Biometric Study Using Hyperspectral Imaging During Stress

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Abstract

To the casual observer, transient stress results in a variety of physiological changes that can be seen in the face. Although the conditions can be seen visibly, the conditions affect the emissivity and absorption properties of the skin, which imaging spectrometers, commonly referred to as Hyperspectral (HS) cameras, can quantify at every image pixel. The study reported on in this paper, using Hyperspectral cameras, provides a basis for continued study of HS imaging to eventually quantify biometric stress. This study was limited to the visible to near infrared (VNIR) spectral range. Signal processing tools and algorithms have been developed and are described for using HS face data from human subjects. The subjects were placed in psychologically stressful situations and the camera data were analyzed to detect stress through changes in dermal reflectance and emissivity. Results indicate that hyperspectral imaging may potentially serve as a non-invasive tool to measure changes in skin emissivity indicative of a stressful incident. Particular narrow spectral bands in the near-infrared region of the electromagnetic spectrum seem especially important. Further studies need to be performed to determine the optimal spectral bands and to generalize the conclusions. The enormous information available in hyperspectral imaging needs further analysis and more spectral regions need to be exploited. Non-invasive stress detection is a prominent area of research with countless applications for both military and commercial use including border patrol, stand-off interrogation, access control, surveillance, and non-invasive and un-attended patient monitoring.

Keywords: Hyperspectral Imaging, Biometrics, Stress, Psychological, Physiological, Skin, VNIR, Near Infrared, Non-invasive

1. INTRODUCTION

Conventional color cameras acquire the color intensity from three broad spectral visible bands, i.e., red, green and blue. Hyperspectral (HS) cameras measure the color intensity over a hundred or more narrow spectral bands. HS cameras depend on the same focal plane array (FPA) sensors and the same type of lenses as ordinary non-HS cameras use. FPA's are tuned to particular broad spectral regions, such as visible (VIS or V), near infrared (NIR), short wave infrared (SWIR), mid-wave infrared (MWIR), and long wave infrared (LWIR). Likewise, the optics in any one camera are limited by chromatic aberration and transmission properties to similar spectral regions. The cameras used for this study were Hyperspectral cameras limited to the spectral range from visible to near infrared (VNIR), which is approximately the wavelength region from 400 nanometer to 900 nanometers. The data sets acquired from the HS-VNIR cameras are the measured intensity, $I_{x,y,\lambda}$ of the narrow spectral band, λ, at the spatial location, x and y, in the image space and is

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referred to as a data cube (see Figure 1). Because each element (pixel) in the FPA differs in its response to light (i.e. gain) and to the presence of no light (i.e. dark current) the raw data is "non-uniform," and Non-Uniform Corrections (NUC) were applied to the raw data prior to the data being recorded. The light source spectral content for this study was kept constant for all patients. The analysis performed is based on the difference in the recorded spectral intensity from the same face from the same local regions prior to, during, and after the situation occurred which may cause stress in a normal subject.

It should be noted that different objects and surfaces that appear to be the same to the naked eye can have uniquely different Hyperspectral signatures[1]. Hyperspectral VNIR imaging has proven useful in finding differences that were not obvious to human observer in other applications. With that in mind, this study was initiated to determine the value of Hyperspectral imaging to aid in assessing whether a person is in stress.

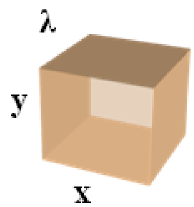

Figure 1 – Hyperspectral Data Cube Structure

1.1 Physiological Assessment of Psychological Stress

Physiological signs of stress have been traditionally measured on the body with contact sensors that measure human vital signs such as pulse and respiration, as seen in Figure 2. These techniques include galvanic skin response, which measures the changes in electrical properties (resistance and conductivity) of the skin in response to stress or anxiety, the electrocardiogram signal (ECG), which is a recording of the electric current of the cardiac cycle used to determine the pattern of a patient's heartbeat, and pulse oximetry, a noninvasive and painless way to measure oxygen saturation of arterial blood, an indicator of breathing. More recently, much emphasis in detecting stress has shifted from measurements taken from vital signs on the body to regional surface signs using contact-free sensing. This has allowed the shift toward enabling remote sensing of physiological changes by ascertaining physiological measurements that can be observed in the face, a body region that is usually exposed and might therefore facilitate remote sensing.

