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Hyperspectral Imaging: A Review and Trends towards Medical Imaging

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Abstract: Hyperspectral Imaging (HSI) is a pertinent technique to provide meaningful information about unique objects in the medical field. In this paper, the basic principles, imaging methods, comparisons, and current advances in the medical applications of HSI are discussed to accentuate the importance of HSI in the medical field. To date, there are numerous tools and methods to fix the problems, but reliable medical HSI tools and methods need to be studied. The enactment and analytical competencies of HSI for medical imaging are discussed. Specifically, the recent successes and limitations of HSI in biomedical are presented to offer the readers an insight into its current potential for medical research. Lastly, we have discussed the future challenges concerning medical applications and possible ways to overcome these limitations.

Keywords: Hyperspectral imaging, spectral imaging, biomedical, deep learning, optical imaging, infrared.

1. INTRODUCTION

The rise of precision medicine and artificial intelligence (AI) provides fertile soil and powerful tools for hyperspectral medical research. It points out the direction for applying hyperspectral technology in new fields. Hyperspectral Imaging (HSI) is developed based on multispectral remote sensing technology. It integrates two traditional optical diagnosis methods of spectral analysis and optical imaging. HSI means a wider spectral range, higher spectral resolution, and more spectral channels to comprehend continuous spectral range imaging [1][2][3][4]. HSI entailed mainly aerial remote sensing promptly, such as environmental monitoring and military tasks. Later, it gradually expanded from the military field to commercial applications, such as food safety testing and industrial quality control [5][6]. To date, with the development of HSI technology and instruments miniaturization, HSI has shown broad application prospects in crop monitoring, archaeology, physical evidence identification, medical health, and other fields [7][8][9].

In recent years, the HSI application has been continuously expanded, and the technology has improved. At present, the application fields of hyperspectral imaging mainly include the following aspects: military, which is used for hyperspectral mine detection, toxic gas warfare agent detection, real-time missile search, and exposing camouflaged targets [10][11][12][13]. In terms of atmosphere, research on water vapor, water layer and prediction of meteorological disasters and hydrology, detect changes of land surface temperature, marine organisms, sediment content in estuaries and coasts, water environment pollution, and underwater resources [14][15].

In agriculture, quantitative analysis of chlorophyll, agricultural monitoring, crop classification and identification, geological aspects, geological disaster monitoring, and archaeological excavation was briefly studied [16][17][18][19]. In terms of food, it is mainly used for quality detection, non-destructive detection, and food safety [6].

In the 21st century, spectral imaging technology has been developed and gradually applied in biomedicine, which has high research value and application prospects [20][21]. HSI technology classifies the degree of cervical cancer and timely understanding cancer's status [22]. There is research on detecting skin tumors by using hyperspectral data and light agents [23]. The oxygen transport mechanism in vascular tumors is perceived by using HSI and labeling proteins with different color light agents. The distribution of blood oxygen saturation in tumor microvessels was obtained [24]. Support Vector Machines (SVM) distinguished the arteries and veins of pigs and assisted doctors in detecting the abnormal parts of blood vessels [25]. The abnormalities in skin tissues were obtained in continuous wavelengths between 400-800 nm. The difference and comparison were recorded between benign fatigue and melanoma [26]. The classification of multispectral bone marrow cell images is done by a C-SVC classifier in SVM [27], and comprehended the quartering of a nucleus, cytoplasm, Red Blood Cells (RBCs), and background, with a segmentation accuracy of 94% [28]. Experiments show that multispectral imaging provides more stable, rich, effective information than other images.

2. BACKGROUND

In the 1970s, some people tried to combine spectral diagnosis and optical diagnosis for medical application. A multispectral imaging system was developed to diagnose burning skin and other changes in skin surface tissues. However, hardware limitations make the imaging system separate near-infrared information from visible light [29].

HSI uses continuous narrowband data to obtain image data from the region of interest. The main hardware equipment is an imaging spectrometer. In 1983, the U.S. Jet Propulsion Laboratory successfully developed the world's first imaging spectrometer. It carried out geological and mineral mapping experiments, biological component analysis, and atmospheric prediction [30]. Since then, the development of imaging spectrometers has always been at the forefront, especially in remote sensing.

