Image and Information Fusion Experiments with a Software-Defined Multi-Spectral Imaging System for Aviation and Marine Sensor Networks

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The availability of Internet, line-of-sight and satellite identification and surveillance information as well as low-power, low-cost embedded systems-on-a-chip and a wide range of visible to long-wave infrared cameras prompted Embry Riddle Aeronautical University to collaborate with the University of Alaska Arctic Domain Awareness Center (ADAC) in summer 2016 to prototype a camera system we call the SDMSI (Software-Defined Multi-spectral Imager). The concept for the camera system from the start has been to build a sensor node that is drop-in-place for simple roof, marine, pole-mount, or buoy-mounts. After several years of component testing, the integrated SDMSI is now being tested, first on a roof-mount at Embry Riddle Prescott. The roof-mount testing demonstrates simple installation for the high spatial, temporal and spectral resolution SDMSI. The goal is to define and develop software and systems technology to complement satellite remote sensing and human monitoring of key resources such as drones, aircraft and marine vessels in and around airports, roadways, marine ports and other critical infrastructure. The SDMSI was installed at Embry Riddle Prescott in fall 2016 and continuous recording of long-wave infrared and visible images have been assessed manually and compared to salient object detection to automatically record only frames containing objects of interest (e.g. aircraft and drones). It is imagined that ultimately users of the SDMSI can pair with it via wireless to browse salient images. Further, both ADS-B (Automatic Dependent Surveillance-Broadcast) and S-AIS (Satellite Automatic Identification System) data are envisioned to be used by the SDMSI to form expectations for observing in future tests. This paper presents the preliminary results of several experiments and compares human review with smart image processing in terms of the receiver-operator characteristic. The system design and software are open architecture, such that other researchers are encouraged to construct and participate in sharing results and networking identical or improved versions of the SDMSI for safety, security and drop-in-place scientific image sensor networking.

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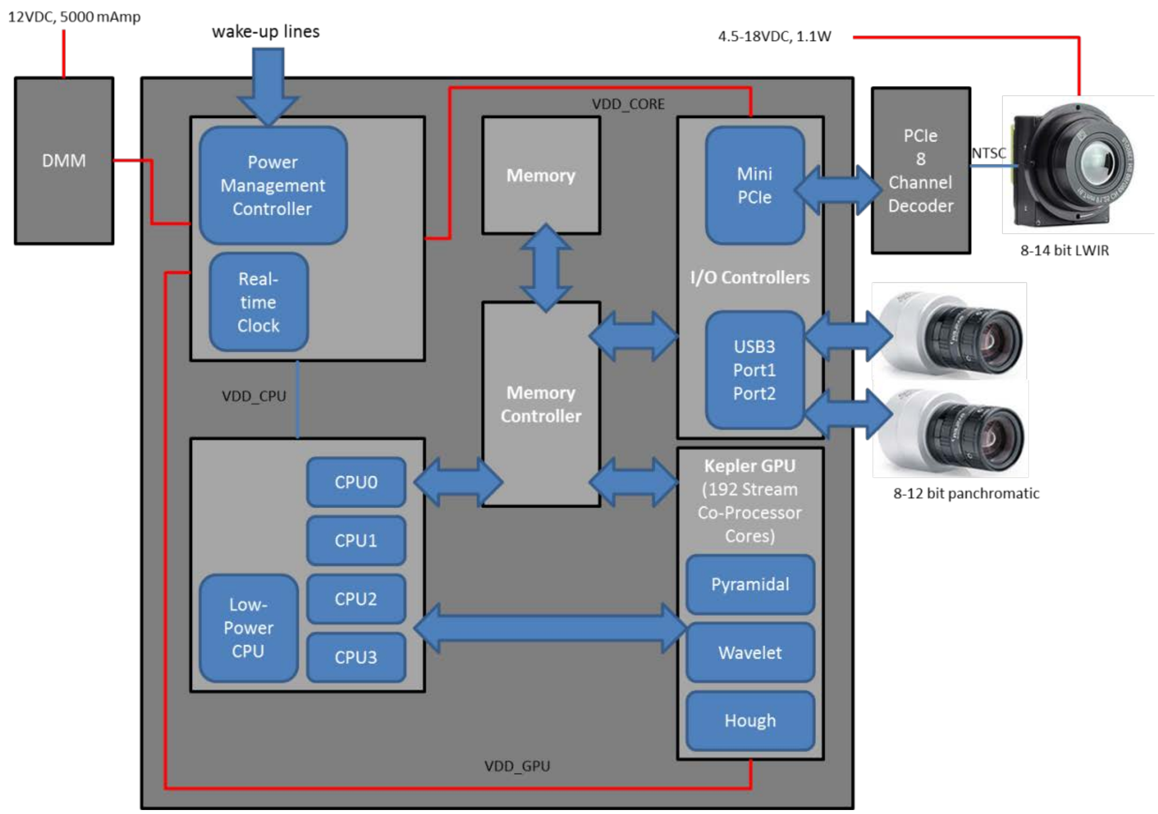
Nomenclature

ADS-B = Automatic Dependent Surveillance – Broadcast, aviation identification and tracking
AIFC = Arctic Information Fusion Concept, an ADAC sensor network prototype
CBONS = Community Based Observing Network System, or human field monitoring
CUDA = Compute Unified Device Architecture, GP-GPU acceleration
DMM = Digital Multi-Meter, used for current monitoring and power use analysis
EO/IR = *Electro-Optical / Infrared instrumentation*
GPGPU = *General Purpose Graphics Processing Unit*
LWIR = Long Wave Infrared, typically 8-15 micron wavelength electromagnetic radiation
MWIR = Medium Wave Infrared, typically 3-8 micron wavelength electromagnetic radiation
NAS = *National Airspace*
NIR = Near Infrared, typically 0.75-1.4 micron wavelength electromagnetic radiation
OpenCV = Open Computer Vision, an open source library in C/C++
Panchromatic = Visible and part of VNIR electromagnetic radiation in 0.45-0.8 micron range
PCIe = Peripheral Component Interconnect Express, a device interface bus
ROC = Receiver operator Characteristic, compares true positive and false positive rates
S-AIS = Satellite Automatic Identification System – automatic marine tracking service
SDMSI = Software Defined Multi-Spectral Imager
SOD = *Salient Object Detector*
SWIR = Short Wave Infrared, typically 1.4-3 micron wavelength electromagnetic radiation
TAP = Trans Alaska Pipeline
UAS = *Unoccupied Aerial System*
USB3 = Universal Serial Bus, Revision 3, operating at 5 gigabits per second (625MB/sec)
USCG = US Coast Guard
VNIR = Visible and Near Infrared, typically 04.4-1 micron wavelength range