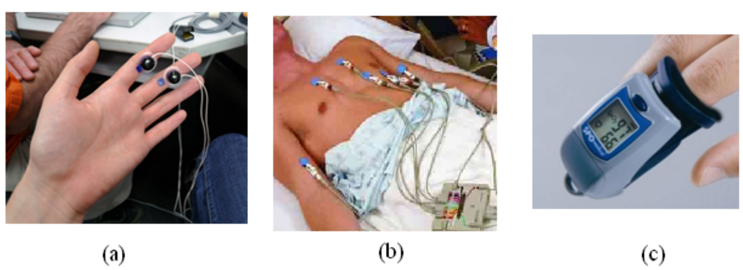

Figure 2 – Conventional Methods of Measuring Stress- (a) Galvanic Skin Response (b) Electrocardiogram (ECG) (c) Pulse Oximetry

Currently, there are many publications on the modeling and interpretation of human behavior based on spatio-temporal characteristics of human motion[2]. One of the approaches implemented utilizes the kinematics of distinctive points on the human body, such as the knees, elbows, and shoulders, to develop 3-D models of human silhouettes in stacked sequential video frames. Video databases containing human movements, such as gait, jumping, and other motions, were used to identify activities of interest. Stochastic approaches of human motion have also been explored using Markov and

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Bayesian models[2]. In these studies, it would be necessary to capture the person's of interests entire body to accurately identify motion, a stipulation that would restrict remote identification of human behavior in an unconstrained environment with uncooperative individuals. In addition to visually observing an individual, the information gathered through facial expressions could possibly be utilized to provide insight into an individual's emotional state and perhaps even infer something about the person's intent by means of behavioral cues. Identifying even subtle conscious or unconscious changes in facial expressions, in addition to suspicious changes in gaze and pose, might provide crucial information regarding a person's emotional and motivational state[3].

The signature of a "fight or flight" response can be thermally imaged due to redistribution of arterial blood flow that changes the temperature within the superficial depth of facial tissue (see Figure 3). Thermal imagery provides a broadband signature, which is dependent on a heat source and can therefore be used to observe an adjustment in blood flow in an individual's face during particularly stressful or emotionally exhausting events. In addition to local physiological changes, vital signs can be measured through thermal imaging of the face[4]. Heart rate can be measured thermally via the carotid artery and heat patterns associated with breathing can also be thermally observed in the nasal area through temperature oscillations[5]. Performing physiological measurements on the face using thermal imaging is challenging due to the fact that these are non-contact measurements on an uncooperative subject - a virtual probe has to be applied on the right tissue location and remain there during motion, causing an image segmentation problem (automatically finding the right area) and an image tracking problem (staying on the region of interest despite facial motion).

Transient stress results in a variety of physiological transformations including redirection of blood, increase in heart rate and blood pressure, increase in respiration, and the release of hormones such as adrenaline and cortisol. Many of these subtle changes manifest themselves visibly. Physiological indicators, such as changes in skin coloration due to subdermal vascular adjustments, emergence of abnormal perspiration, and changes in body temperature, are parameters that may lend themselves to remote spectral analysis to detect the stress-related changes. Oxygenated hemoglobin flow increases subdermally in response to and in proportion to the level of transient stress and thus alters the emissivity and absorption properties of the skin[6]. In addition, perspiration contains water, sodium chloride, potassium, magnesium, and other chemicals that affect the penetration of ambient light on the epidermis and how it is reflected on this top layer of skin, causing an attenuation of certain wavelengths in the electromagnetic spectrum. Monitoring these changes in the spectral domain has the potential to allow for innovations in the noninvasive assessment of the correlation between stress and its manifestation[6].

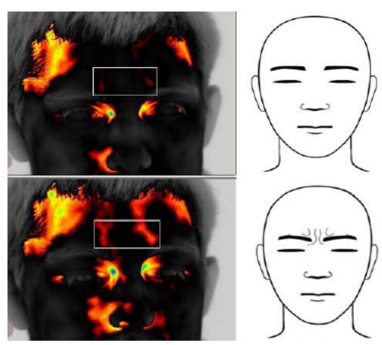

Figure 3 – Facial thermal images relate muscular actions to thermo-physiological changes (Computational Physiology Lab-University of Houston[4]

1.2 Biometric Applications for Hyperspectral Imaging

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A majority of current biometric authentication systems such as face-recognition systems, are configured to function for cooperative user applications and not necessarily for surveillance purposes. These systems analyze images obtained from the visible light portion of the electromagnetic spectrum and are therefore very sensitive to uncontrolled changes in ambient illumination. Studies have indicated that changes in environmental lighting, such as the angle and intensity of illumination, may considerably hinder the ability of a facial recognition system to positively identify a target[7]. More recently, mid- and long-wavelength infrared imaging has been utilized for facial recognition purposes, both in indentifying individuals under uncontrolled illumination situations and even when the face is disguised. Results can be significantly more precise when images from the visible spectrum are compared with those from the infrared spectrum[8]. However, the use of thermal imagery poses many challenges to accurate facial recognition, including interference from varied external environmental and temperature conditions, temperature variability associated with the health of the user, and poor ability to identify eye location. Using imaging in the near infrared (NIR) region provides an alternative measurement for facial recognition. NIR-based facial feature detection uses numerous spectral bands over the wavelength range from 700 to 1000 nm, allowing for multiband spectral measurements of the surface and subsurface of facial skin sampled at various points in a specified region of interest[12]. These useful signatures, which have shown to be exclusive to an individual based upon horizontal and vertical projections of invariant features and are insensitive to ambient light in uncontrolled illumination situations. Although hyperspectral imaging is emerging as a technology used for face detection and identification, the use of hyperspectral data to determine the mental state of an individual based on physiological indicators has not been adequately researched.