Imaging spectroscopy has made many significant achievements. So far, more than 20 countries have developed more than 100 kinds of imaging spectrometers. Biological component analysis and the overall performance of imaging spectrometers are also continuously improved. HSI's new developing technology is also the product of the comprehensive action of spectroscopy, electronics, precision instrumentation, and computer equipment. HSI data has two basic characteristics: image and spectral information. HSI comprehends the combination of two-dimensional spatial information and spectral information of image pixels to obtain the "three-dimensional cube" information of hyperspectral data, which lays a solid foundation for the wide application of HSI.

HSI began to enter in the medical diagnosis in 1990s officially. Firstly, hyperspectral technology was applied to healthcare in 1997. It was pointed out that the combination of hyperspectral technology and medical diagnosis will be a breakthrough for surgeons to broaden their horizons [31]. Then, scientists developed HSI equipment to detect where cancer occurs in tissues besides detecting the degree of cancer diffusion and showing which tissues are cancerous. This is of great significance for the accurate resection of cancerous tissues [32]. In the same year, other scientists made a preliminary exploration on the detection and diagnosis of cervical cancer by using hyperspectral diagnostic imaging technology. This work showed the great potential of combining HSI with the endoscope. It could make tissue image in real-time and also eliminate the pain of invasive diagnoses such as biopsy [33].

The specificity and sensitivity were compared using HSI technology and biopsy to detect cervical cancer through comparative experiments. The results showed that the detection speed of HSI technology was much higher than that of making a biopsy. The test's specificity was similar to that of the biopsy [34]. Meanwhile, Schultz et al. developed an HSI for microscopy. The standard fluorescence microscope is optically coupled with the imaging spectrometer and controlled by Charge Coupled Device (CCD) recorded and tested the samples related to histology, revealing the great application prospect of HSI in the field of optical microscopy [35].

After HSI of tissue and cell sections, it could be analyzed by the morphological features of the object in the image and measured the similarity between its spectrums. Finally, combine these features to accurately distinguish the normal cells, precancerous cells, and cancer cells [36]. HSI can be used to measure the disorder intensity of refractive index fluctuation in the scattering object [37]. Therefore, Linear Regression (LR) is being used with statistical characteristics such as variance to identify normal and cancerous pancreatic cells, which resolved the potential risk of pancreatic cancer being classified as normal by routine microscopic histopathology. Hyperspectral images of prostate tissue were collected and Support Vector Machine (SVM) was used to classify spectral features. The results show that the sensitivity and specificity of the classification method are 92.8% and 96.9%, respectively. This research ameliorated optical diagnosis in prostate cancer research [38][39].

Further, the tensor model was utilized to take the tensor of the pixels in the image according to a certain radius for Tucker decomposition to reduce the input feature dimension while obtaining spectral and spatial features. Then use K-nearest Neighbor (KNN) classifier to classify [40]. SVM was added to the random forest algorithm and carried out region growth based on the random forest algorithm through the probability of classifying some specific seed points by SVM to classify patches of cancer regions and non-cancer regions. It is clear from the above introduction that HSI has made great achievements in medical diagnosis [41]. However, the vast research works majority adopt handpicked features and traditional classifiers such as SVM for classification. In addition, the method is to establish a huge spectral library to match the correlation of new samples.

Many researchers described deep learning (DL) advantages in medical image processing with a review. DL can remove complex feature design links, adaptively extract features, and has worked widely in detection, segmentation, classification, and other tasks [42]. Convolutional Neural Network (CNN) has classified the spectrum of head and neck cancer tissues. DL results also show adequate classification performance without complex manual features and classifiers [43].

