Modern Trends in Hyperspectral Image Analysis: A Review

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Modern Trends in Hyperspectral Image Analysis: A Review

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ABSTRACT Over the past three decades, significant developments have been made in hyperspectral imaging due to which it has emerged as an effective tool in numerous civil, environmental, and military applications. Modern sensor technologies are capable of covering large surfaces of earth with exceptional spatial, spectral, and temporal resolutions. Due to these features, hyperspectral imaging has been effectively used in numerous remote sensing applications requiring estimation of physical parameters of many complex surfaces and identification of visually similar materials having fine spectral signatures. In the recent years, ground based hyperspectral imaging has gained immense interest in the research on electronic imaging for food inspection, forensic science, medical surgery and diagnosis, and military applications. This review focuses on the fundamentals of hyperspectral image analysis and its modern applications such as food quality and safety assessment, medical diagnosis and image guided surgery, forensic document examination, defense and homeland security, remote sensing applications such as precision agriculture and water resource management and material identification and mapping of artworks. Moreover, recent research on the use of hyperspectral imaging for examination of forgery detection in questioned documents, aided by deep learning, is also presented. This review can be a useful baseline for future research in hyperspectral image analysis.

INDEX TERMS Agriculture, document images, food quality and safety, hyperspectral imaging, medical imaging, remote sensing.

I. INTRODUCTION

This human eye is only able to see in a limited part of electromagnetic spectrum and can distinguish between objects based on their different spectral responses in that narrow spectral range [1]. However, multispectral imaging sensors have been developed that are able to acquire an image in infrared and visible segments of electromagnetic spectrum. This allows material identification on the basis of their unique spectral sig-nature in a wide spectral range. Multispectral imaging exploits the property that each material has its own unique spectral signatures. Spectrum of a single pixel in a multispectral image provides information about its constituents and surface of the material.

Multispectral imaging technology is being used for environment and land observation remote sensing in satellite and airborne systems since late 1960s [2]. Multispectral imaging systems acquire data in a small number of spectral bands by using parallel sensor arrays. Most of the multispectral imaging systems use three to six spectral bands with large optical band intervals, ranging from visible to near infrared regions of electromagnetic spectrum for scene observation. However, such low number of spectral bands is the limiting factor for discrimination of various materials. Recent developments in hyperspectral sensing during the past two decades has made it possible to acquire several hundred spectral bands of observational scene in a single acquisition. The increased spectral resolution of these hyperspectral images allow for detailed examination of land surfaces and different materials present in the observational scene, which was previously not possible with low spectral resolution of multispectral imaging scanners.

Hyperspectral imaging (HSI) or imaging spectrometry [3] is a spectral sensing technique in which an object is photographed using several well defined optical bands in broad spectral range. It was originally implemented on satellite and airborne platforms for remote sensing applications but during last two decades, HSI has been applied to numerous applications including agricultural and water resources control [4], [5], military defense, art conservation and archeology [6], [7], medical diagnosis [8], [9], analyses of crime scene details [10], [11], document imaging [12], forensic medicine [13], food quality control [14], [15] and mineralogical mapping of earth surface [16].

This review details the fundamentals of hyperspectral imaging, discusses the common hyperspectral remote sensing terminologies and highlights the modern applications of hyperspectral imagery in the areas of food quality and safety assessment, medical diagnosis, precision agriculture, water resource management, forensic document examination, artwork authentication and defense and homeland security.

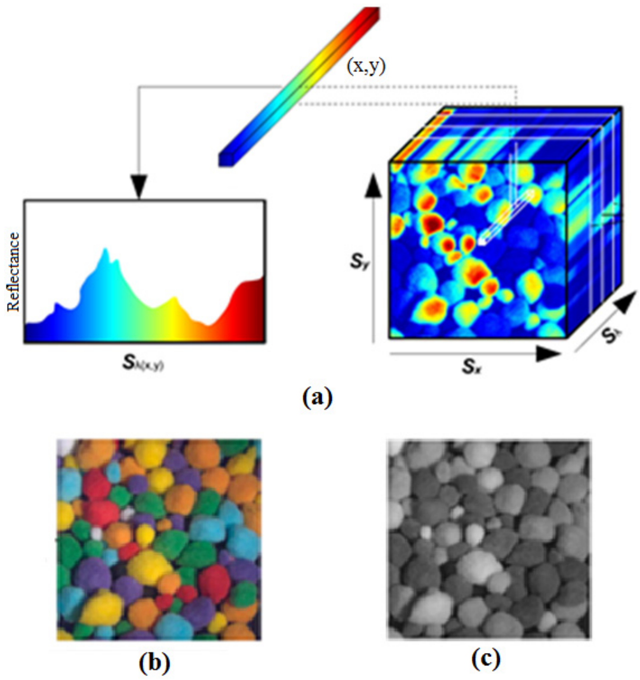

FIGURE 1. (a) A hyperspectral image represented as a 3D cube. A point spectrum on the spectral cube is illustrated at the spatial location (x,y). (b) An RGB image and (c) a grayscale image rendered from the hyperspectral cube.

II. HYPERSPECTRAL IMAGING

Hyperspectral images are characterized by their spatial as well as spectral resolution. The spatial resolution measures the geometric relationship of the image pixels to each other while the spectral resolution determines the variations within image pixels as a function of wavelength. A hyperspectral image has two spatial dimensions (S_x and S_y) and one spectral dimension (S_λ). The hyperspectral data is represented in the form of a 3D hyperspectral data cube in Figure 1 using pseudo-colors in center. A point spectrum on the data cube at the spatial location (x,y) and an RGB image and a grayscale image rendered from the hyperspectral cube are also shown. Each slice of the cube along spectral dimension is called a band or channel. Table I shows the spatial and spectral resolution of the current airborne and space satellite imaging sensors.

