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Survey and Insights into Unmanned Aerial Vehicle-Based Detection and Documentation of Clandestine Graves and Human Remains

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Abstract

Numerous biological and archaeological studies have demonstrated the legitimacy of remote sensing in anthropology. Herein, focus is placed on detecting and documenting terrestrial clandestine graves and surface remains (CGSR) of humans using unmanned aerial vehicles (UAVs), sensors and automatic processing algorithms. CGSR is a complex decision making under uncertainty problem that requires the identification and intelligent reasoning about direct evidence of human remains and their environmental fingerprints. As such, it is as much an engineering and geospatial problem as it is an anthropology problem. This article is a cross-disciplinary effort to survey existing work across disciplines and to provide insights and recommendations to assist future research. To support our claims, preliminary experiments are demonstrated at the Forensic Anthropological Research Farm (FARF) at Texas State University using UAVs, hyperspectral imaging, thermal imaging and structure from motion. Prior work, our experience and preliminary results indicate that there is a combination of great potential yet extreme challenges facing remote sensing in CGSR.

During forensic investigations of missing but presumed dead individuals, a combination of anthropological, law enforcement, and civilian search teams work in cooperation to locate, document and recover clandestine graves and surface remains (CGSR). The goal of the search team is generally "to select a detection and recovery strategy that maximizes data recorded and physical evidence recovered from a scene while minimizing scene and evidence alterations (SWGANTH 2013:2)" while avoiding "unnecessarily destructive or time-consuming search and recovery techniques when less destructive and time-conserving techniques are just as effective" (SWGANTH 2013:2). Traditionally, forensic searches for CGSR involve time- and resource-consuming visual pedestrian surveys, trained human remains detection dogs, and/or geophysical prospecting methods in high probability areas (France et al. 1997, Kalacska and Bell 2006, Ruffell and McKinley 2008). However, accurate CGSR detection is often difficult because of factors such as large geographical areas to cover, vegetative obstructions, rough terrain, and the potential for hazards (e.g., venomous snakes). In addition, these methods have the potential to result in accidental alterations of the scene before it is thoroughly documented.

There are a multitude of tasks in the discovery, documentation (e.g., mapping), collecting, and securing of all transportable and nontransportable evidence. First, there is the task of CGSR detection. Second, there is the task of pre-entry documentation to develop a plan that maximizes data collection and minimizes scene alteration. Third, there is documentations of the scene including spectral and spatial relationships of evidence. Fourth, there is the question of how to use this information post-search (e.g., further analysis or legal purposes). This is not a comprehensive list, it merely stresses the different avenues and lines of CGSR research.

This article is a review and discussion of remote sensing-based CGSR via unmanned aerial vehicles (UAVs) for terrestrial outdoor scenes. We focus on sensors, UAV delivery and algorithms to process that data. While we review existing work in remote sensing for CGSR, we also highlight engineering hurdles and relevant non-CGSR research outside of anthropology. To substantiate and help illustrate our claims, preliminary experiments are provided on infrared, hyperspectral (HS) and structure from motion (SfM) at the Forensic Anthropology Research Facility (FARF) at Texas State University. Our goal is to highlight state-of-the-art, to provide insights and recommendations to guide future work, and to support these claims through references and preliminary experiments. However, this is not a trivial task because CGSR is a multidisciplinary challenge. There is an overwhelming amount of biology, forensics, remote sensing, algorithms, etc. that prohibits our survey paper from doing a deep dive into any one topic. As such, we attempt to review, highlight, and connect, at a high-level, the different pieces of the CGSR puzzle.

In CGSR search, one of the first steps is to identify and secure an area. Multiple factors go into developing the search plan, such as information about the scene, terrain, personnel, resources available, and daylight. Example methods of search include visual or pedestrian searches, animals (e.g., dogs), soil probes, metal detectors, ground penetrating radar, thermal hand-held units, and aerial photography. The initial task is to locate human remains. To this end, the search team has a rough expectation of the forensic scene, an idea of what might be considered “normal” relative to the forensic and search environment and of course they ultimately rely on the genius of human intelligence for tasks like object and anomaly detection. In summary, CGSR search is not a trivial task and technology to date has existed to support, not replace, human search.

In the context of supportive technologies, UAVs are an instrument that has the potential to revolutionize law enforcement. Recently, the U.S. Department of Justice’s (DOJ) Office of

Community Oriented Policing Services (COPS) established guidelines (Valdovinos et al. 2016) to enhance community trust in UAVs. COPS referred to UAVs as game changers for domestic policing, given their characteristics (i.e., accessibility, cost, size, weight, portability and payload possibilities) and ability to fly into dangerous spaces without endangering the life of officers. COPS work is holistic, informative and policy based. Specifically, what benefits do UAVs pose for CGSR? For beginners, many UAV-mounted sensors (e.g., thermal, radar, etc.) detect evidence outside the range of human vision. In general, sensors can be categorized into i) passive or active (the latter emits a signal) and ii) surface or penetrating (the latter allowing for imaging of obscured objects, e.g., in ground). Second, UAVs can help us systematically search large areas and aid in pinpointing high probability areas. Their data can be processed by computers, analyzed by an expert or some combination of the two. Third, UAVs have the potential to provide a cost- and time-effective way to obtain a high resolution (spectral and spatial) output for sake of documentation. The point is, UAVs are being used more often, and what role they can play in CGSR must be determined. Figure 1 highlights the different factors relevant to CGSR detection and documentation.

There are concerns about UAVs for CGSR and anthropology in general. First, UAVs and remote sensing are predominantly engineering tasks. For CGSR, it is vital that experts (e.g., search and rescue (SAR) personnel) performing the searches and scene documentation understand what these sensors and platforms can do and how to work with them. Second, UAVs have emerged as a dominant technology in a short amount of time. As a result, confusion reigns about how to operate them legally (e.g., the Federal Aviation Administration's (FAA) regulations). Third, for UAVs with multiple sensor payloads to be accepted and adopted by the academic and medicolegal communities, standards and protocols need to be developed. In summary, this topic has much uncertainty, which equates to exciting opportunities.

Last, we highlight the reality that CGSR is as much an anthropology problem as it is an engineering and geospatial task. CGSR requires understanding, sensing and processing spatial, spectral and temporal data about the body, environment and body-environment. As such, it is important that we do not reinvent the wheel along the way. A great body of relevant research already exists in areas like computer vision, agriculture, soil science, forestry, and national security and defense, to name a few. While a research article might focus on the detection of a specific material (e.g., detection of blood at the scene using HSI as in Edelman et al. (2013)), many of these methods (algorithms) can be directly used for CGSR or used to identify other materials using the same sensor. Whereas we discuss many such connections below, the reader should also refer to quality geospatial sources like the *Transactions on Geoscience and Remote Sensing*, the *Geoscience and Remote Sensing Letters*, the *Journal of Applied Remote Sensing* and the *Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, to name a few.

Forensic Anthropology Research Facility (FARF) Data Collection

This section summarizes our initial data collection at FARF in May of 2017. Data and preliminary results are presented throughout the article. The collection was designed to explore different sensors and to enable early results to direct future research. It was also about collecting data to determine the key challenges within this domain. Data collection lasted two days, and we operated as close to solar noon as feasible; which translated to an approximate window of 11 a.m. to 3 p.m. to fly the missions. Fortunately, the first day presented ideal weather with no clouds. On the second day there was an overcast throughout most of the collection.

