also been developed and tested. A synthetic environment simulation system has been used to develop concepts of operation. We conclude that present mini-UAS optical sensors are viable for the detection and identification of IEDs and that the effectiveness of these sensors can be improved by using the automatic target detection/identification software. Initial results with the developed autonomous mission management system are promising and demonstrate its viability.

1.0 INTRODUCTION

IEDs are notorious for being difficult to detect and neutralize. IEDs can be packaged in a myriad of objects, such as burlap sacks, trash, toys, dead animal carcasses, buckets or cinder blocks. They can be attached to telephone poles, be placed in guard rails or buried under the road. IEDs can even be packaged to look like a concrete roadside curb. Network enabled, interoperable, autonomous, small, uninhabited aerial systems (UAS) can provide significant information input to the understanding of the battlespace and support Force protection and route reconnaissance for IED detection, especially in today's asymmetric threat world.

UAS technology has evolved dramatically in the past 10 years. Their operational value has been demonstrated often over the past decade, including the recent operation in Afghanistan. The general trend in uninhabited vehicles (UV) is to improve the level of autonomy, communications reliability, airspace integration, information processing and especially for small UAS, the ability to obtain high-resolution images of small targets.

To use UAS effectively to detect and identify IEDs in the complex battlespace of asymmetric warfare, the following is required:

- A sensor system capable of providing enough resolution for IED detection/identification
- Image analysis tools that will aid in the above. This includes:

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- Automatic target detection and identification
- Change detection
- Image mosaicing

- An autonomous mission management system that can minimize operator workload in directing the UV to the target. This includes:
  - Automated mission planning and re-planning
  - Automated collision avoidance capabilities
  - Integration with the sensor

This paper will describe the issues related in the above: namely sensor performance, automated target detection and identification, and autonomous mission management (AMM). First, typical UAS optical sensors will be evaluated to calculate their limits for detecting IEDs using standard image analysis criteria. Then, the DRDC-developed UAS synthetic environment (SE) will be introduced and its use as a test-bed for an automated target detection and identification concept will be presented. Finally, various concepts in AMM will be presented, concluding with a brief description of a prototype DRDC AMM system citing some initial results.

1.1 Uninhabited Aerial System (UAS)

Through Figure 1, we wish to convey to the reader that what has been known as an uninhabited aerial vehicle (UAV) actually encompasses several components: the airborne element (the uninhabited aircraft, or UA), a ground element (Ground Control Station, or GCS), and a high-speed data link between the GCS and the airborne element. The GCS element itself is made up of human managers and computing systems, such as flight planning systems, sensor display systems, image analysis systems, communication systems, etc. The GCS also needs to connect to the overall Command-and-Control (C2) system. The airborne element is itself also made up of several systems: the aircraft platform, the autopilot, the sensor equipment (camera, accelerometers, etc.), and transmission systems. One can see that the whole architecture behind a UAV is actually an intricate system architecture: for this reason we shall henceforth refer to the UAV and its accompanying hardware and software elements as an uninhabited aerial system (UAS). A mini-UAS employs UA's that have a gross takeoff weight of less than ~35 kg. Their GCS software typically can fit into a lap-top computer.

