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Applications of spectral imaging in Biosystems engineering in Iran, A review

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Abstract

Spectral imaging covers hyperspectral and multispectral image acquisition, processing, and analysis. Visible-near infrared hyperspectral imaging captures several image channels in 400-2500 nm bands of the electromagnetic spectrum. Multispectral is the same as hyperspectral imaging but with fewer image channels. Due to the detection of invisible goals via area assessment, the techniques are widely used for research and application purposes in different fields. The techniques are applied to assess the external and internal properties of objects. Besides providing non-destructive assessments, high accuracy, reliability, repeatability, and speed and low cost are advantages of the techniques. Using image processing technology, the acquired images are manipulated to extract and analyze features, and the obtained results are used in decision-making processes. Biosystems engineering is applying engineering science and technology in agriculture, natural resources, and food sectors to move in a sustainable production path. Visible-near infrared hyperspectral and multispectral imaging techniques and their advantages have been discussed. The techniques have been successfully used in Iran for the detection of diseases, ripeness, components, and alterations in plants and plant-based materials.

Keywords Visible-infrared band, hyperspectral imaging, multispectral imaging, image processing, data analysis

1. Introduction

At first, imaging technology was applied to see objects in visible range of the electromagnetic spectrum to do different tasks instead of the human eye. This technology has vast applications because they are non-destructive and accurate, reliable, reputable, fast, and cheap compared to labor-based operations and laboratory methods [1, 2]. Different techniques were applied to acquire object images in invisible ranges of the spectrum such as X-ray and computed tomography (CT) [3, 4]. Invisible techniques can clearly identify internal properties of materials but they are relatively expensive, complex to maintain, and time-consuming in the imaging process. However, spectral imaging techniques offer more advantages such as high-speed measurement capability and lower cost.

Spectral imaging covers hyperspectral and multispectral imaging. Visible-near infrared (Vis-NIR) hyperspectral imaging (HSI) and visible-near infrared multispectral imaging (MSI) as new imaging techniques are widely applied in different fields because of detecting visible and invisible goals. The advantage of spectral imaging over other imaging methods is combining spectroscopy and imaging technology to allow area assessment of different materials via wave analysis in visible-near infrared ranges. So, this method provides detailed information about spectral and structural changes of materials. These advantages allowed the assessment of both internal and external properties of materials [5, 6]. The acquired images by the methods are processed using different methods to extract and analyze image features [7]. Selecting effective wavelengths and efficient features may be done to achieve better results [8].

The HIS and MSI methods have been widely used in the assessment of different goals in indoor [9, 10] and outdoor conditions [11-13]. The techniques have been used in different fields such as industry [14], medicine [15], agriculture [16, 17], natural resources [18, 19], and food [20, 21].

Biosystems engineering covers agriculture, natural resources, and food. Its goals are to improve different operations in these fields to promote technical, social, and economic productivity and reduce environmental burdens [22]. Different techniques are used in these fields to provide food and living mediums for humans

[23] and move on a sustainable production path [24] by applying engineering sciences and technologies. Agronomy, horticulture, and livestock are the main subareas of agriculture while forest, pasture, and fishery are the main subsectors of natural resources. The raw products of agriculture and natural resources are processed to produce final products in the food sector. These sectors are assisted by other subsectors including biosystems, veterinary, agricultural economics, plant protection, agricultural extension, mechanization, and irrigation [25]. The knowledge and technologies of these sectors are used [26] to improve the required operations and subsequently enhance productivity and decrease environmental impacts [20]. As imaging, especially new imaging techniques, are useful tools to improve operations due to their abilities and advantages, the present study aims to introduce HIS and MSI techniques and review their applications in biosystems engineering in Iran. To do this, a search in Persian and English websites was done to collect the cases from the first to the recent applications of HSI in agriculture, natural resources, and food in Iran.

