

Optoelectronic hyperspectral imaging system for the non-invasive detection of dysplastic nevi: a pilot study

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Optoelectronic techniques offer non-invasive tools for assessing pigmented skin lesions by quantifying wavelength-dependent interactions between light and cutaneous chromophores. This pilot study evaluated hyperspectral imaging as an objective method for identifying dysplastic features in melanocytic nevi through pixel-level analysis of melanin distribution. Ten patients with clinically diagnosed nevi located on the back, arms, legs, or neck were examined using a pushbroom hyperspectral system operating in the 400–800 nm range. Images were normalized with white and dark references, cropped to the lesion region of interest, denoised, and processed with in-house software to generate melanin concentration maps based on the modified Beer–Lambert law. The spatial uniformity of melanin distribution was quantified using semivariance, applied as a numerical indicator of local heterogeneity. Common nevi showed homogeneous melanin maps and semivariance values below 0.1, whereas histopathologically confirmed dysplastic nevi presented irregular melanin distribution and values above 0.24. These preliminary results suggest that hyperspectral imaging combined with semivariance analysis may differentiate common from dysplastic nevi objectively, without relying on artificial intelligence or large training datasets. Further validation in larger cohorts is required to establish diagnostic thresholds and clinical applicability and to determine its future potential value as a complementary screening tool in routine dermatological practice.

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1. Introduction

In modern biomedical diagnostics, optoelectronic technologies play an increasingly important role by enabling the non-invasive investigation of biological tissues through the controlled use of light and advanced optical detection systems[1,2]. These methods provide access to structural and functional information that may not be fully available through conventional visual examination alone[3]. In dermatology, where many pathological changes are expressed through variations in color, pigmentation, morphology, and optical response, optoelectronic and spectral techniques are particularly relevant for the assessment of pigmented skin lesions[4]. By analyzing the interaction between light and cutaneous chromophores, especially melanin, such approaches may support a more objective characterization of melanocytic lesions.

Melanocytic lesions, common called nevus and also known as a chronic lesion, can be caused by neoplasia and hyperplasia of melanocytes [5], some hypermelanotic or hypomelanotic [6] pigmentation disorders, is usually a condition of the skin and mucosa [7].

Some nevi (e.g. melanocytic nevus, Spitz nevus) are benign while others (e.g. sporadic atypical naevi, familial atypical naevi) are suspicious and may degenerate in skin cancer. The presence of acquired melanocytic nevi, including both common and dysplastic types, is a well-established marker for the risk of developing cutaneous

melanoma [8]. Due to the high risk of cancer, in recent decades, accurately grading nevus risk has become a crucial task for physicians. Numerous methods have been employed for this purpose, but there is still no consensus on the most effective and practical approach to identifying high-risk nevi.

Currently, dermoscopy is the most commonly used method for assessing nevus risk. While it provides detailed surface-level images, it lacks the resolution necessary for cellular-level analysis. Moreover, its effectiveness depends heavily on the clinician's expertise, leading to variability and potential subjectivity in diagnoses. These limitations have spurred interest in more accurate and objective diagnostic tools, resulting in the development of several advanced imaging techniques. However, each of these alternatives comes with its own drawbacks.

Optical spectroscopic methods [6] and multispectral imaging [9], though valuable in providing biochemical information, often suffer from limited spatial resolution, reducing their effectiveness in structural assessment. Microscopic methods, such as Reflectance Confocal Microscopy (RCM) [10] and Confocal Laser Scanning Microscopy (CLSM) [11], offer near-histological resolution and allow for in vivo visualization of cellular features. Despite their impressive image quality, both techniques are hindered by a shallow imaging penetration depth, limiting their ability to visualize deeper skin layers where malignancies may develop [12].

Tomographic techniques such as Optical Coherence Tomography (OCT) [13] attempt to address this by providing non-invasive, cross-sectional imaging of tissue architecture. However, OCT is primarily optimized for ophthalmological applications, and its resolution may be insufficient for detecting subtle cellular anomalies in skin lesions. Multiphoton Laser Imaging offers better resolution at greater depths, but it remains expensive, complex, and not yet widely adopted in routine dermatological practice.

