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Real-time short-wave infrared hyperspectral conformal imaging sensor for the detection of threat materials

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ABSTRACT

There is a growing demand for effective detection of hazardous materials at safe distances in real-time with a high degree of autonomy. In an effort to address this need, ChemImage Sensor Systems (CISS) in collaboration with the Carnegie Mellon Robotics Institute has developed a novel, adaptable, short-wave infrared (SWIR) hyperspectral imaging system for real-time standoff detection of hazardous materials (e.g., explosives, narcotics, etc.). At the heart of this system is the Conformal Filter (CF), which is a liquid crystal (LC)-based tunable filter that transmits multi-band waveforms. Building on concepts of multivariate optical computing, the CF is tuned electro-optically and dynamically to mimic the functionality of a discriminant vector for classification. The resulting integrated detector response approximates the detection response of conventional hyperspectral imaging with only two discrete measurements instead of hundreds to thousands. Real-time detection is achieved by operating two CFs in tandem within a dual polarization (DP) system, which exploits the polarization sensitivity of the LC filters and allows for simultaneous acquisition of the compressed hyperspectral imagery. This improved sampling rate coupled with advanced object recognition, semantic scene understanding, and image reconstruction algorithms enables real-time (i.e., >10 detection fps), on-the-move detection of targets.

This paper will discuss the development, characterization, and test results of the first generation SWIR DP-CF imaging sensor, with a focus on its application to explosives and narcotic threat detection.

Keywords: hyperspectral imaging (HSI), standoff, detection, explosives, drugs, chemical warfare agents (CWAs), compressive sensing, conformal filter, shortwave infrared (SWIR)

1. INTRODUCTION

1.1 Problem and Opportunity

In today's society, there is a growing need for real-time, adaptable, safe, autonomous, standoff detection of chemical, explosive and illicit drug threats to address the resurgence and proliferation of worldwide terroristic activity. Organizations like the Department of Homeland Security (DHS) and the Drug Enforcement Agency (DEA) encounter daily battles against terroristic threats and illegal narcotic smuggling that would benefit from such capabilities. Additionally, state and local law enforcement agencies demand technologies to aid in detecting and classifying unknown materials in hazmat situations as well as crime scene investigations. Security teams responsible for safeguarding large public venues, such as stadiums during popular sporting events and politic events, also have a need for sensing capabilities to detect a wide variety of threat materials at safe standoff distances in real-time. Therefore, the demand for real-time, autonomous standoff detection of threats is ever present and growing for numerous end users.

Hyperspectral imaging (HSI) sensors have been used to detect and identify a variety of targets in the presence of complex backgrounds at a standoff distance. Unfortunately, current generation sensors are typically large, costly to field, lack adaptability to changing threats, do not usually operate in real time and have limited sensitivity and specificity. Evolving the next generation of HSI technology to address current generation sensor limitations will attend to growing detection needs of numerous local, state and federal law enforcement agencies.

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Over the past decade, ChemImage Sensor Systems (CISS) has been developing, validating and fielding HSI sensors capable of standoff, near real-time detection of chemical, explosive and illicit drug threats in complex, real world environments. One of CISS's most recent advancements is a novel, real-time (>10 detection fps), adaptable, compressive sensing SWIR-HSI sensor based on dual polarization conformal filter (DP-CF) imaging technology.[1-4] DP-CF will be capable of being configured in a handheld or vehicle-mounted sensor that provides stationary or on-the-move standoff detection of threat residues on either moving or motionless surfaces, including people and vehicles. DP-CF may prove ideal for route clearance or combat patrols helping soldiers to quickly detect if there is danger ahead. DP-CF is anticipated to have an impact upon maintaining military forces' competitive advantage, especially when fully matured into a lightweight, compact, handheld or wearable system configuration for the detection of critical targets in the presence of complex or interfering backgrounds in an automated fashion and in real-time.

In addition to defense and law enforcement applications, DP-CF is anticipated to support commercial sensing application needs such as quality assessment of pharmaceuticals, food analysis, precision agriculture, textiles analysis, evaluation of plastics, semiconductor defect inspection, illicit drug screening in mail and forensic trace evidence examination.