Introduction

The purpose of the research presented in this paper is to evaluate the hypothesis that pole-mount cameras on buoys, buildings or towers, and marine vessels can improve situational awareness for the agencies and organizations that manage campuses, ports, airports and other critical infrastructure where drone, aircraft and marine vessels co-operate compared to use of satellite remote sensing and human monitoring. The assertion is that a multi-spectral imaging system defined by software providing concurrent visible and infrared image collection and processing can also be defined and improved through software upgrades over time to perform better than security camera continuous monitoring or occasional satellite imaging. Finally, that the result will be better spatial, temporal, and spectral resolution observing of key areas of interest in regions that are hard to monitor such as Alaska and the Arctic compared to current methods employed. This hypothesis has been initially tested at Embry Riddle by monitoring shared airspace traffic including drones, aircraft and wildlife to test whether the concept of a smart SDMSI might also have value for aerial surveys and surveillance as well as marine environments. The SDMSI system design that has been prototyped and built and tested in Arizona is shown in Figure 1 below. The camera system includes a Tegra K1 SoC (4 processor cores and 192 vector co-processor cores), wireless 802.11, Ethernet wired, USB3, a PCIe card interface, and is able to support 2 USB3 visible cameras and between one and four analog cameras including long-wave infrared. As such, the hardware is a system composed of sub-systems that can be upgraded and the features and function of the SDMSI are totally defined by the software and capabilities of the components in terms of resolution, optics, and frame rates, spectral and dynamic range.

Figure 1. – SDMSI Test Configuration



The system allows for hardware, firmware and software to be open systems, based on embedded Linux running on the processor and emphasis is on the image transforms and salient object detectors that can be run in real-time with power efficiency to support advanced monitoring and observing modes. The power analysis leading to the selection of a GP-GPU co-processor for the SDMSI is presented in detail in previous work [1] and in general the system has a power budget of 20 Watts maximum. The SDMSI system was mounted for testing on the roof of the Embry Riddle Prescott campus and remotely upgraded and accessed with continuous recording of images to compare to intelligent image selection tests. In the future, the project plans to pursue additional installations of SDMSI systems in other geographical locations such as Florida, Alaska, and Colorado. Three main experiments completed and presented in this paper are: 1) sky monitoring of overflying aircraft, 2) sky monitoring of drone operations in shared airspace, and 3) monitoring of avian wildlife activity. The goals include acquisition and storage of images of interest that are unexpected based on criteria such as targets of interest (aircraft not reporting on ADS-B and drones), animal activity for animal hazards and false positives (insects and birds). Some testing was also completed at marine ports, but only to assess basic feasibility of detection and tracking of these objects of interest in addition to the airborne objects of interest. The eventual criteria for object of interest image collection require both information fusion and sensor and image fusion for success. Performance results collected from experiments to date include ROC (receiver operator characteristic) analysis based on human review of the continuous image data (taken as truth based on multiple human frame-by-frame assessments) and comparison to several salient object detector algorithms.

Information Fusion

Information fusion is simple in concept, but requires constant monitoring of aggregated ADS-B information for example to provide expectation for aircraft that should be in view as well as unexpected aircraft detected (services such as flightradar24.com provide this information in real-time) [26]. The same information fusion can be used in marine environments with S-AIS, but based on the experimental locations; this was not validated at this time since most of the aerial objects observed did not appear on flightradar24 at all and in the future a line-of-sight ADS-B receiver will be used for compliant drone and aviation testing. For remote installations on buoys the SDMSI would require line-of-sight ADS-B or satellite ADS-B, which is true as well for marine AIS. The marine environment feasibility results collected to date show promise, as depicted in Figure 2, where for example in marine environments, the use of visible and long-wave infrared images can provide information such as engine and exhaust configuration, which can be compared to database information for S-AIS. Most marine vessels already report and use S-AIS whereas small aircraft (and drones operating below 400 feet) most often do not yet use ADS-B (compliance is required by January 1, 2020).

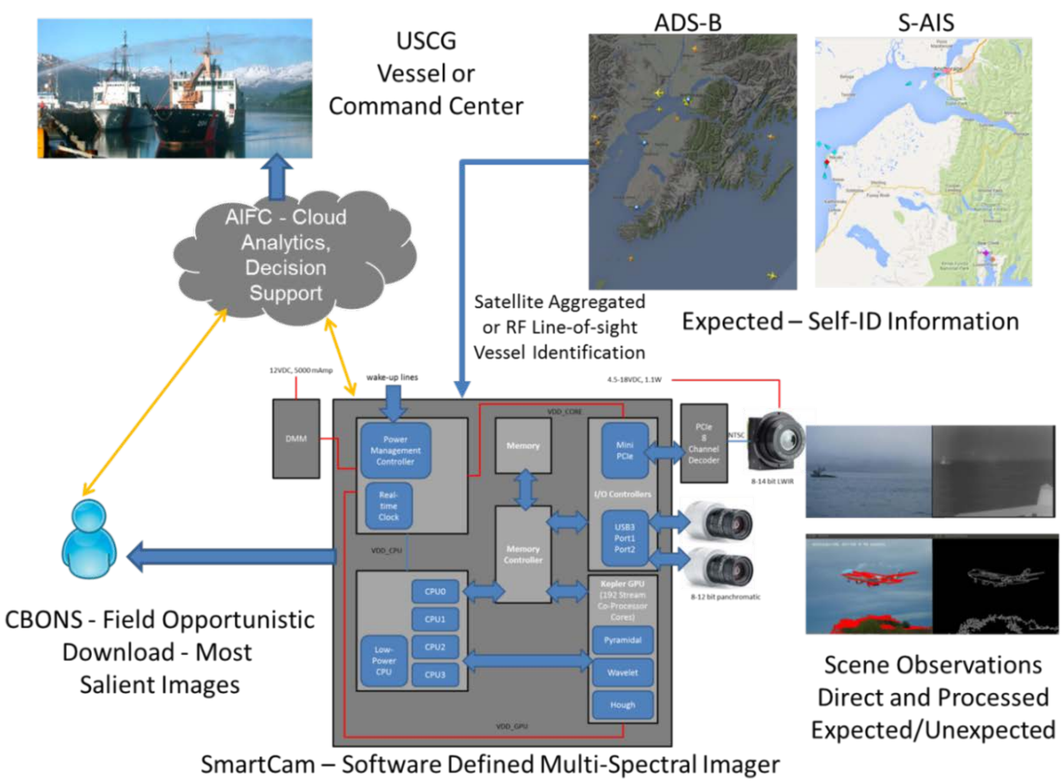
Figure 2. – Example of Marine Vessel Observation in Valdez Alaska of S-AIS reporting Vessels

