ON THE REMOTE DETECTION OF HUMAN SKIN SIGNATURES

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Technical Report CS-2014-25
December, 2014

1. INTRODUCTION

Every year, search and rescue operations are employed to save numerous lives all over the world. In order to achieve this goal, the agencies responsible for these operations strive to reduce the time to find people who are lost or in distress. This is a particularly challenging task, specially when the search is performed on vast and complex environments such as open ocean waters, deserts, mountains, forests and flooded regions. It usually involves visual screenings primarily performed by personnel onboard low-flying aircrafts [1]. During long airborne searches, the performance of the human operators may degrade due to fatigue, which may result in vital target clues to be missed [2].

The fundamental importance of reducing search time and increasing the probability of successful rescues have motivated the development of sophisticated airborne detection systems equipped with multispectral and hyperspectral sensors (*e.g.*, [3, 4]). Due to their real-time capabilities and relatively low cost compared with other technologies, such as synthetic aperture radar [2], these systems have become essential tools for search and rescue operations at sea and on land [1, 3]. Installed on aircrafts operating at relatively high altitudes, they provide information that complements the visual screenings performed at low altitudes, resulting in faster and more complete scene coverage [2].

Despite the significant advances in this area, however, the effective detection of human targets remains an open problem, notably in environments composed of background materials characterized by spectral features that pose limited contrast with spectral signatures of human skin. Such limited contrast may result in false positives, or false alarms, during time-critical search and rescue operations. These situations may hinder the chances of survival of a lost individual, especially under adverse environmental conditions, since valuable time may be unduly employed in their investigation. Accordingly, more comprehensive spectral differentiation techniques based on an expanded spectral coverage are required to mitigate these situations and improve the performance of current detection systems [5].

Recently, these efforts have led researchers to look for insights in an area where similar issues have been extensively studied, namely the remote sensing of vegetation. Since plants represents a fundamental resource for all human and animal life on the planet, many spectral differentiation technologies have been proposed in this area, including more than 150 vegetation indices [6]. These indices are formed from combinations of spectral responses of plants to yield a single value that indicates their vigour and allows their differentiation from surrounding materials such as water and bare soil. Arguably the best known and widely employed vegetation index is the $NDVI$ (Normalized Difference Vegetation Index) [6]. It is based on the characteristic patterns of vegetation reflectance in visible and near-infrared regions of the light spectrum, being computed as $(\rho_{NIR} - \rho_R)/(\rho_{NIR} + \rho_R)$, where ρ_R and ρ_{NIR} correspond to the mean reflectance in the red (600-700 nm) and near-infrared (700-1100 nm) bands of interest, respectively [7].

In 2008, Nunez and Mendenhall [8] proposed an index for the detection of skin signatures inspired in the $NDVI$. This index, termed Normalized Difference Skin Index and henceforth referred to as $NDSI_8$, employs reflectance (ρ) values captured at two near-infrared wavelengths (1100 nm and 1400 nm), being computed as $(\rho(1100) - \rho(1400))/(\rho(1100) + \rho(1400))$. Later in 2009, Nunez *et al.* [9], proposed a modified version of this index, henceforth referred to as $NDSI_9$, in which the NIR reflectances at 1100 nm and 1400 nm were replaced by NIR reflectances captured at 1080 nm and 1580 nm, respectively.

Since the indices proposed by Nunez *et al.* [8, 9] employ two NIR reflectance values, they can effectively detect human targets when the background materials have a light absorption and reflection behaviour markedly distinct from the light absorption and reflection behaviour of human skin in this region of the light [10]. Noteworthy examples include man-made and inorganic materials typically found in urban settings. There are background materials, however, whose interactions with light can result in spectral features similar to skin spectral features in a particular spectral range. These include materials and material combinations typically found in nature, which constitute the focal point of this work. Hence, to reduce the possibility of false alarms in the search for human targets in complex natural environments, it becomes necessary to use multiple probes covering relevant spectral regions in which skin signatures are marked by characteristic features.

In this report, we propose a multispectral index, henceforth referred to as $MSDI$ (Multispectral Skin Detection Index), for the remote detection of human skin signatures based on this premise. More specifically, the proposed index takes into account the distinct spectral trends of human skin in the visible and NIR regions (Figure 1) in which light absorption within the cutaneous tissues is dominated by melanin and water, respectively [11].