1.2 Dual Polarization Conformal Filter (DP-CF) Imaging

Unlike traditional liquid crystal tunable filters (LCTFs), which are engineered to transmit a single optical passband at a time, the CF is a multi-passband spectrometer based on CISS's Multi-Conjugate Filter (MCF).[5] CFs can conform, on demand, to discriminate target from complex backgrounds in real-time. In operation, the CF exploits concepts of compressive sensing, involving intelligent (i.e. sparse) under-sampling to reduce data bandwidth, while yielding information-rich results by utilizing redundancy in information across the sampled signal.[6] The CF also uses concepts of Multivariate Optical Computing (MOC), which encodes a chemometric regression or discriminant vector into the transmission function of an optical filter and removes the need for multivariate analysis post processing of the digital image.[7] Similar to traditional MOC devices, called multivariate optical elements (MOE), a chemical prediction is obtained optically by incorporating the optical filter (i.e. the CF) that contains the embedded transmittance profile of the prediction vector into the imaging system. However, unlike the transmission functions of MOEs, which are fixed at the time of fabrication, CFs are tunable and therefore reconfigurable for a variety of targets and backgrounds.

The CF optical computation is performed by convolving the transmission function of the CF with the incident radiation reflected from the target and integrating the result onto a broadband optical imaging detector. The CF approximates the multivariate response of an HSI system, which improves discrimination performance compared to a univariate response, while only requiring two CF tuning states. Chemometric prediction vectors contain both positive and negative components (see Figure 1, red trace). One approach to achieving this characteristic with the all-optical analog is to use two filter transmission functions, T1 and T2, to represent the positive and negative portions of the vector, respectively (Figure 1, blue solid and dashed traces). Subtracting T2 from T1 produces the detection image, where each pixel represents a projection onto the optical prediction vector. To account for variations in lighting intensity, the difference in T1 and T2 is normalized to its sum (T1+T2). In practice, both T1 and T2 are determined for a single material of interest, but a LC-based CF can be also be tuned for the T1 and T2 characteristic of other materials of interest. Therefore, it is capable of material agile operation and can be readily adapted on demand via software control to align with mission requirements.

DP-CF incorporates two CFs and is shown conceptually in Figure 1. In this approach, light reflected from a surface of interest is directed to a polarizing beamsplitting cube. Half of the light passes through to a CF orientated parallel to the polarized light. This CF is tuned to the T1 conformation for the material of interest. The other half of the light is directed to a second CF, which is oriented perpendicular to the polarized light and tuned to the T2 conformation for the material of interest. The two polarized light channels are recombined with a second beamsplitter and are directed to the FPA. Each conformation occupies half of the FPA and, with the use of sophisticated algorithms, the image is processed to achieve detection of a material of interest. Employing this DP approach allows both filter conformations (T1 and T2) to be acquired simultaneously, thus requiring only one camera readout to achieve a detection and enabling detections at the frame rate of the camera.