TABLE 1. Current space borne and airborne spectral sensors providing data for land mapping.

Sensor	Organization /Country	Optical Subsystem	Spectral Bands	Spectral Range (μm)	Spectral Resolution	Spatial Coverage
Landsat-8	NASA, US.	VNIR-TIR	8	0.45-12.50	8	Global
MODIS	NASA, US.	VNIR-TIR	36	0.40-14.40	250-1000	Global
MERIS	ESA, EU.	VNIR	15	0.39-1.040	300	Global
ASTER	NASA, US & METI, Japan.	VNIR-TIR	15	0.52-11.65	15-90	Global
Hyperion	NASA, US.	VNIR-SWIR	242	0.40-2.500	30	Regional
ALOS	JAXA, Japan.	VIS	1	0.52-0.77	2.5	Local
AVIRIS	NASA, US.	VNIR	224	0.38-2.500	4-20	Local
HyMap	Integrated Spectronics Pty Ltd, Australia.	VNIR-SWIR	128	0.45-2.480	2-10	Local
ROSIS	DLR, Germany.	VNIR	115	0.42-0.873	2	Local
DAIS-7915	GER Corp, US.	VNIR-TIR	79	0.45-12	3-10	Local
AISA	SPECIM, Finland.	VNIR	286	0.45-0.9	2.9	Local
CASI	Itres Research, Canada.	VNIR	288	0.43-0.87	2	Local

A. SPATIAL RESOLUTION

Spatial resolution can be defined as the smallest discernible detail in an image [17] which can be described as the measure of smallest object in an image that can be distinguished as a separate entity in the image. In practical situations clarity of the image is dictated by it spatial resolution, not the number of pixels in an image. Spatial characteristics of an image depend on the design of imaging sensor in terms of its field of view and its altitude [18]. A finite patch of the ground is captured by each detector in a remote imaging sensor. Spatial resolution is inversely proportional to the patch size. Smaller the size of the patch, higher the details that can be interpreted from the observed scene.

B. SPECTRAL RESOLUTION

Spectral resolution can be defined as the number of spectral bands and range of electromagnetic spectrum measured by the sensor. An imaging sensor might respond to a large frequency range but still have a low spectral resolution if it acquires a small number of spectral bands. On the contrary, if a sensor is sensitive to small frequency range but captures large number of spectral bands has high spectral resolution, due to its ability to distinguish between scene elements having close or similar spectral signatures [19]. Multispectral images have a low spectral resolution, thus unable to resolve finer spectral signatures present in the scene. HSI sensors acquire images in numerous contiguous and extremely narrow spectral bands in mid infrared, near infrared and visible segments of electromagnetic spectrum. This type of advance imaging system shows tremendous potential for material identification on the basis of their unique spectral signatures [2]. Spectrum of a single pixel in a hyperspectral image can give considerably more information about the surface of the material than a normal image.

C. TEMPORAL RESOLUTION

In hyperspectral remote sensing, the temporal resolution depends on the orbital characteristics of the imaging sensor. It is generally defined as the time needed by the sensor platform to revisit and obtain data from the exact same location [20]. Temporal resolution is said to be high if the revisiting frequency of the sensor platform for the exact same location is high and is said to be low if revisiting frequency is low. It is normally defined in days.

D. UNDERSTANDING SPECTRAL SIGNATURES

Materials present on the surface of Earth absorb, transmit and reflect electromagnetic radiations from the sun in a unique way. Hyperspectral sensors allows us to measure all types of electromagnetic energy within a specified range as it interacts with materials, thus allowing us to observe the distinct features and changes on earth's surface. Reflectance is the measure of electromagnetic energy bouncing back from a material's surface. It is a ratio of reflected energy to incident energy as a function of wavelength [18]. Reflectance is 100% if all the light energy of specific wavelength striking the object is reflected back to the imaging sensor; on the other hand reflectance is 0% if the entire incident light of specific wavelength is absorbed by the object. In most practical cases reflectance values lie in the range [0,100].

In a specified range of electromagnetic spectrum, the reflectance values of different materials present on the earth's surface such as soil, forest, water and minerals can be plotted and compared. Such plots are labeled as spectral signatures or spectral response curves'' [21]. Figure 2 demonstrates a general model of spectral signatures of different materials present on the earth's surface. Remotely sensed images can be classified using these spectral signature plots, as each material present in an observed scene has its own unique spectral signature. The more the spectral resolution of an imaging sensor, the more classification information can be extracted from spectral signatures. Hyperspectral sensors have high spectral resolution than multispectral sensors and thus provide the ability to distinguish more subtle differences in a scene. Hyperspectral imagery has been utilized by geologists for mapping the land and water resources [16]. It is also utilized to map heavy metals and other hazardous wastes in historic and active mining areas. The spectral responses of green vegetation, dry bare soil, and clean water are compared graphically in Figure 3. It is observed that the reflectance curve for bare soil has fewer variations as compared to that

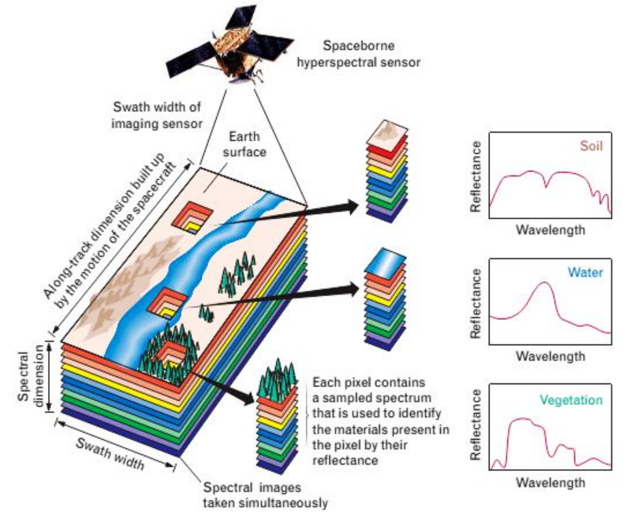

FIGURE 2. A generic scheme of HSI mapping of soil, vegetation and water.