2. APPROACH AND MATERIALS

The proposed index employs reflectance (ρ) values captured at four wavelengths, with two in the visible (450 nm and 650 nm) and two in NIR (1450 nm and 1650 nm) region, being computed as:

$$MSDI = \frac{\rho(650) - \rho(450)}{\rho(650) + \rho(450)} \times \frac{\rho(1650) - \rho(1450)}{\rho(1650) + \rho(1450)}. \tag{1}$$

In order to assess its effectiveness and compare it with the existing indices, we compute $MSDI$, $NDSI_8$ and $NDSI_9$ values (Table 1) for skin specimens with distinct levels of pigmentation (Figure 1). We then computed their values for different materials found in natural environments to determine whether false alarms can occur based on the testing skin detection intervals depicted in Table 1. These computations are performed using actual measured reflectance values available for these materials in the literature. Since these datasets were obtained through distinct data acquisition initiatives [12, 13, 14, 15, 16], one should expect variations in their respective measurement conditions. We note, however, that similar variations are also expected to occur during actual search and rescue operations.

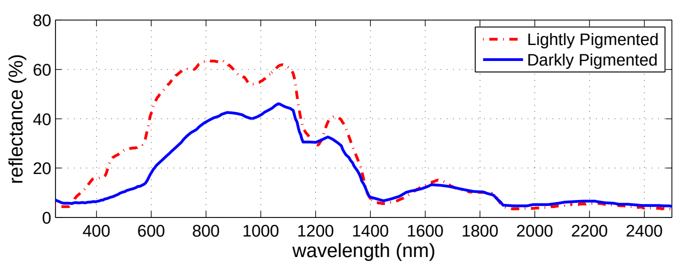

Fig. 1. Reflectance spectra for lightly and darkly pigmented skin specimens provided by Cooksey and Allen [12] and Jacquez *et al.* [13, 14], respectively.

Skin Specimens	$MSDI$	$NDSI_8$	$NDSI_9$
Lightly Pigmented	0.1815	0.7760	0.6776
Darkly Pigmented	0.1588	0.6875	0.5981

Table 1. Computed $MDSI$, $NDSI_8$, and $NDSI_9$ values for a lightly and a darkly pigmented skin specimen whose corresponding reflectance spectra is provided in Figure 1.

3. RESULTS AND DISCUSSION

Initially, we compared the performance of the indices with respect to natural materials whose reflectance profile is characterized by the absence of prominent spectral features at the NIR wavelengths of interest (Figure 2). As expected, since the reflectance of human skin is marked by noticeable features in this region (Figure 1), all computed index values (Table 2) were outside their corresponding skin detection interval (Table 1), suggesting that these indices can effectively differentiate these materials from human targets.

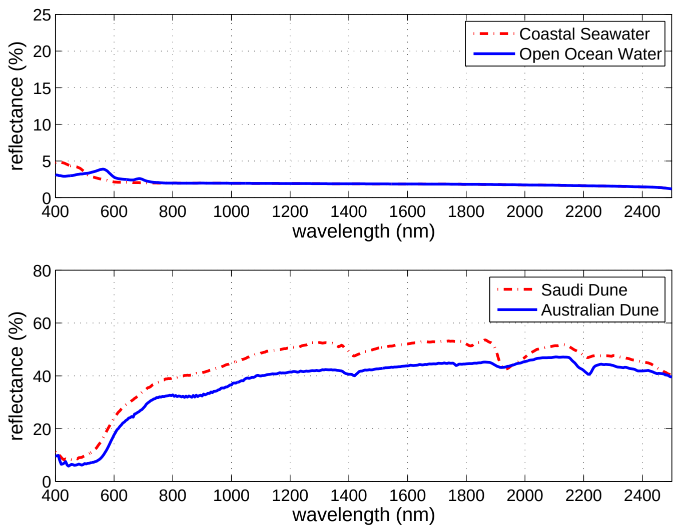

Fig. 2. Reflectance spectra for sample materials characterized by the absence of prominent features at the NIR wavelengths of interest. Top: ocean water samples [15]. Bottom: desert (dune) sand samples [16].