Given these limitations, ranging from superficial penetration depth and high reliance on operator expertise to insufficient biochemical information, there is a clear need for a more comprehensive, objective, and non-invasive imaging technique.

Hyperspectral imaging (HSI) emerges as a promising solution to these challenges. Unlike traditional imaging modalities, it captures a rich spectrum of data across numerous wavelengths for each pixel, enabling the detection of subtle biochemical and morphological changes in tissue. This spectral richness allows for more precise differentiation between benign and malignant nevi. Moreover, HSI method can be combined with machine learning algorithms, as demonstrated by de Lucena et al., who developed a deep learning approach to classify nevus risk based on hyperspectral data [14]. This combination has the potential to significantly enhance diagnostic accuracy, reduce subjectivity, and improve early detection of malignancies in a non-invasive manner. They proposed an automated inspection method that combines HSI method with an epithelial lesion classifier, effectively distinguishing dysplastic nevi based on their spectral information and spatial distribution. Lindholm et al. demonstrated that pixel-wise analysis produced map-like images, classifying pigmented lesions with 87% sensitivity and 93% specificity, and non-pigmented lesions with 79% sensitivity and 91% specificity, correctly diagnosing 41 out of 42 lesions [15]. Aggarwal and Papay reviewed various spectral imaging methods for detecting dysplastic nevi and melanoma, concluding that multispectral and hyperspectral imaging hold great potential in dermatology [6]. Christensen et al. found that HSI method exhibited high sensitivity in detecting malignant lesions in patients with Caucasian skin types [9].

However, a common limitation of multispectral and HSI is their dependence on classification algorithms (deep

learning or supervised) that require extensive training data, which can be difficult to generalize across patients with varying skin types.

In this paper, we propose a new method for the detection of dysplastic nevi based on the analysis of melanin distribution derived from hyperspectral data. The method allows mapping the melanin concentration distribution and its homogeneity.

2. Materials and methods

2.1. Subjects

The study was conducted on 10 patients with ages between 25 and 75 years diagnosed with nevi (located on the back, arms, legs or neck), selected from the Emergency Clinical Hospital for Plastic, Reconstructive Surgery and Burns, Bucharest. The main selection criterion was the clinical diagnosis made by a dermatologist. All cases were subsequently confirmed by histopathological exam as being common or dysplastic nevi.

Each subject was informed about the procedure applied in this study, and the consent was obtained prior to enrollment. The procedure involving human participants was in accordance with the ethical standards of the Emergency Clinical Hospital for Plastic, Reconstructive Surgery and Burns Research Committee (No. 26/14.11.2024) and with the 1964 Helsinki declaration and its later amendments.

2.2. Hyperspectral system

Hyperspectral images of the nevi were acquired using a line-scan hyperspectral system (Fig. 1) consisting of a V8E spectrograph (Specim, Oulu, Finland), a DX4 charge couple device (CCD) Kappa, Gleich, Germany) and 17 mm Xenoplan lens (Schneider Optics, Bad Kreuznach, Germany). The system allows the image acquisition at a speed of 11 frames per second (fps) and a spectral range of 400–800 nm with a resolution of 1390×1040 . The images were acquired at a 4×4 binning so that the spectral and spatial resolution values was of $\frac{1}{4}$ from the maximum resolution.