In 2005, a patent was published to unobtrusively detect physiological stress in an individual by means of hyperspectral imaging using parameters such as sub-dermal blood flow and dermal hydration in an automated and potentially portable system[10]. The patent identifies the wavelengths that would be particularly important in understanding human stress and presents the various hurdles in implementing such a system, including the necessity to have a controlled environment with known illumination conditions and an in-depth understanding of how skin emissivity is influenced by factors such as age, sex, ethnicity, and health condition. Hyperspectral imaging of different regions of the spectrum corresponding to various physiological phenomena may provide subtle clues on the psycho-physiological state of an individual that is not observable in imaging systems currently being used[11]. For example, the 500 - 600 nm range corresponds to the intense absorption of light by hemoglobin in the blood (the phenomenon known as “blushing”), 1400 - 1700 nm indicates water absorption (perspiration), and the 9000 - 12000 nm range and has shown the ability to characterize body temperature[10]. The volume of information available in hyperspectral imaging yields information beyond that possible from broad spectral regions, such as changes in blood and/or perspiration [13].

For this study, we leveraged a pre-existing experiment (see Section 2.1) of the US Army ARDEC’s Target Behavioral Response Laboratory in which subjects were placed in an ostensibly stress-inducing situation and monitored for physiological changes. We focused on the visible to near-infrared range of the spectrum (around 400 - 900 nm) as this is the region in which ambient light is reflected from skin. The near-infrared region of the spectrum has indicated relevance in facial detection as it provides the ability to discern information unseen to the eye through its unique signature derived from spectral properties. This signature may prove to vary based on the emissivity properties of the skin in response to external stimuli, in this case the stress inducing event. The visible range of the spectrum has not been explored in the hyperspectral domain for applications in stress detection; we therefore hope to understanding whether this region provides useful data for non-invasive stress detection as well as developed event-related characterization algorithms for the near-infrared region. Signal processing techniques were used to measure changes in skin reflectance that we hope would prove to be in some way related to the event that was designed to evoke possible stress response. Hyperspectral imaging may eventually provide a noninvasive tool to measure stress changes if we can select and focus on wavelength bands that vary reliably with stress changes. The additional information available in hyperspectral imaging yields supplementary information that could potentially be exploited for identification of psychologically-induced stress (e.g. changes in blood flow and/or perspiration may become more evident in certain wavelength ranges) [13]. The capability to collect data over a range of wavelengths represents an advance in biometric technology.

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2. DATA COLLECTION

2.1 Experimental Design

All biometric data collection and field testing were performed at the U.S. Army's Target Behavioral Response Laboratory (TBRL). The TBRL conducts research on human behavior and physiology in response to stressful or aversive stimuli, and conducts its studies in operationally-relevant situations. The TBRL, working in collaboration with the New Jersey Medical School's Stress and Motivated Behavior Institute, have years of research experience in conducting such studies from construct development, devising human-subject research protocols, recruitment and running of subjects, collection and analysis of biological and behavioral data, and remote-sensing biometric data. The TBRL receives Institutional Review Board approval for all studies to ensure compliance with all federal regulations on the ethical use of human subjects in research.

For this study, we collected hyperspectral images during an experiment designed and conducted by the TBRL in which subjects were placed in a situation that was designed to elicit a robust stress response. The TBRL's experimental purpose involved relating two characteristics of painful blunt impact, the impact's velocity and body location, to a subject's willingness or hesitation to self-deliver a second blunt impact after deciding to deliver the first. The TBRL also measured pain and self-reported stress responses from each subject at several time points during the study. Numerous physiological measures were also taken prior to, during, and following exposure to the blunt impact stressor including heart rate, respiration rate, and pulse oximetry data collection. Due to the difference in intention and anticipated conclusions derived from our studies, it should be made known that the goals of the TBRL and this study are independent. The primary purpose of the study conducted by the TBRL was to assess indicators of escape and hesitation as a function of location and impact velocity of a painful force (administered as a shot from a paintball gun). Subjects (42 males age 18 - 55) were recruited from advertisements placed in local newspapers and posted at Picatinny Arsenal and at local institutions (public libraries, grocery stores, etc.). All subjects went through an informed consent process approved by the U.S. Army Armament Research, Development and Engineering Center (ARDEC) Institutional Review Board (IRB). Subjects were given the opportunity to activate paintball guns, aimed at the center of either their abdomen or thorax, up to two times (this paper will only consider the initial shot for analysis) at velocities of 200 ft/sec and 300 ft/sec. It should be noted that for our study, velocities and the impact location of the shots were not taken into thought and both impact velocities at either site were considered to deliver/induce analogous levels of pain/stress. The subject's task in this experiment was to depress a button which would in turn fire a single paintball shot from a paintball marker at the predetermined velocity and location on his body. Hyperspectral data were collected from two cameras before, during, and after the subject was placed in the position to self-administer paintball hits. In addition to hyperspectral images, conventional physiological stress measurements were also collected (ECG, pulse oximetry, temperature, and respiration) to correlate changes in the hyperspectral images with induced stress.