Four sections of FARF were selected for examination. In one area with 50 to 90 cm high grass, three shallow graves were present (Figure 2). A second area contained visible cadaver decomposition islands (CDIs) from bodies that had been previously removed (Figure 3). The third area contained uncaged and scattered skeletal remains that had previously been used in a vulture scavenging project (Figure 4 and 5). The last area contained approximately twenty caged remains in various states of decomposition (Figure 5 and 6).

Three sensors were used; a thermal imager, a hyperspectral camera, and an RGB camera. These sensors were deployed on three multi-rotor UAVs, including a custom UAV and two Phantom 4 Pro's. The custom UAV is an octocopter (eight propellers); whereas the other two are quadcopters (four propellers). The thermal imager is a FLIR Vue Pro. This uncooled sensor records thermal radiation in the range of 7.5um to 13.5um. The RGB camera is the standard camera that comes with the DJI Phantom 4 Pro. This camera produces images with a ground sampling distance (GSD) of approximately 2cm per pixel when flying at an altitude of 200 feet. This high resolution is required to compute the three-dimensional SfM data. Last, the hyperspectral sensor used is a Headwall Nano-Hyperspec, which senses radiation from 400-1000nm in 269 spectral bands. With a 9mm lens, it captures a GSD of approximately 6cm from an altitude of 200 feet.

Buried Human Remains (BHR)

The act of burying anything, including human remains, results in an environmental *fingerprint*. On a short time-scale, this results in local disturbances in soil compactness, moisture and mineralogical properties. Substantial disturbance (e.g., a soil mound) can often be detected by the eye. As time increases, other methods such as ground penetrating radar (GPR) and HSI are often used. For example, Conyers and Goodman (1997) used a non-aerial platform and GPR to image below the surface. However, most GPR platforms are expensive, heavy, large, and system (antenna, transmit frequencies, etc.) and data (e.g., calibration, collection, positioning, processing, visualization, etc.) challenges usually give rise to higher than desired false alarm rates. Kalacska and colleagues (Kalacska and Bell 2006, Kalacska et al. 2009) explored airborne HSI for detecting mass graves of animal remains in Costa Rica a month post event, with vegetative differences that were observable for up to sixteen months. Weil and Graf (1992), Davenport et al. (2001) and Larson et al. (2011) used thermal imaging for grave detection and showed that it is most productive just before sunrise or just after sunset. Whereas these case studies are promising, in a later section we express concerns about how/if these approaches and findings generalize across environments and forensic scenarios.

Outside of anthropology, a vast array of BHR relevant research exists. For example, Price et al. (2013) used machine learning to detect buried hazards in thermal imagery for humanitarian demining. This is possible because buried objects have different physical properties from their surroundings (e.g., soil) and thus their temperature changes at a different rate. The radiated energy difference forms a pattern at the surface that can be detected by a passive thermal camera. This is an anomaly since it’s a byproduct of the object, not a direct feature. In Hubbard (2010), hyperspectral thermal imaging was used to detect recently dug holes (disturbed earth) for explosive hazard detection. Smith et al. (2017) fused electromagnetic induction (EMI) and GPR to detect buried hazards using a hand-held platform. These are just a few of the sensors, platforms and algorithms to detect buried objects, which BHR is a subcategory. Anthropologists can benefit from such research which has been conducted for more than thirty plus years to save the lives of civilians and soldiers. The above are examples of remote sensing on the ground versus an aerial platform. To the best of our knowledge, no small aircraft UAV GPR solution exists, likely due in part to factors such as weight and power.

Environment

The next source of evidence is the local environment; where local refers to earth altered by CGSR. For example, vegetation can be used to detect BHR because carcass burial influences the plant community (Caccianiga et al. 2012, Watson and Forbes 2008). Compared to surrounding soil, vegetation has higher reflectance in the VNIR range and lower reflectance of red wavelengths. To excavate a grave requires mechanically disturbing soil, and this results in burial sites being devoid of plants. The mechanically disturbed soil destroys established plants and provides a seedbed for the establishment of new plant species, especially herbaceous weed species (Caccianiga et al. 2012, Dupras et al. 2005, Killam 2004, Ward 2013, Watson and Forbes 2008). Surrounding plants can become stressed by the changes in soil nutrients and aeriation. Stressed plants are most easily detected by absorption in VNIR (Carter 1993). Once revegetation occurs, the herbaceous plants growing in the grave soil will differ from the surrounding vegetation in species diversity and then later in lushness for approximately three years (France et al. 1992). Pioneer weed plants become established first and more abundant in the grave soils than the surrounding terrain. HSI may be useful for identifying unusual patches of vegetation. In addition, vegetation growing in recently disturbed soil may be younger than the surrounding plants and detectable in the ultraviolet range (Ruffell and McKinley 2008).

Once again, relevant work exists outside of anthropology. For example, methods like the normalized difference vegetation index (NDVI) and enhanced VI (EVI) (Glenn 2008) can be used to understand the health and stress of plants. Whereas methods like the NDVI and the approaches discussed above exploit spectral and two-dimensional spatial information, SfM, lidar, stereo vision, etc. can be used to build a three-dimensional model of the environment. In Hamraz et al. (2016) and Fujisaki et al. (2008), algorithms were put forth to detect trees from lidar for forestry. Muller-Linow et al. (2015) developed algorithms for plant/leaf segmentation in agriculture and Hasituya et al. (2015) put forth an algorithm for the detection and measurement of carbon in grasslands (i.e., above ground biomass). In summary, BHR has a great wealth of existing work to draw from and BHR impacts the environment in different, complex and hard to predict (in general) ways.

Surface Human Remains (SHR)

In general, SHR evidence is due to the body, accessories (e.g., shoes or clothing) and body-environment interaction (e.g., CDI). Previous research has demonstrated that HSI can be used to detect SHR and CDIs (Des Marais 2014, Isaacks 2015). After death, the body cools until it reaches ambient temperature. However, decomposition processes such as the activity of anaerobic bacteria and insects can generate heat that is detectable with thermal energy. Des Marais (2014) found that detection of human remains was greatest using thermal when the ambient temperatures were between 10 and 35 degrees Celsius. In addition, desiccated skin and other tissues absorb solar radiation differently than surrounding terrain, emitting more heat.

Pilot research at the Forensic Anthropology Center at Texas State (FACTS) has demonstrated that the surface temperature of the skin can be 5-10 degrees Celsius greater than the surrounding soil for more than 30 days. During initial work at FARF, a multi-rotor UAV equipped with a FLIR thermal imaging camera recorded temperature ranges that were greater than expected under ambient conditions. These ranges were recorded in one season (summer) only and causative research still needs to be conducted to determine if the desiccated skin temperature was an effect of radiant energy absorption or generated from ongoing decomposition processes, although the latter does not seem possible. Initial measurements were taken using the isothermic function of the sensor and were subsequently verified using handheld non-contact thermography devices. Additional research needs to determine peak temperature ramp/rise and timeline for decline to ambient temperature.