Note in Figure 2, we see not only the obvious fishing vessel in 10-14 micron LWIR (Long Wave Infrared), but also the engines and exhaust system of the Supertanker at the TAP (Trans Alaska Pipeline), which is more evident with a narrower field of view as shown in Figure 3, but still obscured by fog. With image fusion, the thermally hot pixels in the LWIR image can be overlaid on the visible image in a single image with proper image registration and resolution matching.

Figure 3. – Supertanker detected by LWIR in Figure 2, partially visible with narrow field of view

In general, the concept of information fusion for aircraft and marine vessel situational awareness with the SMSI used in a larger sensor network is shown in Figure 4.

Figure 4. – Integration of the SDMSI into AIFC After Field Trials and Experiments

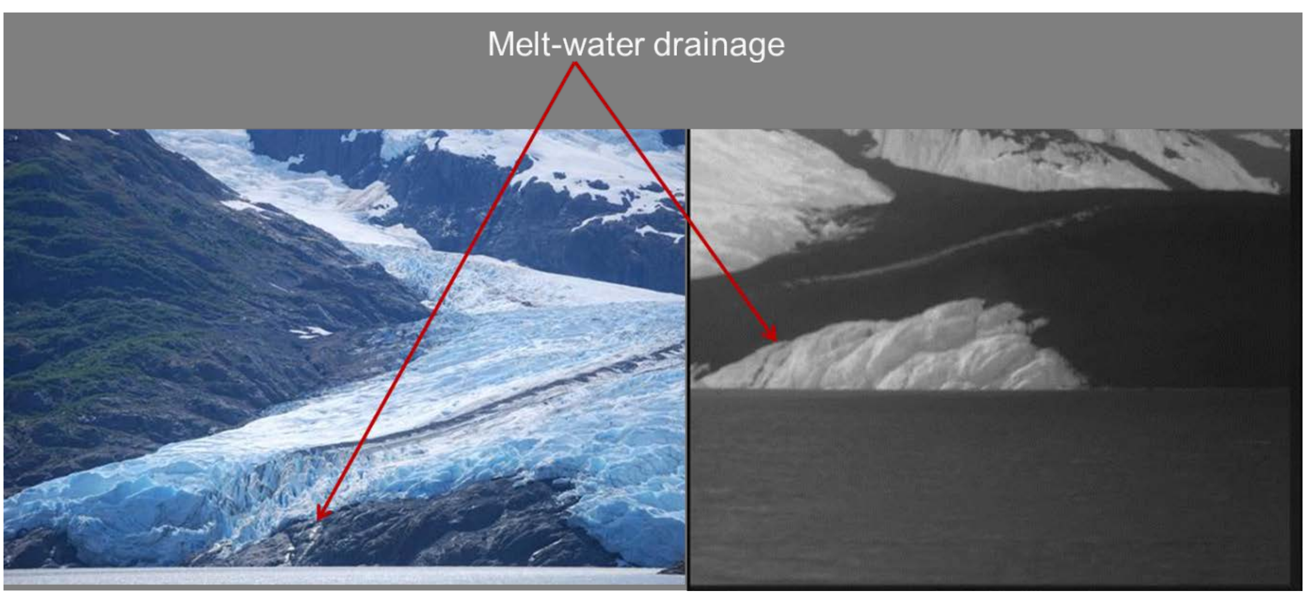


Overall, the goal for information fusion is simply to observe what is expected, but also to note any targets of specific type (marine vessels) that are unexpected based upon saliency metrics for that target type including shape [14], motion, color and contrast, thermal signature and behavior. The marine examples shown in this extended abstract were tested using a prototype of the SDMSI on a tripod. The shared airspace aviation results were collected with a semi-permanent roof-top drop-in-place installation at Embry Riddle Aeronautical University Prescott, with similar goals, but with skyward observations in visible and 10-14 micron long-wave infrared over days to weeks of time during fall 2016.

Image Fusion of Multi-Detector, Multi-Spectral Data

While salient object detection can be performed by the SDMSI in each band (visible and infrared), another option is to process fused images. A long term goal of the project is to determine whether concurrent processing in different bands or fusion and processing of a single stream of fused images provides better detection. Image fusion requires spatial registration [3][4][5][7], matching of resolution through pyramidal up-conversion and/or down-conversion at a common aspect ratio and finally blending of pixels if a single fused image is desired rather than side-by-side comparison. Part of the challenge of performing image fusion in real-time is processing and power required, but based on previous work, we have shown this is quite possible for a system operating well below 10 to 20 Watts of total power continuously up to 30 Hz [1]. Furthermore, based on early work, we have determined that this does not require custom hardware [2]. The value of image fusion, into a single blended image, is reduction in storage and bandwidth required for salient images. Figure 4 shows a tidal glacier with both visible and long-wave images, both which indicate presence of melt-water on the rocks, but with pixel-level fusion can be enhanced.