The present report describes results from analyzing a subset of the hyperspectral data that were collected. Hyperspectral measurements were acquired from 20 of the 42 subjects tested by the TBRL. This report involves analysis of hyperspectral data from six subjects immediately before and immediately after the first paintball hit. Data from the time between paintball hits and from the times during and after the second paintball hit have not yet been analyzed and are not reported here.

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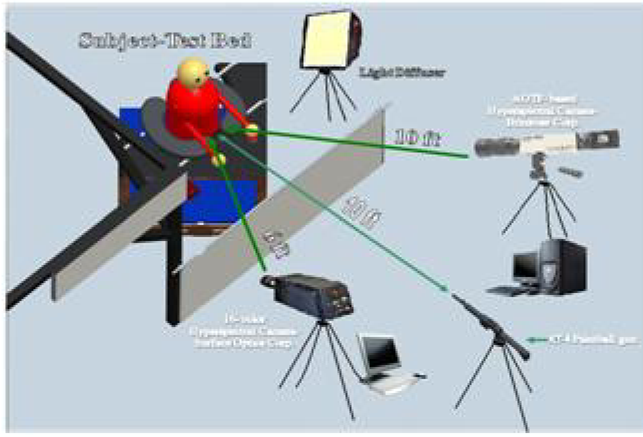

Figure 4 – Experimental Setup for Static Blunt/Stress Study (ARDEC Target Behavioral Response Laboratory)

2.2 Hyperspectral Camera Technologies

The camera that was primarily used for hyperspectral image collection was an acousto-optic tunable filter- (AOTF-) technology-based camera developed by Brimrose Corporation. The AOTF is based on the acoustic diffraction of light in an anisotropic medium and has several advantages over traditional spectrometers. Traditional spectrometers, which are typically based on a filter wheel or a grating, require careful handling and frequent calibration. They also suffer from lower scan speeds and lower reliability. An AOTF is a solid-state tunable filter with no moving parts and is therefore immune to orientation changes or even severe mechanical shock and vibrations. Moreover, the AOTF is a high throughput and high-speed programmable device capable of accessing wavelengths at rates of 100 kHz, making it an excellent tool for *in-situ* spectroscopy. Other advantages of AOTF technology are a broad tuning range (0.4 – 5 μm), a large field of view, and the fact that it is electronically programmable. Using commercial off-the-shelf (COTS) electronics, it is possible for image capture to reach real-time acquisition (30 frames per second or much faster, depending on signal levels).

A secondary 16-color visible-to-near infrared HS camera that uses custom optics and COTS focal plane arrays was also used for this study. The camera was developed jointly by the Acoustics & Networked Sensors Division (U.S. Army-ARDEC) and Surface Optics Corp. It is a portable and lightweight staring system (i.e. acquires a full hyperspectral data cube instantaneously) with no moving parts and can detect objects at up to 400 meters depending on ambient lighting conditions. The camera collects over 30 images per second with real-time target detection and tracking handled by an onboard computer. Although data were collected using this camera, the resolution of the AOTF camera was better suited for this particular application. We therefore performed analysis on only the images collected by the AOTF camera. Cameras were situated to collect data in optimal lighting, field-of-view, and position.

Placement of the equipment is seen in Figure 4. A high-intensity halogen lamp with a light-diffusing shade was placed 5 feet directly to the left of the subject to provide uniform illumination. The AOTF camera was placed 10 feet to the front and left of the subject and the SOC 16-color camera was placed 6 feet to the front and right of the subject to capture sufficient facial data to accommodate the specifications of the lenses being used. An optical standard with known emissivity and reflectance characteristics was also used to calibrate the data with the light source.