External to anthropology, HSI is frequently used to detect materials and people in imagery. For example, VNIR-based HSI has been used to detect blood and skin, respectively, in a forensic context (Mendenhall et al. 2015). Herweg et al. (2012) used HSI to track people according to clothing. Beyond detecting specific signatures of materials (e.g., blood, skin, clothing), there is the topic of directly detecting people and their parts in imagery. The reader can refer to deep learning (DL) methods such as convolutional neural networks (CNNs) (Krizhevsky et al. 2012), which are the state-of-the-art in computer vision (see Ball et al. 2017 for greater details). DL algorithms like YOLO (Redman et al. 2016) and GoogleNet (Szegedy et al. 2015) have produced revolutionary results in categories like people and vehicle detection. In remote sensing, Anderson et al. (2018) demonstrated 90% to 100% accuracy rates on benchmark data sets for the detection of various categories in satellite-based remote sensing (e.g., agricultural, forest, baseball field, residential, etc.). Scott et al. (2017) used transfer learning to bootstrap a CNN on non-aerial social media data and migrated it to aerial remote sensing. Strategies like these could be used to combat limited training data (volume and variety) for CGSR. In summary, techniques like these could be used to detect a SHR or associated objects (skull, bones, shoes, etc.).

In the previous sections, we highlighted the different characteristics relating to BHR, the environment and SHR. Each of these have unique properties that allow different strategies to be applied to best document and detect them. Figure 7 illustrates each of these different properties and their relationship to BHR, the environment or SHR.

Sensors and Platforms

It is vital that the CGSR community has a basic understanding of the physics and hardware (e.g., electronics and optics) that are being used – or could be used – and data collection platforms. Next, we give a succinct review of relevant sensors and platforms, with a focus on open challenges and limitations.

Long Wave Infrared (aka Thermal) Imaging. Infrared (IR) is EM radiation from approximately 700 nanometers to 1 millimeter. However, there is no "official" start or stop point for IR (or any sensor at that). Terms like IR are assigned to portions of the EM and those frequencies are debated within and across communities (in part due to application specifics). Most often, sensors are built for near (0.75 to 1.4 micrometer (μm)), short (1.4 to 3 μm), medium (3 to 8 μm) and long (8 to 15 μm) wave IR. IR has been driven by applications in astronomy and defense (e.g., surveillance). We focus on long wave IR (*thermal*) as it provides a way to detect CGSR evidence.

Since the introduction of the first consumer IR cameras in the mid to late 90s, advances in technology and production have led to significant reductions in their size and cost, which allows for increased applications. Thermal imagers are passive and operate by detecting IR radiation, which is emitted by all objects with a temperature above absolute zero. A thermal imager senses not only the emitted radiation of the object, but also transmitted and reflected radiation. Uncooled thermal cameras use a microbolometer, which is usually a small resistor that has a large temperature coefficient on a silicon element with good thermal insulation, low heat and excellent thermal isolation. Another option is a cooled sensor, which costs substantially more and is likely too expensive for CGSR. Cooled cores are a combination of an imaging sensor and a cryocooler. The cooler brings the sensors temperature down to cryogenic temperatures to minimize thermally induced noise to a level lower than that of the signal from the scene that is being imaged. Beyond cost, cooled thermal cameras offer better magnification capabilities (spatial resolution), sensitivity (better temperature differentials), and spectral filtering (FLIR 2017).

In summary, most CGSR efforts can only afford an uncooled thermal camera. Regardless, reliable determination of accurate temperature in an unknown environment is a challenging task. However, if the temperature variation (e.g., change in body heat due to decomposition or change in the thermal properties of a buried material relative to its surroundings) is large enough then local anomalies will be present. In return, thermal imaging is subject to factors like time-of-day, cloud cover, and shadows. For example, in buried explosive hazard detection the diurnal crossover renders detection challenging (to say the least); moments where the buried objects reach a thermal equilibrium relative to its surroundings. This does not render thermal useless, it simply means that it is a sensing technology that has a place and time (context).

Hyperspectral Imaging (HSI). Whereas the last section focused on a portion of the EM, HSI is simply a reference to high spectral fidelity. Herein, we restrict our discussion to VNIR-based HSI sensors, which operate in approximately the 400 to 1,000/1,400 nm range. For each spatial sample (pixel), the sensor records spectral data in the form of bands, where each band is a narrow part of the EM (e.g., 400nm to 403nm). Typically, HSI data consist of several hundred bands. A goal of HSI is to obtain improved spectral resolution to help detect and discriminate materials. In CGSR, hundreds of spectral bands could be a major asset in high fidelity documentation of forensic scenes. Figure 8 is an example of hyperspectral imagery collected at FARF; as can be seen, the spectral signatures vary, which should allow for the identification of the different materials in the imagery. The reader can refer to Adao et al. (2017) for an introduction to HSI and for its role in remote sensing.

However, HSI is not without flaw. First, the combination of spatial, spectral and temporal data can (and often does) turn into a Big Data problem (Anand et al. 2017). Meaning, we must now address massive amounts of data storage and subsequently processing. This can in return limit flight time and coverage. Furthermore, if a goal is to explore the spatial and spectral data then often we are posed with the task of finding a needle in a haystack. For example, common practice is to perform band selection (Feng et al. 2017) - identify a few bands out of the hundreds to use - or band projection (Islam et al. 2016) - algorithms that reduce the hundreds of bands of data into drastically fewer bands with the goal of ensuring that patterns are still present in the reduced space.

Second, the increased dimensionality (spatial, spectral and temporal) of HS has negatively impacted many signal processing and machine learning algorithms. In general, the problem is there are too many parameters in the system and too little variety and volume data to support learning. Third, it is challenging to visualize (if the human is in-the-loop) high dimensional HSI data.

In the last few years, commercially available HSI payloads for small UAVs have become available. However, their price spans tens to hundreds of thousands of dollars (current average is above fifty thousand dollars for sensor, positioning, etc.), which could easily be outside the budget of law enforcement for CGSR. Now, most of these devices are pushbroom sensors. As such, they have a resolution of a few hundred pixels in a line and hundreds of spectral bands. This is fine if a task calls for single pixel spectral analysis. To build a two-dimensional spectral-spatial image, precise positioning (e.g., GPS/INS) is required. Highly accurate, such as cm level resolution, precision (which costs thousands to tens of thousands of dollars) is needed for documentation and possibly detection. Furthermore, most systems cannot process in real time; the image construction, and analytics must be done offline.

A final HSI topic is calibration and correction. HSI sensors collect radiance data, which needs to be converted into reflectance. Many methods exist to perform atmospheric correction due to gases (water vapor, carbon dioxide, oxygen, etc.). In a research context, most pre-calibrate the optics and use reference panels or emplacement materials (e.g., tarps), both of which temporally and spectrally lose relevance. Furthermore, most fly around solar noon to minimize the impact of shadows, which alters the recorded spectral values. This means that the magnitude in each spectral bin is changing for the same material in different locations and/or temporally. The message is, on the fly calibration and correction for UAV HSI in unknown dynamic environments is not a solved problem, which in return can impact CGSR with respect to documentation. In terms of detection, methods such as the adaptive-cosine estimator (ACE) exist to exploit the “shape” (angle) of the spectral signal versus exact magnitude values (Manolakis et al. 2009). Meaning, the community has developed ways to work around (within reason) such limitations.

In summary, HSI has multiple hardware, calibration, correction, and processing challenges. Many of these current shortcomings are likely achievable in the foreseeable future, to some degree, and the result is an abundance of rich spatial-spectral data for detection and documentation. However, the goal of documentation is to collect as much information as possible. On the other hand, detection likely requires fewer bands and therefore a less expensive sensor.

