Models for Recognizing Faces in Hyperspectral Images

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Abstract

Hyperspectral sensors provide useful discriminants for human face identification that cannot be obtained by other sensing modalities. The spectral properties of human tissue vary significantly from person to person. While the visible spectral characteristics of a person's skin may change over time, near-infrared spectral measurements allow the sensing of subsurface tissue structure that is difficult for a subject to modify. The high spectral dimensionality of hyperspectral imagery provides the opportunity to recognize subpixel features which enables reliable identification at large distances. We propose methods for the identification of humans using properties of individual tissue types as well as combinations of tissue types. Intrinsic models for facial tissue types for a person can be constructed from a single hyperspectral image. These models can be used to generate spectral subspaces that model the set of spectra for a face over a range of facial orientations, environmental conditions, and spectral mixtures.

1 Introduction

Spectroscopy is a valuable tool for a large number of applications. Spectral measurements from human tissue, for example, have been used for many years for characterization and monitoring applications in biomedicine. The introduction of hyperspectral imagers has led to the development of techniques that combine spectral and spatial information. In remote sensing, researchers have shown that hyperspectral data can be used for material identification in scenes for which competing sensing modalities are ineffective [4]. As hyperspectral imagers have become readily accessible, computational methods developed initially for remote sensing problems have been transferred to biomedical applications [5]. Given the vast person-to-person spectral variability for different tissue types, hyperspectral sensing has the potential to significantly advance the capability of automated systems for human identification.

Algorithms for Multispectral, Hyperspectral, and Ultraspectral Imagery VII, Sylvia S. Shen, Michael R. Descour, Editors, Proceedings of SPIE Vol. 4381 (2001)

The hyperspectral image of a person in an outdoor scene is highly variable due to spatial and temporal variation in the illumination and atmospheric conditions. We have shown in previous work that the dimensionality of the set of sensor spectra for a fixed material as conditions change is significantly smaller than the dimensionality of the hyperspectral measurement space [4]. This result is based on a detailed physical model for hyperspectral image formation. The low dimensionality of hyperspectral signatures allows for the accurate subpixel identification of low-contrast materials in cluttered backgrounds over a wide range of conditions.

The best current approaches to automated human identification via face recognition, e.g. [2] [9] [19], utilize discriminants that are based on the geometry of facial features in an image. These algorithms have demonstrated accurate recognition performance on mugshot/DMV type photographic databases of over 1,000 people [12]. Performance degrades somewhat, however, for images taken under different lighting [11]. In addition, these approaches have limited utility for applications where distant humans must be identified using only a few pixels.

The dependence of face recognition systems on spatial information can be relaxed if other sources of information are available. Color distributions over image regions, for example, have been demonstrated for recognition in controlled indoor scenes [16]. Approaches based on matching color distributions, however, break down quickly in the presence of illumination changes. Ideally, we might hope to generate representations with useful discriminatory power in cases where faces occupy a small number of pixels. Unfortunately, the spectral distribution of natural illumination has at least three degrees of freedom [7] [13] and the sets of possible RGB measurements for different materials often overlap. Thus, any strictly local approach to identification using color images acquired under unknown conditions will be unreliable.

The use of hyperspectral imaging provides the possibility that people can be recognized using only local information. Hyperspectral images contain a large number of contiguous spectral bands at each image location. As with RGB images, recognition in hyperspectral imagery is complicated by the fact that spectral measurements depend on the illumination and atmospheric conditions. For example, the two curves in figure 1 contain normalized 0.4μm-2.5μm spectra obtained by the same hyperspectral imager for the same surface under different illumination conditions. Even after normalization, the spectra in figure 1 are significantly different. Correspondingly, an algorithm that attempts to recognize a material using a normalized spectrum for that material that was measured on a different day will incur many false alarms in a typical outdoor scene [4].