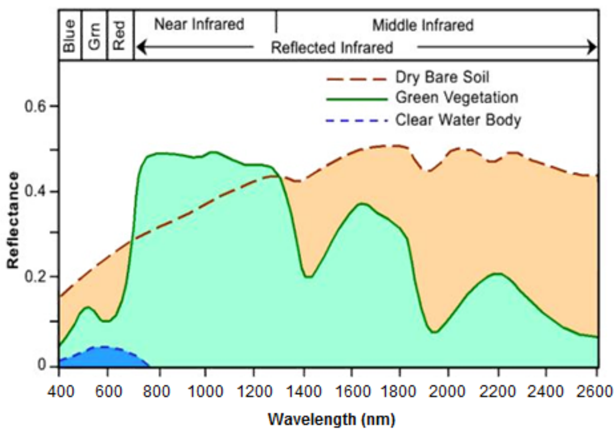

FIGURE 3. Spectral response curves of soil, vegetation and water.

of green vegetation. This is because of the fact that the factors that affect soil reflectance vary in a narrow range of electromagnetic spectrum. These factors include soil texture, presence of minerals such as iron, surface roughness and moisture content in soil [21].

Spectral signatures of green vegetation have basins in the visible range of the spectrum that indicates the pigmentation in the tissues of the plant. Chlorophyll is the primary photosynthetic pigment in green vegetation [18], it absorbs strongly in red (670 nm) and blue (450 nm) regions called the chlorophyll absorption spectral bands. When a plant is under stress so that the chlorophyll growth is reduced, in such cases the amount of reflectance in red (670 nm) regions increases [18]. The spectral response of water has distinctive characteristics of absorption of light in near infrared and beyond. Common factors affecting spectral response of water are the suspended sediments and increases in chlorophyll levels. In each case spectral response will be shifted accordingly showing the presence of suspended sediments or algae in water [22].

III. MODERN APPLICATIONS OF HYPERSPECTRAL IMAGING

Hyperspectral imaging (HSI) is increasingly being used for a wide variety of commercial, industrial and military applications. In this section, we focus on the applications of HSI to food quality and safety, image guided surgery and medical diagnosis, remote sensing such as precision agriculture and water resource management, forensic examination such as document forgery detection and artwork authentication and defense and homeland security.

A. FOOD QUALITY AND SAFETY ASSESSMENT

Due to the growing need for high efficiency and low production costs of food products, the food industry is facing numerous challenges such as ensuring the quality and safety of food products while avoiding liability issues. Food quality and safety is assessed by the examination of various physical, chemical and biological attributes of food. The traditional methods based on visual inspection and chemical and biological inspection of food are destructive, time consuming and also environmentally unfriendly in some cases.

Technological advancements in instrumentation engineering and computer technology enabled efficient and faster assessment of food. Computer vision and machine learning based methods using color image processing have been successfully applied for assessment of external attributes of food [23]–[28]. These methods are unable to examine the internal characteristics of food because they lack the ability to capture broad spectral information. Near Infrared (NIR) spectroscopy helped overcome this limitation of machine vision based methods due to close relationship between food components and NIR spectra [29], [30]. However, NIR spectroscopy could not help in examination of heterogeneous materials due to the lack of ability to capture spatial information [31], [32].

Hyperspectral imagery contains rich amount of spectral as well as spatial information which makes HSI based methods well suited for assessment of food quality and safety [37]. Hyperspectral image analysis has been used for identification of defects [35], [36] and detection of contaminations [33], [34] in food items.

Valenzuela *et al.* [38] employed visual and infrared (VIR) hyperspectral imaging to examine the firmness and solid content of blueberries. Prediction accuracy of 87% and 79% was obtained for firmness and solid content respectively. Huang *et al.* [39] determined mealiness of apple using VIR hyperspectral imaging, achieving classification accuracy of 82.5%. Huang *et al.* [40] employed Grey Level Co-occurrence Matrix (GLCM) and Gabor Filter to determine fat content between muscles in pork achieving a classification accuracy of 89%. HSI is also used to determine color distribution in salmon fillet [41]. Ivorra *et al.* [42] used NIR hyperspectral imaging to detect expired vacuum packed salmon, reaching a classification accuracy of 82.7%. In [43], Principal Component Analysis (PCA) and PLS-DA based classification model is presented for classification of oat and grout kernels in NIR hyperspectral images. The proposed method [43] achieved a high classification rate of almost 100% and thus, showed the efficacy of HSI as an industrial tool in food analysis.

B. MEDICAL DIAGNOSIS

Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) have been traditionally used for clinical analysis. Paty *et al.* [121] compared the potential of MRI and CT for detection of multiple sclerosis (MS) during the evaluation of over 200 patients. Hovels *et al.* [122] used both CT and MRI diagnosis of lymph node metastases in prostate cancer. MRI yielded better results in clinical diagnosis. Over the past decades, modern spectral imaging techniques have proved their significance in medical imaging by providing added potential to medical experts at higher speed and accuracy. The optical characteristics of tissues provide valuable diagnostic information. Hyperspectral image analysis is being widely used for medical diagnosis due to its ability to provide real time images of biomarker information and spectral information of tissues. Besides diagnosis, HSI systems are also used in image guided surgery.