Structure from Motion (SfM). Three-dimensional imaging is very different from the last two sections. First, many objects, or attributes of objects may require three dimensions for identification. For example, Shafiekhani et al. (2017) showed that plant features like height, leaf-area (which provide biologically relevant canopy information) and light exposure can be accurately estimated from three-dimensional data. Second, three-dimensional data can be used for accurate sensor registration (linking measurements) and making quality data (e.g., orthorectification of a pushbroom HS sensor). These are just a few of the many benefits of three-dimensional data, beyond documentation.

Three-dimensional imaging is not new in any respect. Stereo (passive) and more recently lidar (active) have gained attention due to applications like smart cars and a need to operate across weather and illumination (e.g., day and night). Herein, we focus on SfM, a method to extract dense three-dimensional data from a single camera on a moving platform. The reader can refer to Ozyesil et al. (2017) for a recent survey of SfM algorithms. SfM is attractive for UAVs because it leverages existing (typically inexpensive) sensors, which in return leads to less weight, lower cost and greater flight time. As such, non-CGSR applications in anthropology have begun to explore UAV-based SfM to build three dimensional reconstructions for various archaeological purposes (Levy et al. 2014). In general, SfM requires sufficient overlap between consecutive images, and it works by identifying and exploiting common features across images to solve the underlying transforms.

Whereas SfM is a mature topic and tools (algorithms and software packages) exist, SfM has challenges that forensic anthropologists and SAR teams need to understand. First, real-time SfM on cost, weight and power efficient hardware is not trivial. Currently, SfM typically occurs offline (i.e., post data collection). This is important as it can make or break a CGSR search. Just now are solutions (algorithms and drones) emerging that might be able to satisfy these needs. Second, most UAVs pick predetermined flight patterns based on coverage versus environment. An unsolved problem is how to let a UAV, or UAV team, autonomously determine an optimal flight pattern on the fly to accurately map a complex scene. It is also not clear what percentage of a scene must be imaged for CGSR detection versus documentation. Third, most SfM works are focused on structured environments (e.g., urban areas). However, CGSR most often occurs in remote and discrete locations where challenges like tall grass, bushes and other vegetation exist. We are unaware of any quantitative studies that outline how well SfM works (and respectively degrades) in such environments. For example, if we are looking for a burial mound then SfM from a commercially affordable RGB sensor on a UAV at 200 feet (which boils down to a specific GSD) will most likely not detect its features if we cannot image the ground through the vegetation. The message is, new SfM research from UAVs and multi sensor systems operating in complex and dynamic CGSR environments is needed.

In summary, UAVs have gained much interest recently due to engineering advancements and a lessening of FAA flight restrictions. Whereas UAVs have become increasingly easier to fly, this does not mean in any respect that accurate data (HSI, thermal, SfM, etc.) collection has become any simpler; perhaps it has become more complex and difficult. It is extremely important to have a competent pilot and a thorough understanding of the sensor(s) being used. Without these aspects working in harmony, a successful data collection is highly unlikely. This is a big concern for non-engineering CGSR experts. Furthermore, there are many parameters that must be jointly optimized (e.g., flight speed, altitude, flight pattern, the type of sensor(s), the sensor(s)' focus, exposure, and frame rate). The point is, although UAVs are a promising technology, hype surrounds them, and there are big unsolved challenges in this emerging and exciting field.

Unmanned Aerial Vehicles (UAVs)

In this subsection we discuss three factors; i) regulations, ii) UAV platforms, and iii) sensor payloads. Before the most recent FAA regulations were put into place (FAA 2016), UAV flights were authorized on a case-by-case scenario (a waiver). Needless to say, it was challenging to obtain authorizations. Under the new regulations, an individual may obtain a certification to fly, but there are rules. A few of directives include a maximum weight (55 pounds) for the UAV, a maximum altitude (400 feet), and the UAV must always be in line of sight. These rules exist for safety of the UAV, people, and property. The imposed regulations allow for many applications to operate unaffected. With respect to CGSR detection and documentation, the current rules do pose a concern with respect to deploying UAVs out of line of sight, the current weight restrictions restrict sensor payloads, and altitude restrictions impact factors like area of coverage and GSD (e.g., 1 cm versus 100 cm resolution). However, the FAA's Special Government Interest (SGI) process allows for exceptions in areas of emergency; e.g., firefighting, SAR, law enforcement, etc.

The two main platforms are fixed-wing and multi-rotor systems. A fixed wing model is an airplane; whereas, a multi-rotor system has multiple propellers oriented horizontally (Figure 9). The fixed-wing style generally allows for a longer flight time; whereas, a multi-rotor can hover and obtain more methodological and dense data. This begs the question of which platform is the best for CGSR? Fixed-wing can cover larger areas but are less for exploratory detection and/or documenting a scene from multiple viewpoints. In general, determining the ideal platform is application specific. The reader can refer to Iqbal et al. (2015) for a recent UAV survey.

The next topic is sensor payload. For example, consider a HSI pushbroom sensor (Figure 9). A faster flight corresponds to less environmental disturbance (e.g., wind). However, flight speed is determined by the frame rate, and for a HSI sensor the maximum frame rate is determined by exposure, which in return is determined by the current radiance of the sun. The point is, setting a data collection up for success may require knowledge of not only the data's domain, but also an understanding of how each of the flight parameters impact each other. Setting the parameters independently could result in data collection failure. The ideal scenario is a platform with sensors recording the entire EM. However, such a platform would violate the FAA weight limit and exceed any budget for CGSR. This begs the question of, what is the optimal set of sensors for CGSR, what does optimal mean (what are the metric(s)), and is optimal the same with respect to detection and documentation? Furthermore, while it sounds like a good idea to “add more sensors," multi-sensor fusion (Khaleghi et al. 2013 for a recent comprehensive review) is an unsolved challenge that includes factors like registration of sensors and interpreting the data (mathematics and algorithms). Last, it is worth mentioning that most advanced sensor technologies in remote sensing are currently satellite- and plane-based, due to their size, weight, and power requirements. Advanced sensors for small UAVs are only just now making it to the marketplace and the ones that are cost effective have several restrictions currently.

In summary, UAVs have great potential but there are many theoretical and application questions and concerns. Three aspects are flight regulations, UAV platforms and sensor payloads. It is our belief that for CGSR detection and documentation to become a reality, something like best practices and forensic protocols need be established nationally. This is a daunting task in and of itself. However, UAV-based CGSR also likely requires intelligent operators that understand forensic anthropology and engineering. This leads to a large question, do the overall benefits of this technology outweigh the “cost" of not using the technology?

CGSR Detection

In this section, we explore CGSR detection. We divide-and-conquer detection according to the criteria of supervised versus unsupervised. To start, there is the question of do we know the “signature” (spectral and/or spatial signal) of the quantity to detect (e.g., blood, skin, bones, or CDI)? If yes, then we refer to the subsequent approach as supervised. Otherwise, if we are looking for anomalous locations that deserve additional analysis (by a supervised method or expert), it is unsupervised. With respect to supervised, there are a few details. First, there is the question of is inner class variation present? Most of the time the answer is yes for CGSR. Examples include the visual appearance of individuals, decomposition stages (which can result in non-rigid deformations like bloating), and bones for different people that have undergone destruction due to taphonomic factors. Second, there is the question of is data of sufficient variety and volume available to train an algorithm? With respect to unsupervised, we divide methods by the amount of knowledge that is present. For example, if we know absolutely nothing, then the goal is to search for locally anomalous (spectral and/or spatial) areas. However, in general the false alarm rates for this approach will likely be (too?) high. Usually, some knowledge will be exploited (e.g., approximate shape and/or size properties of a human, bone, etc.). In the remainder of this section we discuss different methods in machine learning, signal/image processing, and remote sensing.