2. Imaging technology

Imaging is defined as the acquisition of objects' photos. In this technology, the acquired images in different wavelength bands of visible and invisible ranges of the electromagnetic spectrum are produced [5, 6]. Conventional visible imaging cameras record images in visible wavelengths of the spectrum (400-700 nm) from the surface of objects. These vision systems are limited to surface properties such as color, shape, and texture [27, 28]. Although few internal properties of different materials are assessed in relation to their surface properties [29, 30], their internal applications are limited. So, invisible imaging techniques such as X-ray, infrared thermal imaging, near-infrared hyperspectral imaging, and near-infrared multispectral imaging were developed [31]. The techniques receive wavelengths emitted from objects in invisible bands of the spectrum [3, 5, 6]. The images in invisible bands are changed to be visible in grayscale or pseudo-color form.

The advantages of imaging technology are high speed, accuracy, reliability, and reputability [3, 6]. They can be applied in real-time operations and are used instead of labor. In these cases, they are better than laborers due to lower operations costs and more simplicity. Moreover, most imaging techniques are non-destructive because the objects are not destroyed during the imaging process.

2.1 Hyperspectral and multispectral imaging

Visible-near infrared (Vis-NIR) hyperspectral imaging (HSI) or chemical imaging means acquiring objects' images in both visible (400-700 nm) and near-infrared (700-2500 nm) bands of the electromagnetic spectrum. Like spectroscopy, several wavelengths are studied in this method. Only three image channels (red, green, and blue) are obtained in conventional visible imaging. Although visible-near-infrared spectroscopy provides abundant information across multiple wavelengths and has been widely studied due to its high resolution, it is applied to point measurement studies. However, the spatial distribution of spectral information is studied in HSI because an image channel is obtained corresponding to each wavelength or a narrow band (2-10 nm) in the near-infrared range.

A spectral imaging system typically consists of a hyperspectral detector or camera, optical components, a light source, and a computer equipped with image acquisition and processing software to control the imaging process and subsequent processing such as digitization, storage, modeling, and decision-making [6, 32-36]. The optical components of these systems include lenses, a spectrometer (or spectral scattering unit), optical filters, and calibration elements. The appropriate selection of these components plays a crucial role in enhancing the performance of the HSI system and capturing accurate and high-quality hyperspectral images. The precise choice of the light source's spectrum, intensity, stability, and characteristics, based on the specific needs of each application is essential [22, 37]. They include area (single-shot), line, and point scanning systems [38]. For indoor imaging, tablet HSI and MSI systems are used while satellite, aircraft, and UAV-mounted and handheld imagers are applied for the outdoor image acquisition process [12].

The obtained image in HSI is called hypercube because the number of the acquired image chanels are high (more than 75 channels). Hypercube is a matrix including spatial (x and y directions) and spectral reflectance (z direction) information of the objects [3].

The recorded image is MSI is similar to HSI, but the number of the wavelengths are lower. Image acquisition in HSI is time consuming come pare to MSI that only image channels related to the effective wavelengths are acquired. So, the MSI has not limitation of real time applications compared to HSI. Another advantage of MSI is dealing with data with lower volume compared to HSI.

2.2 Hypercube processing and analysis

Image processing and analysis include image preprocessing, feature extraction, feature selection, and feature classification [6, 39]. Hypercube processing and analysis is like conventional visible image processing plus wavelength selection step [22].

After image preprocessing, it is essential to reduce the volume of input data to reduce computational complexity. Therefore, the effective wavelengths must be found to extract and use key data from the corresponding image channels. As a large number of image channels are acquired corresponding to different wavelengths, the effective wavelengths must be found to reduce the dimension of the hypercube in z-direction (spectral dimension). This step is necessary to provide a multispectral image with a decreased number of wavelengths. Different methods are applied to select effective wavelengths such as principal component analysis (PCA), independent component analysis (ICA), kernel

PCA, local tangent space analysis, local linear coordination, local linear embedding, hessian local linear embedding, multilayer autoencoders, diffusion maps, isomap, linear discriminant analysis wavelet transform (LDA-WT), multidimensional scaling (MDS), Fourier transform (FT), and Laplacian eigen maps [38, 40, 41]. The effective image channels of the corresponding effective wavelengths are used in other image-processing steps [20].