Kumar *et al.* [44] proposed a PCA and Fourier Transform Infrared (FTIR) Spectroscopy based imaging system for diagnosis of breast cancer. FTIR was applied on histopathological specimens of breast cancer with various histological grades and spectral changes near carcinoma were reported. The data was analyzed using PCA. Prominent features were found in the 5882∼6250nm band which could be used for cancer identification. The reflectance spectra of tongue were non-invasively measured and analyzed by Liu *et al.* [45] for tumor detection. Dicker *et al.* [86] distinguished between malignant and benign dermal tissue in the spectral domain in the routine H&E stained samples. In their findings, the spectral signatures differences could be seen if the section thickness and staining time are controlled. A melanoma lesion and interstitial areas are shown in grayscale representation in Figure 4.

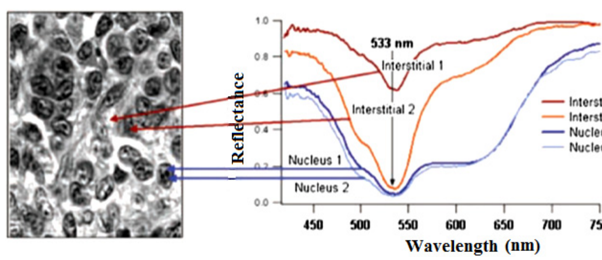

FIGURE 4. A grayscale representation of a melanoma lesion showing the transmission Spectra in the nuclear and interstitial areas.

Mitra *et al.* [46] scanned the biliary structure using both fluorescence and reflectance imaging for classification of different tissues and identification of the biliary anatomy. Fluorescence imaging provided dynamic information about

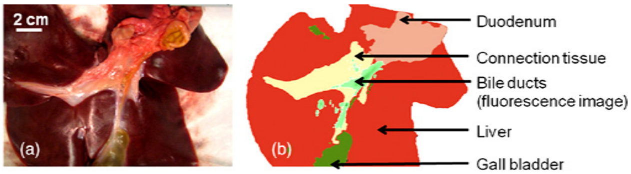

FIGURE 5. The structure of biliary tissue. (b) HSI based classification of the biliary tissue types.

movement and flow in the surgical ROI whereas the hyperspectral image information helped in identification of the bileduct shown in Figure 5. The hyperspectral information also allowed for safe exclusion of contaminant fluorescence in tissues which is not included in the biliary anatomy.

In [46], the biliary structure of tissues was scanned using fluorescence and reflectance imaging for identification of gall bladder diseases. Spectral analysis and image processing techniques were employed for identification of biliary anatomy and classification of tissues. Dynamic information of motion in the surgical region was provided by fluorescence imaging while hyperspectral imagery allowed for safe exclusion of contaminated fluorescence from tissues and provided valuable information for the identification of the bileduct.

Campbell *et al.* [47] have proposed the use of Laparoscopic Partial Nephrectomy (LPN) for diagnosis of renal cortical tumors. Olweny *et al.* [48] used Digital Light Processing (DLP) based HSI for computer assisted LPN to characterize renal oxygenation. The clinical study was performed in eighteen patients. The proposed system was able to successfully characterize dynamic changes in renal oxygenation during LPN.

C. PRECISION AGRICULTURE

Many studies have indicated that the world's crop production needs to be doubled by the end 2050 due to the rapidly growing population in the world [49]. However, various studies have shown that the crop yields are no longer increasing at a rate to fulfill the growing population needs [50], [51]. Recent studies have also indicated that increasing crop yields without using more land for cultivation, is the most effective way for ensuring food security [52], [53]. Global poverty and undernourishment can directly be reduced by increasing crop production; moreover most of the poor and undernourished population consists of farmers themselves [54]. Zhang *et al.* [124] reviewed the state of the art deep learning techniques for representative feature extraction and scene understanding in remote sensing hyperspectral images,

Traditionally crop monitoring for disease, water stress, nutrients and insect attack was carried out by manual visual inspection from the ground. These methods were limited by the fact that the visual symptoms often appear at later stages of disease, thus making it difficult to restore plant health. Advancement in airborne and ground based HSI methods has made possible the evaluation of crop stresses, analyzing soil and vegetation characteristics in a cost effective manner, thus replacing the traditional scouting methods.

Drought stress is an important factor affecting crop yields. Chances of a successful crop can be highly increased by timely detection of water related stresses. High water level stresses are noticeable in variations in photosynthetic pigments. These changes lead to yellowish tint in crops, due to the increase reflectance of red wavelength. Unlike human eye, HSI sensors can detect these changes at earlier stages. Colombo *et al.* [55] indicated that changes in leaf equivalent water thickness (EWT) were responsible for changes in leaf reflectance in the visible and infrared spectrum. They stated that hyperspectral regression indices calculated from HSI were powerful tools for estimation of water content at leaf as well as at landscape level. Rascher *et al.* [56] used a portable HSI system and photochemical reflectance index to estimate water stress in leaves of tropical tress and observed the temporal effects of dehydrations on tree leaves. Rossini *et al.* [57] found that HSI is useful in detecting drought stress at farm level with corn. They showed that irrigation deficits can be accurately mapped well before drought stress affected the canopy structure.