Figure 5. – Visible and LWIR Images of Tidal Glacier and Meltwater



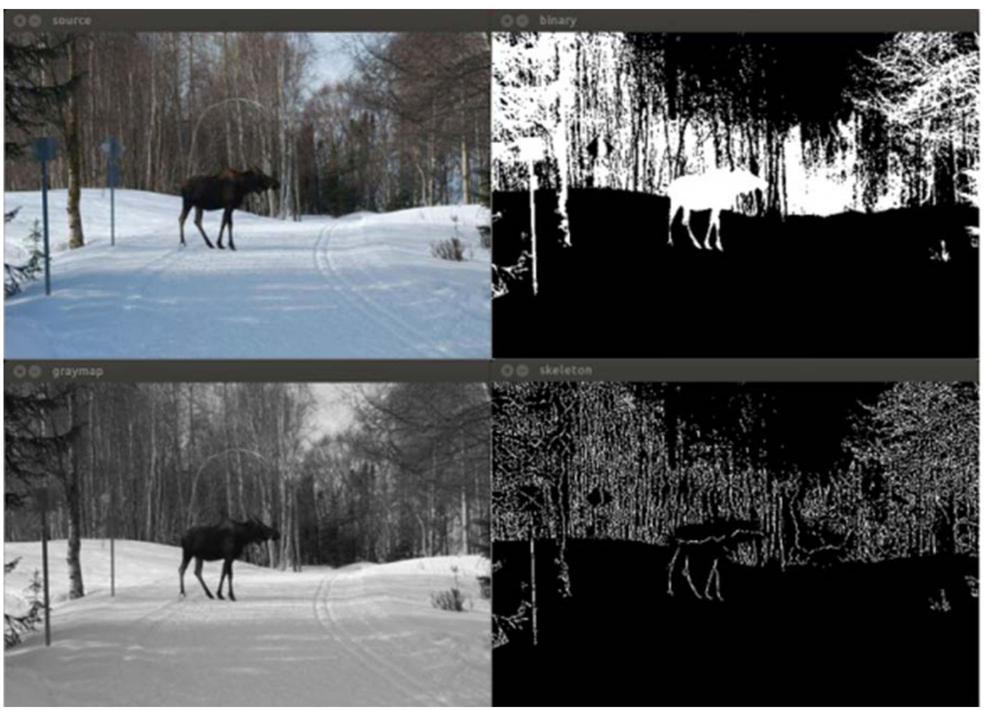
The use of LWIR and visible extends the spectral resolution at a common spatial and pixel resolution with much better temporal resolution than occasionally over flights by satellite remote sensing for field monitoring of geological locations of interest.

The mathematical and algorithmic methods for co-registration of images from fixed mount cameras (that don't share a common bore-sight) and pixel-level fusion are well established [8]. However, use for a range of targets of interest for the experiments planned can also benefit from specifics of the targets of interest, requiring additional image analysis in real-time.

Image Analysis

Image analysis for saliency and to determine whether targets that are either expected or unexpected might pose a threat or may be going through significant change requires more advanced and intelligent computer vision such as segmentation, identification of components of foreground targets and behavior. For example, a Moose in Alaska is a significant threat to human safety and to motorist safety and the animal can not only be recognized by shape, but by a skeletal transform which can also indicate behavior as sown in Figure 6.

Figure 6. – Skeletanization of a Moose Crossing Roadway



Saliency of foreground targets can range from simplistic motion triggered capture to much more complex threat analysis that involves machine learning, for example of animal gate and postures which indicated aggressive behavior [9][10][11][12][13]. Once the camera systems are in place, a wide range of saliency metrics will be evaluated by using OpenCV algorithms along with CUDA accelerated transforms to compare methods. Numerous saliency map and salient object detector algorithms can be used with the SDMSI, but one of the goals for research beyond the basic system design and analysis methods outlined here is to test hypothesis for which characteristics can best help classify flying objects for example. A summary of potentially distinguishing characteristics is enumerated in Table 1 as an outline for future investigation based on SDMSI use.

Table 1. – Hypothesized Saliency Characteristics for Aerial Objects of Interest

	Object					
Characteristic	**Insect**	**Aircraft**	**Drone**	**Birds**	**Ground Clutter**	**Clouds and Atmospheric Variations**
Shape	X	X		X		X
Motion and Behavior	X	X	X	X		X
Color, Contrast and Texture		X				X
Physical Properties (electromagnetic reflection, absorption, emission)			X		X	
Audio signatures		X	X			
Thermal and radiometric infrared signature			X		X	
RADAR/LIDAR cross section		X			X	X
ADS-B or Flightradar24 tracking information		X				

The long-term goal for the SDMSI is to use a variety of passive and active sensing modalities along with any information already known about objects such as cooperative aircraft that report their position to increase probability of correct classification of each objected detected and segmented. Overall the SDMSI is envisioned to eventually be able to detect objects, classify them, track them and ideally identify them if possible by correlating to information sources such as ADS-B for compliant aircraft and drones, but also to log all unexpected air traffic in the NAS (National Airspace). The use of EO/IR instruments similar to the SDMSI have been shown to be one of the most effective ways to detect and track UAS drones [27]. Using active LIDAR and RADAR along with passive observing, it is imagined that the SDMSI can provide processing to assess safety issues (e.g. birds near civil aviation activity, drones within geo-fenced localities, and drones in the vicinity of people and buildings). Security and safety logs along with select imaging are imagined to be available for selective downlink to tablets or smart phones by users of the system. The SDMSI can in fact be integrated into the Cloud for uplink as well as accessed point-to-point (paired with) over 802.11 and/or Bluetooth Low Energy.

For human monitoring, location of individuals, such as the trespassers shown in Figure 7 on a USCG facility caught in field testing. Trespassing is most often detected through motion, but for example the distinction of human trespassers compared to wildlife activity is a more intelligent form or image saliency and additional cues such as audio can be helpful. The acceleration provided by GP-GPU at the transform layer is likely to be critical to provide real-time skeletal transformation, shape saliency and other more advanced metrics to distinguish wildlife from human activity.

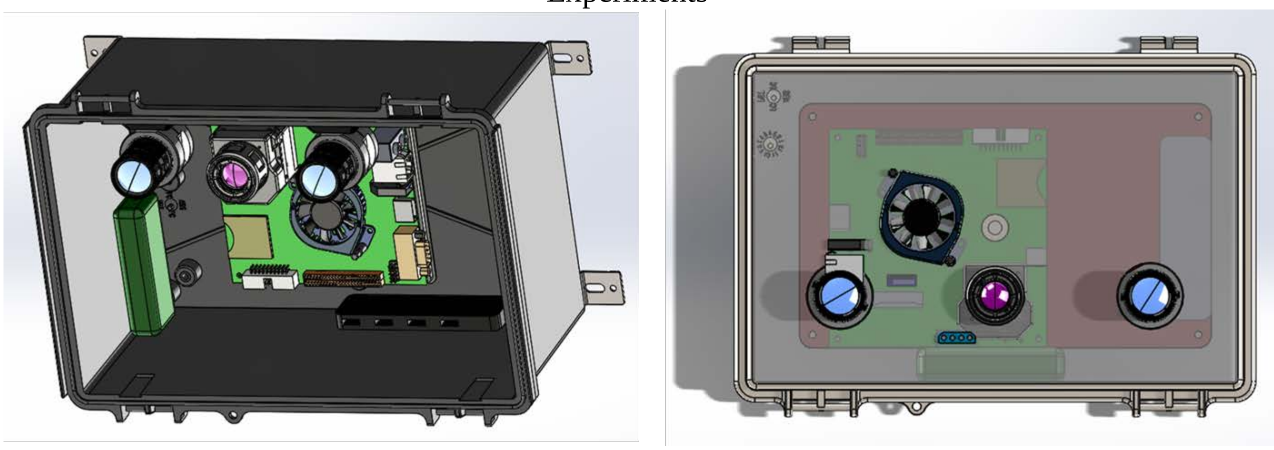
The results from the three basic planned experiments (aviation monitoring, drone monitoring and aerial wildlife) have been analyzed to support or refute the basic hypothesis that a low-cost drop-in-place SDMSI can add value to overall situational awareness when integrated into a network. Likewise, limitations and characterization of spatial, temporal and spectral resolution has been shown to be improved locally compared to other existing options such as satellite remote sensing, human patrol, or continuous capture security cameras systems operating in more limited spectral ranges.