2.1. Deep Learning (DL)

Since Hinton's theory, DL has been an AI research hotspot [44]. It has been widely used in image classification, object detection, face recognition, etc. [45][46]. DL usually needs to build multilayer neural networks involving different levels of data expression, initialize through unsupervised learning, and fine-tune the model via supervised learning [47][48]. This structure can learn essential deep features as well as extract the abstract and invariant features. It has excellent generalization ability and provides the possibility to break through the research bottleneck of the medical field. According to the patient's disease data, the DL model can obtain the typical characteristics in the data set, predict the type and incidence of abnormal lesions, and complete the rapid automatic diagnosis. The diagnosis results can effectively avoid the influence of subjective factors, provide an effective reference for doctors and improve the diagnosis efficiency. For example, multi-platform tumor data are modeled by Multimodal Deep Belief Network (DBN), and then subtypes of lung cancer and ovarian cancer are classified [49]. Modeling human fundus images through CNN and then grading the severity of cataracts [50][51]. CNN was used to study mitotic breast cancer cell images [52]. DBNs modeled human brain waveforms to detect abnormalities [53]. Magnetic Resonance Imaging (MRI) classified Alzheimer's disease and mild cognitive impairment [54][55]. DL models are also widely used in data sequencing [56], gene expression [57], emotion analysis [58], image classification [59], and object segmentation [60][61] of clinical data, and its effect is better than the traditional Machine Learning (ML) methods. In addition, in recent years, DL has gradually entered pathology. Based on many clinical digital pathological samples, the DL model can automatically learn the image characteristics of cancerous tissue and effectively divide the cancerous and normal tissue region, which assists doctors in pathological analysis. With DL, the computer-aided pathology diagnosis will be continuously improved to provide patients with a more accurate medication guide.

3. HYPERSPECTRAL IMAGING SYSTEMS

Hyperspectral Microscopic Imaging (HMI) systems are classified in many ways according to different standards. If classified according to other working bands, it can be divided into ultraviolet, visible, near-infrared, and midinfrared. According to different types of measurement spectrum, it can be divided into reflection type, fluorescence type, Raman type, etc. According to the way of collecting hyperspectral datasets, there is the whiskbroom, staring, pushbroom, and snapshot [62]. Along with the spectral dispersion mode, there are prism grating types, tunable filter types, single-lens imaging types, etc. Here, we analyze and compare some imaging systems from HSI data set acquisition/dispersion modes and introduce the microscopic system. The HSI system is built, and the specific parameters can be referred to [63]. The main purpose of HSI is to use this system to study different biological cells.

An HSI system mainly consists of the following parts: light source, optical imaging system, spectroscopic system, detector, sample platform, and computer system. Ultraviolet light is generally used as the excitation light source to excite fluorescence effectively. The fluorescence spectrum imager can be divided into the filter, dispersion (including prism and grating), and interference types. Spatial dispersion spectroscopy is mainly dispersive and interferometric, cooperating with the receiver spatial scanning. The non-spatial dispersion beam splitter is an imaging device filter type that can be connected to receive spectral images directly. Compared with the first two types of spectral imaging, the filter type has the advantages of easy implementation and the highest maturity. The filter type is also the mainstream spectral imaging technology used in optical remote sensors.

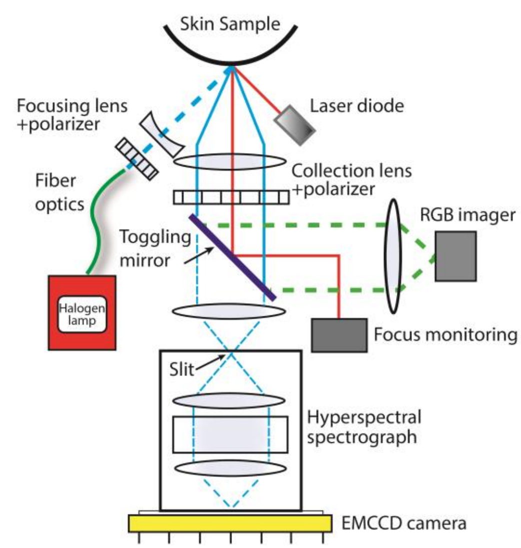

Figure 1. Schematic setup of a hyperspectral camera [64]

The basic phenomenon of the HSI is to capture the light through a special lens and disperse it into distinct spectral lengths with the help of an element like diffraction grating or prism. It is also application-specific to record wavelengths with their respective positions [64]. In MHSI, Complementary Metal-Oxide Semiconductor (CMOS) and CCD detectors are very common, which record the data inherent from captured light as in Figure 1. The HSI cameras can be rearranged as per the requirement of the application. Moreover, the critical part is the light calibration. The specific image of the tissue exhibits the multicolor complex dataset. Distinct spectra are required to extract this color information accurately. Nevertheless, MHSI can spot tumors. So, nanoparticles have bettered visualization for several years with accurate detection/imaging systems beating old approaches [65].