We have shown that as conditions change the set of spectral radiance functions observed

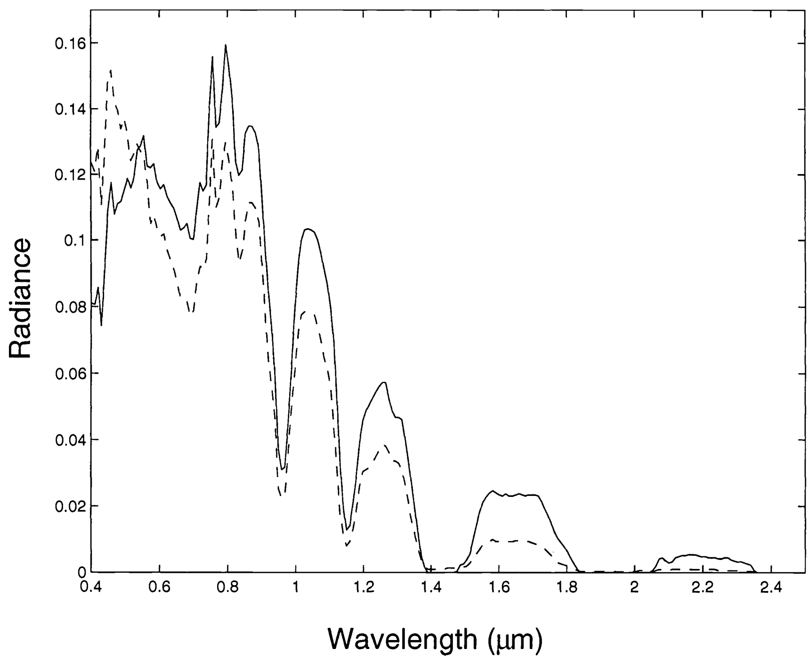

Figure 1: Spectra measured for same surface at different times

for a fixed material lie in a low-dimensional subspace of the hyperspectral measurement space [4]. This result enabled the development of a pixel-based material labeling algorithm that is invariant to spatial and temporal variation in the illumination and atmospheric conditions. A related algorithm has been demonstrated for the labeling of materials under changes in surface orientation [14]. These results can be applied to the problem of identifying distant humans under unknown conditions.

2 Physical Modeling

The spectral characteristics of human tissue vary significantly from person to person and therefore provide useful information for human identification. By utilizing spectral measurements over the near-infrared (NIR), we also gain the ability to observe subsurface tissue structure that is difficult for a person to modify. In this section, we review some of the biological and physical principles that relate to the spectral characteristics of human tissue.

The interaction of light with human skin has been analyzed in great detail [18]. The epidermal and dermal layers of human skin constitute a scattering medium that contains several pigments such as melanin, hemoglobin, bilirubin, and β-carotene. Small changes in the distri-