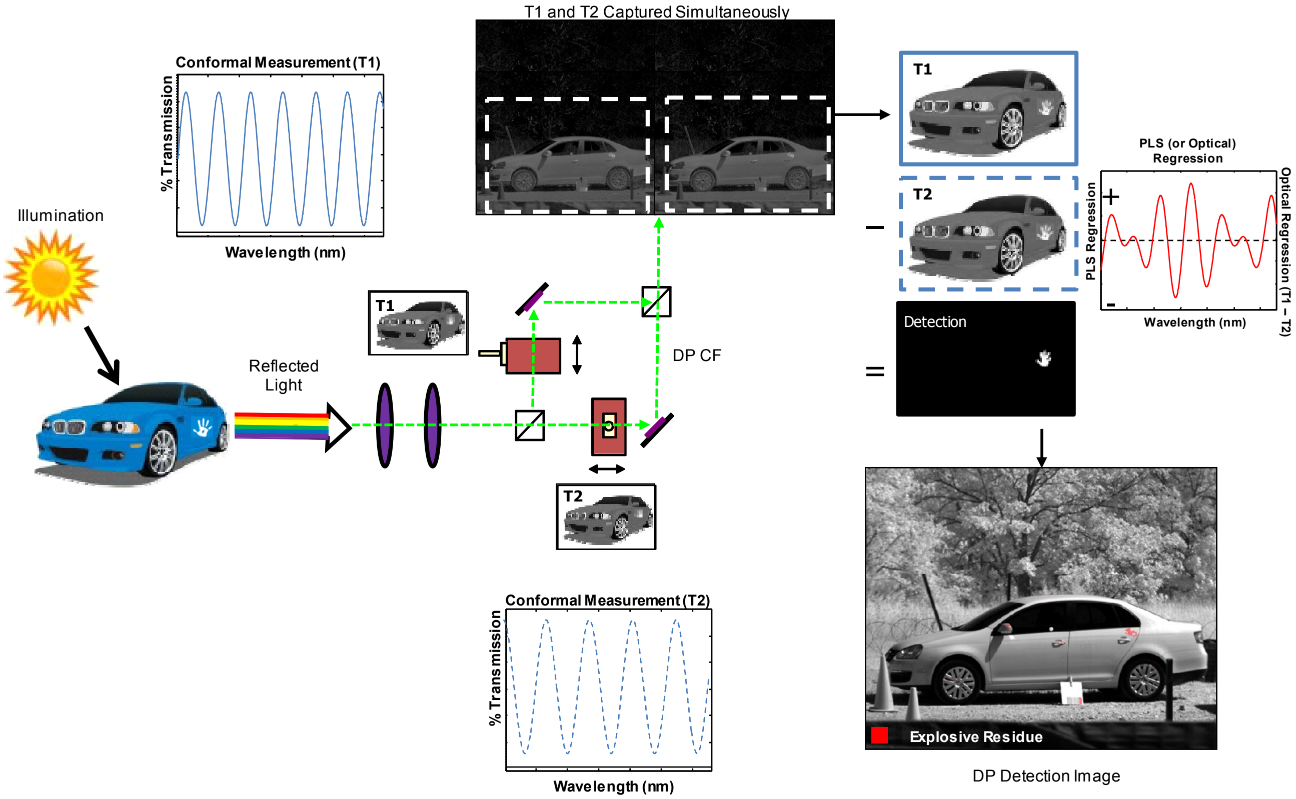

Figure 1. Dual-Polarization Conformal Filter (DP-CF) Imaging Concept. DP-CF produces optimized spectral passbands on demand, which can readily be re-configured, to discriminate targets from complex backgrounds in real-time.

1.3 Multivariate Sensor for Mobile Platforms Program

To address limitations of currently fielded HSI systems, CISS has partnered with Carnegie Mellon University's School of Computer Science (Robotics Institute) in a prototype real-time DP-CF based HSI sensor development effort entitled, "Multivariate Sensor for Mobile Platforms". The primary objectives of this self-funded effort were to explore the capabilities and limitations of the DP-CF technology at a fundamental level and assess potential deployment across strategic robotics applications. We report here a summary overview of results from our internal research and development effort.

2. METHODOLOGY

2.1 Prototype Hardware

In order to validate the DP-CF imaging approach, CISS designed and built a prototype DP-CF sensor. Figure 2(A) shows a labeled diagram of the internal sensor head components and Figure 2(B) shows a photograph of the final prototype mounted on a tripod equipped with a pan/tilt unit. In operation, solar radiation or artificial lighting illuminates targets of interest. Photons are selectively absorbed and/or reflected depending on the chemical makeup of the materials present in the field of view.

In traditional sequential tunable filter-based HSI, a full hypercube of SWIR hyperspectral images, or a smaller set of SWIR multispectral images, are collected via a liquid crystal-based imaging spectrometer to an uncooled FPA detector. With a full hypercube each pixel in the image has a fully resolved spectrum associated with it; therefore multiple components in the field of view will be distinguishable based on the varying absorption that the materials exhibit at the individual wavelengths. The spatially-resolved SWIR spectral signatures are compared to a SWIR-spectral library using pattern-matching algorithms. The individual components of interest are uniquely identified based on the absorbance properties. The same technology may be operated in a near real-time mode by collecting a smaller set of SWIR multispectral images (less than 10 images) and identifying components of interest through model building or image processing on this subset of spectral bands. However, true real-time (i.e., >10 detection fps) cannot be achieved using the traditional sequential tunable filter-based HSI approach.

DP-CF technology provides a means for true real-time HSI imaging. The DP-CF imaging spectrometer unit incorporates two CFs. The CFs are derived from ChemImage's multi-conjugate filter (MCF)[5] and utilize a subset of the MCF filter stages. The details of the design process (i.e. selection of the appropriate filter stages) and fabrication of the SWIR CF has been discussed previously.[1] The CFs used in the experiments described below consist of two MCF stages (of six possible), in which a single voltage controls the transmission function of each stage and the convolution of the two stage profiles determines the final CF transmission function.

The DP-CF spectrometer unit (Figure 2(A) splits the light captured by the front end optics into opposite polarizations via a polarizing beamsplitter. Each polarization of light is directed through a different conformal filter. The filtered polarizations of light are then recombined by a second polarizing beamsplitter and each is focused onto one half of the FPA. A set of polarizers are also attached to the front of the FPA in order to reject any light coming from the adjacent image in order to minimize polarization crosstalk. The DP-CF prototype provides spatial sampling of approximately 5 mm/pixel at a 10m standoff distance correpsonding to a 16° horizontal angular field-of-view (FOV) and a 10° vertical angular FOV after taking into account the coregistered T1 and T2 conformations imaged onto adjacent portions of the FPA.

