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Optimal Edge Perservation in Volume Rendering Using Canny Edge Detector

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Abstract— This paper presents a method to preserve sharp edge details in splatting for volume rendering. Conventional splatting algorithms produce fuzzy images for views close to the volume model. Computing the weighted average of the pixel values in a window is a basic module in many computer vision operators. The process is reformulated in a linear vector space and the role of the different subspaces is emphasized Within this framework well known artifacts of the gradient-based edge detectors, such as large spurious responses can be explained quantitatively. Initialization of weights between the input and lone hidden layer by transforming pixel coordinates of the input pattern block into its equivalent one-dimensional representation. Initialization process exhibits better rate of convergence of the back propagation training compare to the randomization of initial weights. We propose a new guide edge linear interpolation technique via address filter and data fusion. For a pixel two sets of observation are defined in two orthogonal directions, and each set produces an estimated value of the pixel. Both multispectral (MS) and panchromatic (PAN) images are provided with different spatial and spectral resolutions. Multispectral classification detects object classes only according to the spectral property of the pixel. These estimates of direction, following the model the different measures of the lack of noisy pixels are fused by linear least mean square estimation error (LMMSE) technique in a more robust estimate, and statistics two sets of observations. Panchromatic image segmentation enables the extraction of detailed objects, like road networks, that are useful in map updating in Geographical Information Systems (GIS), environmental inspection, transportation and urban planning, etc. It also presents a simplified version to reduce computational cost without sacrificing much the interpolation performance.

Index Terms— Canny Edge Detection, Edge Preservation, Image Interpolation, Image Segmentation, Local Content Preservation, Optimal Weight Cubic Interpolation, Bilateral Filtering, Multispetural Images.

1 Introduction

THE morphological techniques are becoming more and more popular in variety of image processing areas such as image enhancement, object recognition, granulometry, and image segmentation. Among many algorithms of image segmentation, the segmentation algorithms based on edge detection are widely used because of good accuracy and high speed. The main advantage comes from the fact that gray-scale values at edges change largely compared with the other places. Therefore, it is a good idea to find edges first and then connect them o form the outline of the leaf. At present, the edge detection algorithms based on spatial-domain differential operator such as Roberts, Sobel, Prewitt etc. are used widely. They carry out edge detection pixel by pixel. All of these operators are based on the change of derivative impacted by gray-scale mutation. The weakness of these operators is that there is a trade-off between the noise immunity and the precision of edge detection.

Detection of edges in an image is a very important step towards understanding image features. Edges consist of meaningful features and contained significant information. It's reduce significantly the amount of the image size and filters out information that may be regarded as less relevant, preserving the important structural properties of an image and also provide low-level cues, which can be utilized in higher level processes, such as object detection, recognition, and classification, as well as motion detection, image matching, and tracking. Edges and textures in an image are typical examples of high-frequency information. High-pass filters remove low-frequency image information and therefore enhance high-frequency information such as edges. Many approaches to image interpretation are based on edges, since analysis based on edge detection is insensitive to change in the overall illumination level. The Canny Edge Detector is one of the most commonly used image processing tools, detecting edges in a very robust manner. It is a multi-step process, which can be implemented on the sequence of filters to find edges by isolating noise from the image without affecting the features of the edges in the image and then applying the tendency to find the edges and the critical value for threshold. The accuracy of image segmentation will impact the efficiency of succeeding tasks.

2 Preliminaries

2.1 Proposed Algorithm

The algorithm proposed is implemented in Matlab. Its implementation is discussed in detail below:

Step 1: The first and the foremost part of the algorithm is image acquisition. The image is obtained from various sources. Images acquired can be of any format and orientation.

Step 2: Obtained image has to undergo various modifications such that it is suitable for performing the operations on them. Image is cropped to the necessary dimensions such that it is a square image. Cropped image is then converted to gray scale image such 3-dimensional images is converted into 2-dimensional images.

Step 3: Resulting 2-dimensional image might be a noisy image. Image is then filtered to remove the unwanted noise. Various filtering techniques were applied in the image. Spatial filters, frequency domain filters and adaptive filters were applied on the image, since periodic noise was predominant compared to other noise present in the image. Frequency domain filters were singled out. Butterworth filter in band pass type proved to be most efficient filter. The threshold of the

filter is dynamically chosen by the filter based on the image. Threshold varies from image to image depending on the image intensity, major factor deciding the threshold of the image is the variation of intensity between the foreground and the background image.