Deficiencies in nutrients and soil contamination cause various symptoms that can be assessed by HSI. Schuerger *et al.* [58] used HSI to observe zinc deficiency and toxicity for identification of chlorophyll levels relating to stress symptoms. They indicated that traditional direct sampling methods are much more costly than HSI. Dunagan *et al.* [59] analyzed mercury levels in mustard plants and found that spectral signatures were notably related to the contaminant levels. Osborne *et al.* [60] showed that biomass, yield under stress, nitrogen and phosphorous concentrations can be estimated by using HSI. Mahlein *et al.* [61] studied different development stages of diseased sugar beet leaves using HSI. Figure 6 shows spectral signatures of healthy as well as diseased sugar beet leaves. This study also showed that HSI has a great potential for analyzing plant diseases.

Analysis of soil characteristics can play a vital role in increasing crop yields. Ben-Dor *et al.* [62] al successfully mapped vital characteristics of soil in a field scale experiment including moisture, soil organic matter and soil sanity. Gomez *et al.* [63] estimated the organic carbon content in soil with accuracy. Growth monitoring of crops has made it possible to forecast production. Liu *et al.* [87] improved winter wheat yield prediction using new spectral parameters. The fine classification technology in agriculture has also matured greatly. Figure 7 shows the HSI based fine classification of vegetable growing regions.

D. WATER RESOURCE AND FLOOD MANAGEMENT

Water is one of the most important resources available on Earth as is vital for survival of humanity. For this reason, managing the water resource efficiently, analyzing and monitoring the quality of water has attracted a lot of attention from the researchers [64]–[69]. Hyperspectral remote sensing technology has found enormous applications in water resource management. Accurate estimates of water resource parameters are possible by analyzing spatial, spectral and

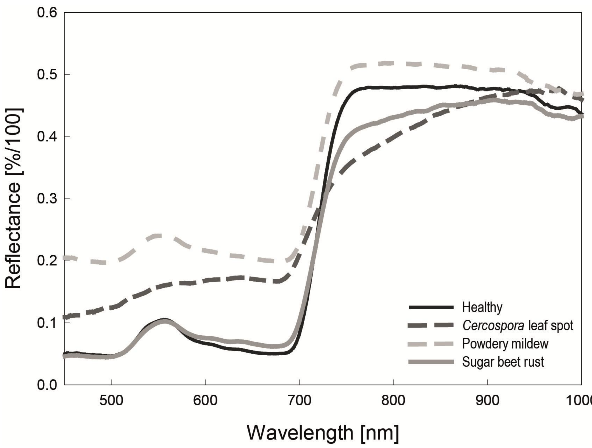

FIGURE 6. Spectral signatures comparison of healthy and diseased sugar beet leaves.

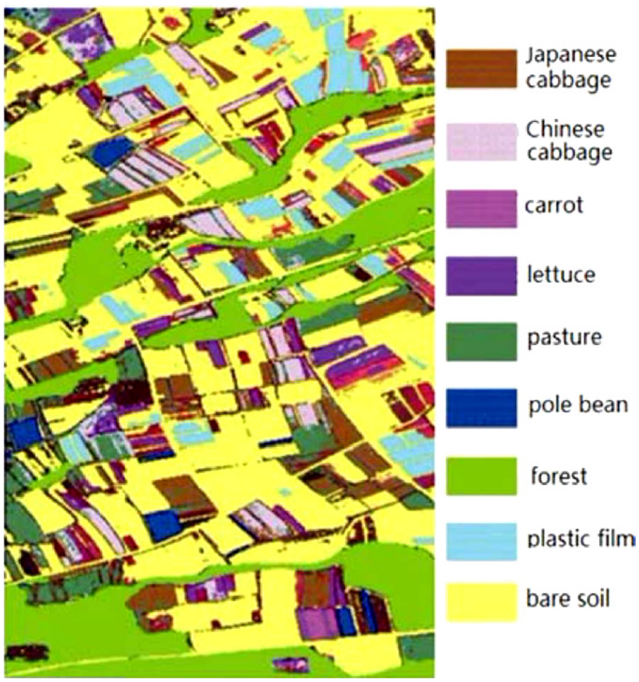

FIGURE 7. HSI based fine classification of vegetable growing regions.

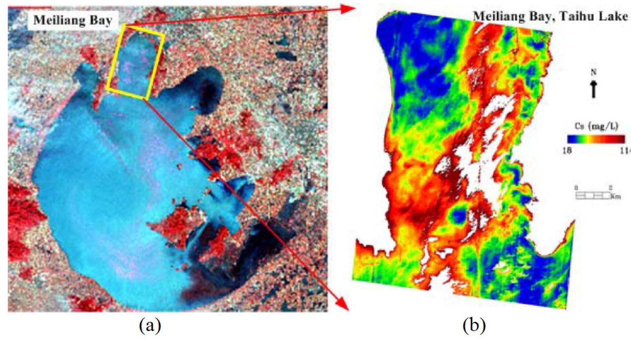

FIGURE 8. Distribution of the suspended matter concentration of Meiliang Bay of Taihu Lake. (a) LANDSAT TM image of Taihu Lake. (b) Estimation result using CHRIS data.

temporal variations in water bodies. Xingtang *et al.* [88] systematically introduced their research on key technologies related to robust hyperspectral water resource monitoring system in China. This work was used by Li [89] to estimate the suspended matter concentrations of Meiliang Bay of Taihu Lake using the CHRIS data as shown in Figure 8. The efficacy of flood detection and monitoring system is limited by their incapacity to get important information about water conditions from airborne and ground observatories in a timely manner. Recent improvements in remote sensing technology has improved the early flood warning system and vastly reduced the time of detection and reaction to flood events to a few hours [70]. US geological survey and NASA are incorporating space borne observations of rainfall resources, rivers and land topography into early warning systems with potential global applications [71]. Glaber and Reinartz [72] studied the optimal procedure for detection of flooded areas with remote sensing data. They investigated the erosive impact of floods, moisture content in flood plain areas, accumulation of sediments. Roux and Dartus [73] explored the flood hydrographs and estimated the river discharge from remotely sensed data. They optimized their model to minimize the error between system response and their proposed model to estimate the river discharge. Honkavaara *et al.* [128] presented various challenges regarding data processing faced by hyperspectral sensors in adverse meteorological conditions and proposed radiometric correction to minimize the effects of radiometric variations in varying illumination conditions.