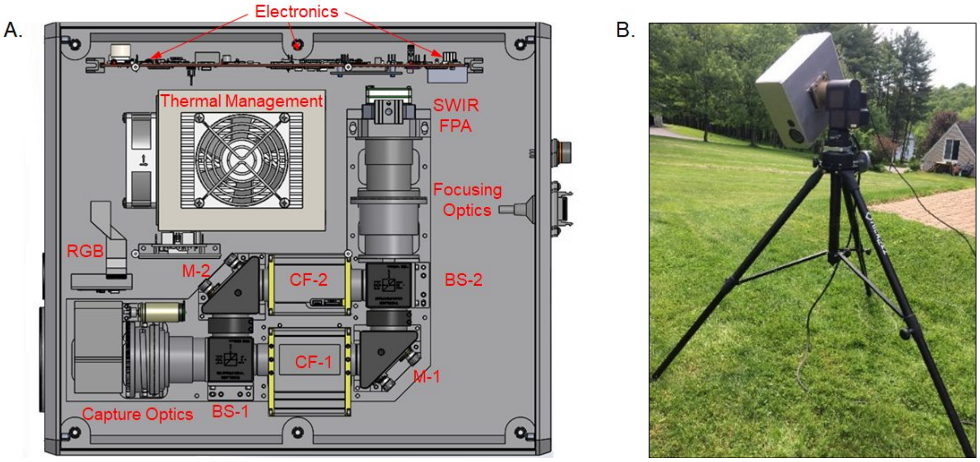

Figure 2. Solid model schematic of the internal sensor head components (A) and digital photograph (B) of the DP-CF prototype sensor.

2.2 Prototype Software

Two software packages were used to carry out the testing and subsequent data analysis. CISS's Conformal Optimization software was used to control the CFs and InGaAs FPA as well as to produce Receiver-Operator Characteristic (ROC) curves. The Conformal Optimization software provides a means to optimize the liquid crystal voltage selection in order to maximize the distinction between target and background pixels based on area under the ROC curve (AUROC) values as well as to co-register and flatfield the T1 and T2 portions of the DP-CF images. CISS's Spectral Kitchen™ software was used to load optimized voltage settings from the Conformal Optimization program and to set and apply detection threshold parameters to enable real-time, autonomous detection imagery.

2.3 Detection Image Formation

Chemical-based detection images are generated from score images derived from the pixel intensities measured at a particular CF tuning state. Here, score images are calculated as the difference of two CF tuning state images, T1 and T2, normalized to their sum: T1-T2/T1+T2. The difference of the pair mimics the result produced by taking the inner product of a target spectrum and the positive (T1) and negative (T2) lobes of a discriminant vector. Division by the sum of T1 and T2 acts as a normalization factor to account variations in light intensity. T1 and T2 images are collected simultaneously on the same FPA (at different pixel locations) with two different CFs, one tuned to T1 voltages and the other to T2 voltages.

Prior to score image calculations, the raw T1 and T2 images are corrected for dark current noise and uneven illumination of the FPA, which may result from uneven illumination of the FOV as well as a spatially non-uniform response of the lenses, filters, and other optics. A single dark current image is collected with no light entering the sensor and is subtracted from all raw images. The flatfield correction images are collected of a 99% reflectance standard with a specific set of voltages applied to the CF. Each dark current corrected data image is flatfield corrected via division. The dark current, flatfielded FPA image is then cut into two vertical images and co-registered.

The final step in detection image formation is to process the DP-CF generated score imagery using Spectral Kitchen's Shortwave Infrared Automated Detection Algorithm (SWIR-ADA). SWIR-ADA is a real-time autonomous detection algorithm that is designed to detect and display the location of residue to bulk amounts of threat materials within a scene by false-colorizing pixels that spectrally match target materials for which the sensor has been trained. The algorithm process applies spatial, spectral and temporal processes to optimize detections performance.

2.4 Samples

CONOPs-specific target materials were selected to test the performance of the prototype DP-CF sensor. These materials included an illicit drug simulant (acetaminophen or APAP), two explosive precursors (HME-1 and HME-2), and one chemical near-neighbor to HME-2. Threat simulant material amounts were approximately 1 g for range-dependent measurements. Limit-of-detection (LOD) samples were prepared for HME-1 using a spray deposition technique on white ACT car coupons. LOD sample concentrations varied between 0 $\mu g/cm^2$ (control) and 2,000 $\mu g/cm^2$. Moving target example deposition concentrations varied from $\mu g/cm^2$ to mg/cm^2 quantities for residue depositions and g/cm^2 quantities for bulk material studies.