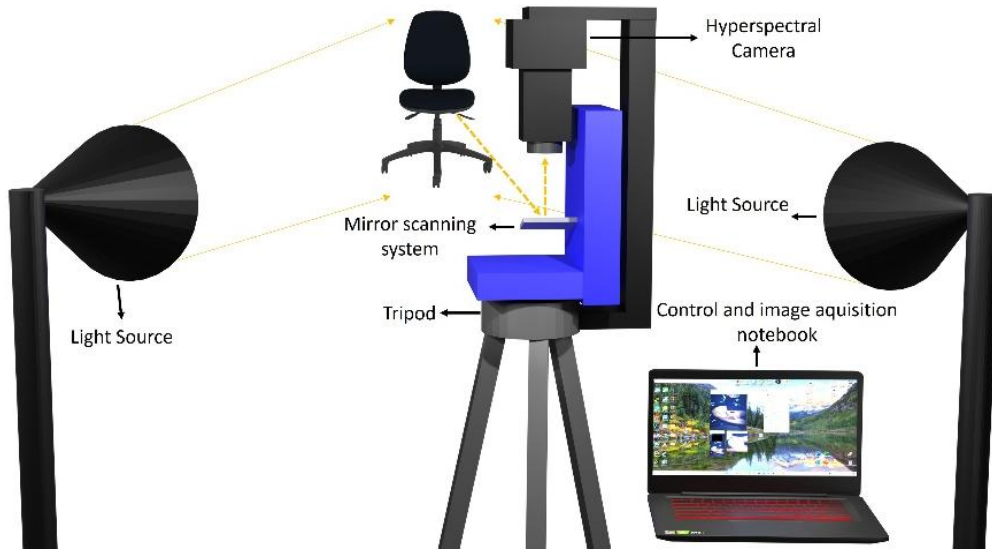


Fig. 1. Experimental set-up for hyperspectral image acquisition of the nevi (colour online)

2.3. Normalization of the nevi hyperspectral images

The normalization of hyperspectral images (HSI) was done with black and white references to convert the hyperspectral data to reflectance values. As a white reference sample, a 98% polytetrafluoroethylene (PTFE) tile (WS-2, Avantes, Netherlands) was used. The white tile was placed in the investigated scene near the targeted area. The dark reference image was acquired by covering the HSI system lens with its cap. The calibrated hyperspectral data was calculated using Eq. 1:

$$R = \frac{I_s + D}{E - D} \quad (1)$$

where: R is the normalized reflectance, I_s [DN] (*Digital Number*) is the original hyperspectral image, D [DN] is the dark reference image, and E [DN] is the white reference image.

2.4. Processing of the hyperspectral images

The processing of nevi hyperspectral images was performed in two steps. Firstly, the normalized hyperspectral images were processed to reduce their dimension only to a region of interest (ROI) related to nevi area, thus avoiding unnecessary further data analysis (Fig. 2).

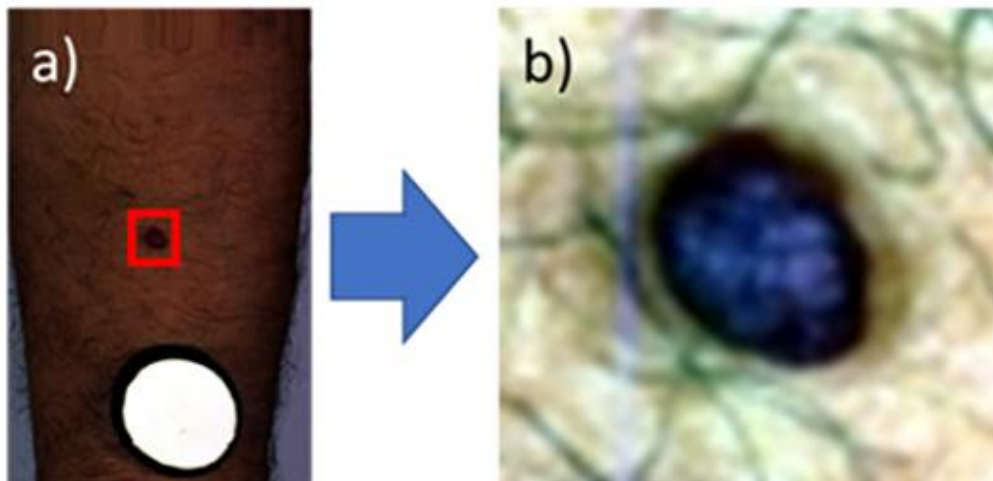


Fig. 2. Selection of region of interest from hyperspectral image. a) original hyperspectral image; b) selected region of interest (colour online)

Secondly, a wavelet denoising algorithm, described in previous work [10], was applied for removing any CCD induced noise.

