

SKIN DETECTION IN HYPERSPECTRAL IMAGES

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Dedication

To small kids with big dreams

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SKIN DETECTION IN HYPERSPECTRAL IMAGES

by

STEPHANIE MICHELLE SANCHEZ

THESIS

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Abstract

Hyperspectral imagers collect information of the scene being imaged at close contiguous bands in the electromagnetic spectrum at high spectral resolutions. Hyperspectral images are organized in a data cube where the x and y axes contain spatial information and the z-axis contains spectral information. The number of applications for these imagers has grown over the years as they are now used in various fields (i.e. agriculture, surveillance, chemical imaging, environmental, medical, etc.). Many algorithms are described in the literature for skin detection using color imagery. However increased detection accuracy, in particularly over cluttered backgrounds, and of small targets and in low spatial resolution systems can be achieved by taking advantage of the spectral information that can be collected with multi/hyperspectral imagers. The ultimate goal of our research work was the development of a human presence detection system over different backgrounds using hyperspectral imaging in the 400-1000nm region of the spectrum that can be used in the context of search and rescue operations, and surveillance in defense and security applications. The 400-1000 nm region is chosen because of availability of low cost imagers in this region of the spectrum. This thesis presents preliminary results in the use of combinations of normalized difference indices that can be used to detect regions of interest in a scene that can be used as a pre-processor in a human detection system. A new normalized difference ratio, the Skin Normalized Difference Index (SNDI) is proposed. Experimental results show that a combination the NDGRI+NDVI+SNDI results in a probability of detection similar to that of the NDGRI. However, the combination of features results in a much lower probability of false alarm.

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