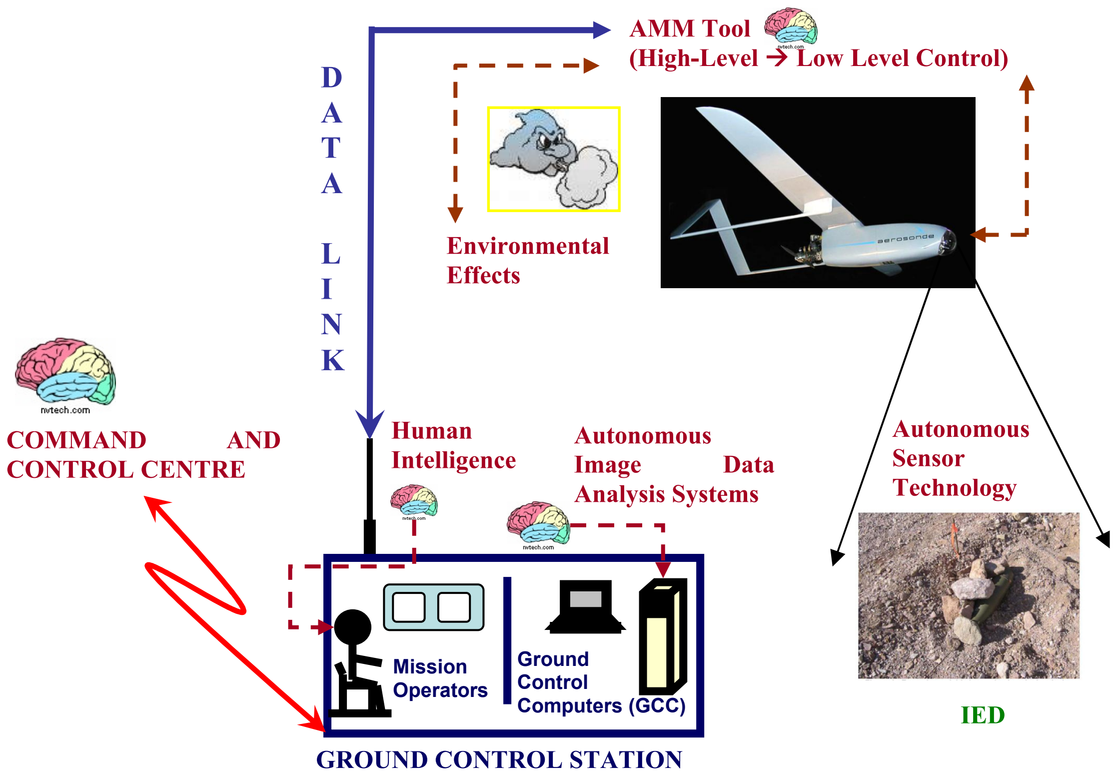

Figure 1: UAS

2.0 THE UAS SENSOR SYSTEM

We employ a procedure which utilizes standard criteria to evaluate a given camera's performance. We begin by measuring the camera's modulation transfer function (MTF) and hence the point spread function [1]. Typical results for a commercial digital camera are shown in Figure 2. The camera's picture height is specified as 2848 pixels. However, the number of resolvable equivalent pixels will be less than the specified 2848 because of imaging system limitations (lens quality, atmospheric effects etc.). The point spread function is used to determine the number of resolvable pixels. At the Rayleigh contrast limit [2], the full width half maximum (FWHM) of the point spread function can be used to determine the minimum resolvable features on the target. Therefore, knowing the camera and lens parameters, we can predict the detection and identification criteria for various targets using the following arguments.

The Johnson criteria [3] states that to recognize/classify a target, 8 resolvable image elements over the critical dimension (64 elements on target if it is square) are required. However, using the camera described above, this criterion is multiplied by a factor of 1.39 because of the camera's limitations. Thus 11.2 actual pixels are required. Using the Targeting Task Performance (TTP) criteria [4] for the same type of target, 14.5 resolvable elements are needed, resulting in 20 actual pixels using the above mentioned camera. For a square target, this translates to 210 resolvable pixels and 400 actual pixels. For identification, the TTP criteria indicated that about 23 resolvable elements are needed indicating that about 1000 actual pixels would be needed to identify a square target. If we use the Johnson criteria for identification (16 resolvable elements) this would give about 500 actual pixels on a square target.