2.5. Generation of melanin concentration maps

The method to generate the melanin concentration maps proposed in this paper is based on the modified

Lambert–Beer law[13] which describes the relation between the absorption spectra of each pixel and the pure spectra of main skin constituents (oxyhemoglobin, deoxyhemoglobin and melanin) with specific spectral features in the investigated spectral range. Considering the most significant spectral differences between the above-

mentioned skin chromophores, in this study the spectral range was limited to (650 - 700) nm.

According to modified Beer–Lambert law, the contribution of each skin constituent to normal skin absorbance measured in a pixel (i,j) of the hyperspectral image can be expressed by Eq. 2[11]:

$$A_{i,j} = \varepsilon_{oxy}(\lambda) \times C_{oxy} \times d + \varepsilon_{deoxy}(\lambda) \times C_{deoxy} \times d + \varepsilon_{mel}(\lambda) \times C_{mel} \times d + G_{i,j} \quad (2)$$

where: $A_{ij}(\lambda)$ is the skin absorbance in the pixel (i,j) at a given wavelength λ , $\varepsilon_{oxy}(\lambda)$, $\varepsilon_{deoxy}(\lambda)$ and $\varepsilon_{mel}(\lambda)$ represents extinction coefficients [$cm^{-1}/(\mu g \cdot mL^{-1})$] for oxyhemoglobin, deoxyhemoglobin and melanin, C_{oxy} , C_{deoxy} and C_{mel} are the concentrations [$\mu g/mL$] of the main skin chromophores, d is the average distance traveled by a photon within the tissue [cm], and G_{ij} is a term that accounts the light scattering effect on the skin.

In the particular case of vitiligo stains, the melanin concentration is zero ($C_{mel} = 0 \mu g \cdot mL^{-1}$) and the Eq. 2 becomes Eq. 3 [11]:

$$A_{i,j}^v = \varepsilon_{oxy}(\lambda) \times C_{oxy} \times d + \varepsilon_{deoxy}(\lambda) \times C_{deoxy} \times d + G_{i,j} \quad (3)$$

Replacing the Eq. 3 into the Eq. 2 results Eq. 4:

$$A_{i,j} = A_{i,j}^v + \varepsilon_{mel}(\lambda) \times C_{mel} \times d \quad (4)$$

Melanin contribution at the skin spectrum is defined by Eq. 5:

$$A_{i,j}^m = \varepsilon_{mel}(\lambda) \times C_{mel} \times d = A_{i,j} - A_{i,j}^v \quad (5)$$

To solve the Eq. 5 and derive the C_{mel} values in each individual pixel and generate melanin concentration distribution maps on nevi area, melanin extinction coefficients provided by Sarna and Swartz [16] from Oregon Medical Laser Center [17] were used, $A_{i,j}^v$ values were extracted from hyperspectral images of patients diagnosed with vitiligo.

On the other hand, the experimentally measured value of the skin absorbance in each pixel (i,j) is given by the relation:

$$A_{i,j}^S = -\log_{10} R_{i,j}^S$$

where $R_{i,j}^S$ is calibrated skin reflectance and $A_{i,j}^S$ is the measured skin absorbance.

The parameters C_{mel} and d were computed for each pixel (i,j) in the image using a non-linear least squares method. This approach minimized the sum of squared differences between the experimentally measured values $A_{i,j}^S$ and the estimated values $A_{i,j}^m$, as defined by Eq 6.

$$\sum_{k=1}^n [A_{i,j}^S(i,j,\lambda_k) - A_{i,j}^m(i,j,\lambda_k)]^2 \rightarrow \min \quad (6)$$

The minimization was performed using the most popular Levenberg–Marquardt algorithm, resulting in generation of the C_{mel} distribution maps presented as color-coded images.

2.6. Statistical analysis

The uniformity of melanin concentration distribution in nevi, calculated according to Equation 5, was assessed using the semivariance parameter. In this context, semivariance serves as a numerical indicator of image homogeneity, without the construction of variograms or spatial models. Specifically, it quantifies the average squared differences between neighboring pixel values, offering a straightforward measure of local variability within the image[18].