The first method discussed is simple but theoretically well-grounded. It has been used in numerous applications ranging from radar to image (spatial and spectral) processing. The matched filter works on the premise that we know a reference signal, s, for the quantity to detect (e.g., we have an HSI signature for blood, skin, bone, etc.). In the case of inner class variation - of the object itself or how an environment has modified it - a bank (set of filters) is typically used. Convolution is the mechanism used to compute similarity of a new signal, x, under question to our reference signal, r=conv(s,x) and a threshold (i.e., if $r > \tau$) is used to declare alarms.

The second method is the current state-of-the-art in machine learning, deep learning (DL). The most popular flavor of DL is convolutional neural networks (CNNs). The reader can refer to our recent survey of DL in remote sensing (Ball et al. 2017); which reviews algorithms, libraries, applications and various open challenges. A CNN is a hierarchy of filters and convolution is the heart of its computation. Filters closer to the input data typically learn low-level shapes and colors, whereas filters at deeper layers learn increasingly more complex combinations (e.g., faces) of filters and eventually high-level semantics of the underlying problem. CNN are a good candidate for spatial, spectral and temporal detection if enough training data is present (variety and volume). However, this is likely not the case for CGSR. For example, it is unlikely that we will have access to an overabundance of data in various sensors for different individuals at different decomposition stages in different environments. This is not to say that CNNs are not a viable option. Scott et al. (2017) took CNNs trained on hundreds of object classes (people, cars, etc.) in social media imagery as a starting point and limited remote sensing data from an aerial platform with different object classes was used to update the CNN. This approach, called transfer learning, is one way to combat limited training data. Another method is data augmentation. In Scott et al. (2017), benefit was shown in data augmentation for remote sensing by altering affine (e.g., rotation, translation, scale), illumination and other factors of imagery. In Figure 10, we show automatic detection results using the DL architecture YOLO (Redman et al. 2016). Our YOLO was not trained to detect postmortem bodies. Furthermore, the thermal image was converted into a grayscale image for YOLO. Even without transfer learning, YOLO can amazingly enough detect bodies in thermal as there are common underlying features (e.g., shape of head, body, and shoulders).

The next topic is supervised HSI methods. A well-grounded and consistent technique is the adaptive cosine estimator (ACE) (Manolakis et al. 2009). ACE is simply the Mahalanobis distance of *x* (new signal) to *s* (target signal) with respect to some context (environment covariance matrix). In practice, ACE varies with respect to local (covariance is calculated on a small local patch of data), global (covariance is calculated for a larger area – e.g., all data) and adaptive (local but updated as we search across the data). It is important to note that methods like these are not specific to CGSR, nor are the objects/materials we desire to detect. What is specific to CGSR is the material signature(s), which allows us to exploit previous research results. Various algorithms exist to operate on its data. Last, we want to highlight that DL is applicable to HSI data (if sufficient data to approximate its parameters is present) (Peterson et al. 2016).

Examples of unsupervised learning include the size contrast filter (SCF) and the Reed-Xiaoli (RX) detector (Manolakis et al. 2009). The RX detector is simply the Mahalanobis distance of the observed signal *x* from the center of the background distribution. No target signal *s* is required. The RX is measuring how different, thus anomalous, a sample is. As in the case of the ACE, there are local, global and adaptive versions of the RX. In practice, *x* is the sample under investigation, a "guard band" is used (sample set directly surrounding x that provides flexibility for *x* to span a few samples or be mixed with its direct surroundings and not impact the overall calculation) and the local statistics are determined outside *x* and the guard band. The SCF operates in a similar way. There is the idea of an inner window (region being analyzed), guard band and outer window. Statistics are computed for the inner and outer regions and a divergence measure, typically the Bhattacharya distance, is used to detect how anomalous the inner window is (Dowdy et al. 2017). Regardless of the specifics of the algorithm, methods like these operate on some crude notion of size and shape (i.e., the size and shape of the inner window, guard band and outer window). In CGBR, these methods can be used to detect changes in vegetation. BHR is similar to our work in buried hazard detection using thermal data, where the SCF and RX are used (Anderson et al. 2012). These methods can also be used to detect a cadaver decomposition island (CDI) with HSI, thermal or other sensor data. However, due to the large amount of inner class variability of vegetation, it is likely that a set (bank) of filters with different sizes and shapes would likely be needed for BHR and SHR detection.

The last approach we discuss is unsupervised spectral unmixing. In many cases a single image pixel, which represents an area of earth, is a combination of different materials. Zare et al. (2014) used clustering to automatically discover endmembers and mixture ratios. An example endmember is blood, soil type, etc. Mixture ratios tell us how much (percentages) of each material (endmember) is at each location (pixel). Anderson and Zare (2012) introduced validity measures to guide parameter selection and ensure quality endmembers. By definition, it is assumed here that we know nothing about a scene (image). The big question in unsupervised spectral unmixing is, what do we do with the results (endmembers and mixture ratios)? In the context of hazard detection, hazards are typically rare to a scene and as such their endmembers are anomalous. In CGSR, this concept could be used to find anomalous materials that are different globally (e.g., a shoe in a field) or locally (e.g., vegetative differences).

In summary, various algorithms exist outside of anthropology that can be used or adapted to the detection and documentation of human remains. We made these connections at a high-level and examples from our FARF collection were used as a proof of concept. Figure 11 highlights the algorithms that are reasonable mechanisms to evaluating forensic data. A major concern of ours is that supervised methods might not have sufficient data to support parameter estimation for robust detection of objects with great inner class variation and across environments. On the other hand, unsupervised methods have great potential but unless more is done their false alarm rates might prove to be too great. Regardless, our hope is that bringing all of these resources into a single publication is useful for those looking to improve or invest in CGBR.

CGSR Documentation

The next topic has utility in planning purposes and post analysis. First, each sensor must be registered, to one another or to a common world system (e.g., Universal Transverse Mercator (UTM) and Easting, Northing and Altitude coordinates). In general, this requires procedures like precise positioning of the sensors, platform and often common tie points that can be seen in the various sensors (EM spectra) to make the needed associations. Registration is not a trivial task, not even for a fixed payload. Each sensor generally has different spatial and spectral resolutions, frame rates, fields of view and are located at different physical locations on the UAV(s). As such, they have a small overlapping observable joint space and objects are imaged at different locations and with different resolutions. In general, what is important is what we want to do with that data. There is not sufficient space to go into depth on scientific visualization here. Visualization (of the raw data and/or results of algorithms) is a challenge because each input has different magnitudes, areas of coverage, and if they are co-located then the question of how one sees multi-dimensional data arises. The reader can refer to related geospatial visualization work on multi-dimensional weather prediction data (Sanyal et al. 2010). If the goal is to process the registered data, then the reader can refer to our work on fusing EMI and GPR for hazard detection (Smith et al. 2017); in which we discussed soft linkage methods, based on resampling to a common underlying grid, and hard linkage, or discovering the one-to-one or one-to-many data mappings.

Second, there is the matter of sufficient coverage or mapping of a scene. This has two parts, sensor payload instillation and flight specifics. For example, if we imaged only the front of an object and the forensic information was on its backside then we failed to correctly document the scene. The general approach is to fly a predetermined path. An example is flying in a waffle pattern where straight lines are flown in one direction and then another similar sweep is made in the orthogonal direction to maximize visibility of all surfaces of objects (minus the obvious case of occluding objects). The problem with this approach is that it is too general. It does not ensure coverage, and it is likely not the most efficient. When it comes to CGSR, we really need a metric for what is a quality mapping, and it is an optimization problem with parameters in sensor configuration and flight pattern.