2.5 Testing and Data Analyses

One objective of our testing was to demonstrate target analyte (material or class) detection in the presence of interfering species and background materials in both controlled indoor settings and less controlled outdoor (i.e., "real-world") settings. In addition to the experiments and results discussed below, the sensor was evaluated for basic optical performance (i.e., spatial sampling, FOV and spatial resolution), noise performance (noise equivalent absorbance (NEA) and stray light), impact of other variables on detection (i.e., location of target in the scene, lighting levels and integration time optimization).

Detection Performance vs Range (Pd, Pfa, Td, Latency)

Detection performance versus range studies were conducted to understand the impact of range on probability of detection (Pd), probability of false alarms (Pfa) and time to detect. The DP-CF sensor was initially trained to detect HME-1 using CISS's Conformal Training software. Detection imagery was then captured of approximately 1mm thick target and confusant samples sandwiched between 1" x 3" glass microscope slides taped to a dry erase board covered with 97% reflective paper using the prototype DP-CF sensor positioned at 1m, 5m and 10m ranges to target, respectfully. The 97% reflective paper was used to enable light level assessments from the perspective of the sensor at the various standoff distances. Data was processed to assess Pd, Pfa, Td, score value and image signal-to-noise ratios (ISNR) as a function of range. Detection latency was accessed using a stopwatch to measure the difference in time between an action and the subsequent detection response as displayed to the user on the computer screen.

Sensitivity (LOD)

Limit-of-detection (LOD) studies were conducted to understand the analytical limits of detection associated with the DP-CF sensor. Nine (9) LOD coupons containing HME-1 were imaged sequentially over three replicate measurements at a standoff distance of 1.5m. Score image pixel-based AUROC values were computed for each deposition relative to blank coupon from which a plot of AUROC versus concentration was generated. The LOD was then computed by fitting the linear portion of the plot. The LOD was computed as the concentration corresponding to two standard deviations of the mean blank sample AUROC.

Selectivity (Powder Discrimination)

Selectivity studies were conducted to assess the discriminating power that conformal sensing provides for a wider range of materials. DP-CF images were captured from a selection of 103 white powders by iterating two voltages from 1.5V to 4.5V at a step size of 0.1V. This resulted in 961 images associated with the T1 CF channel and 961 corresponding images associated with the T2 CF channel. The data was aligned and white balanced. "Signature images" associated with all 103 samples were generated resulting from the normalized response for each material for each voltage setting. Support vector machine (SVM)[8] and k-nearest neighbor (KNN)[9] data analyses were applied to the "signature image" data using a leave-one-out testing methodology to assess the overall accuracy in discriminating edible from non-edible powders.

"Real-World" Real-Time Moving Target Detection Examples

Two "real-world" examples were used to demonstrate the feasibility of DP-CF sensing in such settings. In the first example, HME-1 simulant material was applied to both a stationary car door and a back pack being carried through the sensor FOV by a human subject at a ~10m sensor to target range. Detection image movies were generated in real-time (~15 detection frames/sec). In the second example, a small plastic baggie containing a bulk amount of HME-1 was attached to a drone and flown in random directions at a nominal 30 m sensor to target range. Again, detection image movies were generated in real-time as the drone was moving about the scene.

3. RESULTS

3.1 Detection Performance vs Range (Pd, Pfa, Td, Latency)

Figure 3 shows representative detection performance results as a function of range. Detection images were generated at 1m, 5m and 10m standoff after training the DP-CF sensor to detect HME-1. Detections were obtained for the HME-1 sample at each distance without any false alarms. Figure 3A and 3B show detection images at 1m and 5m, respectively. Pixels with red false coloring provide an indication of where in the image HME-1 is detected. With this target set at these sample concentrations, Pd=100% and Pfa=0% at each distance (Figure 3C). The impact of score values associated with HME-1 and the background pixels versus distance is shown in Figure 3D. As range increases, the score values for both target and background decrease, but at a faster rate for the target score values. Figure 3E shows ISNR plotted against standoff distance. Over these three distances, the ISNR is fairly constant around 100:1.