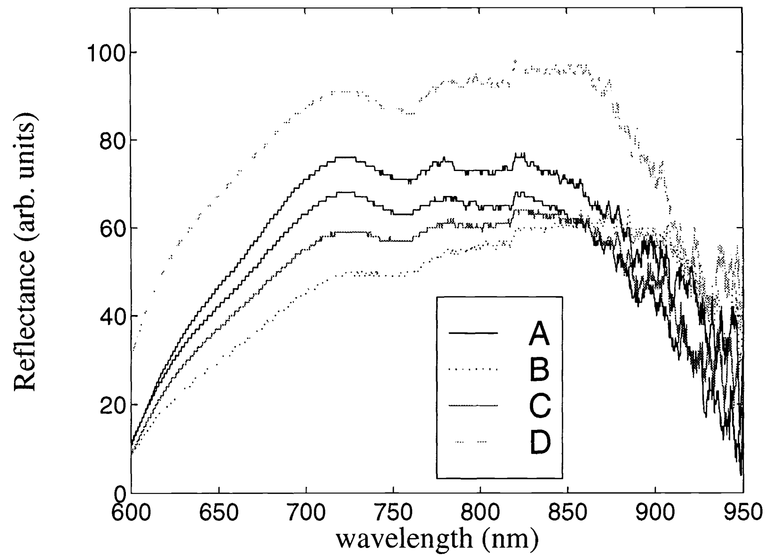

Figure 2: Skin reflectance spectra measured at BLI

bution of these pigments induce significant changes in the skin's spectral reflectance [1]. The effects are large enough, for example, to enable algorithms for the automated separation of melanin and hemoglobin from RGB images [17]. In the near-infrared, skin has a significant penetration depth enabling the imaging of subsurface characteristics [6]. The water content of skin provides evidence of a subject's age among other factors and can be recovered from NIR spectral measurements [8]. Figure 2 presents an example of the spectral variability in human skin using measurements obtained at UC Irvine's Beckman Laser Institute (BLI). In the figure, reflectance spectra were measured from the right cheek of four subjects over a subset of the visible and near-IR (600nm-950nm). Two reflectance spectra were acquired for subject A in order to compare within-class and between-class variability. We see that there are significant differences in both the amplitude and spectral shapes of the reflectance curves for the different subjects while the spectral reflectance for subject A remains similar from trial-to-trial. Similar results were obtained for other facial skin samples that we measured. In summary, the spectral properties of skin vary significantly from person to person and certain properties, particularly those observed in the NIR, are relatively stable over time.

Characteristics of human eyes can also be exploited for identification. The spatial structure of the iris as imaged in high resolution VNIR iris scans has been shown to enable very accurate identification over large databases of people. Unfortunately, iris scans are difficult to obtain at significant distances. The spectral reflectance of the human iris over the VNIR also provides a distinctive signature for human identification that is typically stable with time. The spectral properties of the iris are determined by the number and distribution of pigment cells known as chromatophores and melanocytes that vary from person to person. The high spectral dimensionality of hyperspectral images allows for the identification of specific iris spectra even when the eye occupies a small fraction of a pixel in the image.

The spectral properties of human hair also provide useful discriminatory information in certain situations. Although easily modified, the visible spectral reflectance of hair varies from person to person and leads to observables that can be measured at large distances. In addition, information about the water content of human hair can be obtained using near-infrared spectral measurements [10].

3 Human Identification

A human face can be represented as a geometric arrangement of tissue types where each tissue type has physical attributes that determine its interaction with light. A general recognition problem would require identifying a specific person from an image under unknown pose and unknown environmental conditions. Recognizing faces in RGB images under unknown conditions from a small number of pixels would be an impossible task since different faces could give rise to the same measurements. However, the high spectral dimensionality of hyperspectral imagers suggests the possibility that faces can be recognized under unknown conditions using just a few pixels.

Consider a face that is viewed by a hyperspectral sensor. For a given facial orientation and sensor location, we can synthesize the spectral vector for each face pixel given the environmental conditions using the models described in section 2. Models for facial tissue types for a person can be efficiently constructed from a single image of the person acquired under unknown conditions [15]. Since we consider scales for which several tissue types will frequently mix in a pixel, a pixel spectral vector will often change with subpixel translations of the image plane. By considering a large set of pixel grid locations relative to the face, we can generate a representative set of possible spectral vectors that will be observed for face pixels for this pose and environment. This set of spectra can be used to build subspace models for face recognition. Once the face spectral subspaces have been generated, a projection-based method [4] can be applied separately over an image for each subspace to identify pixels on the face of the person of interest. Since face models were built pixel-by-pixel and the recognition method can identify face pixels that also contain background materials, this method has the potential to recognize faces even in the presence of partial occlusion.

4 Experimental Data

Our data collection utilizes a hyperspectral camera from Opto-Knowledge Systems, Inc. (OKSI) that is based on a tunable filter [3] made by Cambridge Research Instruments. A standard configuration supports the capture of 40 bands over the visible and near-infrared (0.65μm-1.05μm) with 256×256 spatial resolution. Figure 3 is the band at 800 nm for a face image acquired with this sensor. Figures 4-6 plot the near-infrared radiance spectra for various tissue types. Figure 4 is a spectrum measured from the subject's cheek, figure 5 is a spectrum measured from the subject's iris, and figure 6 is spectrum measured from the subject's hair. We see that the spectral properties of the different tissue types are significantly different. This diversity of spectral information for a human face can be exploited for face modeling and recognition.

5 Conclusion

We have discussed models and methods that utilize hyperspectral imagery for human identification at a distance. The high spectral dimensionality of hyperspectral imagery in combination with physical models will likely lead to advancement in human identification technology in several areas. Hyperspectral imagery holds the unique advantage of enabling the use of local illumination invariants [4]. This facilitates illumination-invariant identification over over a range of poses and levels of obscuration. Hyperspectral data also enables the subpixel identification of facial features which increases the distance over which a system is useful. Spectral imaging over the visible and near-infrared allows measurement of both surface and subsurface tissue properties which provides a rich set of observables for discrimination. We expect that the new methods can be combined with methods that exploit other classes of observables to develop systems that satisfy the requirements for a large set of applications.