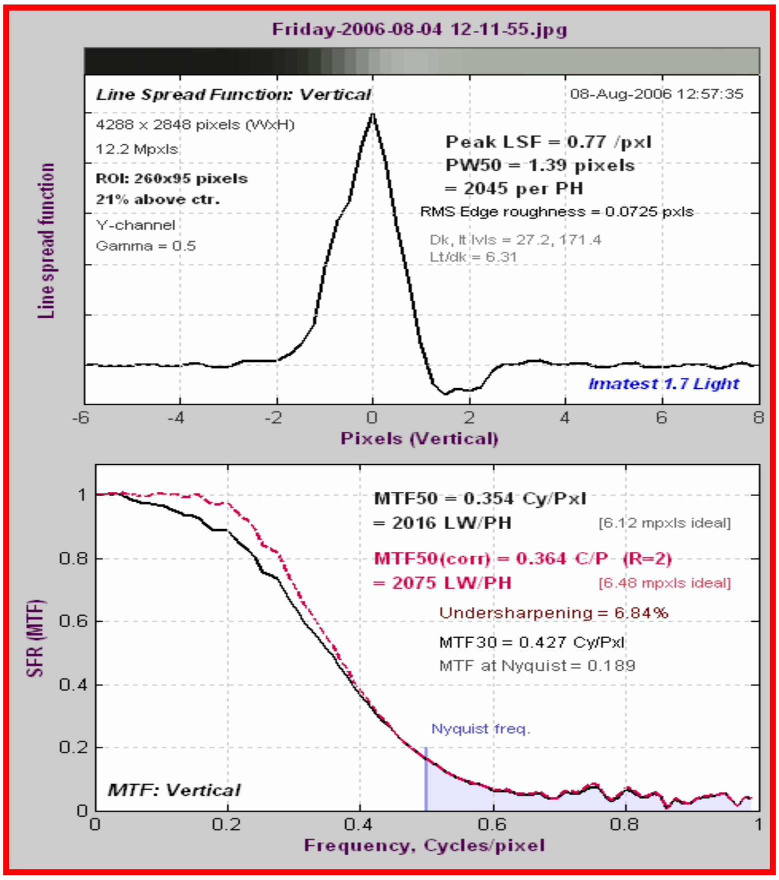

Figure 2: MTF and Line spread function for Camera

The camera/lens combination under discussion has a 47° field-of-view (FOV). Hence, under the best possible conditions (no atmospheric effects, vibration etc.), to recognize a small IED (say, approximately 0.1 m^2 in area) and assuming the TTP criteria as valid (~400 actual pixels on target), a UAS must be flown to within about 55-60 m of the IED target. Naturally, the range would increase if the FOV is reduced by zooming.

This maximum range of 55-60 m for IED classification is typical for high-end digital cameras such as the Nikon DX2 or the Canon S50. However, for a typical video camera (400 NTSC lines of resolution), classification is not possible under the above-mentioned conditions (FOV of 47 degrees) and normal UAS operating altitudes.

Given the considerations above, we can surmise that if a small video camera is used for situational awareness and a high-resolution digital camera is used for IED detection/classification, the concept of using a mini-UAS for this purpose may be feasible.

It should be noted that both the Johnson and the TTP criteria require significantly fewer pixels on target for detection (2 for Johnson and 2-5 for TTP). However, in a complex environment with significant clutter, targets must not only be detected, they must be classified and identified. Using just the detection criteria, the false alarm rate will be too high to make the system viable. Therefore, we have chosen to design and test a system that is capable of providing classification resolution for primary target detection.

3.0 THE DRDC UAS SYNTHETIC ENVIRONMENT

The DRDC Ottawa UAS synthetic environment (SE) simulation system was configured to provide a simulation capability to develop CONOPS for UAS IED detection operations and to test different concepts in autonomy such as automatic target detection and identification, automated mission planning, etc. A 6-DOF mini-UAV model was used to describe the flight characteristics. Sensors were configured to simulate a colour video camera, a high-resolution digital camera and a low resolution, bolometric IR camera. The sensors were implemented using the META-VR scene generation and visualization package [5]. The virtual imagery was modified by altering the pixel resolution, noise, contrast and dynamic range to provide simulated data similar (but not identical) to that which would be produced from real mini UAS airborne images, as per the considerations in Section 2.0. The characteristics of the small UAS are as follows:

- Flight speeds 30-40 kts (~15-20 m/s);
- Gross takeoff weight 10 kg;
- Autopilot controlled speed, altitude, heading and waypoint following;
- Autopilot controlled bank angle maximum 30 degrees;
- Operator heading override;
- Wingspan 3 m;
- Flight duration ~1 hour.

The UAS is integral to the aerospace environment and acts in concert with air operations. The system ground control station has the ability to do pre-mission planning and waypoint navigational procedures as well as control the operation of the sensor payload using a STANAG 4586 compliance. The simulation has the capability to support convoy route reconnaissance, intelligence gathering, battle damage assessment (BDA), and numerous other military applications.