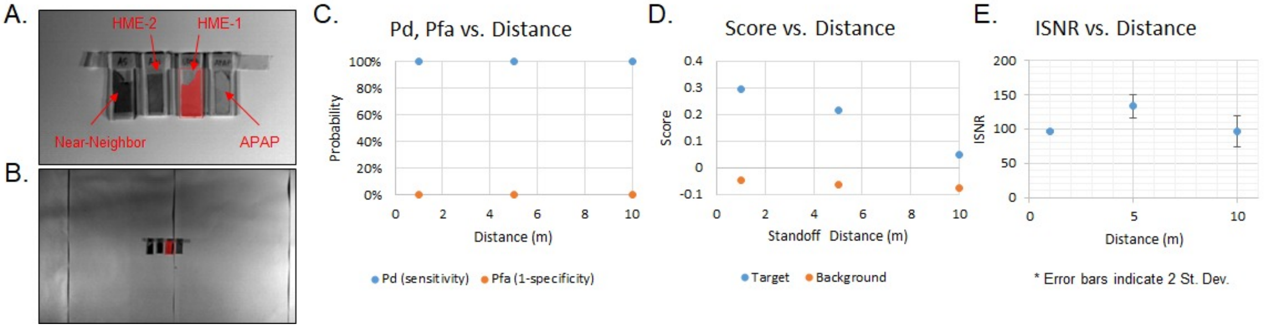

Figure 3. DP-CF prototype detection images of test targets at 1m (A) and 5m (B); Pd / Pfa versus distance (C); target / background score values versus distance (D); and target ISNR versus distance (E) for HME-1.

Td and detector latency was also assessed during this portion of the experimentation. The Spectral Kitchen software provides an indication of the detection frame rate achieved. The detection frame rate fluctuated slightly over time, but averaged around 12 detection fps. The detector latency fluctuated between 1.5s and 2.0s.

3.2 Sensitivity (LOD)

Figure 4 shows a representative digital photograph (Figure 4A) and HME-1 score imagery from 254μg/cm^2 (Figure 4B), 1,091μg/cm^2 (Figure 4C) and 1,976μg/cm^2 (Figure 4D) coupon samples, respectively, captured using the DP-CF prototype sensor. LOD computation was performed based on the linear portion of the calibration curve (Figure 4E). HME-1 LOD based on AUROC was estimated to be 135 μg/cm^2.

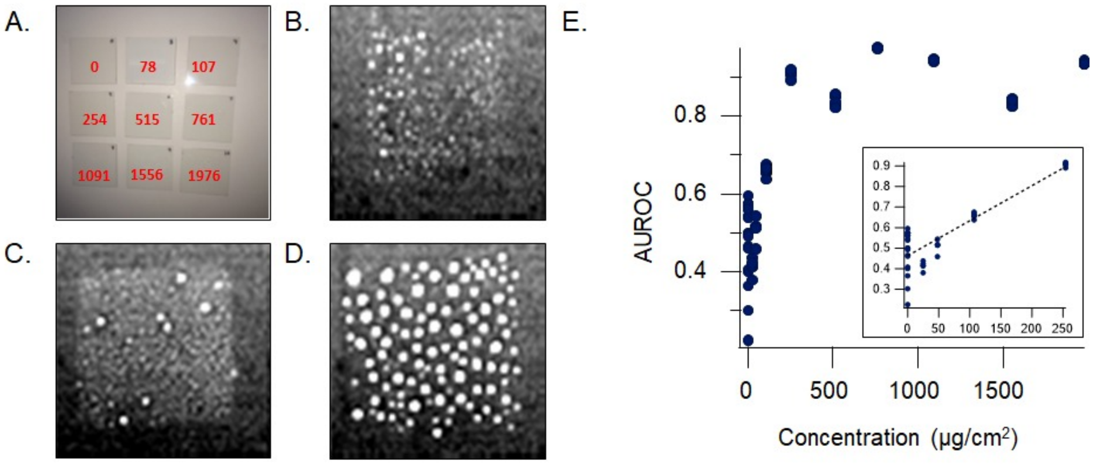

Figure 4. Limit-of-detection (LOD) results during prototype testing: Digital photograph of all LOD samples (A); DP-CF score images of 254µg/cm^2 (B), 1091µg/cm^2 (C) and 1,976µg/cm^2 (D); and calibration curve used to estimate LOD (E).

3.3 Selectivity (Powder Discrimination)

Figure 5A shows a representative digital photograph of one of the 103 powder samples (i.e., cane sugar sample (left) and a reflective white patch (right) for white balancing). Figure 5B and 5B' show SWIR imagery captured of the cane sugar and white patch sample with the DP-CF prototype through the T1 and T2 channels, respectively, for a variety of voltage settings. Figures 5C and 5C' show example SWIR spectra associated with the T1 and T2 channels, respectively, as measured by a Fourier Transform Infrared (FTIR) spectrometer. Figures 5D and 5D' show "signature images" for the T1 and T2 channels, respectively, associated with all 103 powder samples where each square area within the image is a 31 x 31 pixel image with normalized response for each unique voltage setting. Qualitatively, the unique "signature image" that each powder demonstrates the inherent specificity associated with the underlying DP-CF technology.