3.1. Hyperspectral Data Acquisition

The Whiskbroom imaging method comes from the acquisition process of image data in remote sensing. When UAV obtains the reflection spectrum data of surface objects from high altitude, it needs to adjust the mounted optical path so that the sensor can receive the information of various points on the surface. This process uses a rotating mirror that can move back and forth. Because the swing scanning direction of this mirror is perpendicular to the flight path, only a single pixel can be collected at a time, so this acquisition method is also called point-by-point scanning. As in Figure 2 (a), the transformation of the focused point can be understood by moving the sample along with the X and Y directions or moving the detector. Combined with microscopic imaging, because the swing sweep type requires an electric platform control that can translate in both horizontal and vertical directions, the system with this structure is often complex in hardware, time-consuming, and inefficient in data acquisition [62].

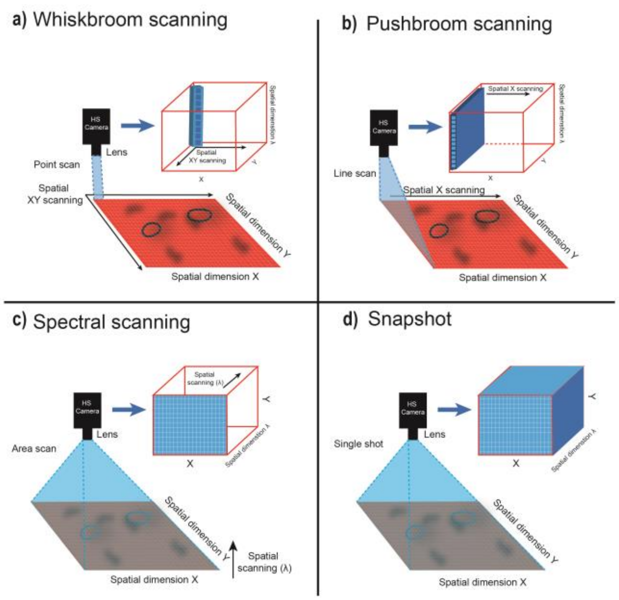

Figure 2. Hyperspectral data acquisition systems [66]

Pushbroom is also called linear scanning. Unlike the swing sweep, it can obtain the spatial information and spectral information of a column of pixels at a time. Figure 2 (b) depicts adding one-dimensional spatial data. The detector needs to be upgraded to two-dimensional imaging. On the other hand, the push sweep method obtains one column of data at a time, which means that it stays at a certain position longer than the swing sweep method to receive more photons, so the push sweep system has a higher spectral resolution. Like swing sweep, push sweep also needs to solve frame synchronization and mosaicing problems. Because microscopy is sensitive to external disturbance, the above two mechanical scannings require additional shockproof facilities [67].

Staring can obtain the object's spatial information in a single band at one time. The staring type in Figure 2 (c) requires two-dimensional filter elements to comprehend each acquisition of one band, such as Liquid Crystal Tunable Filter (LCTF), Acousto-Optic Tunable Filter (AOTF), Linear Variable Filter (LVF) [35][68][69][70][71]. The function of these filters is to filter the original spectrum into a narrowband spectrum and then project it onto the detector. In a sense, this filtering method can be regarded as the push sweep of spectral dimension. Compared with a one-dimensional push-broom system, staring filtering is faster and avoids complex mechanical settings [35][68].

The snapshot system directly projects hyperspectral data cubes onto the detector in a single shot without scanning. Generally, these systems rely on the spatial redundancy of hyperspectral and increase the spectral resolution by sacrificing the spatial resolution. If there are relevant reports, Digital Micromirror Device (DMD) [72] modulates spatial information to multiplex spectral information to understand HSI. In addition, such systems also need to use complex restoration algorithms to reconstruct the collected data. Because the fast viewing type cannot simultaneously improve spatial and spectral resolution, it also has some limitations. Several methods integrate different imaging systems to overcome these limitations in literature [62]. The distinguishing HSI characteristics appear in Table 1. Moreover, the developments and benefits of biomedical imaging are highlighted to understand the current technologies.