Hyperspectral remote sensing provides efficient and reliable information about water quality parameters which contain biochemical, hydro-physical and biological attributes [74]–[76]. HSI enable us to measure chlorophyll, turbidity and chemical oxygen demand and phosphorous in water resources. Chlorophyll content in water is extensively studied by hyperspectral remote sensing, which gives an estimate of algal level and hence water quality. Studies have been carried out for evaluation of ammonia changes for wetland [77], classifying different parameters of lakes [78], estuaries [79] and analyzing algal blooms [80]. Wetland mapping has played a significant role in order to enhance the quality of our ecosystem [81]. Hyperspectral imagery has helped in detailed understanding of vegetation characteristics of ecosystem. Extensive research studies have been carried out using remote sensing to explore the significance of acquiring timely data for monitoring and mapping aquatic vegetation [82], which is said to be an important aspect in ecosystem reconstruction and restoration.

E. FORENSIC DOCUMENT EXAMINATION

Traditionally, forensic document experts and paleographers used chemical solution based methods to study the extrinsic and intrinsic components of the important historic documents [83]. This is due to the fact that the inks used on documents throughout the history were composed of diverse substances having distinct chemical and physical properties. All of these substances have their own unique way for reacting with different substrates depending upon the reaction environment. These chemical solution based methods helped in document analysis. But unfortunately these techniques were time consuming, sensitive to temperature changes and destructive in nature i.e. harms to the important documents were irreversible.

To overcome such limitations, HSI has emerged as an effective non-destructive tool for improving readability [84], ink aging and forensic document analysis [13]. Hyperspectral document imaging works on the principle that each ink present in the document has its own unique spectral signature. Many mathematical tools that are being used in hyperspectral remote sensing can be used on hyperspectral document images for classification, improving legibility of extremely deteriorated text, ink aging and fraud detection. Moreover HSI is non-destructive, automated and environment insensitive tool for document examination. In hyperspectral document imaging, ink mismatch detection analysis provides important information to forensic document examiners to determine the authenticity of legal documents. Forgery, backdating and fraud can be detected using ink analysis of documents.

HSI has been used for forensic document analysis in the past [106]–[108]. The HSI based techniques have had a significant impact on forgery detection as compared to the traditional techniques. Different inks were successfully classified after obliteration of the text in a document [106]. Abbas *et al.* [85] proposed hyperspectral unmixing for discrimination between inks from different pens in a document. Recently, we have worked on a nondestructive automated forgery detection system, which was able to successfully discriminate between different visually similar inks taken from the publicly available UWA Writing Ink Hyperspectral Images (WIHSI) Database [85] with different number of inks and different mixing ratios (Combination A∼H). Initially, we used Fuzzy C-Means Clustering (FCM) to differentiate two inks present in a multispectral document in different mixing ratios [129]. In our latest work, the state of the art deep learning technique, Convolutional Neural Network (CNN) has been employed for classification of spectral responses of ink pixels for forgery detection in hyperspectral document images. Figure 9 shows the final segmentation results of our proposed technique. 98% classification accuracy was achieved which shows the high potential of HSI and deep learning in document forgery detection.

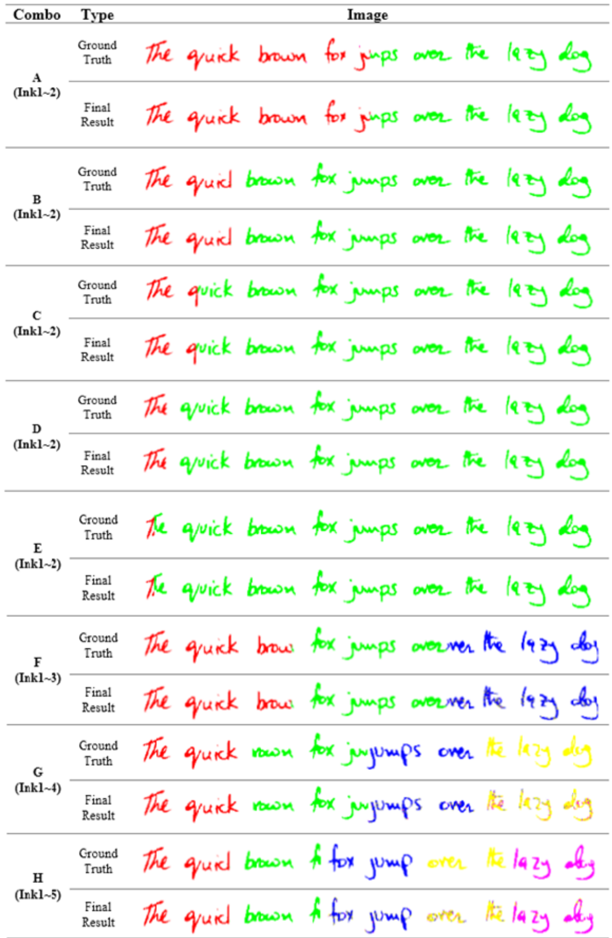

FIGURE 9. Comparisons of ground truth images of documents with mixed inks and our final segmentation results.

