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Vision Paper: Hyperspectral Analysis of Finger Skin Reflectance for Resilient Biometric Systems

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***Abstract*—Hyperspectral imaging (HSI) outperforms the ability of RGB and multi-spectral imaging by conveying information through hundreds of contiguous wavelength intervals. This emerging technology can enable real-time monitoring of spatially resolved spectral information of materials. This paper explores the use of HSI classification to analyze the spectral structure of the human skin of fingers. The spectral reflectance of human skin is believed to vary significantly between individuals, but finding a typical signature for human skin reflectance and what its distribution is across a population are open research questions. The skin spectra acquired through a spectrograph from a diverse population are proven to be interspersed, thus the system using it would not be challenged by ethnicity. Existing related studies are using spectrophotometers only to explore features of human skin reflectance. Rather than use biochemistry, this research enables the design of image-based hand-crafted features to determine its representation. Although the lack of a biochemical component limits identity verification to extrinsic factors, reflectance has the potential as an identifying factor. As the first research to use HSI to assess reflectance, we focus on determining the extent of that potential, including its potential use in machine learning applications for identity verification.**

***Index Terms*—Skin reflectance, hyperspectral biometrics.**

I. Introduction

The trustworthiness of biometric technologies has been challenged by advancing spoofing methods, e.g., fingerprint scanners can be deceived by sophisticated 3D printing techniques [1]–[3]. Such deceptive practices, referred to as presentation attacks, pose a significant threat to the correct operation of biometric systems, demanding robust liveness detection techniques to detect malicious attempts. The 2024 Identity Fraud Report discusses the enormous increase in digitally forged identities in 2023 due to the increasing availability of user-friendly generative AI tools. Enriching human identity with more discerning characteristics can overcome these issues.

Each individual is inherently different from one another based on certain factors including, but not limited to, his/her genetic makeup, environment, and lifestyle. As such, the biochemical composition of each person greatly differs. The concentrations of these sweat components are person-specific and can be exploited to differentiate individuals based on trace amounts of sweat. In this paper, we focus on existing evidence about the person-specific biochemical content of sweat, known to contain various amino acids and other low molecular weight compounds. These biomarkers can be detected in sweat metabolites at wavelengths covered by imaging spectrometers. The content present in the sweat left behind, namely the amino acids, has been used to determine the gender of the originator as well as the number of people present at a crime scene. The process involves a non-invasive analysis based on collective responses from chosen metabolic compounds in sweat which exhibits a great potential for biometric, cybersecurity, forensic as well as medical applications. We review the scientific literature on this topic.

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HSI can analyze a wide spectrum of light; thus, hypercube data will be able to provide a rich representation of the subject's identity and is inclined to discover hidden features since it measures continuous spectral bands. Image analysis, machine, and deep learning (transfer learning) algorithms will be investigated. There is ongoing research on the idea of acquiring in a contactless manner from the skin of fingertips and processing it in the hyperspectral imaging (HSI) domain [4], [5]. HSI technology not only can capture spatial information that encodes extrinsic characteristics but also corresponding spectral signatures that can encode intrinsic features undetectable by traditional imaging systems [6], [7]. The spectral reflectance of human skin is believed to vary significantly between individuals, but finding a typical signature for human skin reflectance and what its distribution is across a population are open research questions. The skin spectra acquired through a spectrograph from a diverse population are proven to be interspersed, thus the system using it would not be challenged by ethnicity. In darker-skinned subjects, spectra from an area with no melanin (*i.e.*, the palm) were found to exhibit the same curvature as the plots of the back of the hand suggesting no impact due to the skin tone [8]. NIST is also studying human skin reflectance but using spectrophotometers only [9]–[13]. Although the lack of a biochemical component limits identity verification to extrinsic factors, reflectance has potential as an identifying factor. As the first research to use HSI to assess reflectance, we could determine the extent of that potential, including its potential use in machine learning applications for identity verification [14], [15].