Table 1. Assessment of monochrome, RGB, spectroscopy, multispectral, and hyperspectral features [62]

Feature	Monochrome	RGB	Spectroscopy	Multispectral	Hyperspectral
Spatial information	Yes	Yes	No	Yes	Yes
Band Numbers	1	3	From several dozens to hundreds	3 to 10	From several dozens to hundreds
Spectral information	No	No	Yes	Limited	Yes
Multiconstituent information	No	Limited	Yes	Limited	Yes
Sensitivity to minor components	No	No	Yes	Limited	Yes

The typical HMI system consists of CCD, microscope, optical devices, and light source. With the distinguished optical sensors configuration, this microscopic system has fluorescence HMI (FHMI), near-infrared/visible HMI (NIR/Vis HMI), and Raman HMI (RHMI) [73]. Several organic substances hold intrinsic fluorescence, i.e., irradiate after light absorption at a specific wavelength like monochromatic or ultraviolet laser light, varying from the excited state to the ground state. Fluorescence has been emitted once the fluorophores return to the ground state. Generally, fluorescence analysis conducts by analyzing the difference of exciting and emitted wavelengths [74][75][76]. This imaging system is well known as Fluorescence HMI (FHMI). Mostly, vegetables and fruits in agriculture products could emit light in near-infrared or visible regions after absorbing energy and identified with the help of NIR/Vis HMI [77]. The inelastic dispersion of Raman bands can attain spectroscopic information. The individual component can be recognized in the food matrix with the help of a Raman spectrometer [78].

4. HYPERSPECTRAL IMAGING APPLICATIONS

HSI is widely used in biomedical fields, such as evaluating dental structures health, gastrointestinal disease, ear/nose/throat disease, and real-time medical diagnostics, etc., as in Figure 3. Furthermore, HSI helps RBCs analysis [79], metabolism analysis of algal cells [80], detection of cutaneous melanoma [81], etc. Because the changes of internal material components often accompany the pathological changes of tissue and cells. When the incident light acts on the pathological tissue to produce absorption, scattering, and fluorescence effects; the detected absorption spectrum, Raman spectrum, and fluorescence spectrum will differ from normal tissue and cells. Based on this, one can achieve non-destructive and rapid detection of lesions. Arteries and veins can be distinguished in bright-field images; RBCs carry oxygen molecules. To analyze the oxygen concentration distribution in tumor microvessels, HSI studied RBCs.

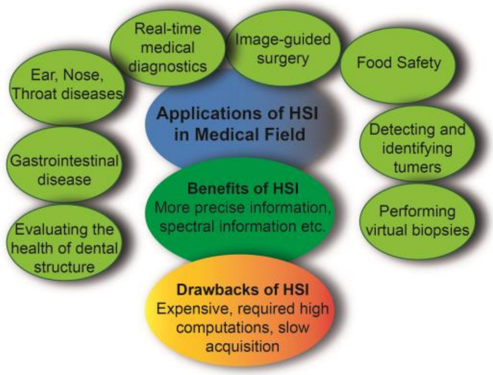

Figure 3. HSI applications, benefits, and drawbacks

HSI unveils great evolving potential for surgical guidance and noninvasive disease diagnosis. Light is distributed to the biological tissues and experiences multiple scattering from biological structures' non-uniformity. It primarily shows melanin, hemoglobin, and water absorption because it transmits through these tissues [82][83]. When there is any disease advance, scattering characteristics vary. Fluorescence and absorption can guide treatment [84]. So, HSI sensors' recorded signals deliver a lot of meaningful tissues information for obvious diagnosis [34][84][85][86]. Recent HSI evolutions and computational power have proceeded towards several medical applications, as Figures 4 and 5.