3. Biosystems applications

In biosystems engineering, HSI and MSI have been applied to improve different activities in agriculture, natural resources, and the food sector because they combine the advantages of infrared wave analysis in spectroscopy and area assessment in imaging technology. The applications of HSI and MSI in biosystems engineering have been listed in Table 1. These applications were sorted by year. The effective wavelengths of several types of research have been presented in this table. The effective wavelengths are those that better show the goals. This is due to the effects of the goals on the value of the selected near-infrared waves.

Table 1 Applications of hyperspectral imaging in Biosystems Engineering.

Material	Purpose	Effective Wavelength (nm)	Reference
Pistachio kernel	Fungal infection	1090, 1280, 1700	[34]
Pear fruit	Ripeness	450	[42]
Pomegranate fruit	Titratable acidity, total soluble solids, pH	700-800-900-1000	[43]
Orange fruit	Green mold	500-800-900	[44]
Fish	Spoilage	488, 542, 576, 602, 626, 706, 764, 857, 951	[45]
Fish	Total volatile basic nitrogen	459,552,616,629,695,760,896,956,986	[46]
Cucumber fruit	Nitrogen content	715,783,821	[47]
Apple fruit	pH changes	Nine wavelengths from 650 to 950	[48]
Apple fruit	Total phenol, titratable acid, soluble solids content, pH	450-4000	[49]
Apple fruit	Peroxidase activity changes	540, 547, 589, 606, 611, 619, 644, 694, 900	[50]
Maize grain	Variety	190-1150	[51]
Orange fruit	Bruises	630,691,769,786,810,875/550-900,691-769	[52]
Wheat flour	Flour types	601.33, 620.34, 696.41, 730.31, 821.26, 841.11	[53]
Cinnamon powder	Adulteration	Nine wavelengths from 591.40 to 936.20	[8]

In 2011, researchers used a hyperspectral imager with a spectral range of 350-2500 nm to capture the reflectance of the leaves of different rice cultivars. They reported that analysis of variance using Tukey's paired test differentiated the reflectance of Nemat, Khazar, Neda, Fajr, Hybrid, Shiroudi, and Tarom leaves [54].

In 2012, fungal contamination (*Aspergillus flavus)* of pistachio kernels was detected. In this research, a snapshot imager (model: SU640-1.7RT-D Sensor Unlimited Inc., Princeton, NJ, USA) was used. The spectral range of the HSI systems was 960 to 1700 nm. The extracted features were classified using linear and quadratic discriminant analysis, support vector machine, K-fold cross-validation, and artificial neural network methods to classify the samples with 70-100% accuracy [34, 55].

In 2017, Khodabakhshian and Emadi [42] used a line scan hyperspectral imager (model, DL-604M, Ireland) with a range of 425-1000 nm to classify the ripeness level of pear fruit. The researchers classified spectral data by applying linear discriminant analysis (LDA), partial least square-discriminant analysis (PLS-DA), and soft independent modeling of class analogy (SIMCA). They stated that the PLS-DA method had the highest accuracy (87.86%) in the classification of unripe, ripe, and overripe fruits. Khodabakhshian et al. [43] used estimated chemical compositions of pomegranate fruit. They used the partial least square method to analyze the spectral data. The properties were titratable acidity, total soluble solids, and pH.

In 2018, an area scan SCB-2000P Samsung (South Korea) hyperspectral imaging camera with a spectral range of 400-900 nm was used to detect green mold of orange. The researchers classified the extracted features from the acquired hypercubes of healthy and infected orange fruits using the artificial neural network with an accuracy of 96.84% [44].

In 2019, Khoshnoudi-Nia and Moosavi-Nasab [45] used a line scan hyperspectral imaging to assess fish spoilage. They captured HSI images from 430 to 1010 nm. The spoilage criteria were psychrotrophic plate count, sensory score, and total-volatile basic nitrogen. They obtained accuracies of 85.3 to 92.1% using the partial least-squares regression, least-squares support vector machine, back-propagation multiple-linear regression, and back propagation artificial neural network. Zolfi et al. [56] used HSI and support vector machine to recognize ground meats and reported an error range of 11.56-19.66%. The studied meats were lamb, beef, and beef 70-lamb 30%. Hosseiny et al. [57] used the convolutional neural network for the detection of different land regions and reported 92.35-98.14% accuracies.