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3. DATA ANALYSIS

3.1 Histogram Analysis

Hyperspectral imaging provides a host of information within the spectral bands that can be used for classification of responses to events. Classification can be done through the analysis of intensities within the spectral bands. A one-dimensional histogram provides a graphical interpretation of the distribution of data within a single spectral band. This allows for the clustering of the number of pixels that have a particular intensity level. However, rather than identifying only the number of pixels that correspond to a particular intensity level, it may be more beneficial to identify the regions within an image that correspond to that specified intensity level. When observing a histogram constructed from two separate bands obtained from the same pixel, significant differences in the histograms indicate different (and perhaps valuable) information. Each peak (absolute maximum occurrence of a particular intensity) within the histogram is separated from neighboring peaks by valleys called the "modes" (absolute minimum occurrence of a particular intensity) of the histogram. These modes often represent a specific feature within the pixel and the occurrence of numerous modes indicates that various features corresponding to a particular phenomenon have been imaged. Classifying the number of pixels in each mode allows for the understanding of the relative size of areas within the image with similar spectral characteristics. The "spectral signature" of a pixel is a mixture of its intensity levels in the two bands and may be plotted in a two-dimensional histogram. The bars within the 2-D histogram are sometimes called "vectors" and represent the frequency of occurrence of that particular set of intensity levels found in the original image and the entire plot is the spectral signature.

In this study, it would be necessary to classify without prior knowledge, requiring the ability to identify areas with similar spectral properties within an image without knowing the spectral changes resulting from a particular incident. This method, known as 'unsupervised classification' involves no prior knowledge or training of spectral features of interest. In this technique, classes are created based upon statistical measurements spanning across the image. This eliminates the necessity to train using a sample, which may not be representative of the entire image to be mapped due to variability. Numerous mathematical algorithms exist in which the objective is to identify and separate statistically related groups within the feature space caused by some significant trend. A majority of these algorithms are based on locating regions within the feature space with high pixel density separated by regions with low density[14]. In this study, histogram analysis was used to identify groups of pixels with similar intensity within spectral bands and observe their changes relative to the subject being shot during the experiment which induced stress and identify bands that exhibited dependence in response to the condition imposed.

3.2 Principal Component Analysis

Principal Component Analysis (PCA) is a mathematical procedure that alters potentially correlated variables into a sub-set of uncorrelated variables called principal components. The first and major component within a dataset corresponds to a significant amount of variability within the dataset and identifies any underlying trend within that dataset. PCA is a major tool used for exploratory data analysis and is used in predictive modeling. PCA represents an orthogonal linear transformation, transforming data to an alternate coordinate system in which there is a maximal variance by any projection of the data onto any of its components. PCA can be defined as the optimal least squares transformation for a given data set.

Below the mathematical representation of a linear combination is given in Equation 1[15]:

$$y_1 = \sum_{k=1}^{n} w_{k1} x_k = w_1^T \ x \tag{1}$$

In which $x_1, \ldots, x_n$ are the elements of the vector x. The $w_1, \ldots, w_{n1}$ are the scalar coefficients or weights, elements of an n-dimensional vector w_1, and the w_1^T term is the transpose of vector w_1.

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The term y_1 is the principal component of x if the variance of y_1 is maximally large. Due to the fact that the variance is dependent on the orientation and norm of the weight vector w_1 and grows proportionally to the growth of the norm, it is necessary to enforce a constraint that the norm of w_1 is constant with a value of 1. It then allows for the identification of a weight vector $w_1$that maximizes the criterion for PCA

$$J_1^{PCA}(w_1) = E\{y_1^2\} = E\{(w_1^T x)^2\} = w_1^T E\{xx^T\}w_1 = w_1^T C_x w_1 \tag{2}$$

for the constraint $\|w_1\| = 1$

Here, $E\{.\}$ is the expectation over the unknown density of the input vector x, and the norm of w_1 (given in Equation 3d and defined as the Euclidian norm) is:

$$\|w_1\| = (w_1^T w_1)^{\frac{1}{2}} = [\sum_{k=1}^{n} w_{k1}^2 \,]^{1/2} \tag{3}$$

The matrix C_x shown in Equation (1) is the $n\; x\; n$ covariance matrix of x for the zero-mean vector x by the correlation matrix

$$C_x = E\{xx^T\} \tag{4}$$

The solution that therefore maximizes Equation (1) is thus

$$w_1 = e_1 \tag{5}$$

And the first principal component of x is

$$y_1 = e_1^T \tag{6}$$

3.3 Moment Statistics

Statistical parameters including mean, mode, median, and variance were calculated for the histogram for each band within the hyperspectral datasets to identify indicators of stress and regions of interest along the facial surface. Kurtosis measurements were also calculated to describe how outlier-prone the distribution of data was in addition to quantifying the degree of statistical "peakedness" within the data. Skewness of the dataset was also calculated to define the degree of asymmetry. The kurtosis function is provided below in Equation (7)

$$k = \frac{E(x-\bar{x})^2}{\sigma^4} \tag{7}$$

and the skewness function is provided in Equation (8):

$$\gamma_1 = \frac{E[(X-\bar{x})^3]}{E[(X-\bar{x})^2]^{3/2}} \tag{8}$$

4. RESULTS

Based on our observations from all the various spectral bands from which data was acquired (technology dependant from the visible to near-infrared region) as seen through the histogram analysis, we were able to observe the most regular variability amongst subjects in spectral band 13 which corresponded to a wavelength in the near-infrared region of the electromagnetic spectrum. A measurable change in density (calculated using a density parameter) within the histogram

