JOINT SPATIO-SPECTRAL BASED EDGE DETECTION FOR MULTISPECTRAL INFRARED IMAGERY

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1. Introduction

Image segmentation is one of the most important and difficult tasks in digital image processing. It represents a key stage of automated image analysis and interpretation. Segmentation algorithms for gray-scale images utilize basic properties of intensity values such as discontinuity and similarity [1]. Detection of discontinuities in gray-scale images is typically based on spatial masks whose response at any pixel in the image can be thought of as a finite difference approximation of a differential operator. Among the most popular gray-scale edge detectors are Canny, Sobel, and Prewitt, to name just few [1, 2]. However, it is possible to enhance edge-detection capability by means of using spectral information provided by multispectral (MS) or hyperspectral (HS) imagery. In this paper we consider image segmentation algorithms for multi-color images with particular emphasis on detection of multi-color edges. More specifically, we develop an algorithm for joint spatio-spectral (JSS) feature selection. By "joint" we mean simultaneous utilization of spatial and spectral characteristics of a given MS or HS image. JSS feature selection offers unique opportunities for image processing and remote sensing as it enables taking advantage of the correlation between spatial and spectral features. At the same time, pursuit of JSS algorithms poses additional technical challenges. In this paper we report on a novel approach for JSS-based edge detection, termed Spectral Ratio Contrast (SRC) edge-detection algorithm, which uses the novel concept of spectral ratio signatures. The SRC is verified using MS and HS imagery from a quantum-dot in a well (DWELL) infrared (IR) focal plane array (FPA) [3], and the Airborne Hyperspectral Imager (AHI), respectively. The DWELL FPA is a special type MS imager, characterized by the unique property that its spectral bands are selected electrically by altering the applied bias as shown in Fig. 1.

2. Challenges associated with multi-color edge detection

Transition from a gray-scale to a multi-color image complicates edge detection significantly. Standard definition of a gray-scale edge as a "ramp," or "ridge" between two regions [p.573, 1] is no longer appropriate since a multi-color image has multiple image planes, one for each spectral band. More importantly, depending upon the scene, two distinct regions may exhibit the same intensity for one or more bands. In other words, with respect to such *iso-luminant* bands, the edge between the two regions is characterized by a jump in color rather than intensity. Clearly, iso-luminant edges cannot be detected by a standard gradient operator, see for example Blomgren and Chan [4]. Extension of other gray-scale processing techniques to multi-colored images, such as those based on differential operators, faces similar difficulties. One example is the Rudin-Osher-Fatemi's total variation de-noising method [4].

3. Prior work

Extension of differential edge detection to multi-color images has followed two principal paths. A straightforward approach [5] is to apply differential operators such as the gradient separately to each image plane and then somehow integrate this information to obtain edge and segmentation information. Blomgren and Chan in [4] point out that this can result in undesirable segmentation because information in separate channels is treated as independent whereas in actuality it is not. A second approach to multi-color edge detection is to embed the variations of all color channels in a single measure, which is then used to obtain the edge maps [5]. Typically, this approach is developed by starting from a given gray-scale operator, which is then extended consistently to multi-color images. By "consistently" we mean that the extended multi-color operator reduces to its original gray-scale prototype when applied to a single color image. Two representative examples of this approach are the multi-color gradient (MCG), proposed by Di Zenzo in [6], and the morphological color gradient (MoCG) of Evans and Liu [7]; the former is used as a benchmark in this paper to compare our algorithm to. While multi-color gradient and related ideas have been used with great success computation of the multi-color gradient for multi-color images with large numbers of bands can be quite expensive.

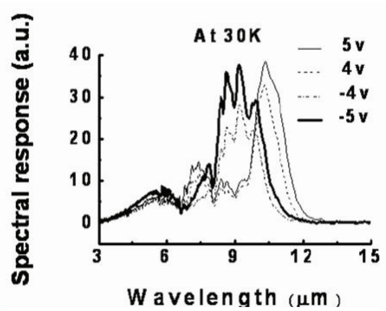

Fig. 1 Bias tunable spectral bands of a DWELL sensor**.**

4. Methodology for the spectral ratio contrast (SRC) edge-detection algorithm

Our main idea is to use the notion of *spectral ratio contrast,* namely band ratios, to define an edge signature (index) for an edge between two materials. The edge signature represents an optimized combination of spectral ratios calculated using bands that enhance the spectral contrast between the two materials. In conjunction with a spatial mask, the edge signatures give rise to a multispectral operator that can be viewed as a *non-separable* with respect to the spectral and spatial domains, three-dimensional extension of the spatial mask. In the extended mask, the third (spectral) dimension of each hyper-pixel can be chosen independently. Such a mask does not operate in a single image plane but instead fuses information from multiple planes. The idea of the non-separable spatio-spectral mask is shown in Fig. 2.