The semivariance is define as follows (eq. 6)[19]:

$$\gamma = \frac{1}{2N} \sum_{i=1}^N (I(x_i, y_i) - I(x_i + \Delta x, y_i + \Delta y))^2 \quad (6)$$

where:

- γ is semivariance value (scalar)
- $I(x_i, y_i)$ is pixel intensity (melanin concentration value) at (x_i, y_i) coordinates
- $I(x_i + \Delta x, y_i + \Delta y)$ is the intensity of the neighboring pixel at a fixed offset $(\Delta x, \Delta y)$
- N is the number of valid pixel pairs considered (those for which neighbors exist within image boundaries)
- $(\Delta x, \Delta y)$ is the offset vector defining neighborhood (e.g. (1,0), (0,1), or 8-neighborhood)

Although traditionally used in geostatistics and spatial analysis to evaluate spatial dependence, semivariance can also be applied in image processing to characterize texture and detect irregularities. A lower semivariance value indicates a more uniform distribution of pixel intensities, suggesting a homogeneous region, while higher values reflect greater variability, which may be indicative of structural heterogeneity or atypical features.

In this study, semivariance was employed solely as a statistical tool to distinguish between homogeneous and inhomogeneous melanin distributions. This enabled a simple and effective method to flag potentially dysplastic nevi based on texture irregularity, without the need for

constructing semivariograms or analyzing spatial correlation at multiple lag distances. The approach enhances the objectivity of the analysis and supports the identification of anomalies that could be relevant for further clinical evaluation.

3. Results

The representative melanin concentration distribution maps and the hyperspectral images for common and dysplastic nevi are shown in Fig. 3.

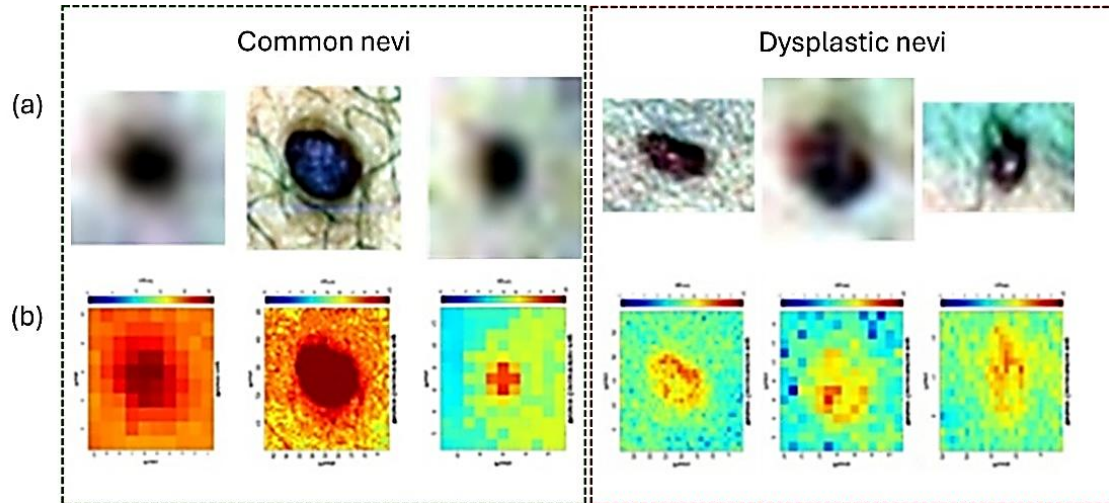


Fig. 3. Side by side comparison between dysplastic and common nevi. a) Original hyperspectral images (top row); b) Melanin concentration distribution maps (bottom row) (colour online)

At a first visual examination of Fig. 3, it can be seen that dysplastic nevi have an irregular shape with poorly defined borders, while common nevi have well-defined borders (a feature that is better observed in the melanin concentration distribution maps). A more striking feature is the non-uniformity of the melanin concentration in the dysplastic nevus, compared with the common one. But an objective parameter is needed to detect this difference. The calculated semivariance values serve this purpose, as semivariance effectively measures spatial variability within a dataset. By using semivariance, subtle differences in melanin concentration distribution can be quantified, providing a more precise and objective analysis. The semivariance values for all the cases in the study group are shown in Table 1.