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distribution was identifiable within all cubes for this specified wavelength when comparing hyperspectral images at varying points in time 1 second pre and post shot relative to the self-administration of the paintball shot. As mentioned beforehand, only the first shot applied to the subject was considered for this analysis. Due to the instantaneous nature of the shot being administered and the limitations of the hyperspectral hardware, it was difficult to collect data simultaneous to the blunt-impact hitting the subject. The 1-sec time frame for comparison was chosen to allow a standard comparison between subjects relative to the event that was expected to change subjects' stress and pain levels. While we ultimately hope to relate hyperspectral data to the degree of stress experienced by the subject, further analysis of the present data and perhaps additional data collection will be required before we can comment on that relationship. The data described here represent varied facial responses at two times during a period that is expected to reflect changes in a subject's stress and pain experience, before and after a self-administered paintball hit, and may possibly represent the stress change that we seek to quantify with hyperspectral measurement. Hyperspectral data was collected for twenty subjects in this study and analysis was performed on a subset of six subjects. These subjects were selected due to the uniformity amongst their datasets in reference to the timeframe in which they were collected (closest to the 1-second pre and post-shot reference point previously mentioned), providing for a more robust inter-subject comparison.

The histogram of the pixel intensity distribution for spectral band 13 in the forehead region-of-interest for three sample subjects randomly selected from the six subject datasets studied is provided in Figure 5.

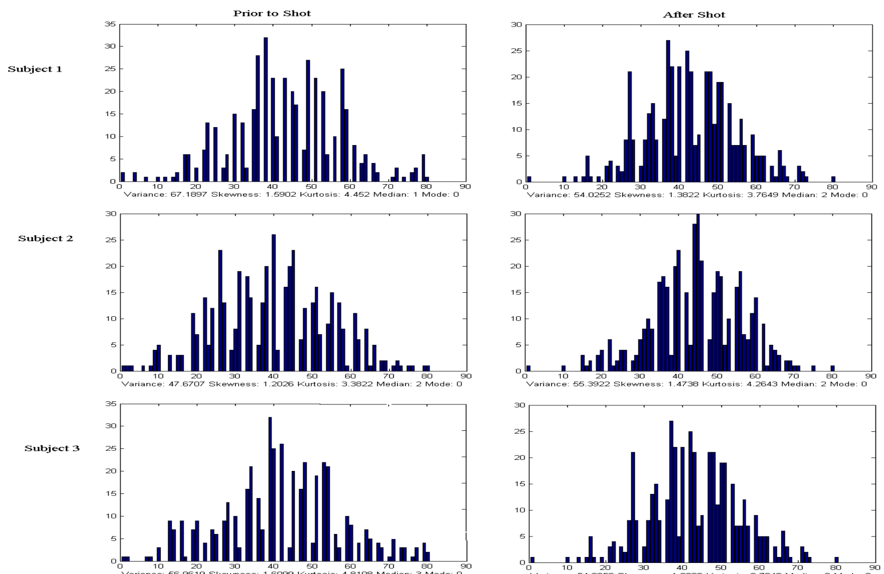

Figure 5 – Histogram Density Plots for spectral band 13 for three subjects in a hyperspectral snap shot image 1-second pre- and post-shot

As seen in Figure 5, there is a noticeable histogram intensity difference when comparing the time intervals before and after the subject was shot. This is represented in the histograms as the density of the clustered pixel intensities increasing markedly following the shot. This apparent trend was observable in all of the six subjects studied in band 13 within the given region-of interest (shown in Figure 6) and although these alterations in histogram density cannot be attributed to any specific psychological or physiological change, the timing of the change relative to the paintball hit suggests that it may be associated with the stress changes or other psychological states associated with the painful event and their physiological manifestations in the subject. A density parameter was calculated to quantify the changes in histogram density pre and post- shot. The density parameter was measured across the entire run length (x-axis which is the relative intensity for a given wavelength) of the histogram and quantified based on the absolute minimum occurrences along the

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length for the histogram bins and can be visualized as the average number of data bars per group. Essentially, the number of bars per subgroup within histograms clusters (observed from the number of bars per subgroup in the histogram) were calculated and averaged for the histogram. The mean histogram density parameter for the six subjects observed before the shot was 3.13 (± 0.13 SEM) and after shot was 5.92 (± 0.28 SEM).