II. Previous Use of Biochemicals from Finger Tips for Discriminating among Individuals

Mass-spectroscopy-based methods, including bio-affinity systems, have allowed researchers to measure up to hundreds of metabolites in a single sweat sample, but due to the need for reagents, these approaches are inconvenient, not conducted in real-time, high in cost, and cause degradation of the sample [16]. The technique separates metabolites using liquid chromatography (*i.e.*, chemical reagents) and detects them based on their unique mass-to-charge ratio and induced fragmentation.

Although matching latent fingerprints has been a universally accepted and reliable identification method, researchers have demonstrated that pictorial comparison does not exploit the information content in a latent fingerprint to its full potential. In 2015, Huynh *et al.* directed attention to the biochemical content in a fingerprint (i.e., concentrations of specific amino acids) using a biocatalytic assay rather than analyzing only the physical image [17]. Their work is the first proof of a system that can use the content of sweat left on a surface to estimate the gender of the originator. In 2018, Mindy *et al.* discussed the use of biocatalytic enzyme cascades to differentiate people based on lactate, urea, and glutamate metabolites detected in sweat [16]. Results confirm that the levels of all three markers sufficiently differ among people. In 2017, Agudelo *et al.* proposed the use of amino acids in skin secretions as a multi-factor identity verification mechanism for continuous tracking [18]. In this system, a sensor is placed at the points of skin contact with a device to acquire sweat samples. The user's profile is built by continuously measuring sweat levels at various times of the day during a monitoring period. The biochemical input is converted into output signals that are then statistically analyzed to verify the identity of the person holding or wearing the device. This approach is contact-based, and the process is slow, with no imaging utilized.

In 2021, Brunmair *et al.* discussed a study on finger sweat analysis that provides evidence about both the feasibility of sampling unstimulated sweat from fingertips and its potential as a rich source that can enable successful metabolic biomonitoring in humans [19]. In this work, more than a thousand sweat samples were collected from 40 different individuals, and a total of 250 metabolites were identified and verified - by using external standards. Furthermore, dynamic metabolic responses of individuals were successfully obtained regarding a controlled ingestion of caffeine: subjects were asked to fast, and then take various amounts of caffeine, and the after-ingestion sampling occurred at intervals of 15 minutes. The authors were able to detect 35 coffee-derived metabolites. Principal component analysis (PCA) applied to those metabolites revealed that the samples clustered according to individuals, which indicates that the molecular composition of sweat associated with a given person dominates variance across multiple samples. These findings suggest that metabolic phenotyping from the sweat of fingertips in conjunction with mathematical modeling is a promising approach to obtaining dynamic patterns from individuals.

III. Hyperspectral Technology and Its Potential for Human Identification

One example of this application is the determination of ownership (authentication) for cell phone access based on the measurable amounts of specific metabolic compounds on the surface of the skin. The proposed analysis has great potential in forensic science as well. Conventionally, latent fingerprints are not readily visible and imaging often requires to use of intrusive manners. In certain instances, latent fingerprints cannot be acquired by existing methods. Therefore, there is interest in the forensic community to improve understanding of the chemical character of latent fingerprints HSI techniques provide a possibility to efficiently extract fingerprints in a non-intrusive manner when coupled with well-designed image analysis algorithms [20]–[24].

There is ongoing research on the idea of acquiring in a contactless manner from the skin of fingertips and processing it in the HSI domain [25]–[27]. HSI technology not only can capture spatial information that encodes extrinsic characteristics but also corresponding spectral signatures that can encode intrinsic features undetectable by traditional imaging systems. HSI has gained a lot of interest in various fields including agriculture and medical research. HSI technology can capture rich spectral information, for object identification, chemical analysis, identifying materials, and even biometric application. A hyperspectral image is a three-dimensional hypercube over many contiguous spectral bands, unlike traditional color images, the rich 3-D channels empower HSI to perform superior ability in feature extraction. HSI combines imaging with spectroscopy by generating data in hundreds of wavelengths to encode characteristics that are undetectable with traditional imaging systems. Adopting HSI can provide richer spectral information which can be used for several applications including identifying gender-related features from biometric images.