A Semi-Automated Force (SAF) software package generates the entity level platforms (targets) such as infantrymen, tanks, ships, airplanes, munitions, buildings, etc., which interact at the individual level in a synthetic natural environment. The individual entities are task organized into appropriate units for a given mission and can be controlled as units or single entities. Realistic environmental effects such as visibility, wind and turbulence are also included.

4.0 AUTOMATIC TARGET DETECTION AND CLASSIFICATION CONCEPT

This section describes a detection and classification system for IED targets in imagery from a mini UAS. This is accomplished using a holographic neural intelligence algorithm called HNeT™ to detect and classify the targets [6],[7], according to the above concepts for the detection of IEDs. To develop the concept of operation for the mini UAS and to provide initial training and testing imagery, the synthetic environment (SE) simulation facility was used. Following the SE simulations, mini UASs have been used to acquire imagery of targets both to validate the simulations and to provide a realistic expectation as to the performance of the automatic target detection and classification system.

4.1 The HNet™ Algorithm

The HNeT algorithm [6] is typical of most neural artificial intelligence algorithms in that it provides a learned response to a stimulus. To accomplish this, the algorithm must learn the appropriate responses from a training data set. In this case the training data was a series of images of the target object at a number of different contrast and pixels-on-target ratings as a function of target depression, rotation about the line of sight and azimuth angles. The targets were counter-trained against the natural background in the images. Previous experience with HNeT has indicated that only minimal training data sets are required (i.e. every 10-20 degrees of azimuth and elevation over a range of target ratings appropriate for the operation of the system); however any additional training data will add to the performance of the system.

To train the algorithm, an automated routine was developed that presented imagery to the operator (either from the simulated or the real imagery) allowing the operator to mark and identify the target. The information was then automatically segmented and added to the training database. The HNeT cell assemblies were generated from the training data sets. Subsequent testing was performed on an independent data set.

4.2 Imagery Used

To test the concept of operation, imagery from a mini UAS outfitted with a small video camera (480-line resolution, 50-degree field of view) capable of providing data in an NTSC format with 24 bit colour was used. Daylight colour video of vehicles over various slant ranges and clutter environments were obtained. The SE sensor imagery was generated to suit these camera's characteristics. Real flight data was restricted in quantity; however, a statistically significant sample was obtained to allow validation of the SE derived results.

A systematic approach to measuring the quality of the imagery, the performance of image capture devices, and the effects of image processing algorithms was necessary. We have used a quantitative evaluation of the image quality by measuring the number of pixels-on-the target as well as the target contrast with the surrounding background. The performance of the automatic detection/classification algorithm as a function of the pixels-on-target and target contrast was evaluated. Although these targets were not typical IEDs, they will allow an evaluation of the concepts as the results will allow the determination of the number of pixels on target that are required for HNeT to provide reasonable probabilities of correct classification.

4.3 SE Results

To test the applicability of this concept with simulated imagery, two different targets were generated and placed in a complex synthetic environment. Training sets were provided by a series of images (1000 pixels-on-target, contrast > 10%) in which the targets were rotated in azimuth angle by about 5 degrees between each image at constant elevation angle and target range. The algorithm was trained using this data. Test data sets were generated by observing the targets at random azimuth angles and slant ranges at approximately the same elevation angles.

The results indicate that approximately 200 pixels-on-target are required for HNeT to be able to classify the target. The results are shown in Figure 3. For these tests the contrast ratio was 20%. HNeT was trained using targets with greater than 1000 pixels-on-target even though targets with as few as 50 pixels were used in the test data set. It is suggested that although this type of synthetic imagery is useful for testing the algorithm, considerable care must be taken to ensure realistic results from classification/identification algorithms on synthetic data of this type.