F. ARTWORK AUTHENTICATION

The global art market is increasing rapidly over the past decades [90]. A 7% year on year increase in total sales of art and antiques was recorded in 2013 [91]. Most of these high value dealings were made using non-scientific expertise in art. Forensic testing was not used to assure authenticity of the traded object. However, only a limited number of artwork evaluations can be carried out by an experienced specialist. Foolproof evaluations can be carried out if supported by non-destructive scientific tests [92], [93]. Fourier Transform Infrared (FTIR), X-ray fluorescence, and Raman spectroscopy have been used previously for artwork authentication [94], [95].

HSI is proposed as a novel and non-destructive artwork examination method in the recent literature. HSI limits the number of invasive tests needed and provides more information from a sample. Several methods employing pigment analysis provided by HSI and classification techniques have been proposed in the recent literature [7], [96]–[100] for conservation and restoration of artworks such as paintings. These methods allow for identification of restored regions in paintings and distinguish them from the important regions in the original painting. Hyperspectral images captured in the infrared range also revealed useful features of painters such as preparatory drawings [101]. Two forged paintings and the results of IR hyperspectral imaging and SVM classification proposed in [105] are illustrated in Figure 10. The broad spectral information provided by HSI combined with signal processing also allows for identification of the underlying material in artworks. Materials which are clearly visible in a specific band and obscured in the other bands are reflective within the same band and thus easily detectable by the

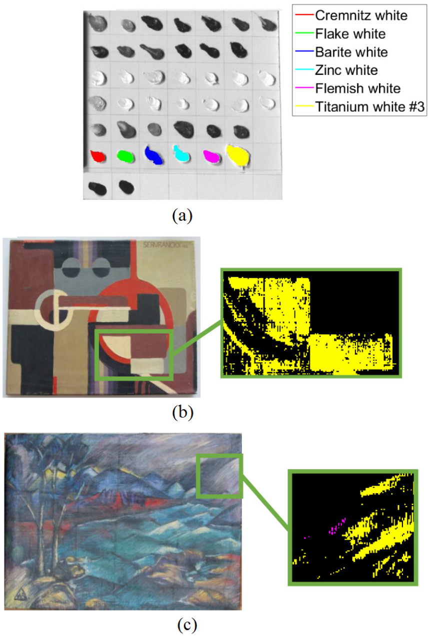

FIGURE 10. **Two paintings with forgery. (a) Grid canvas and color coded pigments. (b-c) Forged Paintings with classification results.**

HSI system [102]. The appropriate bands in the HSI data of historic texts and manuscripts allow for identification of inks and pigments for dating of manuscripts [103] and recovery of erased and overwritten scripts [104].

G. DEFENCE AND HOMELAND SECURITY

The usage of HSI has quickly spread to various civilian applications and more recently to sectors of defense and homeland security [109]. HSI is generally used as a counter-countermeasure for detection and recognition of camouflaged targets in military applications. HSI can easily detect strategic deployments in unpopulated areas such as forests, desserts and mountains, where targets such as military vehicles and mines are distinct from the background even if camouflaged.

Anomaly detection methods [110]–[112] that use spectral information to differentiate between targets and background without any prior knowledge have gained significant popularity over the past few years. Yuen and Bishop [110] proposed an HSI based anomaly detection algorithms "MUF2", which uses a multiple approach fusion methodology. Experiments were performed on images with crops, vegetation and bare soil from the Barrax dataset. An image from the Barrax dataset and the results of target detection using MUF2 algorithm are shown in Figure 11. An extremely high detection rate of 100% was achieved at a false alarm rate of 2×10^{-4}. Remote detection of small targets such as mines is a very challenging task. MUF2 algorithm [110] was also tested for detection of camouflaged land mines as shown in Figure 12. Due to the very small area of the target in the images and noise in the dataset, 60% detection accuracy was achieved at a false alarm rate of 3×10^{-3}. Suganthi and Korah [113] proposed an Artificial Neural Network (ANN) based technique

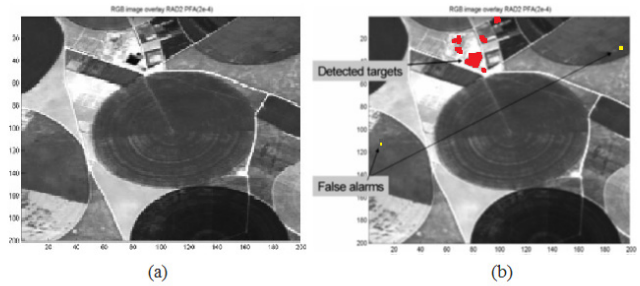

FIGURE 11. **(a) A scene with crops and vegetation from Barrax HSI dataset, (b) Target detection using HSI based MUF2 anomaly detection algorithm.**

for landmine detection and segmentation in infrared images. Letalick *et al.* [114] tested the possibility and feasibility of using multiple optical sensors and concluded that HSI has high potential in detection and recognition of semi-hidden, hidden and camouflaged landmines if prior knowledge of the spectral signature of the target. However, limited detection rate is achieved when landmines are completely hidden or camouflaged with vegetation.