Figure 7. – Trespassers Detected by Audio Cues and LWIR Motion

Experiments with Aircraft and Drone Detection

Following feasibility testing in marine environments, the SDMIS was prototyped and tested on the roof of Embry Riddle Aeronautical University during the fall semester of 2016. Two tests were conducted including aircraft and drone detection, with aerial wildlife detection as an unavoidable by-product of the environment. The aircraft detection experiment was based on a common motion based detection algorithm that used number of pixels changed, maximum deviation of those pixels, and a threshold for that change to trigger positive detection – this simple salient object detector was used as a compare-to baseline for other salient object detectors. The SDMSI was prototyped for these experiments using a weather resistant NEMA (National Electrical Manufacturers Association) enclosure, two visible cameras, one FLIR LWIR camera, and an embedded Linux system for data acquisition and real-time display. Figure 8 shows the based camera physical design.

Figure 8. – SDMSI Prototype Physical Design Used in Aircraft and Drone Detection Experiments



Analysis and Results

ROC (Receiver Operator Characteristic) has been used for RADAR sensitivity and detection performance analysis [17, 18]. The SDMSI makes use of EO/IR (Electro-Optical / Infrared) sensing, which is passive compared to RADAR, but the fundamental sensitivity analysis and performance using an ROC is possible by adjusting algorithmic thresholds as sensitivity. The analysis presented in this paper considers every frame collected during tests. In order to provide ROC analysis of the data, the frames were also graded as P (positive), N (negative) or B (bug) by human reviewers. Several reviewers performance independent grading of the images frame by frame and agreement was within 93.68% or better for a total of 28773 frames reviewed from the two tests (disagreement of only 75 frames for the entire corpus) [21]. A rapid preview tool with simple buttons to classify each and every frame as P, N, or B was used to automate the human assessment used as a truth model. This process was validated and is intended to form a standard method for analyzing and comparing candidate salient object detectors, machine learning for detection and classification (an ROC is a simple two class classifier), which will be further developed as the project progresses. Using this human truth model, the sensitivity of the motion detector was then adjusted up and down to produce the ROC in Figure 9. In this paper we present the results for our baseline motion detector and the BinWang14 saliency map generator which we modified to first do background elimination and to use our motion detector with thresholds to trigger positive identification for objects of interest.

Figure 9. – Receiver Operator Characteristic for Aircraft Observed by SDMSI

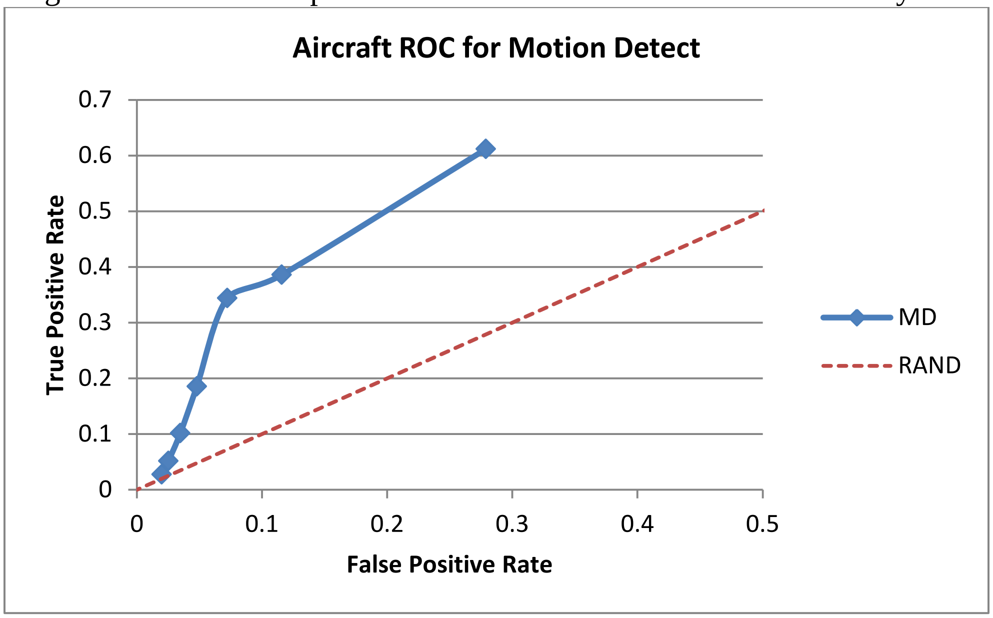
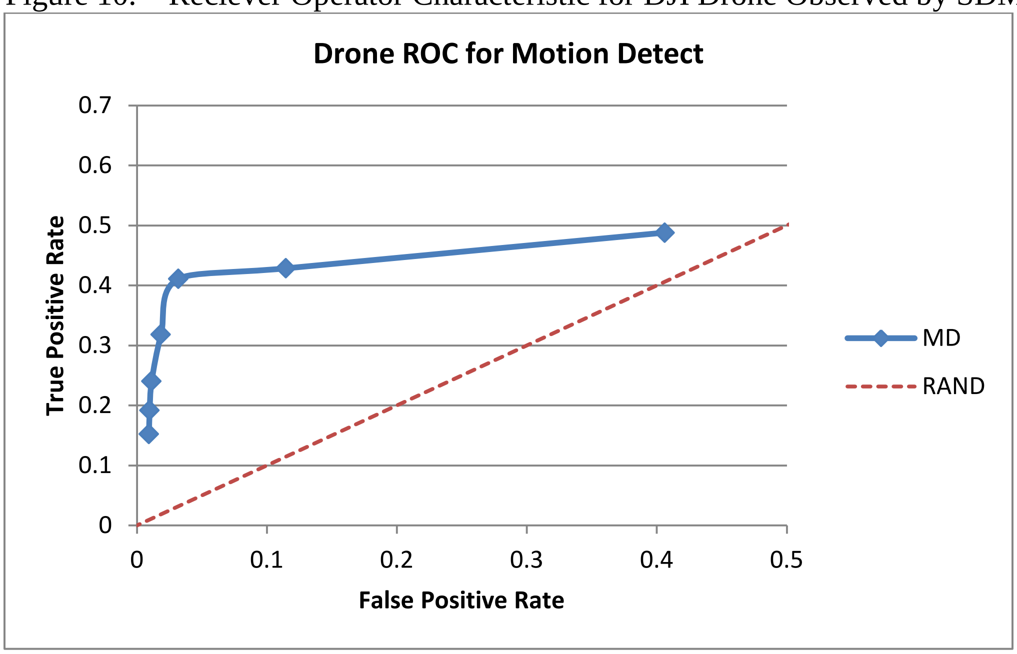