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Figure 3: 800 nm band from near-IR hyperspectral camera

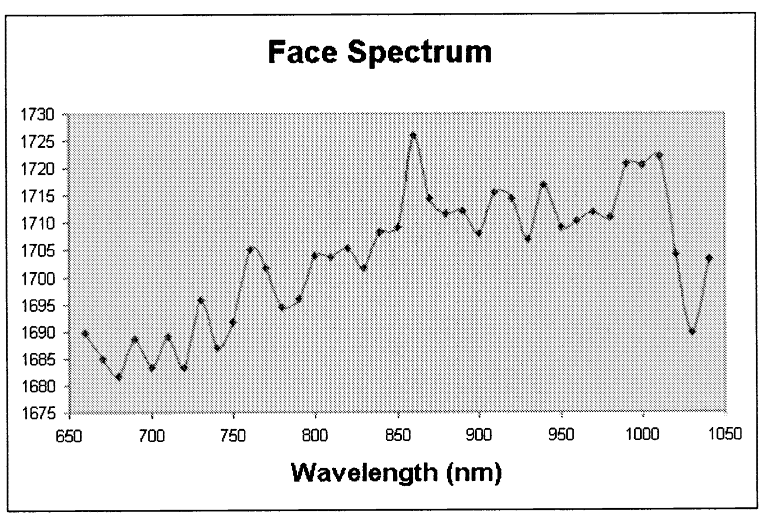

Figure 4: Near-IR spectrum from subject's cheek

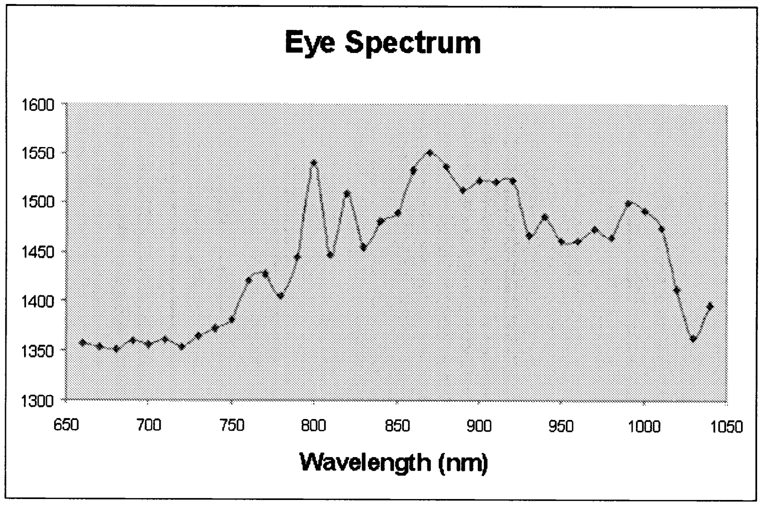

Figure 5: Near-IR spectrum from subject's eye

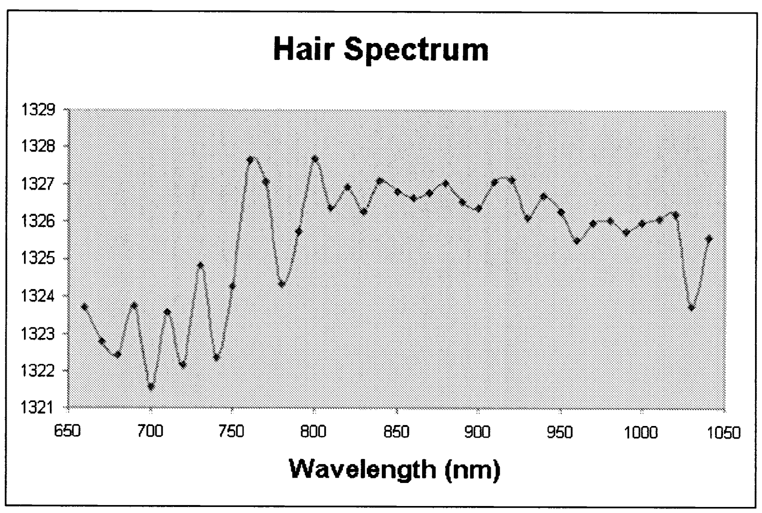

Figure 6: Near-IR spectrum from subject's hair

References

[1] E. Edwards and S. Duntley. The pigments and color of living human skin. *Am. J. Anat.*, 65:1–33, 1939.