In summary, CGSR documentation is difficult for many reasons like accurate multi-sensor registration, scientific visualization challenges, and challenges in ensuring efficient and effective coverage. Figure 11 shows the factors that are related to CGSR documentation.

Summary and Future Work

In a forensic case, the ideal scenario is accurate and time-efficient automated technologies to find and document scenes. This is not trivial because it requires advancements in many fields, from anthropology to engineering, meteorology, and soil science, to name a few. One promising technology is UAVs with multiple sensors. To date, UAVs have been mainly used in anthropology for tasks like three-dimensional mapping of archaeological sites. Herein, we investigate the state-of-the-art and limitations of UAVs with respect to detecting and documenting CGSR. Specifically, we highlight challenges related to UAVs, best practices and protocols, FAA and legal concerns, sensing limitations, and algorithms from machine learning and remote sensing. Preliminary experiments at FARF using HSI, infrared and SfM were also provided to illustrate and support claims. Overall, this paper exists to inform and incite future cross disciplinary research.

Whereas this paper succeeds in reviewing and raising awareness of different CGSR topics, ultimately it is a high-level investigation. Future work, by our group and others, should focus on collecting and establishing freely available benchmark data sets of cases across forensic contexts, environments and environmental conditions. This process has been extremely beneficial in fields like computer vision and remote sensing as it has helped to establish reproducible research, and it allows for comparative analysis across investigators. Furthermore, our goal is to focus on not only advancing algorithms, platforms and sensors but to make progress in the establishment of standard operating procedures and protocols. Otherwise, it will all remain academic and these tools will not make it to the hands of those who will use them in the field and in a legal context.

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Figure 1.

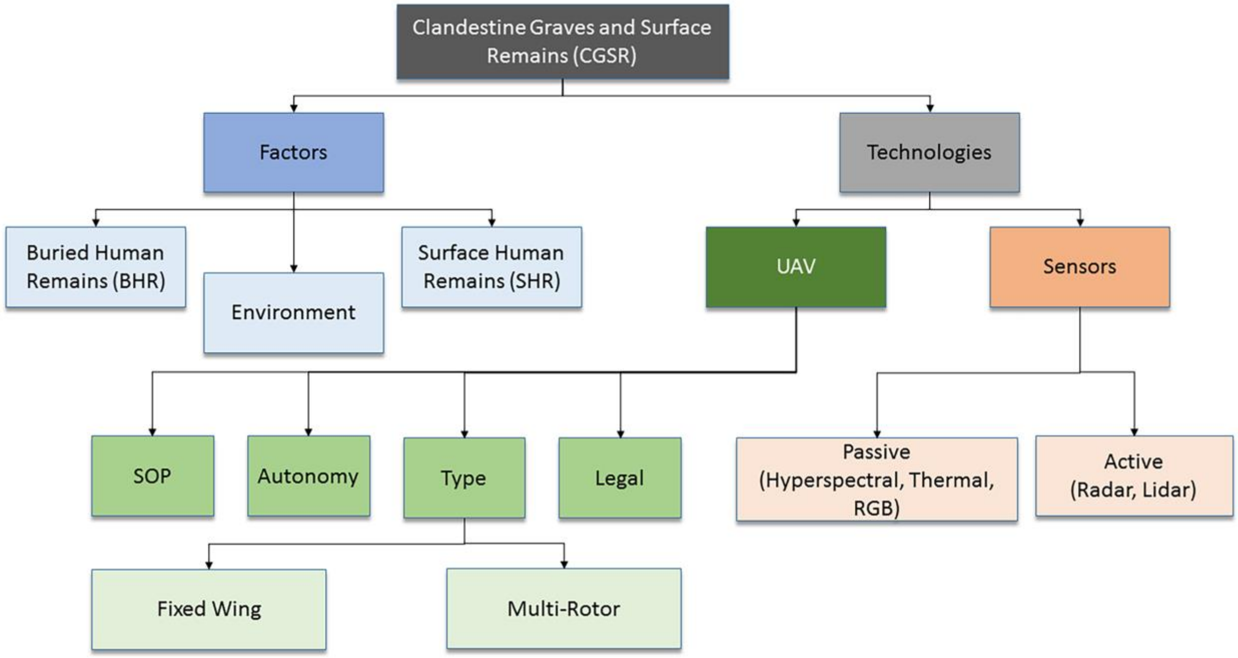


Figure 2.

Figure 3.

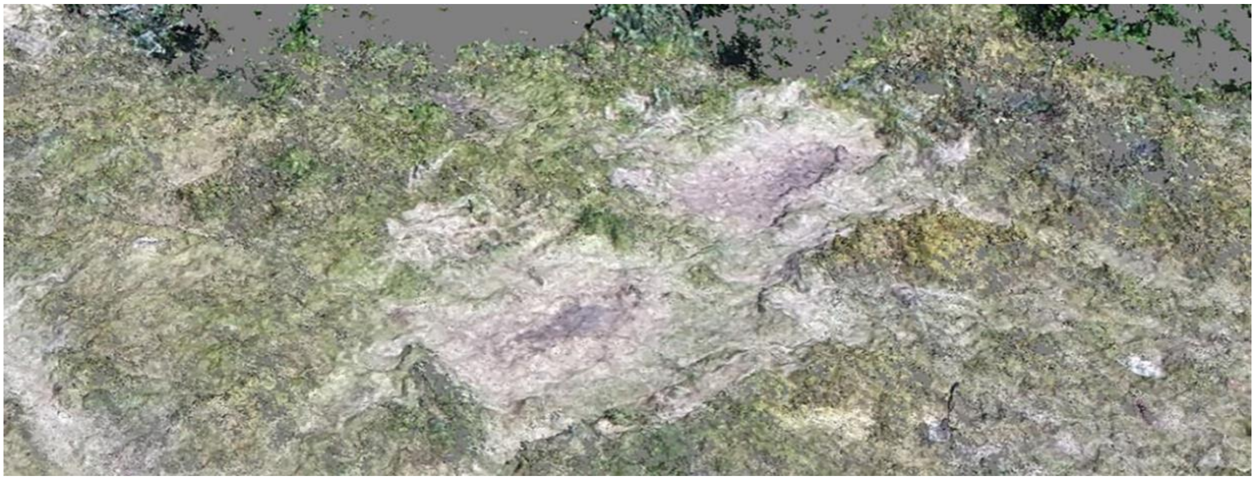


Figure 4.

Figure 5.