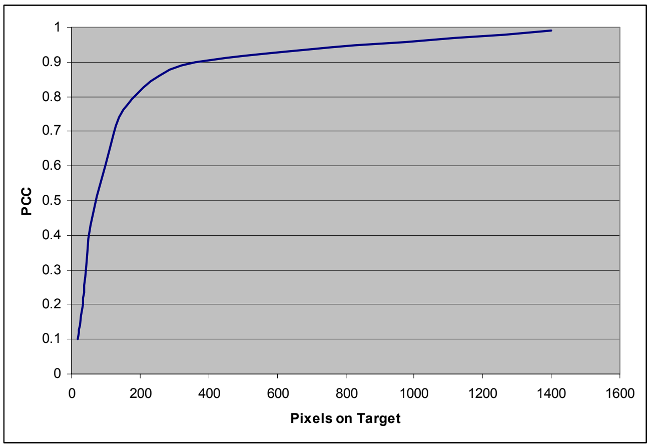

Figure 3: Probability of Correct Classification (PCC) vs. Pixels-on-Target for HNeT - SE Results

4.3 Validation UAS Results

To test the capability of the HNeT algorithm, images were gathered from the mini UAS. Video sequences were captured and then processed using the HNeT concept of operation. Separate training and test sequences were used. A typical image from the video sequence is shown in Figure 4 and the PCC for this data is shown in Figure 5.

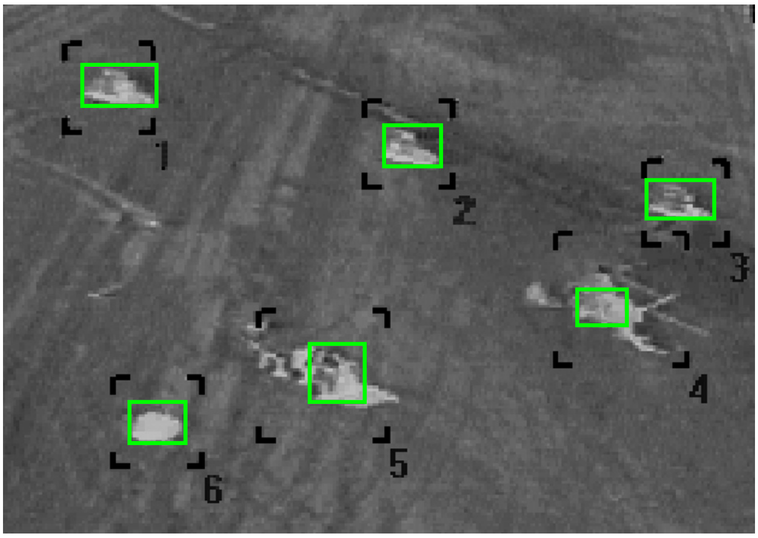

Figure 4: Typical image from Mini UAS imagery being processed with HNet

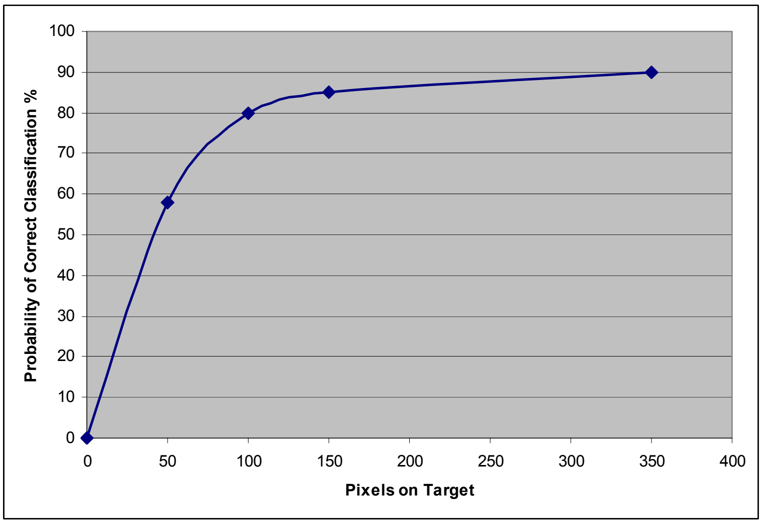

Figure 5: PCC as a function of Pixels-on-Target - UAS results

Trends are similar to the SE results. The results indicate that it is possible to automatically classify targets in video imagery using the HNeT algorithm. The detected targets can be identified if an appropriate number of pixels-on-target can be provided. Reasonable probabilities of correct classification can be provided with as few as 50 pixels-on-target; however, performance improves with more resolution and larger training data sets. For a PCC of 90%, ~400 pixels on target would be needed.