Sample Materials	$MSDI$	$NDSI_8$	$NDSI_9$
Sand (Saudi Dune)	0.0206	-0.0068	-0.0381
Sand (Australian Dune)	0.0146	-0.0078	-0.0476
Coastal Seawater	0.0008	0.0104	0.0236
Open Ocean Water	-0.0039	0.0104	0.0236

Table 2. Computed $MDSI$, $NDSI_8$, and $NDSI_9$ values for samples of ocean water (from Atlantic Ocean) [15] and desert sand (from Saudi and Australian dune field) [16].

In our next round of comparisons, we considered natural materials with a reflectance profile marked by the presence of prominent spectral features at the NIR wavelengths of interest (Figure 3). Since $MSDI$ takes into account spectral features in both visible and NIR regions, it provides values (Table 3) outside its detection interval computed for the skin specimens considered in this work (Table 1). On the other, since the $NDSI_8$ and $NDSI_9$ consider only spectral features in the NIR region, they are more prone to result in false alarms when the natural background is composed by materials whose spectral signatures are characterized by spectral features similar to those found in the spectral signatures of human skin within this region. This can verified by the $NDSI_8$ and $NDSI_9$ values depicted in boldface in Table 3, which are within the $NDSI_8$ and $NDSI_9$ detection intervals computed for the skin specimens considered in this work (Table 1). We note that the computed skin detection intervals presented in Table 1 should be viewed as relative references since some variation should be expected with respect to individuals characterized by more extreme pigmentation levels. In addition, they can be further broaden by physiological changes, such as water loss and erythema [11], caused by exposure to harmful environmental stimuli.

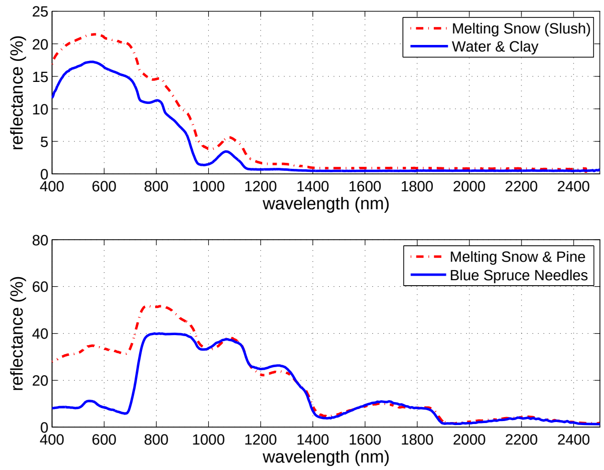

Fig. 3. Reflectance spectra [15] for sample materials characterized by the presence of prominent features at the NIR wavelengths of interest. Top: melting snow (slush) and water mixed with clay (1.67 g/L). Bottom: melting snow mixed with forest vegetation (pinion pine) and fresh blue spruce needles.

Sample Materials	$MDSI$	$NDSI_8$	$NDSI_9$
Melting Snow (Slush)	0.0001	**0.6975**	0.7232
Water & Clay	0.0000	**0.6883**	0.7540
Melting Snow & Pine	0.0086	0.6163	**0.6403**
Blue Spruce Needles	-0.0604	0.6811	**0.6268**

Table 3. Computed $MDSI$, $NDSI_8$, and $NDSI_9$ values for samples of melting snow (slush), water mixed with clay (1.67 g/L), melting snow mixed with forest vegetation (pinion pine) and fresh blue spruce needles. These samples were collected at different locations across North America [15].

Although comprehensive *in situ* tests are required to fully asses the capabilities of detection indices under different operation conditions, the results of our investigation indicate that the proposed index can mitigate the number of false alarms that may occur in search and rescue operations in complex natural environments. Hence, we believe that even though it requires the acquisition of reflectance values at four different wavelengths and within a spectral range broader than the usual range (*e.g.*, 380-1100 nm) covered by the most widely used detection systems (*e.g.*, [3, 4]), it can effectively contribute to the reduction of search time, and thus increase the survival chances of those who are lost. Moreover, as pointed out by Eismann *et al.* [5], such systems were developed based on spectrometer hardware that were both reliable and relatively inexpensive at the time they were proposed. However, current hyperspectral technology continues to evolve, and devices such as the InGaAs detector arrays can provide low-cost solutions for extending the spectral coverage of existing detection systems up to 1700 nm [5]. Finally, as appropriately stated by Leonard *et al.* [1], since time is a critical factor, anything that can be done to reduce the search time and lead to a successful rescue is of value for these operations aimed at saving lives.

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