Step 4: The final process in the algorithm is edge detection, once the image is filtered, a pure sample from which crack has to be detected is obtained. The edge detection algorithm is applied on the sample. Numerous edge detection algorithms are available. Canny edge detection algorithm is best suited among the available edge detection methods; it is used to detect minute cracks present in the image, providing the maximum number of cracks present in the image.

2.2 Canny Edge Detector

The Canny edge detector [8] is based on computing the squared gradient magnitude. Local maxima of the gradient magnitudes that are above some threshold are then identified as edges. This threshold local peak detection method is called non-maximum suppression, or NMS. The motivation for Canny's edge operator was to derive an "optimal" operator in the sense that minimizes the probability of multiply detecting an edge, minimizes the probability of failing to detect an edge and minimizes the distance of the reported edge from the true edge.

The first two of these criteria address the issue of detection, that is, given that an edge is present will the edge detector find that edge (and no other edges). The third criterion addresses the issue of localization, which is how accurately the position of an edge is reported. There is a tradeoff between detection and localization the more accurate the detector the less accurate the localization and vice-versa.

The objective function was designed to achieve the following optimization constraints:

1. Maximize the signal to noise ratio to give perfect detec tion. This favours the marking of true positives.
2. Achieve perfect localization to accurately mark edges.
3. Minimize the number of responses to a single edge.

This favours the identification of true negatives, that is, non edges are not marked. Gaussian filter was used to perform image smoothing. Then, the sharp edge map produced by implemented canny edge detector is added to the smoothed noisy image to generate the enhanced image.

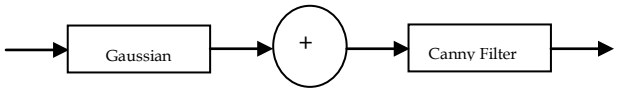

Fig.1.Block Diagram using Canny Edge Detector

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2.3 Four Stops of Edge Detection

Formulation of the edge detection problem as a problem of cost minimization. Their edge estimator is defined to be the edge configuration that minimizes a cost function, defined as a weighted average of the following five cost factors: edge curvature, dissimilarity of the regions separated by the edges, number of edge pixels, fragmentation of the edges, and edge thickness.

(1) Smoothing: suppress as much noise as possible, without destroying the true edges.

(2) Enhancement: apply a filter to enhance the quality of the edges in the image sharpening.

(3) Detection: determine which edge pixels should be discarded as noise and which should be retained usually, thresholding provides the criterion used for detection.

(4) Localization: determine the exact location of an edge sub-pixel resolution might be required for some applications, that is, estimate the location of an edge to better than the spacing between pixels. Edge thinning and linking are usually required in this step.

The canny edge detector first smoothen the image to eliminate noise. Then it finds the image gradient to highlight regions with high spatial derivatives. After that it performs tracking along these regions and suppresses any pixel that is not at the maximum. The gradient array at this moment can further be reduced by hysteresis which is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero. If the magnitude is above the high threshold, it is made an edge. Major application of canny edge detector is for remote sensing images which are inherently noisy.

The Gaussian filtering is combined with Laplacian to break down the image where the intensity varies to detect the edges effectively. It uses linear interpolation to determine the sub pixel location of the edge .The digital implementation of the Laplacian function is made using the mask given in below figure.

0	-1	0
-1	4	-1
0	-1	0

Fig.2. Gaussian mask for Intensity Variation

Upgrading of the algorithm to multi-channel images

Up to now, only gray values have been considered. However, in the ongoing project colour images will be used too, making it necessary to have the algorithmic conception transformed into the colour space. It is obvious, that an upgrading of the gray value formulas into multi-channel formulas is quite simple.

First, the criterion for the detection of the area of maximal homogeneity has to be replaced. It is of convenience to check the variances within the different channels separately and then to select that area, where the maximum of the standard deviations of all channels is minimal. Second, the judgement of the radiometrical correspondence of pixels from the larger neigh-

bourhood has to be extended to all channels. This will be done by combining the results for each channel. If for this aggregation a logical addition of the investigations in all individual channels is used, one furthermore gets the advantage to increase the stability of the results.

3 Preservation of Image Structure

Compares the effect of some smoothing filters on a gray value edge with a low signal/noise-ratio. The effect of the Gaussian Kernel Filter is a blurring of the edge, while the two other algorithms preserve the edge significantly. Obviously, this problem cannot be solved in one step, but only iteratively using a procedure in which feature computation and segmentation are performed alternately. In the first step, the features are computed disregarding any object boundaries.