Table 1. Semivariance values for all 10 patients

Patients	Semivariance Value	Nevus type
P1	0.247	Dysplastic nevus
P2	0.063	Common nevus
P3	0.078	Common nevus
P4	0.048	Common nevus
P5	0.047	Common nevus
P6	0.251	Dysplastic nevus
P7	0.540	Dysplastic nevus
P8	0.360	Dysplastic nevus
P9	0.250	Dysplastic nevus
P10	0.243	Dysplastic nevus

It is noted from Table 1 that for common nevi investigated in this study the semivariance values are under 0.1, while for dysplastic nevi, the semivariance values are all above 0.24. Therefore, there is a significant difference between the two types of nevi. It is important to point out that higher semivariance values mean a non-even melanin distribution, a feature that characterizes the histopathological confirmed dysplastic nevi. Thus, semivariance calculated from melanin concentration distribution maps (extracted from HSI images) proved to be a reliable objective parameter for distinguishing common

and dysplastic nevi (in perfect concordance with histopathology results).

4. Discussions

The determination of nevus risk grade has been a critical task in dermatology, aimed at identifying high-risk nevi to prevent the development of cutaneous melanoma. Our proposed method is aimed at enhancing the detection of chromophore concentration and structural changes in

nevi and highlighting their homogeneity by using melanin concentration distribution maps generated using our dedicated software. This software analyzes the melanin concentration distribution from hyperspectral images, providing a detailed and objective assessment of nevi. By focusing on melanin distribution, our approach seeks to identify subtle changes that may indicate the early stages of dysplastic transformation, thereby improving early detection and intervention and having the potential of a powerful screening tool. The degree of uniformity of the distribution of melanin across the nevus area based on the semivariance values calculated from the hyperspectral images could be considered as an easy way to differentiate between dysplastic and common nevi and may support physicians in making a correct decision regarding the treatment modality. The proposed method uses spectral and spatial characteristics directly derived from hyperspectral images without the need for complex analysis using artificial intelligence. Therefore, the method also has the advantage that it does not need an extensive database of training samples, as required by the neural networks reported in literature [14,20]. In addition, it is not sensitive to the variations in pigmentation of different patient skin types reported by Lindholm et al. and Aggarwal and Papay [6,15].

Recent advancements in hyperspectral imaging and deep learning algorithms have led to promising results in distinguishing between common and dysplastic nevi as reported by de Lucena et al., 2020 [14]. Encouraging results were also reported by Paoli et al. [20] in differentiating melanoma from pigmented basal cell carcinomas. Some pigmented lesions were also classified with high sensitivity and specificity by Lindholm et al. [15].

All these studies emphasize the potential of HSI method to provide detailed and accurate diagnostic information, which is crucial for effective clinical decision-making. However, the variability in skin pigmentation across different patient populations remained a challenge, as highlighted by Aggarwal and Papay [6].

In response to this challenge, the method proposed in this study proved to be able to differentiate common from dysplastic nevi based on their chemical composition (melanin concentration) and tissue structure (melanin concentration distribution maps). Furthermore, these parameters provided are not affected by the patient's skin tone. Therefore, the proposed method could be considered a useful tool in medical decision-making.

However, the present study has some limitations. The main drawback of our study is that it was tested on a limited number of subjects. That is probably one of the reasons for such a good result, with semivariance values very well grouped for the two types of nevi. Future studies are required to establish a good boundary for the semivariance value that separates dysplastic nevi from common nevi.

5. Conclusions

The identification of dysplastic nevi plays a vital role in maintaining skin health and preventing the progression

to melanoma. By using our proposed new method, based on semivariance values of melanin distribution maps derived from hyperspectral images of nevi, we can improve public health outcomes and reduce the chances of skin cancer apparition by taking early actions.

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Declaration of interest statement

The authors declare that they have no known competing interests.

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