In 2020, Jaberi Aghdam et al. [58] applied outdoor multispectral imaging to monitor corn plant nitrogen. The researchers used unmanned aerial vehicles to acquire remote-sensing MSI images. They found a high correlation between vegetation indices and nitrogen content and reported the potential of the method to detect nitrogen stress.

In 2021, the highest HSI accuracy of 96.11% was reported by Sabzi et al. [59] in the detection of nitrogen in cucumber plants. To this end, they applied hybrid neural networks and imperialist competitive algorithms. Moosavi-Nasab et al. [46] applied a line scan HSI (Opt Co., Kashan, Iran) at the range of 430-1010 nm to estimate nitrogen content in fish. They applied a linear deep neural network and support vector machine and reported higher accuracy of the SVM (89.7%). Zolfi et al. [60] used HSI to classify healthy and aflatoxin-contaminated pistachio kernels. The levels of infection were low, medium, and high contamination. They emitted 360 nm fluorescence light to the kernels.

In 2022, Aslani [61] detected nitrogen content in tomato leaves using HIS and reported an accuracy of 92.55% using artificial neural networks. Golmohammadi et al. [50] successfully estimated peroxidase activity with an accuracy of 94% using an HSI system (Fanavaran Physics Co., Iran) at the range of 400-1000 nm and partial least squares method while 98.0% accuracy was obtained using the same methods in detection of apple pH [48]. Research conducted by Pourdarbani and Sabzi [47] focused on estimating nitrogen content in cucumber fruit using hyperspectral imaging. They employed a line scan HSI imager (Imantajhiz Co., Iran) and various machine learning techniques including the hybrid neural network-cultural algorithm, multilayer perceptron neural network, and support vector machine to predict nitrogen levels based on the HSI features. They reported accuracies of 92.00, 78.97, and 89.51%, respectively. In another study, Hashemi-Nasab and Parastar [62] utilized 400-950 nm HSI to detect adulteration in saffron spice. They mixed various substances rubia, calendula, turmeric, safflower, and saffron style with saffron. They successfully classified all samples by applying partial least squares-discriminant analysis. Alimohammadi et al. [51] employed HSI at a range of 400-1000 nm. Their findings indicated that linear discriminant analysis outperformed artificial neural networks, achieving an impressive accuracy of 95% in distinguishing maize varieties. Hasanzadeh et al. [49] employed the partial least squares method to analyze data acquired from an HSI system (FSR, Optical Physics Technologists, Tehran, Iran). They proved the high ability of the method in predicting titratable acid, soluble solids content, total phenol, and pH of apple (98.99-99.99%).

In 2023, Bagheri et al., [63] used multispectral sensing using a UAV system to estimate the nitrogen content of corn in Varamin, Tehran. They reported that MSI provides accurate results to be used by the farmers in determining the correct fertilizing time.

In 2024, Nargesi et al. [64] detected adulteration levels of chickpea and wheat flour and sea foam powder in cinnamon powder using a line scan HSI imaging system (model Specam, Parto Sanat C., Zanjan, Iran) with a spectral range of 400-950 nm. The developed artificial neural network model classified 0, 5, 15, 30, and 50% adulteration levels of the mentioned adulterants with 100, 100, and 98.9%, respectively. Pourdarbani and Sabzi [52] used 400-110 nm HSI for detecting sound and bruised orange samples and reported significant differences between the reflectance of the samples by applying Dunkan's multiple range test. Molayi et al. [65] utilized a line scan HSI imager (model: AvaSpec-2048) to assess various characteristics of sugar beet, including soluble solids, sugar content, moisture content, pH, and mechanical properties. By capturing HSI images at the 400-1100 nm range and applying least square regression for analysis, they achieved an impressive accuracy of 95-98% in their estimations. Koochakzaei et al. [66] identified natural dyes and mordant types in dyed wool fibers using spectral imaging methods. The researchers employed principal component analysis and hierarchical clustering to distinguish different fibers based on mordants and dyes. They reported that MSI at 430-830 nm had the best accuracy in clustering fiber groups. Ebrahimi et al. [67] approved the ability of remote sensing models to map degradation severity in Baluchistan using Sentinel-2 MSI data. Nargesi et al. [53] classified the efficient HSI features of wheat confectionery flour and the flours of Samoun, Sangak, and Tafton flours using 400-950 nm HSI (model: Specam, Parto Sanat C., Zanjan, Iran) and machine learning techniques. The classifier models were based on artificial neural networks, support vector machine, and linear discriminant analysis methods. The researchers reported that artificial neural network had higher accuracies compared to other methods using efficient features (98.1%) than all features (96.9%).