5.0 AUTONOMOUS MISSION MANAGEMENT UAS SYSTEM (AMM)

5.1 The Need for AMM

By Mission Management (MM) for UAS, we want to encompass pre-flight planning, in-flight re-planning and management of flight and mission systems for an uninhabited aircraft. It has been noted that UAS require too much human-operator workload associated with mission management [8]. One of the primary duties of a UAS is to provide the mission commander with increased situational awareness. This would arise from a thorough analysis of the sensor data. It would be a benefit to UAS operators and mission commanders that the task of getting the UA, and hence the UA's sensor, on the target be handled autonomously by the UAS because it would allow them to concentrate their efforts on analyzing the UAS sensor imagery for IED detection. User-friendly and well-integrated flight management systems that reduce the human-operator tasks help to reduce his or her workload. However, the stated goal of military planners to have several uninhabited aircraft managed through complex missions by a single human manager [9] will require a new mission management paradigm, namely, an **autonomous** mission management paradigm: this will entail devolving mission management responsibilities from human managers to the UAS software [8]. In the present paper, we briefly describe the different AMM paradigms used in several of the NATO countries, followed by a brief description of an in-house (DRDC) AMM tool under development [10].

5.2 Different AMM Paradigms

There is a widespread use of agent-based architecture in the military UAS R&D community as a means for accomplishing AMM. Many UCAV (Uninhabited Combat Aerial Vehicle) related agent-based studies have been published in the past 5 years (see [11],[12] and references therein). A practical example of the use of agent systems is in the mission system of the U.S. Army/NASA Autonomous Rotorcraft Project [13]. American military establishments that are developing agent technology as a means of AMM are the US Army, NASA Ames and DARPA [8]. Other prominent defence R&D research on agent based AMM comes from Australia, where the Defence Science and Technology Office (DSTO) and their collaborators produced one of the most publicized UAS applications of agents: Jack Intelligent Agent*TM* [14]. Other organizations which have published on agent-related work are listed in [8] and [15].

The agent-based architectures pose numerous software implementation challenges specifically because they are based on human-cognitive models which cannot always be stated in a well-posed mathematical formulation. The challenges of incorporating human-cognitive based models for AMM with the low-level UA autopilot - which is constrained to the dynamics of the aircraft, are also a serious concern for agent implementation for AMM.

AMM Architectures that are not based on agent concepts can be termed as “Enhanced Autopilots with Mission Layers”. Some AMM systems for UAS have been designed by adding mission control layers to a conventional or advanced technology autopilot. This is a natural approach for control engineers because it is conservative from a safety point of view, since conventional application of system safety assessments can easily be applied. This approach gives the UAS autonomy deterministic bounds to produce a high degree of predictability in meeting mission goals, while reliably staying within the bounds defined by the physical, operational or regulatory environments [8].

An example of this type of AMM system is found in ONERA's (France's *Office National d’Études et de Recherches Aérospatiales*) UAS Mission Management Architecture [16],[17]. Other examples of this type of paradigm are listed in [8],[18],[19],[20] and references therein. Clearly, this type of architecture lends itself much more readily to a well-posed mathematical formulation. Hence, the issue of establishing trust in this kind of system is quite manageable; conversely, establishing trust in an agent-based system is a very serious problem.

5.3 DRDC AMM Prototype

The enhanced autopilot with mission layer approach was used to develop a DRDC prototype AMM for UAS [10]. At the present stage of development, the AMM system is responsible for generating an optimal trajectory for the UA, specified as objective waypoints by the operator. This optimal trajectory for the UA takes into account its flight dynamics and the order in which objectives are executed, while avoiding obstacles. The initial mission objectives are specified by the operator prior to take-off. If the mission objectives change during the mission, the AMM is responsible for calculating a new optimal trajectory. This new calculation (termed “on-line re-planning”) must take place as quickly as possible. The required knowledge of the terrain is incorporated in a “Knowledge Base” with a Hybrid Octree Representation [21] while the optimal trajectory is calculated using a Genetic Algorithm (GA) formulation [22],[23] which relies on the information in the knowledge base.