[2] K. Etemad and R. Chellappa. Discriminant analysis for recognition of human face images. *J. Opt. Soc. Am. A*, 14:1,724–1,733, 1997.

[3] N. Gat. Imaging spectroscopy using tunable filters: a review. In *SPIE Conference on Algorithms for Multispectral and Hyperspectral Imagery VI*, Orlando, April 2000.

[4] G. Healey and D. Slater. Models and methods for automated material identification in hyperspectral imagery acquired under unknown illumination and atmospheric conditions. *IEEE Trans. Geosci. Remote Sensing*, 37(6):2706–2717, November 1999.

[5] G. Healey and D. Slater. Lessons learned: technology transfer from terrestrial spectroscopy to biomedicine. In *SPIE Volume 3920, Spectral Imaging: Instrumentation, Applications, and Analysis*, San Jose, January 2000.

[6] M. Hiraoka, M. Firbank, M. Essenpreis, M. Cope, S. Arridge, P. van der Zee, and D. Delpy. A Monte Carlo investigation of optical pathlength in inhomogeneous tissue and its application to near-infrared spectroscopy. *Phys. Med. Biol.*, 38:1859–1876, 1993.

[7] D. Judd, D. MacAdam, and G. Wyszecki. Spectral distribution of typical daylight as a function of correlated color temperature. *J. Opt. Soc. Am.*, 54:1031–1040, 1964.

[8] K. Martin. Measurements of water in skin by near-infrared reflectance. *Appl. Spec.*, 52:1001, 1998.

[9] B. Moghaddam and A. Pentland. Probabalistic visual recognition for object recognition. *PAMI*, 19(7):696–710, July 1997.

[10] Y. Ozaki, T. Miura, K. Sakurai, and T. Matsunaga. Nondestructive analysis of water structure and content in animal tissues by NIR spectroscopy. Part I: human hair. *Appl. Spec.*, 46:875–878, 1992.

[11] A. Pentland. Looking at people: sensing for ubiquitous and wearable computing. *PAMI*, 22(1):107–119, January 2000.

[12] D. Phillips, H. Wechsler, J. Juang, and P. Rauss. The FERET database and evaluation procedure for face recognition algorithms. *Image and Vision Computing*, 16(5):295–306, 1998.

[13] D. Slater and G. Healey. Analyzing the spectral dimensionality of outdoor visible and near-infrared illumination functions. *J. Opt. Soc. Am.*, 15(11):2913–2920, 1998.

[14] D. Slater and G. Healey. Material mapping for 3D objects in hyperspectral images. In *SPIE Conference on Algorithms for Multispectral and Hyperspectral Imagery V*, Orlando, April 1999.

[15] D. Slater and G. Healey. A spectral change space representation for invariant material tracking in hyperspectral images. In *SPIE Proceedings Vol. 3753, Imaging Spectrometry V*, pages 308–317, Denver, July 1999.

[16] M. Swain and D. Ballard. Color indexing. *Int. J. Comp. Vision*, 7:11–32, 1991.

[17] N. Tsumura, H. Haneishi, and Y. Miyake. Independent-component analysis of skin color image. *J. Opt. Soc. Am. A*, 16(9):2169–2176, 1999.

[18] M. van Gemert, S. Jacques, H. Sternborg, and W. Star. Skin optics. *IEEE Trans. Biomedical Eng.*, 36(12):1146–1154, December 1989.

[19] L. Wiskott, J.-M. Fellous, N. Kruger, and C. von der Malsburg. Face recognition by elastic bunch graph matching. *PAMI*, 19(7):775–779, July 1997.