Before analysis, HSI data needs to be calibrated to ensure the images produced are adjusted for the color of lighting present; the camera software may have this option, but if it does not then the data can be calibrated after it is captured. The lighting is calibrated using a known white balance target, which is imaged by the camera system. This target will reflect a known percentage of light over the spectrum, for example, 99% across the entire working spectrum of the camera. Additionally, the system must correct for electrical noise present from the sensor in the absence of light (called dark current) by taking an image with the camera in the absence of any light and using the resultant low-level noise readings to adjust future measures. Uneven illumination can occur, and the type of light source chosen needs careful consideration; it should not have high-intensity peaks throughout the spectrum or across the image plane. Human skin is known to have both piezoelectric and pyroelectric properties originating from the presence of polar keratin, elastin, and collagen fibers with unique orientations, which enable human skin to precisely perceive and differentiate mechanical and thermal stimuli. All these microstructures and receptors enable human skin to simultaneously perceive and differentiate between multiple spatio-temporal tactile stimuli. In a recent study, a snapshot of a hyperspectral imaging system for skin features morphological analyses and temporal quantitative monitoring. A typical HSI system uses white light sources to provide illumination and collects the skin reflection images with a snapshot hyperspectral camera. The camera used in this work is assembled from a fast CMOS sensor and a Fabry-Perrot interference filter array, giving 16 specific sensitive bands covering a spectral range from 470 nm to 630 nm. This disclosure is not limited to this HSI camera system; it is relevant to all imaging systems that have the capability of imaging wavelengths of light that excite the metabolites of interest.

A classic RGB image is an image represented by three layers or bands: Red, Green, and Blue while the hyperspectral image is represented by hundreds of bands. A hyperspectral image is represented by a data cube of two spatial dimensions (X and Y) and a spectral dimension Z. Each pixel corresponds to a spectrum of wavelengths, generally corresponding to the visible and near-infrared domains (400 to 2500nm). NIR hyperspectral images have two spatial dimensions in the form of a matrix, where each element of the matrix can be considered to be a pixel of an image. A hyperspectral image file is known as a hyperspectral cube, or a "hypercube", as it is three-dimensional. Further to the spatial dimensions of a hyperspectral image is a spectral dimension. The data of such a file contains both chemical and physical information. The terms hyperspectral image and hypercube are used interchangeably and denote a three-dimensional data structure containing two spatial axes and one wavelength axis. A single scalar data element in a hypercube is a voxel, but within the context of a two-dimensional image from a single wavelength channel, it is termed a pixel. The set of pixels at the same location in all wavelength channels is a vector, traditionally called a spectrum. The researcher must make decisions about how much spectral resolution to use, and how much to discard. If your camera collects 800 spectral bands, you must ask yourself if you need all 800 or whether binning into 400 or 200, etc. bands are sufficient [14], [28].

Standard Reference Materials (SRMs) are used to allow the transformation of the instrument signals into reflectance or absorbance units, permitting comparisons between different sample spectra. SRMs are needed to calibrate and correct raw spectra for variations in both wavelength and intensity axes. Hyperspectral images can be unfolded to create a two-dimensional dataset to make use of second-order analysis procedures. Sets of spectra are removed from a hyperspectral image one row of pixels at a time and arranged sequentially. Standardization of images will guarantee that a uniform response will be accomplished for all pixel areas at all frequencies inside a solitary hyperspectral picture whether the raw instrument signal will be changed.

IV. A Look At The Signals and the Challenges

Despite several benefits in various domains, hyperspectral images are complex and their analysis is challenged by different factors including high volume since they contain a large amount of spatial and spectral information, data capturing due to variations in illumination, sampling, and storage [29]. The light striking each pixel is broken down into many different spectral bands to provide more information on what is imaged. HSI datacubes can contain absorption, reflectance, or fluorescence spectrum data for each image pixel. A spectral signature is a plot of the amount of light energy reflected by an object throughout the range of wavelengths in the electromagnetic spectrum. HSI data is spectrally sampled at 300 equally distributed wavelengths and extends beyond the visible range.