The initial results show that this AMM software could perform this task in the required timeframe: Figure 6 shows the optimal trajectory calculated by the software for a mission with two objectives. The terrain used was a fictitious, mountainous one.

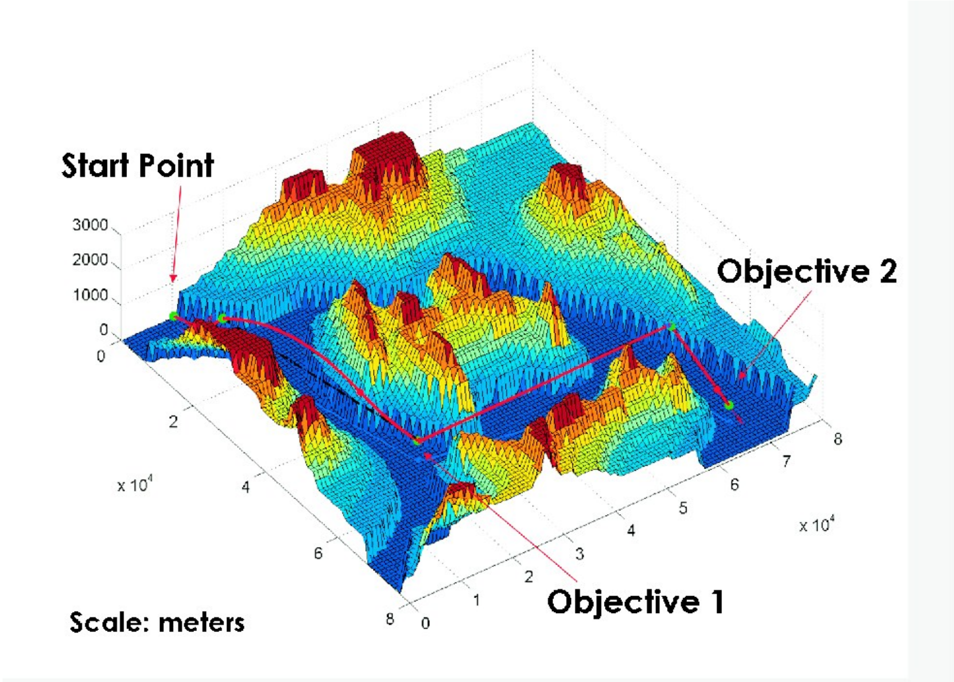

Figure 6: Trajectory computed by AMM system for a two-objective mission

Computational time for this case was about 20 seconds which can be improved by code-optimization and implementation of the software tool on a Field-Programmable-Gate-Array (FPGA). This is the subject of on-going work. The computational times could be improved by at least one order of magnitude, which would make the use of this AMM tool feasible for realistic applications. The obvious next step is to integrate this AMM system in the UAS SE and conduct further testing.

6.0 CONCLUSIONS AND FUTURE RESEARCH

From the considerations reported above, we can make the following conclusions:

- SEs provide an excellent test-bed with which to experiment with developing autonomous UAS systems, however, care must be taken to ensure that the imagery depicted in the SE produces similar detection/classification/identification results as those of real data;

- SEs provide an excellent test-bed for evaluating mission concepts of operation for using a UAS to detect IEDs;

- Detection of IEDs with present UAS and associated sensor systems is feasible;

- Automatic target detection, tracking, and classification of targets with the HNeT concept presented in Section 4 are viable; however, adequate training data sets will be required;

- Autonomous mission management using an "enhanced autopilot with a mission layer" approach is more conducive to short-term development rather then an agent-based approach because of its better ability to establish trust. The AMM prototype tool developed at DRDC Ottawa based on a Genetic Algorithm approach shows promise as a viable system.

Future research will focus on the following issues:

- Integration between the sensor system, the automatic target detection, tracking, and identification system and the AMM system
- Obstacle collision and avoidance
- Validation of autonomy concepts with SE and live experimentation

7.0 REFERENCES

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