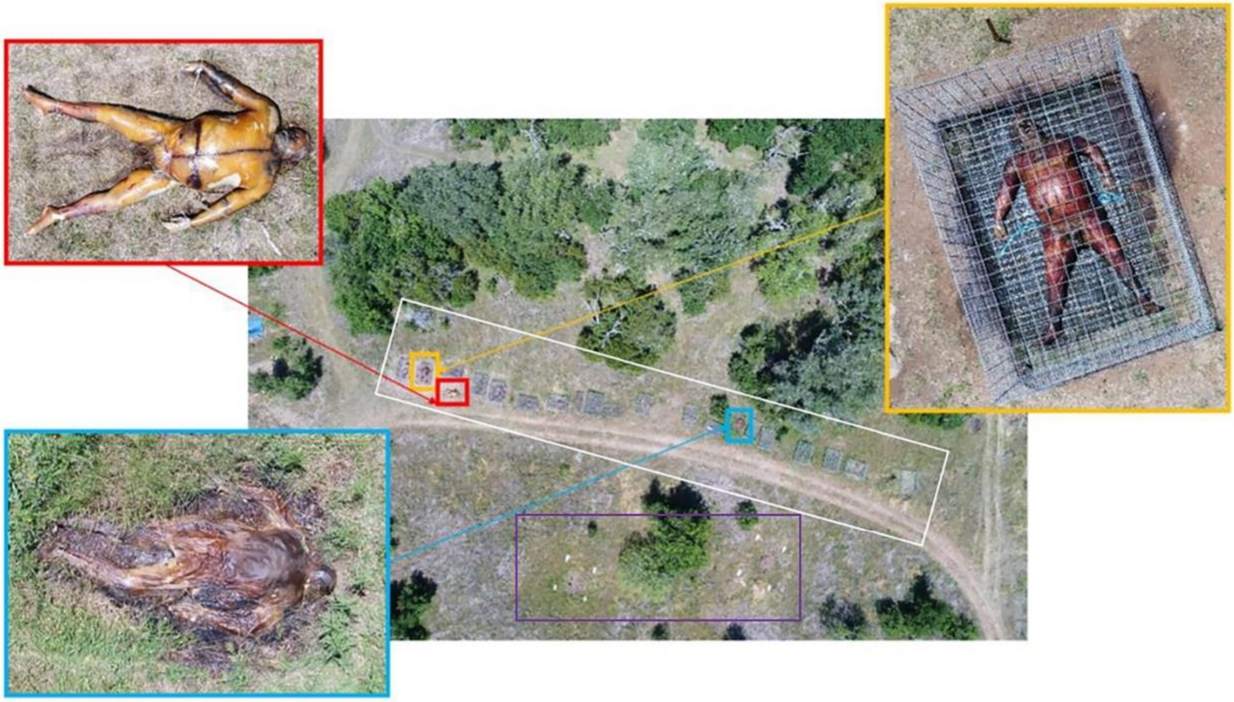
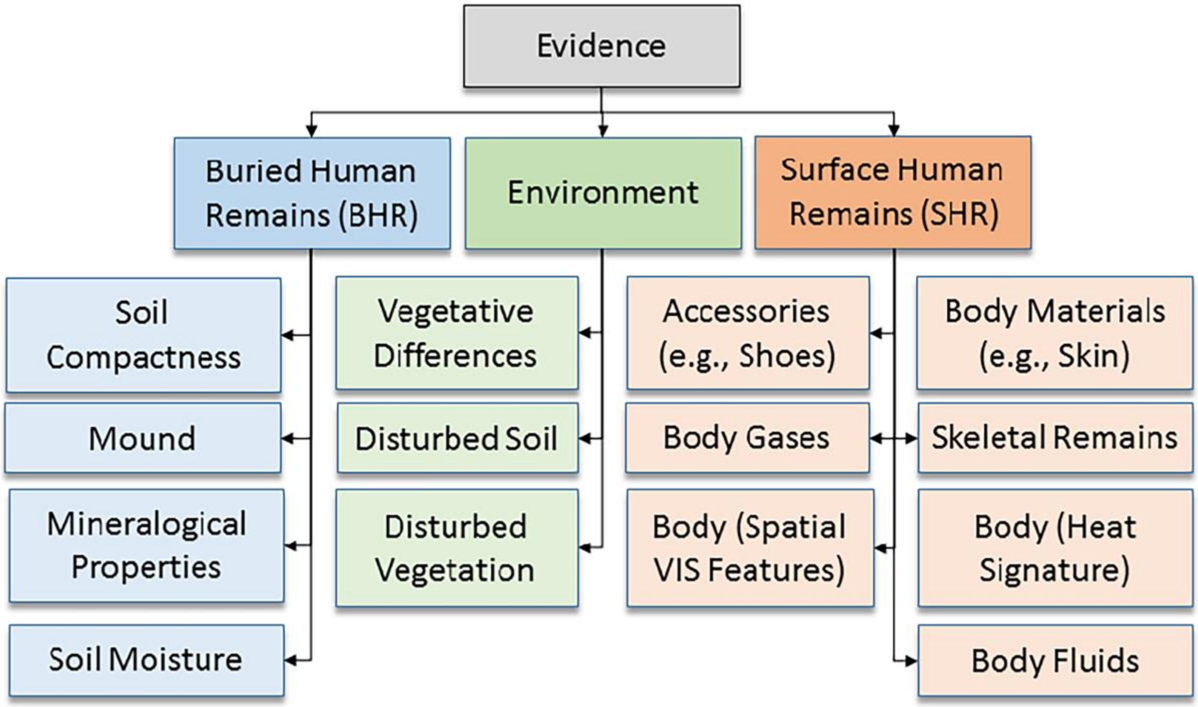


Figure 6.

Figure 7.



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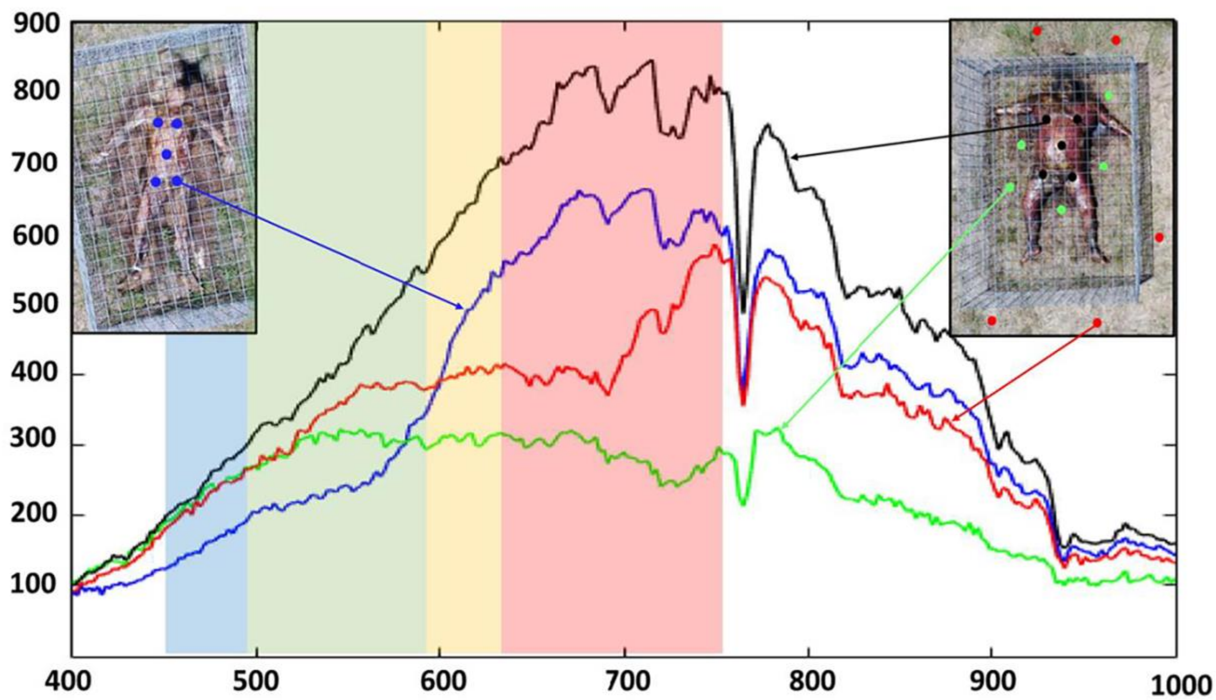

Figure 9.