For this research, we are using the Mason publicly available database Finger Hypercubes Sanitization with Demographics (FHSD) [30]. The finger hypercubes were collected from the left and right index of 100 subjects along with their demographics (age, gender, and ethnicity) across 281 channels in an indoor environment with a white background under proper lighting conditions using the Resonon bench-top Pika-L hyperspectral imaging system (400–1000 nm) [31]. The subjects are mostly students, their families, and friends who are 18 years of age or older and free from metabolic diseases, malfunction of the genetic disorder of metabolism, and who are of normal weight. The data was acquired from individuals with a wide range of ages and backgrounds. To better understand the spectral variations three hypercubes were collected at each instance for every subject. Sample RGB images are illustrated in Fig. 1. The Resonon Pika-L instrument uses a push-broom technique according to which all spectral data about a specific location is recorded simultaneously, thus potential distortions due to changes in illumination can be excluded. However, chromatic aberration may occur.

Since hyperspectral cameras have several bands (i.e., channels) where bands contain a list of wavelengths measured in nanometers. Examples of RGB images obtained at different wavelengths are shown in Fig. 2. The wavelength-to-color relationship and the conversion of the data cube to RGB scheme were approximated by using Bruton's tool [32], [33].

The proposed analysis consists of qualitatively comparing spectral images and extracting statistical information from user-defined regions of interest (ROIs) [26], [34], [35]. The protocol focuses on finding the ROI that can optimally characterize the uniqueness of the mean spectra across individuals. HSI has been proven to be robust in determining the conditions of substrates under degradation due to environment (e.g., temperature, light, humidity). Hyperspectral images depend on the spectral characteristics of the light source illuminating the targeted object as well as on the instrument's properties. On the other side, spectral reflectance is a property of the object itself. The value of a pixel represents a precise measurement of the portion of light that is reflected from the corresponding location in a certain wavelength band. Within a single image, we can extract reflectance versus the bands (i.e., wavelength) and display each pixel's spectral features, as illustrated in Fig. 3.

This paper can inspire researchers in other fields, such as biomedical, to bridge spectroscopy with AI. The profiles created for the application under study can enable the use of algorithms that determine the similarity between an image spectrum (representing an unknown material) and a reference spectrum (representing a known material). For example, the Spectral Angle Mapper (SAM) treats the spectral profiles as n-dimensional vectors and computes the spectral angle

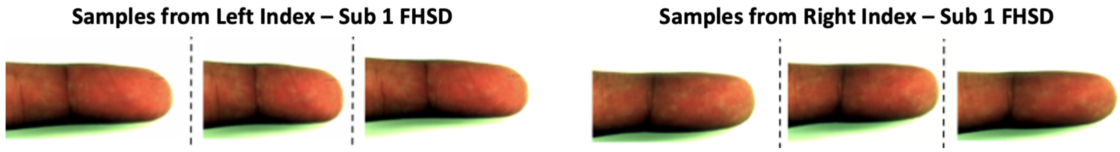
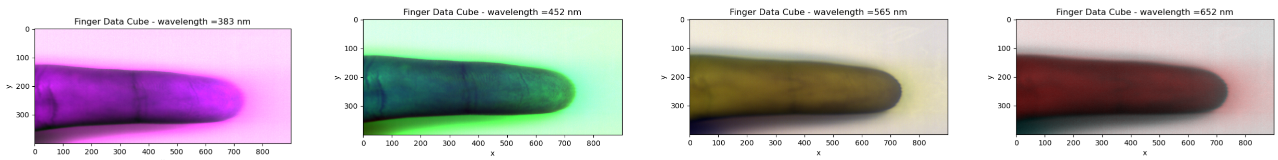
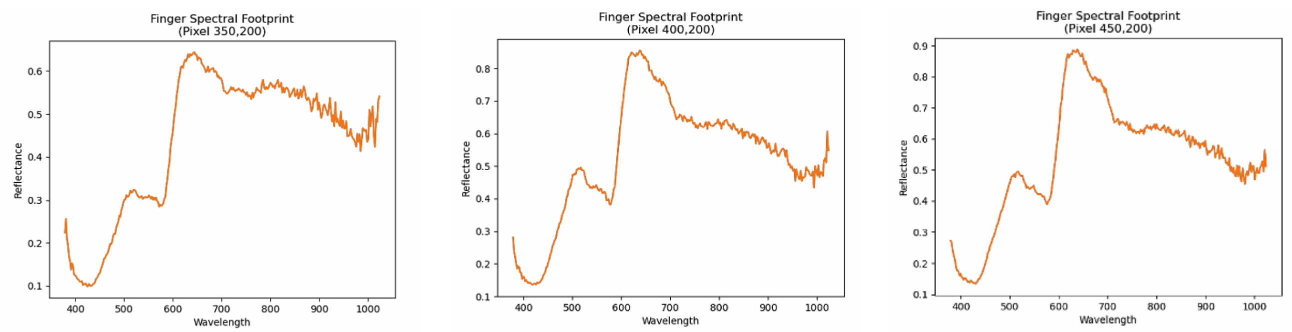