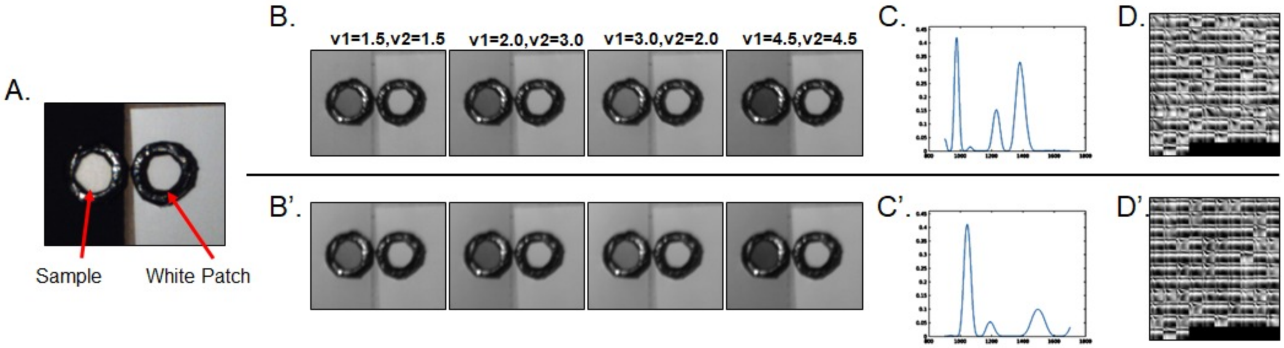

Figure 5. Sensor selectivity testing: Digital photograph of cane sugar and a white reflector (A); SWIR images at various voltages for T1 (B) and T2 (B'); Representative SWIR spectra associated with T1 (C) and T2 (C'); and composite "signature images of all 103 powders for T1 (D) and T2 (D').

Figure 6 shows a hierarchical clustering dendrogram analysis result generated from the "signature images". In this analysis, each normalized response from the 31 x 31 voltage settings is treated as a point in a 961 point spectral vector. Each of these spectral vectors was then fed into KNN and SMV algorithms using a leave-one-out test in order to assess the accuracy of classifying each powder as either edible or non-edible. The KNN produced a classification accuracy of 84.5% while the SVM analysis resulted in an accuracy of 82.5%. The spectroscopic basis for this result is likely closely tied to whether or not the material in question contains certain organic compound group functionalities that are assessable in the SWIR spectral range. Many organic chemical compounds are readily assessable in the SWIR spectral range while most inorganics are not.