Then a preliminary segmentation is performed and the features are computed again, now using the segmentation results to limit the masks of the neighborhood operations at the object edges to either the object or the background pixels, depending on the location of the center pixel. To improve the results, feature computation and segmentation can be repeated until the procedure converges into a stable result. Relevance value is calculated for each region. This relevance value is directly influenced by the score values of the pixels surrounding the according region. The final segmentation mask is then created by removing all regions that have a relevance value below a certain threshold.

New parallel region segmenting and labeling algorithm is available, that is applicable to gray-scale images, and is appropriate to coarse scale parallel programming. The key feature of this algorithm is the geometric splitting of the image into rectangular blocks, with one pixel overlap at joins. Then using Cohen's one pass, each region is separately labeled. Then by examination of the overlap regions, the connectivity of different region labels is determined, through connectivity tables, and finally the overall image is completely segmented into connected domains of common gray-scale. The parallelizable algorithm for the segmentation of gray-scale images involves performing the one-pass algorithm on rectangular subimages, with a single row or column overlap.

Every sub-region in an image is sufficiently uniform so that the transition between two sub-regions can be determined on the basis of discontinuities alone. When this statement is not valid, region-based segmentation, discussed in the next section, regularly provides more reasonable segmentation outcome. Basically, the idea underlying most edge-detection techniques is the computation of a local derivative operator. Edge-based active contours are strongly connected to the edge-based segmentation. Most edge based active contour models consist of two parts: the regularity part, which determines the form of contours, and the edge recognition part, which attracts the contour towards the boundaries. Edge-based active contour models have a little disadvantages compared to the region-based active contour models, discussed in the next section. Because of the constant term, edge based active contour models evolve the contour towards only one way, each inside or outside.

4 Expriments

To construct an edge detector using contrast operator, one first defines a neighborhood. Around a given pixel f(x, y). The contrast is then measured between the given pixel and every other pixel in the neighborhood using the contrast operator.

Finally, the weighted sum of these contrast measurements is taken to determine the likelihood that the pixel is an edge. Due to the importance of accurate edge detection for a number of image processing applications, it is necessary to continue researching more accurate and effective edge detection methods. It is common for edge detection algorithms to make use of first or second order derivatives because an edge can be classified as a unit step.
The following edge detection formula:

$$E(x,y) = {}^{1}/_{4} * (f(x,y) + f(x,y+1) + f(x+1,y) - f(x+1,y+1)$$

While such ideal edges are rarely seen in practice, most effective edge detectors see an edge as a region of high contrast. This is because the unit step can be effectively detected as a region of high contrast, even in the presence of noise.

$$C = \max[f(x,y), f(x',y')] - \min[f(x,y), f(x',y')]$$

It is independent on the intensity level of the illumination and it is robust in small scale changing illuminations, specifically at the pixel-by-pixel scale.

In preparing images for used in geographic information systems (GIS) this segmentation is usually followed by the production of a vector representation for each region. The original algorithm for segmentation, developed by Rosenfeld-pfaltz, described a two pass 'sequential algorithm' for the segmentation of binary images. The key feature of the Rosenfeld-pfaltz algorithm is that the image is raster-scanned, first the forward direction, from top left to bottom right, then backwards. During the forward pass, each pixel is located a region label, based on information scanned through; the regions so demarcated may have pixels with more than one label therein. During the backwards pass, a unique label is assigned to each pixel. Hence this classic algorithm can be described as a two pass algorithm.

The Edge-preserving mean

A pixel is considered to define its postulated neighborhood [22]. A rectangular window is centered with size $n*n$ on considered pixel. A sample in the window is a postulated neighbor of pixel if there is not any edge between that sample and pixel. The edge-preserving mean of pixel i is considered as the average value of samples in the postulated neighborhood of I as follow:

$$\bar{X}_i^e = \sum_{j \in I} e_{ij}\, x_j$$

The value of e_{ij} is one if sample j is the postulated neighbor of pixel i otherwise it is zero. Sometimes there is not any sample in postulated neighborhood of a pixel in this case; median

of the neighborhood distance is considered as edge-preserving average with the help of the following formula:

$$\bar{X}_i^e = \bar{X}_i^e + \left(\sum_{j \in I} e_{ij} = 0\right) * median\ (x_i)$$

Neighborhood information is incorporated in clustering process. Depending upon the similarity in pixel intensities we can partition the image into object and boundaries.