Figure 9 shows that simple motion triggered detection of aircraft results in detection better than random (the dashed diagonal shown on the ROC), but to detect more than 60% of all passing aircraft, the false positive rate with a sensitive threshold configuration is almost 30%. This same simple motion detector was also tested with flights of a DJI Inspire drone to determine detectability compared to aircraft. Figure 10 shows and ROC for this drone test.

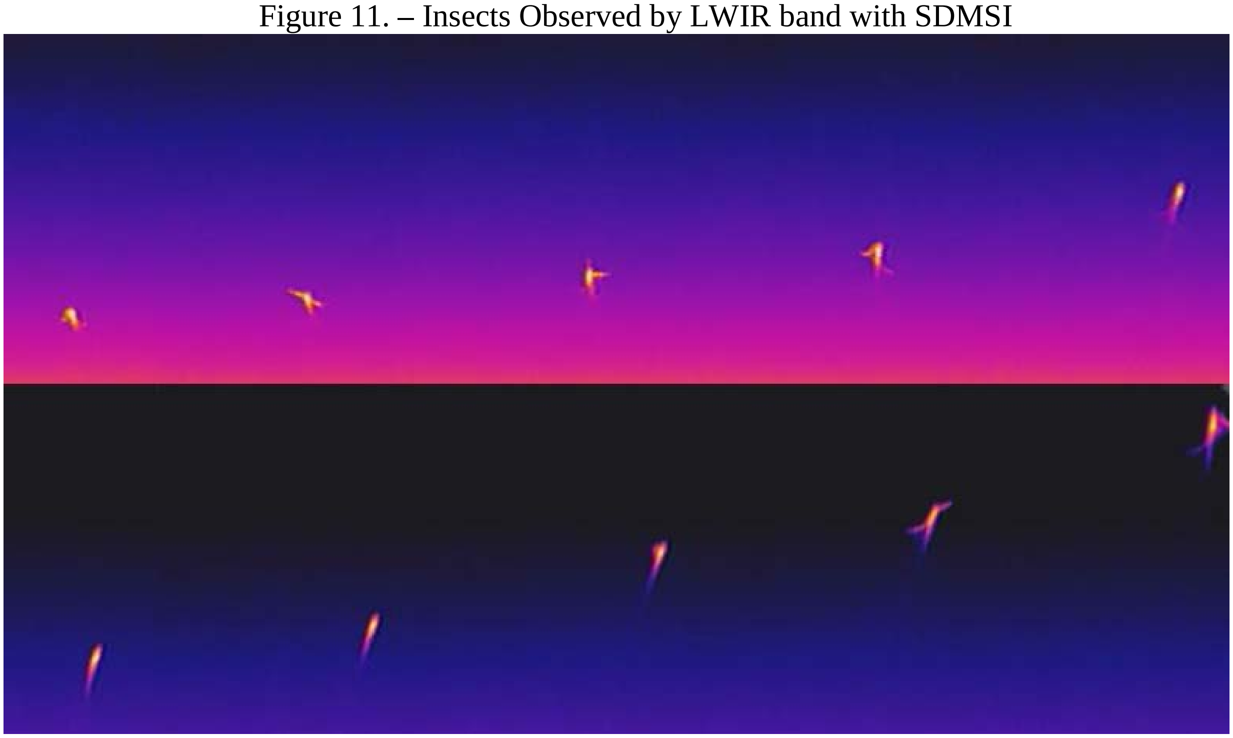
Figure 10. – Reciever Operator Characteristic for DJI Drone Observed by SDMSI



In both cases, the ROC is better than random and has generally positive detection, but with higher false positives as sensitivity is increased and not much better than 50% true positive detection for the drone. Since motion detect is the most widely deployed and used security method for image selection for display and storage, we felt this was a good compare-to baseline for all proposed new methods of salient object detection and more advanced object classification. Our team implemented several other salient object detectors including a color and contrast histogram methods [22, 25], super-pixel [23] and the BinWang14 found as an example in OpenCV [19]. Presently the only advanced method of salient object detection we have been able to make produce comparative results is BinWang14. Salient object detectors are sensitive to parameters and thresholds and often segment images to form saliency maps rather than detecting specific objects of interest. While we have not found a SOD that is better than our baseline, we present what we found using our modified BinWang14 SOD as an example of our methodology for comparing detectors to be used in our aviation and marine domain which includes significant challenge to minimize false positive rates in an ROC.