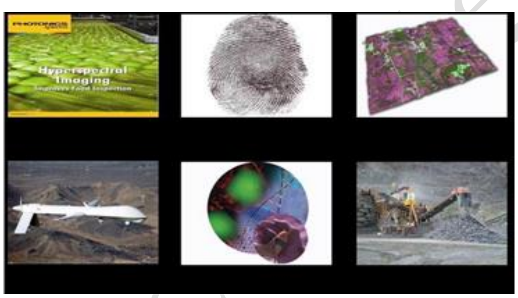

Figure 4. Common applications of HSI [87]

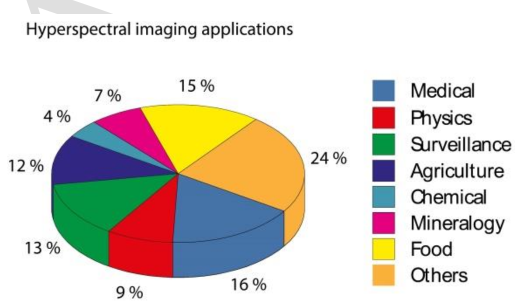

Figure 5. HSI applications in different environments

HSI is a nonintrusive modality that manifests the early recognition of cancer and as well as several other diseases. Among them, medical health is the fastest-growing application field of HSI. The U.S. market research and consulting company predict that the average HSI annual growth rate in the health market will reach 16% by 2019, as in Figure 5. In the schematic process of HSI, spectral signatures have vital diagnostic information for the perfect observation of the disease and precisely analyze the biological tissues. Still, standard cancer diagnoses involve tissue biopsy and pathological assessments carried out by pathologists using microscopes [88]. Still, an effective cancer diagnosis depends on the pathologists' concentration and experience. HSI's extreme importance and its spectral health signatures involvement are recorded in ongoing research, exhibiting the cumulative employment of HSI towards medical diagnosis. From 2001 to 2021, HSI is exponentially being used in the medical field. Figure 6 depicts Medical HSI (MHSI) and Medical Spectral Imaging (MSI). The highest number of MSI papers published was 160K over 2012-2015. Then, it declined after 2015. These statistics also reveal the increasing demands of MHSI.

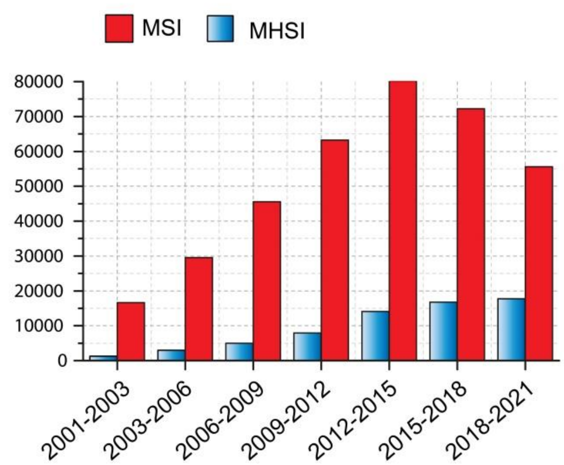

Figure 6. MSI and MHSI Comparison

5. CONCLUSIONS AND FUTURE WORK

HSI offers ample information acquisition, wideband range, label-free, non-contact and high accuracy about tissue samples' spatial and spectral information. It can effectively obtain evidence reflecting the external structural, physical structure traits such as sample size and shape, besides providing information on internal sample structure and chemical composition. Thus, HSI innovates noninvasive, rapid disease detection and a visual assistant surgery tool. Prior research confirmed HIS's vital progress in surgical guidance and medical diagnosis research. This paper treats HSI medical applications. Current market studies point out coming demands for medical diagnosis. The basic HSI principle is inherited from prior applications such as remote sensing and geographical surveying. The HSI medical imaging focus will devise better analyzers to treat and diagnose more exactly.

In ML, there are many algorithms such as CNNs, Principal Component Analysis (PCA), SVMs, Fisher discriminant model, etc. It is necessary to discuss further and analyze to find an optimal algorithm and improve diagnosis discrimination accuracy by using full HSI technology with non-toxic, harmless, green, and pollution-free carbon nanodot dyes to identify exact tissues. Many diseases are difficult to diagnose in some healthcare facilities (i.e., general hospitals). These diagnoses can rely on HSI, but researchers need further exploration and verification. It is tense to mark the labeled data with enough DL and application to practical application, which requires a lot of human and material resources. The use of weakly supervised, semi-supervised, or even unsupervised learning will become a direction of future research. DL combined with spatial spectrum can be extended to other medical images, e.g., ultrasound imaging, computed tomography (CT), MRI.

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The authors have no conflicts of interest, financial or otherwise.

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