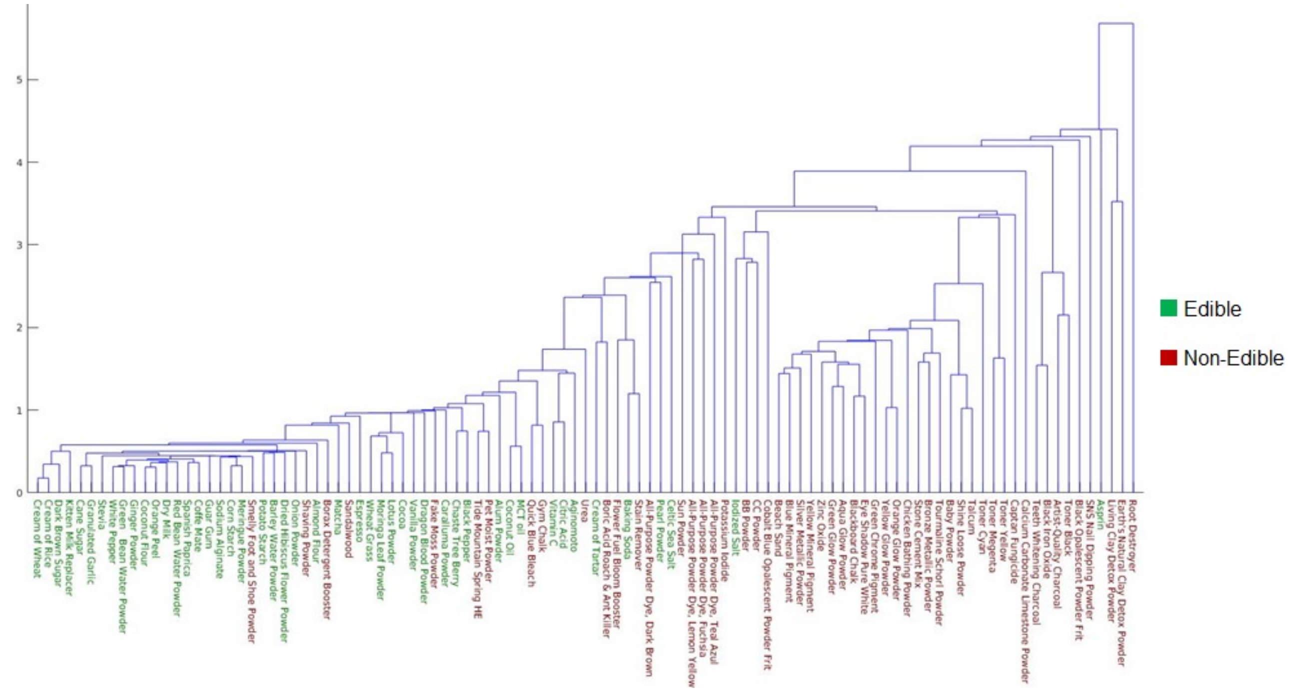

Figure 6. Hierarchical clustering dendrogram analysis of “signature images” associated with 103 powders classified as either edible or non-edible.

3.4 “Real-World” Real-Time Moving Target Detection Examples

Figure 7 shows results from recent “real-world” testing of the DP CF prototype. Figure 7A shows a digital photograph of a plastic bag containing bulk amounts of HME-1 attached to a small drone. Figures 7B-D show select time-sequenced HME-1 detection imagery generated by the DP-CF prototype of the drone carrying HME-1 around the tree tops approximately 30m from the sensor. Figure 7E shows a digital photograph of a backpack containing HME-1 residue. Figures 7F-H show select time-sequenced detection imagery generated by the DP-CF prototype of the backpack being picked up and carried away by a person. Figure 7F and 7G also show stationary depositions of HME-1 applied to a car door also in the scene. This result demonstrates the ability to capture residue-level detection imagery of threat target materials that are both stationary and moving in a common scene. In each case, the sensor was trained to detect HME-1 using the Conformal Filter Training Software. Real-time, continuous detections at a frame rates up to 16 detection fps were achieved using Spectral Kitchen.

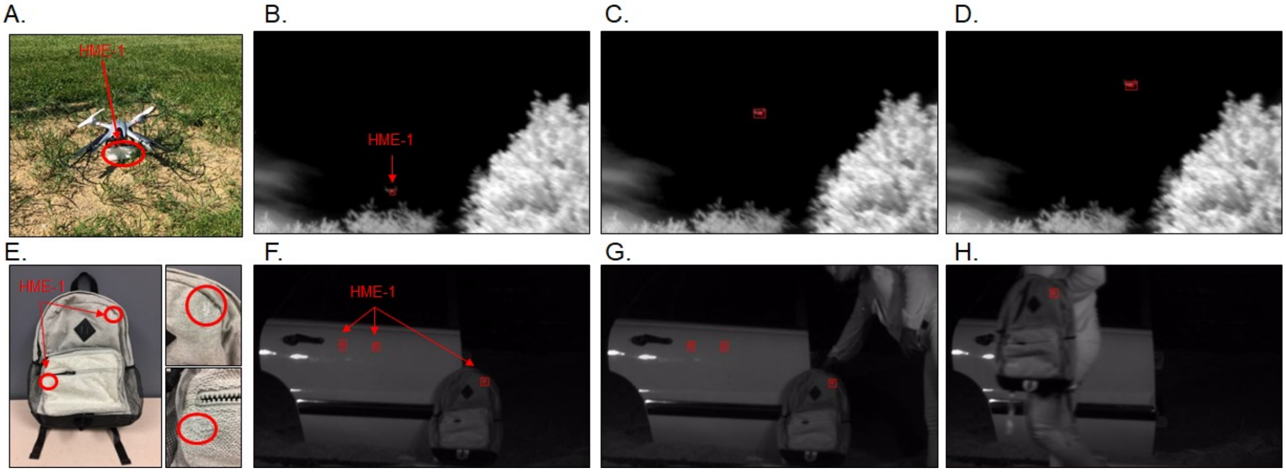

Figure 7. Digital photographs of a drone carrying a small bag of HME-1 (A) and a backpack containing HME-1 (E) and a series of detection images from HME-1 detection video of the drone flying (B-D) and the backpack being picked up and carried away by a person (F-H) generated using the DP-CF prototype.

4. CONCLUSIONS

CISS has successfully designed, built, and conducted preliminary testing of a prototype DP-CF sensor to establish the feasibility of Conformal Imaging for real-time, real-world, moving target applications. Preliminary test results demonstrate the potential for DP-CF as an autonomous, multi-material, real-time standoff threat detection device. Further, DP-CF addresses many shortcomings of current generation systems and offers improvements in operational agility and detection performance, while tending to sensor weight, form factor and cost needs. DP-CF has the ability to conform to a variety of explosive, narcotic and chemical threat detection applications across numerous market segments. DP-CF may be configured to be portable, robot-mounted or standalone - each providing added safety to operators and equipment by enabling operation at standoff distances.

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