SRC has two stages. The first stage is a training, which identifies the bands that maximize the spectral contrast between two given materials. A small subset of ratios that can reliably discriminate the edge between two materials from other spatial features is selected. We call such a subset *spectral ratio*

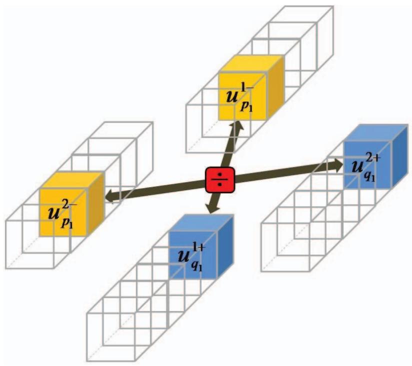

Fig. 2. Joint spatio-spectral mask.

index or *signature* of the edge. In order to extract spatial features such as edges, the edge signatures must be combined with a suitable spatial mask to obtain a joint spatio-spectral SRC mask; this is the second stage of SRC. Note that in SRC, a spatial mask is used in a fundamentally different manner from the standard use of mask in the context of gray-scale images. Whereas in gray-scale edge detection the response is single-valued, in SRC the response is multi-valued, returning the ratios of suitably defined pixel pairs from that structuring element. Starting from a given spatial mask we define a joint spatio-spectral (JSS) SRC mask by retaining the spatial domain of the former and redefining its action in terms of spectral ratios corresponding to the bands from a given edge signature.

The presence of two stages in SRC is one important distinction from the MCG-based edge detection and other unsupervised edge detection algorithms. A second key difference is that SRC is not derivative based, i.e., edge detection is effected by matching a given edge signature rather than by measuring the gradient magnitude. Because the edge signatures and the associated tolerance values are determined independently for each pair of classes of materials, the edge extraction depends only on the quality of the selection criteria used to obtain the edge signature for a given pair and not on the strength of the edge as measured by its MCG value. As a result, the SRC approach is particularly well suited to situations where the edge between two given materials is "weak," as measured by its MCG value.

5. Results and conclusions

Fig. 3 Left to right**:** (i) AHI image; (ii) SRC edge map; (iii) MCG edge map.

Figure 3 (ii) and (iii) compares edge maps derived using the SRC algorithm with those obtained by the MCG approach applied to AHI test image (i). The results show that compared to MCG approach, the SRC generates slightly improved edge map. Figure 4 compares the edge maps derived using the SRC algorithm with those obtained by the MCG approach and by the application of two well-known grayscale edge detectors to individual DWELL FPA spectral bands. Figure 4 (ii) clearly shows the ability of the SRC to capture the very weak, almost iso-luminant edge between the granite and limestone classes in this scene (as pointed out by the arrow), which is missed by the other approaches. Based on these and other results obtained using AHI and DWELL FPA imagery, we have concluded that for moderately difficult scenes in which the edges are of approximately the same strength, as measured by their MCG values, the SRC and the MCG edge detectors generate essentially identical edge maps. However, for more challenging imagery containing both "weak" and "strong" edges, the SRC outperforms the MCG edge detector by a wide margin. The single, non-adaptive threshold in the MCG algorithm requires increase in the tolerance to a point where the noise level may become unacceptable. As such, the MCG is not adaptive to types of materials while the SRC is a supervised approach with more degrees of freedom to suit various edges from different materials. This shows the tenet of the SRC approach.

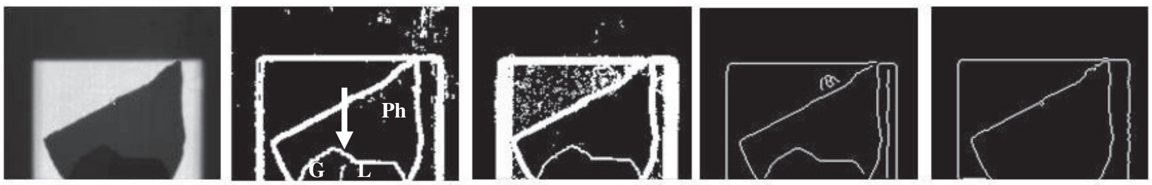

Fig 4. Comparison between edge maps obtained by the SRC and three benchmark edge detectors. Left to right: (i) DWELL FPA image comprising of phyllite (Ph), granite (G) and limestone (L) at bias 0.7 V; (ii) the SRC edge map where the detected weak edge between granite and limestone is identified by the red arrow; (iii) the MCG edge map; (iv) the Canny [3] edge map at 0.5 V; (v) the Sobel edge map at 0.5 V. The DWELL FPA imagery is produced in the authors' laboratory at the University of New Mexico.

In summary, application of spectral ratios to define MS and HS operators for edge detection in this paper is a novel and previously unexplored direction. Besides the potential for significant data compression in HS and MS image processing, spectral ratios appear to be particularly well-suited for intelligent sensing modalities using the spectrally tunable sensor such as the electrically tunable DWELL FPA. Indeed, the training stage of the proposed SRC approach extracts information about the most informative, with respect to edge detection, bias voltages (bands) in the sensed image. Image acquisition for a scene can then be carried out using only the relevant biases, thereby significantly reducing the amount of data necessary for the image segmentation.

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