Figure 10.

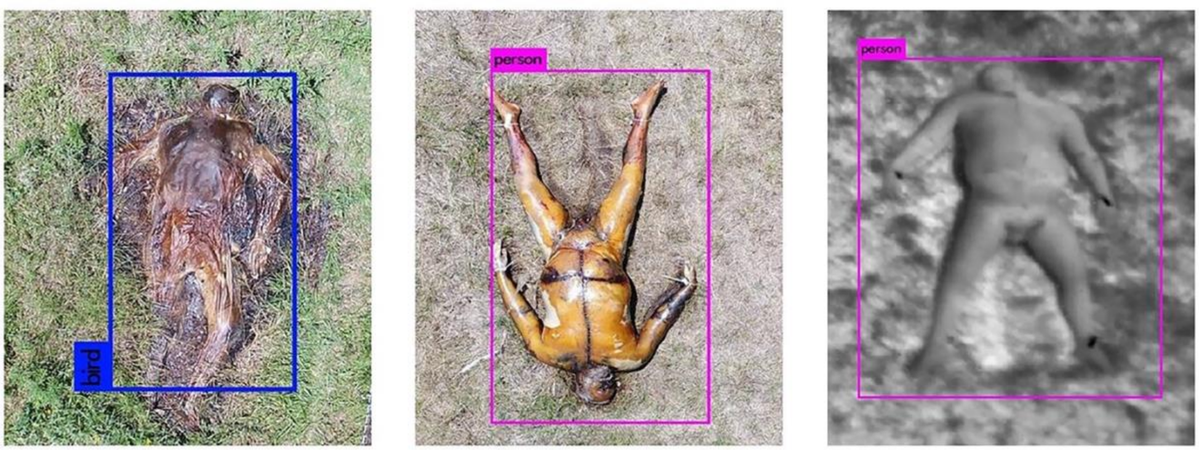

Figure 11.

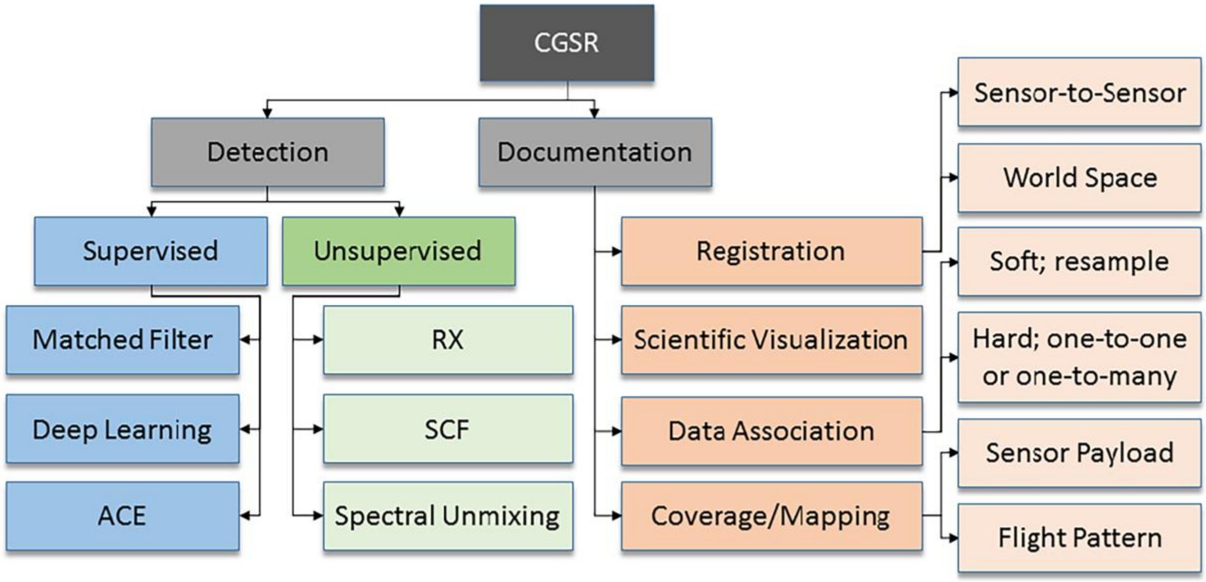
CGSR
Detection
Documentation
Supervised
Unsupervised
Matched Filter
Deep Learning
ACE
RX
SCF
Spectral Unmixing
Registration
Scientific Visualization
Data Association
Coverage/Mapping
Sensor-to-Sensor
World Space
Soft; resample
Hard; one-to-one or one-to-many
Sensor Payload
Flight Pattern

Figure Captions

Figure 1. Illustration of different factors (sources of evidence) and technologies discussed herein for the detection and documentation of CGSR.

Figure 2. Birds eye view of SfM data that has three burial mounds in the lower center part of the image (can you see them?). These mounds were in an area where grass was between 20 to 90 cm high. As such, SfM, relative to factors like the GSD and frame rate, does not image the grass nor ground well and as a result one cannot truly make out the mounds in the data. One mound is highlighted (zoomed in and rotated for a better view).

Figure 3. SfM data for two surface remains (gray areas) whose skeletal remains were removed after approximately a year. The reader can clearly see local environment anomalies (e.g., lack of vegetation, soil differences, roughness differences, etc.).

Figure 4. Human surface remains and “accessories" (e.g., shoes and clothing). The body was disturbed by animals; vultures specifically. Left image is RGB and right image is SfM data (simple pixel colored point cloud, not a tessellated surface with image texture applied) for the UAV at approximately 200 feet.

Figure 5. FARF areas with uncaged, mostly skeletonized remains (purple box) and caged bodies at different stages of decomposition (white box).

Figure 6. SfM data (three dimensional points) for the FARF area containing caged remains in Figure 5. SfM could not--relative to sensor and drone parameters (which ultimately give rise to GSD)--map the swaying grass and ground between the bodies and trees. As a result, the surface looks ``bumpy'' and small details like the cages around bodies are not detected. The SfM data is “raw", meaning no post SfM algorithm filtering is applied (e.g., if there are too few of neighborhood points, remove). Regardless, one can still make out vital remains information such as shape and size.

Figure 7. Examples of different sources of evidence related to BHR, SHR and environment.

Figure 8. Average HS signature for skin on two bodies at different decomposition states and ground versus its corresponding CDI. X-axis is wavelength (nm), y-axis is sensor output (radiance values that have not yet been converted to reflectance; but since they come from close locations in the same flight they are relatively comparable), black curve is average (of five different points) skin response for one remain, blue is the other remain, red is for the ground and green is the ground but in the CDI.

Figure 9. (left) DJI Matrice 600 multi-rotor UAV with a gimbal mounted hyperspectral sensor and (right) closeup of Headwall hyperspectral sensor with a GoPro camera.

Figure 10. Example automated algorithm detection and localization results for YOLO. (left) Misclassified case in an extreme decomposition state. (middle) Correct detection in an early

decomposition state. (right) Correct detection (same body as (middle) case) in thermal (without any transfer learning).

Figure 11. Example of different algorithms and factors in the detection and documentation of CGSR.