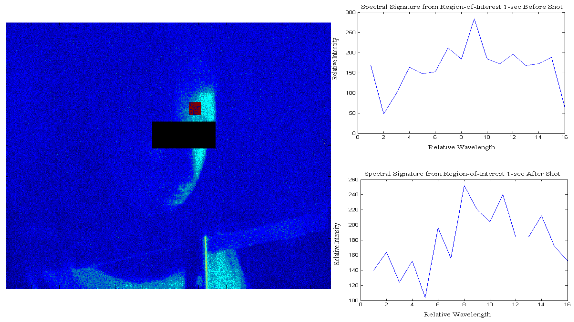

Figure 6 – Left-Hyperspectral image with highlighted region-of-interest (shown in red on the forehead); Right-Spectral Signature attained from subject from region-of-interest 1 second before and after shot 1

Principal Component Analysis (PCA) allowed us to develop a set of mutually orthogonal basis vectors upon which to project data, such that the axes correspond to the directions of maximum variance in the data. In this way, trends within the target data were distinguished to show which variables within the data vary mutually. Generated below are various graphs of the principal components and the first component variances for each band of interest (Figure 7 shows band 6, corresponding to a band in the red region of the visible color spectrum, as an example) for one subject.

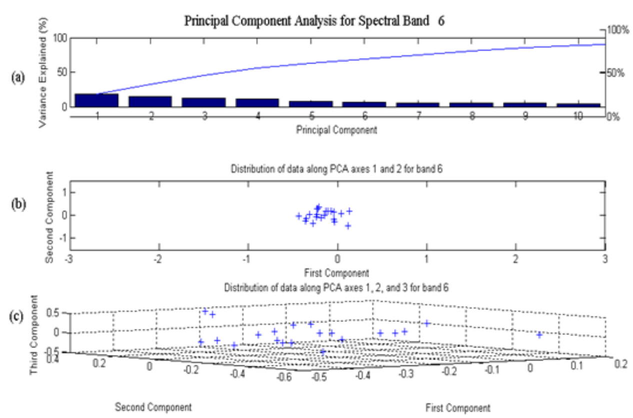

Figure 7 – Principal Component Analysis performed on hyperspectral data for spectral band 6: (a) Variance in principal components for band 6, (b) Data projection plot for primary and secondary principal components, (c) 3-dimensional plot of first two principal components

The 2 and 3 dimensional PCA plots (plotted in Figure 7) should show distinguishable directions of data for a particular band.

If the same data trend were to be observed in observed spectral bands from stressed and unstressed individuals, then one may be able to correlate a particular data pattern associated with the event and thus provide insight on features that present themselves based on the stressed vs. unstressed conditions. (Note that there was no unstressed condition associated with the present study, so such a comparison cannot be made within this report even if large variations were to

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be observed.) Figure 7a shows the variation in the first 10 components. Typically the first 4 components are expected to accentuate the most variance in data. No distinguishable features were observed in the various spectral bands when performing PCA. This inability to identify any patterns may be due to the large volume of data within the hypercubes, and features of principal components may be more evident once data reduction processing is performed.

5. CONCLUSION

The preliminary results reported for this study described in this paper is part of a multi-level study to develop robust algorithms for stand-off biometric sensing using hyperspectral-imaging. Preliminary analysis shows some consistent variation across several subjects at constant time points around a painful and stressful event. This variation suggests the potential for extracting changes in physiological stress information through its emergence on human skin. A framework has been developed for algorithmic techniques to characterize spectral changes in skin; however these and other techniques need to be further explored and optimized. Histogram analysis, in conjunction with alternate processing techniques, implies the possibility to separate datasets corresponding to subtle event-related statistical variations in hyperspectral data. It will however, require significant analysis to determine whether these changes are stress-induced responses or whether they represent other underlying phenomena such as muscle activation, emotional responses to painful events, or other emotional responses. Results indicate a good reason to further explore the near-infrared region for the application of hyperspectral imaging for identification of stress-related changes, however further investigation is needed to validate whether hyperspectral imaging in the visible regions will provide useful information on event-related spectral changes. Other analysis that could be valuable would involve the comparison of images acquired during alternate intervals of time during the blunt-impact study described in this paper. Comparing pre-1st-shot readings with post-2nd-shot readings, especially several seconds post-shot, could indicate a time of relief, the opposite of the stress that is believed to be evident at all time points prior. Furthermore, comparing post-1st-shot readings with immediately-pre-2nd-shot readings could take into account expected decreases in the emotional response to pain within the observed hyperspectral changes. If the prominent changes observed thus far were due to a pain reaction, we would expect the pain response to dissipate quickly, reflected through a histogram density that would be lessened just before the second shot. This would allow for a disentangling of these two confounded variables that coexist in the data set that has been analyzed so far. In addition, it could be highly enlightening to see whether the few subjects for which there are clear hyperspectral data all came from the low-velocity impact group or the high-velocity group, or whether there was a split that is reflected by the degree of pixel-intensity change observed. That might provide the strongest evidence of all toward a stress or pain related hypotheses.