Fig. 1. Sample hyperspectral finger data cubes from the Mason FHSD database.



(a) (b) (c) (d)

Fig. 2. Sample Finger Data Cube in the Visible Spectrum at different wavelengths: (a) 383 nm, (b) 452 nm, (c) 565 nm, and (d) 652.



(a) (b) (c)

Fig. 3. Reflectance of three different pixels: (a) Pixel (350,200), (b) Pixel (400,200), and (c) Pixel (450,200).

between them. Smaller angles represent closer matches to the reference spectrum. The Spectral Feature Fitting (SFF) algorithm performs a band-by-band, least-squares fit between each reference spectrum and the pixel spectra and produces a root mean squared (RMS) image for each reference spectrum.

This research enables the creation of a new applied science for human identity verification that can exploit both extrinsic and intrinsic biometric characteristics, to overcome the limitations of existing technologies often based on matching between absolute positions. This research aims to define human identity through richer signals—not only spatial features but also associated chemical content—captured by a hyperspectral imager without the use of reagents. The knowledge produced through this research bridges advances in chemical sweat analysis to imaging that enables AI-powered systems without the inconvenient use of reagents. This project inspires a holistic perspective on identity in which intrinsic factors complement extrinsic factors to provide a more nuanced, accurate, and fair digital representation.

Electromagnetic radiation (EMR) is energy in the form of electromagnetic waves. The most familiar form of EMR is visible light. When electromagnetic radiation strikes a solid, liquid, or gas, it undergoes one or more of the three processes including reflection, when the EMR is turned back from the surface of the substance, absorption, when the EMR is absorbed by the substance, and transmission, when the EMR passes through the substance. A portion of the light is reflected, a portion may be absorbed while a portion may be transmitted. The physical characteristics of the substance and the wavelengths of the incident light determine how much light is absorbed, reflected, and transmitted. Substances interact with EMR in different ways. They absorb, reflect, or transmit various wavelengths of EMR differently. Light entering biological tissue undergoes multiple scattering and absorption events as it propagates across the tissue. The penetration depth of light into biological tissues depends on how strongly the tissue absorbs light. Spectral distortion may occur [23], [36].

V. Conclusions

HSI has emerged in recent years as one of the most advanced fields of science with exponential rates of development. Capturing biometric data through hyperspectral devices offer very rich and useful characteristics for research purpose. The purpose of this research is to explore the human fingertip skin's unique spectral signature in terms of reflectance in the wavelength range of both near-infrared and visible spectra. Extracting reflectance values in the NIR and visible range from hyperspectral data and using the spectral curves to find an optimal representation of human identity enables the design of systems that are more secure against spoofing. This paper focuses on the new idea of analyzing skin reflectance of fingertip skin, an emerging biometric modality, via HSI. HSI holds great potential for exploring meticulous properties of biometric traits by accessing chemical content, properties that are not accessible by using traditional imaging sensing systems. The spectral signature conveys useful information about the structural and chemical composition of a biometric trait being imaged.

The proposed study promotes interdisciplinary research on advances in computer vision, biochemistry, statistics, and artificial intelligence while discovering new and advanced models for human skin. Miniaturization of HSI technology will direct the systems to cost-efficient solutions that can become an alternative to human recognition methods.

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