In 2025, Nargesi et al. [68] employed hyperspectral imaging to detect different adulterations black pepper powder. The adulterants were sea foam and chickpea and wheat flours with 0–50 % levels. The wavelength selection, feature selection, and classification were done using principal component analysis, sequential feature selection, artificial neural networks methods. The researchers suggested the technique to detect adulteration levels (100% accuracy). Nargesi and Kheiralipour [69] classified different levels of potassium oxide in potash fertilizer using hyperspectral imaging technique. The reported that the classifier model based on artificial neural networks method had relative higher efficiency using all extracted features (92.9%) compared to selected efficient features (91.3%). Nargesi and Kheiralipour [70] predicted the sucrose, proline, ash, and fructose/glucose ratio of date syrup using hyperspectral imaging and partial least squares regression, support vector regression, and artificial neural networks methods. Artificial neural networks had higher performance compared to others with the prediction accuracies of 99.99, 100, 99.99, and 100 %, respectively.

4. Conclusions

Infrared spectral imaging covering HSI and MSI techniques has been applied to assess different goals in agriculture, natural resources, and food sectors in Iran. HSI and MSI methods are widely applied to assess different external and internal goals with high accuracy and low cost. As non-destructive techniques, they allow for studying near-infrared reflectance of full area of objects in different fields. The methods are more applicable compared to conventional visible imaging due to studying not only the infrared domain but also working in the visible range. Moreover, the accuracy of the techniques can be enhanced by applying and evaluating different methods to process and analyze spectral images. HSI and MSI techniques have been used for assessing different goals in agriculture, natural resources, and food in Iran. Soil, water, plants, fruits and vegetable, and food products are the main materials that have been assessed by the techniques. However, the methods have not been applied in animal and fishery sectors that can be considered in the future, e.g., evaluating animal feed, detecting body status and diseases, and assessing animal products. Future research may focus on increasing the accuracy of the methods. Moreover, real-time and online applications of MSI can be considered in the future due to the higher speed of image acquisition in MSI technique to acquire the image channels in just effective wavelengths.

In the future, the techniques can be been utilized in animal production [71] to assess body [72], feed quality, and welfare of livestock [73]. The techniques have been applied in natural resources for assessing wild animals living, land use, and sea environment [18, 74-76] that can be considered in future research and applications in Iran. These methods can be applied in precision agriculture to increase the accuracy and decrease the cost of detecting different goals such as plant and product diseases, by indoor or outdoor imaging systems.

HSI technique has a limitation due to the time-consuming hypercubes acquiring step because many image channels at whole covered wavelengths be the imagers are recorded. So, the method technique is applied in laboratory-scale research. For real-time and online applications, MSI can be developed based on the HSI results. In Fact, MSI decreases imaging time by acquiring just image channels corresponding to the effective wavelengths. Also, image processing is a faster step compared to HSI because the efficient features of just the effective wavelengths are extracted and analyzed. Moreover, future developments are appreciated to increase the image-acquiring speed in HSI and MSI. These findings indicate the potential for developing an advanced multi-product imaging system that utilizes hyperspectral and multispectral image processing technologies for precise sample analysis. By leveraging spectral data processing algorithms, this system can effectively identify and classify various product features. Furthermore, the development of a real-time system for industrial applications can significantly reduce detection time while enhancing the accuracy of quality control processes. Such a system can be applied across various industries, including agriculture, food, and pharmaceuticals, playing a crucial role in optimizing production processes and minimizing waste in Iran.

Author Contributions

Kamran Kheiralipour: writing, editing, Farzaneh Sajadipour: Writing, Mohammad Hossein Nargesi, Writing.

Competing Interests

No conflicts of interest exist.

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