Due to the complexity of human physiology it will be necessary to correlate the findings presented in this paper to the conventional physiological measurements collected during this study (pulse oximetry, respiratory ECG) to compare trends within the spectral data to biological events. As well as identifying this correlation, it will be necessary to understand how this relationship is influenced by additional factors, such as skin color, ethnicity, age, gender, and health condition, providing novel insight into the ability to robustly quantify psycho-physiological changes. To properly assess the ability of hyperspectral imaging to detect stress, it will be necessary to investigate the variability in human physiologies and normalize biological differences to accurately perform inter-subject analysis. Furthermore, additional variables should also be researched, such as the ability to discriminate between psychologically induced stress and thermal and blood-flow changes that are stimulated aerobically, as well as context conditions, such as ambient humidity and temperature on the physiological processes involved in the measurements. It would also be necessary to identify other possible parameters that may allow for a valid and reliable indication of the presence of stress. Later we anticipate the extension of this study into Hyperspectral SWIR, MWIR and LWIR spectral domains. Further application of these techniques must be performed on more extensive sets of data to derive strong conclusions on whether the use of hyperspectral imaging is a practical sensor for stress detection.

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REFERENCES

[1] Hernandez, O., Kleiman, M. S., "Face Recognition Using Multispectral Random Field Texture Models, Color Content, and Biometric Features," 34th Applied Imagery and Pattern Recognition Workshop,204-209 (2005)

[2] Masoud, O., and Papanikolopoulos, N., "Recognizing Human Activities," Proc. Of IEEE Conference on Advanced Video and Signal Based Surveillance, 157-162 (2003)

[3] Yanushkevich, S., Shmerko, V., Stoica, A., Wang, P., and Srihari. S., [Synthesis and Analysis in Biometrics] Biometric Technology Laboratory: Modeling and Simulation, University of Calgary- Canada, (2007)

[4] Dowdall, J., Pavlidis, I., and Bebis, G., "Face Detection in the Near-IR Spectrum," Image and Vision Computing, IEEE 21(1), 565-578, (2003).

[5] Shusterman, V. and Barnea, O. , "Spectral characteristics of skin temperature indicate peripheral stress-response," Applied Psychophysiology and Biofeedback, 357-367 (2005)

[6] Meglinski, V., and Matcher S. J., "Quantitative assessment of skin layers absorption and skin reflectance spectra simulation in the visible and near-infrared spectral regions," Physiological Measurement, Vol 23, 71-753 (2002).

[7] Chague S., Droit B., Boulanov O., Yanushkevich S.N., Shmerko V.P., and Stoica, A. "Biometric-based decision support assistance in physical access control systems," ECSIS Symposium on Bio-inspired Learning and Intelligent Systems for Security, 11-16 (2008)

[8] Li, S., Chu, R., Liao S., and Zhang, L., "Illumination Invariant Face Recognition Using Near-Infrared Images," IEEE Transactions on Pattern Analysis and Matching Intelligence 29(1), 627-639, (2007)

[9] Li, S.Z., Chu, R.F., Ao, M., Zhang, L., and He, R., "Highly Accurate and Fast Face Recognition Using Near Infrared Images," Proc. IAPR Int'l Conf. Biometric, 151-158 (2006)

[10] Rice, R.R. and Whelan, D.A., "Hyper-spectral Means and Method for Detection of Stress and Emotion," Harness, Dickey & Pierce, P.L.C. PATENT 10657338, Sept. 8, 2003.

[11] Kakadiaris, I., Passalis, G., Toderici, G., Lu, Y., Karampatziakis, N., Murtuza, N., Theoharis, T., "Expression-invariant multispectral face recognition : You can smile now!" Proceedings of SPIE, the International Society for Optical Engineering 6202, 620202.1-620204.7 (2006)

[12] Pan, Z., Healey, G., and Prasad, M., "Face Recognition in Hyperspectral Images," IEEE Transactions on Pattern Analysis and Machine Intelligence 25(1), 1552-1560 (2003).

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[13] Rowe, R. K., Meigs, A. D., Ostrom, R. E., and Nixon, K. A. "Multispectral skin imaging for biometrics," Frontiers in Optics OSA Technical Digest Series Optical Society of America (2004)

[14] Alföldi,T.T., [Introduction to Digital Images and Digital Analysis Techniques: A Basic Course for the Appreciation of Digital Analysis of Remotely Sensed Multispectral Data], Canada Centre for Remote Sensing – Ottowa, (1996).

[15] Hyvarinen,A., Karhunen, J, and Oja, E., [Independent Component Analysis], John Wiley & Sons –Wiley Interscience Publishing , New York & Toronto, 125-143 (2001).

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