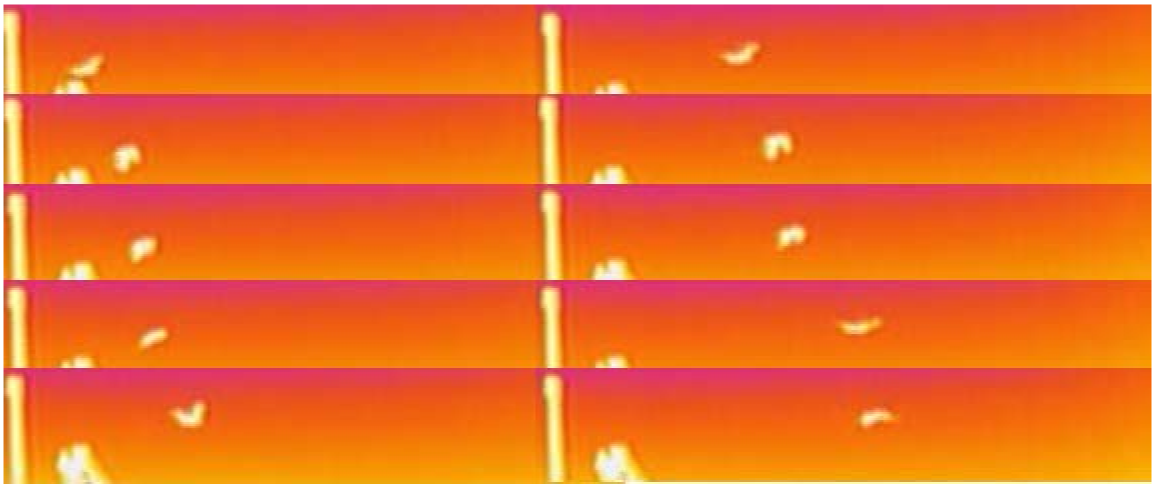
One biggest challenge with EO/IR detection methods, which will also be an issue for the SDMSI, is false positives triggered by other flying objects which require more than just motion characteristics to distinguish. These false positives could either be filtered (rejected) or perhaps correctly classified in a multi-object-of-interest scheme. For example, during the SDMSI tests, many insects and birds were detected and were not readily distinguishable from drones or aircraft with simple motion detection. Figure 11 shows insects, which were easily distinguished by human review based upon shape, flight trajectory, and behavior. Shape and motion behavior are saliency metrics that can be codified and used to enhance detection and classification to distinguish insects form aircraft and drones [20, 24].

Figure 11. – Insects Observed by LWIR band with SDMSI



Likewise, numerous birds and flocks of bird were observed during testing as shown in Figure 12, where a single large hawk (or similar bird) was observed.

Figure 12. – Bird Observed by LWIR band with SDMSI

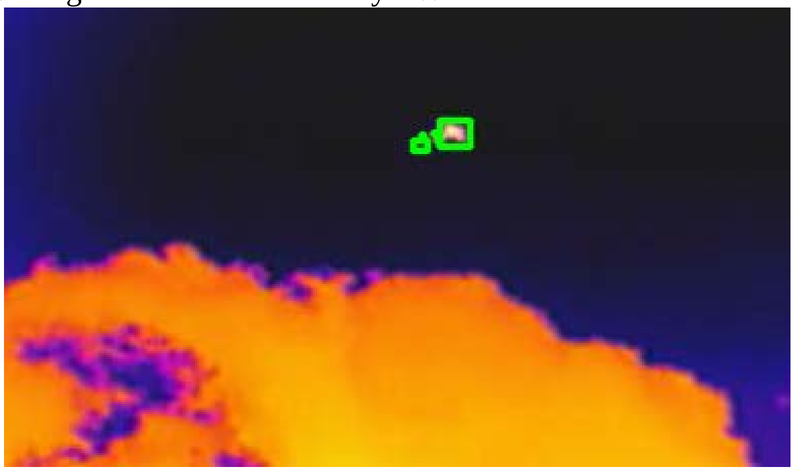


At this stage of SDMSI development, visible images were tested along with 10-14 micron LWIR, but not yet fused. Rather both were tested with the same object detection algorithms. For example, drone detection was evaluated using both LWIR and visible images in one combined test as shown in Figure 13.

Figure 13. – DJI Inspire Drone Observed by LWIR and Visible band with SDMSI

Figure 14 shows one of the many aircraft detected by simple motion based detection during the two experiments completed.

Figure 14. – Light Aircraft Observed by LWIR with SDMSI and Marked Positive

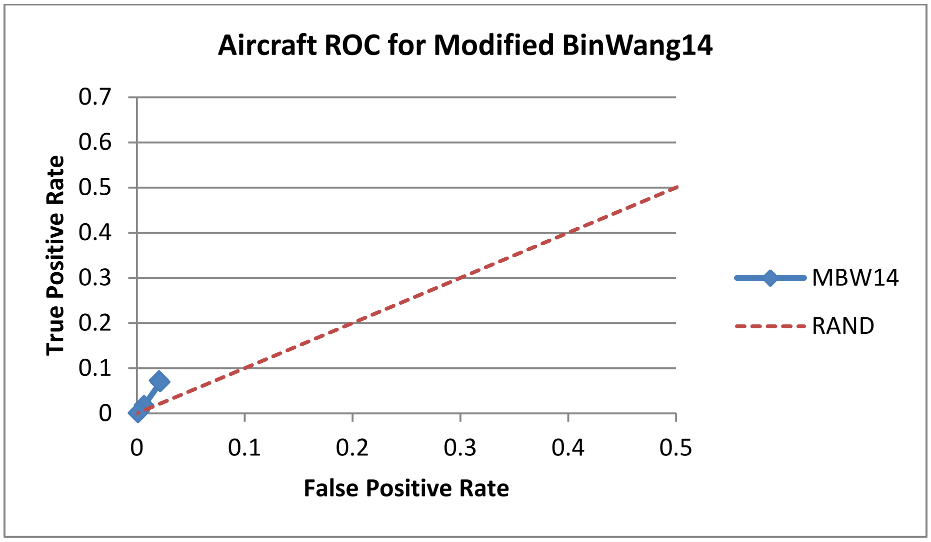


The work presented here has established methods of analysis using ROC for our group so we can compare basic motion detection to shape, behavior, color/contrast/texture, physical characteristic salient object detectors to each other and in hybrid (combined) configurations. For example, the video frames collected in the two experiments were re-played and evaluated using the BinWangApr2014 salient object detector [19]. The BingWang14 SOD (Salient Object Detector) is a motion based detector similar to our simple binary threshold detector with statistical significance thresholds, but it is described as having superior saliency segmentation. We use BinWang14 preceded by background elimination and with the saliency map output processed by our basic motion detector.

The goal was to see if we could improve ROC performance. So far with our limited results with just one alternative SOD, we have not been able to show improvement. For follow-on work we plan to test more candidate SODs and to potentially construct novel methods that account for multiple salient characteristics such as combined shape, behavior, thermal signature, audio cues and color/contrast. Based on our preliminary investigation reported here it seems that the main limitation of most SODs is that they focus on just one characteristic.