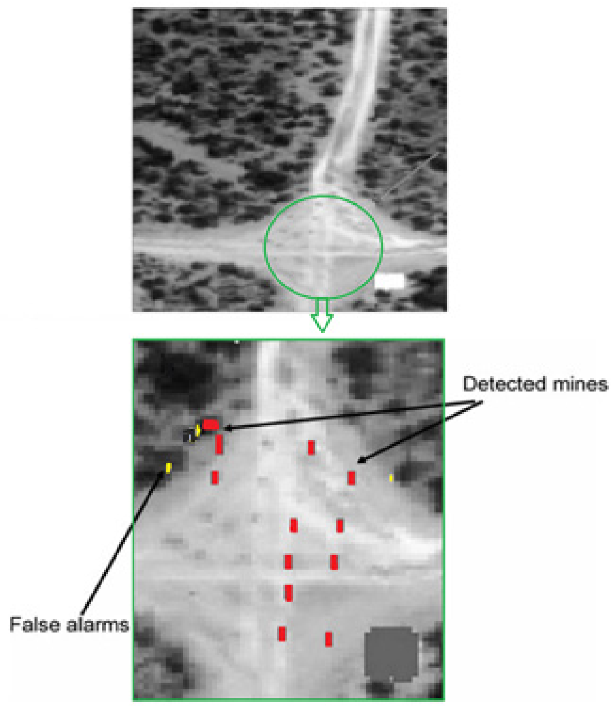

FIGURE 12. **Land mine detection using HSI based MUF2 algorithm.**

Zhao *et al.* [123] proposed a sparse learning technique for hyperspectral anomaly detection, in which they employed dictionary based transformation of background features and iterative reweighting to exaggerate the differences between anomalies and background. Du *et al.* [125] proposed a hybrid sparsity and statistics anomaly detector to overcome the limitations of sparsity models in hyperspectral images containing spectral variability with limited endmembers. Discriminative metric learning method [126] and local geometric structure features [127] have also been used for hyperspectral anomaly detection in the recent literature.

Thomas *et al.* [115] conducted a research on detection of grid patterns of landmines to improve the efficacy of landmine detection in LWIR hyperspectral imagery. Anomalies are detected using Dual Window based Eigen Separation Transform (DWEST) and pattern parameters are extracted. A pattern projection image is formed using the extracted parameters followed by pattern based reduction of false alarm rate. Higher detection probability at lower false alarm rate was noted which shows that the use of spatial pattern parameters in anomaly detection improves land mine detection [115]. Gagnon *et al.* [116] used hyperspectral image analysis to detect buried targets using a LWIR airborne hyperspectral camera. The temperature of disturbed soil over the buried target was found to be higher than the temperature of undisturbed soil around the target area. Classification techniques such as SVM and linear unmixing are used to distinguish between the targets and naturally hot areas.

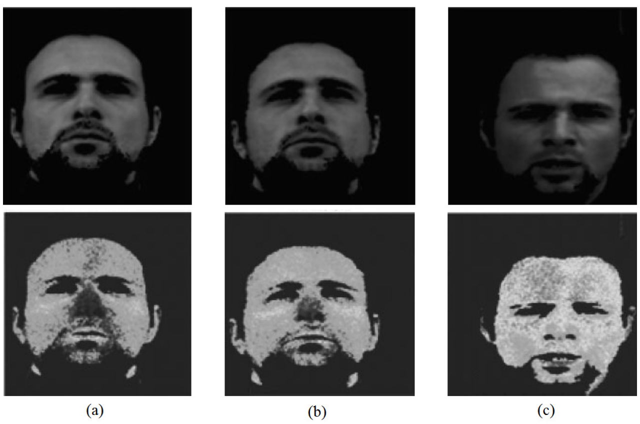

FIGURE 13. **Results of stress detection by HSI based sensing of variations in blood oxygenation due to stress of different intensities.**

In the 21st century, development of state-of-the-art technologies for counterterrorism is one of the fastest growing demands. One of the significant ideas proposed for counterterrorism is detecting improvised explosive devices (IED). It is a technical challenge to directly detect explosives packed in airtight and light manner. Contrary to the direct detection of IEDs, cognitive methods use effective computing to analyze the contextual and body language, behavior, gestures, facial expressions and activity to assess the intent of a person. Mental stress is one of the key indicators of threat which is a short term induced neurological imbalance caused by any situation which involves a possible threat or danger. During neurological stress, the sympathetic nervous system induces adrenaline hormones to the blood triggers increase in blood flow to muscles and dilation of pupil. These unavoidable physiological changes during stress are detected as an indication of stress level using HSI [25]. Assessment of hemoglobin oxygenation using spectroscopic tuning is proposed in [26] and [27]. Figure 13 shows the oxy-hemoglobin levels of a person at different levels of stress.

IV. CONCLUSION

Among remote sensing technologies, the role of hyperspectral imagery in the geo-observation, identification and detection of materials and estimation of physical parameters cannot be stated enough. Due to this very reason there is increasing number of airborne and spaceborne hyperspectral platforms based applications being researched. Recent advancements in sensor technologies have encouraged researchers to use hyperspectral imagery in many modern applications. Many mathematical tools and algorithms are being researched such as data fusion, hyperspectral unmixing, hyperspectral classification, anomaly detection and fast computing for efficient utilization of hyperspectral data. These mathematical tools can be used on hyperspectral data across many different applications.

In general, this review focuses on the vast extent to which hyperspectral imaging has been used to increase and maintain the crop yields, managing water resources, assessment of food quality and safety, diagnosing diseases, authentication of artworks, forensic examination of questioned documents, detection of military targets and counterterrorism. Promising results have been found in the proposed automatic forgery detection system based on HSI and deep learning. Future research is being carried out for further improvement as well. This review can be a useful baseline for future research in hyperspectral image analysis.

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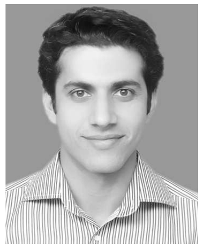

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