New extensions for Expectation Maximizing (EM)

Two new extensions for EM are introduced. In first Extension, in order to make EM more roust against noise, this method is more robust than any other method. We have to minimize the energy by the function as followes

$$minE(C, c_1, c_2) = \int_C (f - c_1)^2\, dx\, dy + \int_C (f - c_2)^2\, dx\, dy + \lambda length(c)$$

Represents the average pixel value inside C and represent the average the pixel outside C.λ is the regularizing parameter which gives weightage in the minimization process .We can c1 and c2 calculate by the following equations.

$$c1 = (\int f(x,y) H(\emptyset) dx\, dy) / (\int H(\emptyset) dx\, dy)$$

$$c2 = (\int f(x,y)(1 - H(\emptyset)) dx\, dy) / (\int 1 - H(\emptyset) dx\, dy)$$

We use calculus of variation for calculating $\emptyset$ using the

$$(\partial \emptyset) / \partial t = -\partial E / (\partial \emptyset)$$

Experimental results are demonstrated to show that our proposed algorithm has a good compromise between the edge-preservation effect and the color contrast enhancement effect when compared to the previous algorithm [13, 20]. Besides, some experiments are carried out to demonstrate the edge-preservation benefit of our proposed color image segmentation algorithm when running it on the enhanced color image obtained by the proposed color contrast enhancement algorithm. For convenience, the enhanced color image obtained by the previous color contrast enhancement algorithm is called the previous obtained enhanced color image; the enhanced color image obtained by our proposed color contrast enhancement algorithm is called our obtained enhanced color image.In this variation of the bilateral filtering both the intensity and position of each pixel is replaced by a weighted average of its neighbors.

5 RESULTS

We have applied the edge segmentation scheme on three satellite images with the same size *(256×256)*. In order to evaluate the proposed scheme, we have compared it with others approaches. Indeed, the Kovesi approach [5], Ben Robbins method based on stretched Gabor filter [8] and Susan method are utilized. Usually, in the literature the 2D stretched Gabor filter use the power of cosine as angular component.

One of the primary motivation, we use a modified angular component (11) of the stretched Gabor filter. In fact, for the Kovesi method, we have used similar parameters in [5]. These filters were constructed directly in the frequency domain as polar functions. It is characterized by two components a stretched Gabor function in the radial variation (13) and a modified power of cosine (11) in the angular direction. In the angular direction, the sharpness of the orientation *m* was set to 2. In the radial direction, the width of the Gaussian envelope was set at $\sigma = 3$, the frequency at the origin value $\nu_0 = 0.05$ was used, and λ was set to 2.

The stretched Gabor filters is defined for four orientations and three scales. In the phase congruency measure, a noise compensation *k* value was set to 3. The value of ε was set at 0.001. The segmented image was obtained by performing non-maximum suppression and the hysteresis thresholding of the phase congruency map. The low and high values of hysteresis thresholding are set for different methods at [0.3-0.2]. The extracted features of pixels are the mean value and variance of the intensity of a size-fixed window centered at each pixel of the image. Inthis experiment *k* is 4, so the size of widow is shown for 64 ×64 as

(a) (b) (c)

Fig.3. Results Image (a) Original Image, (b) Segmented Result of Iteration (c) Segmented Result of Proposed Method.

6 CONCLUSION

In this paper a feature-preserving volume filtering method has been presented. With a three-component penalty function, approximation of the original values, feature preservation and curvature minimization can be controlled efficiently. Images generated by direct volume rendering from the filtered data contain only reduced point like noise andstaircase artifacts. Furthermore, the sampled smooth surfaces and fine details can be reconstructed at the sametime. Unlike local convolution-based filtering techniques,our method provides a global smoothing effect because ofthe global curvature minimization. The scalability is ensured by the weighting parameters of the three-component penalty function. Due to the applied FFT method filtering is performed efficiently. Our approach is not restricted to binary data or segmented iso-surfaces, unlike previous techniques based on iterative solution. Although the presented filtering algorithm has been illustrated on a specific 2D and a specific 3D example it can be considered as a general mathematical tool usable for image or volume-processing purposes. Among the possible 2D application fields we mention feature-preserving smoothing or zooming, image restoration, and terrain-modeling. In the 3D case, our technique is

applicable to gradient-driven or shape-based interpolation, and smoothing of binary segmented masks.

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