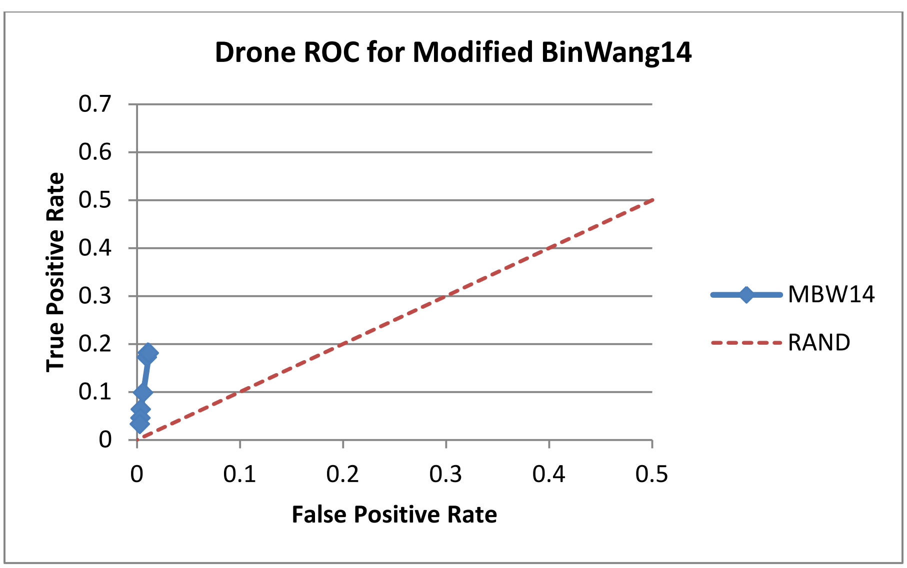
Our negative result with BinWang14 seems to indicate that in fact improved algorithms for saliency mapping by one characteristic method does not lead to improvement in detection performance. The negative result therefore appears to support our hypothesis that multi-modal sensing and multi-characteristic salient object detection is required. As such, in future work we plan to combine SODs into hybrid algorithms that make use of first principle characteristics such as those enumerated in Table 1, or to make use of machine learning methods to extract more rich components for detection with higher dimensionality. Figure 15 shows the resulting ROC for the same aircraft video frames processed and summarized by our motion detect algorithm in Figure 9. It is possible that we have not appropriately used the BinWang14 saliency map with our method of detection, but it does not look promising that a single characteristic approach based on motion alone will provide significant improvement over our simple baseline method.

Figure 14. – ROC for Aircraft Observed by SDMSI and Processed using Modified BinWang14 Saliency Segmentation



Interestingly the BinWang14 saliency map reduced ROC performance despite simplifying the foreground and background segmentation. Based on subjective observation, the most likely reason is over filtering of the salient segments. The goal in using BinWang14 was simply to test the compare-to design for use of a wide range of SODs with the SDMSI. Long term, the goal is to allow for rapid comparison of SODs for both aviation use and use in marine environments where image and information fusion can be used together to optimize detection and classification. The modified BinWang14 was also tested with the drone flights and likewise found not to perform better than a simple motion detector as can be seen by comparing Figure 10 and Figure 15.

Figure 15. – ROC for DJI Inspire Drone Observed by SDMSI and Processed using Modified BinWang14 Saliency Segmentation



Previous work to select the most power efficient processing for the SDMSI has shown that GP-GPU co-processing is one of the most efficient approaches and the NVIDIA Corporation Tegra K1 system on chip was used for all experiments. At peak power, the system draws no more than 20 Watts for processing and for operation of all three cameras concurrently and is nominally operating at 12 Watts of power consumption during bench test measurement with a DMM for the experiments presented [1]. At this time, this is well within requirements for roof operation, but further work on power efficiency is being pursued to enable battery, alternative power source and fuel cell operation of the SDMSI for operation off-grid.

The ultimate goal for the field trials and experiments with the SDMSI is to determine feasibility and value of using this software defined smart cameras for deployments such as buoys, vessels and UAV systems as depicted in Figure 8. The current bill of materials for the experimental configuration is well under $5,000, which is very low cost for a multi-spectral sensing system that has similar spectral resolution to Worldview 2 and 3 (panchromatic, NIR multi-spectral, and longer wave infrared bands) for example if NIR and SWIR cameras are added to the system [15] [16]. Clearly with far less coverage, but with spatial resolution as good or better than sub-meter resolution from satellite remote sensing systems and with far better, continuous temporal coverage of specific areas of interest. The final manuscript will include comparative Worldview 2 image data of the same regions where the cameras are located at times where salient images were collected to compare overall situational awareness provided and to compare spatial, temporal and spectral resolution and features of both as well as cost of monitoring by both methods.

Future work planned includes systematic evaluation of SODs by type and combined configurations of SODs tested in the aviation domain for drone and aircraft tracking as well as marine environments. Further, it is envisioned that other institutions and researchers can easily fabricate our SDMSI using our open reference design so that networks of cameras within one locality or more widely geographically separated regions can share information. This exploration has led to the idea for a “Drone Net’, where SDMSI instruments are networked in the cloud to share detection and tracking information, potentially updating ADS-B and RADAR data aggregation services such as flightradar24 [26].

Conclusion

The SDMSI demonstrates the value of software-defined image analysis systems design, which allows for low-power, low-cost high spatial, temporal, and spectral resolution commonly found in more costly, less compact larger instruments. The software definition requires significant processing capability, but system-on-chip technology enables on-camera transform, fusion, and saliency processing such that uplink of images is selective and pre-processed to reduce bandwidth requirements. The ease of use has been demonstrated and the design allows for upgrade of the SDMSI over time, both hardware components and software. The smart image ranking and selection features provide a significant advantage compared to continuous image capture with processing done only in the cloud, but reducing storage and link bandwidth requirements. The total power is such that the SDMSI can be operated from a LiPo battery for stand-alone aviation deployments or from fuel cell and alternative energy sources in remote Arctic locations. The long term intent of the project is to provide and open hardware, firmware and software design so that other researchers can reconfigure and reuse elements of the SDMSI test configuration presented here, to realize the software-defined goals. For some applications, the cost of custom multi-spectral instrumentation can be reduced by using a software-defined approach as presented here if similar or better overall spatial, spectral and temporal resolution can be provided by multiple cameras integrated and fused by software processing.

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