APPLICATION OF THE SELF - AVOIDING RANDOM WALK NOISE REDUCTION ALGORITHM IN THE COLOUR IMAGE SEGMENTATION

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Abstract. The paper presents a new technique of colour image enhancement. The algorithm is based on a concept of a virtual particle, which performs a special kind of random walk - the so called self-avoiding random walk. Segmentation effect obtained using this method, together with its ability to eliminate impulsive and Gaussian noise, makes the new method an interesting pre-processing tool for colour image segmentation.

1. INTRODUCTION

Colour image processing has been the subject of extensive research during the last years. With the expanding use of colour in various applications, the interest in the preprocessing of colour images has been growing rapidly. As a result, a large number of techniques of colour image enhancement has been proposed. These techniques seek to reduce the image noise, while preserving important image details, such as edges and image texture. Especially the edge information is of high importance to human perception and therefore its preservation and possibly enhancement is a very desired feature of the performance of the filtering techniques. In this paper a new approach to the colour image enhancement is presented. The new filtering technique is based on a self-avoiding random walk and it enables the suppression of noise and contrast enhancement of document images.

2. SELF-AVOIDING RANDOM WALK ALGORITHM

The algorithm described here, enables the suppression of noise and contrast enhancement of colour images. This combination is quite novel since the commonly used algorithms are mostly not able to perform both of the tasks simultaneously, as the new procedure does [1,2,6,8]. The standard techniques of noise elimination, like low-pass filter, median filtering, Fourier transform based operations, cause the blurring of edges, which is a very undesirable effect. Unfortunately, the contrast enhancement of noisy images makes the noise component even stronger, so that a compromise has to be found. The presented algorithm solves this dilemma, by performing at the same time contrast enhancement and noise smoothing.

In this paper the concept of a walking particle performing a self-avoiding random walk is introduced for the enhancement of colour images. Self-avoiding random walk (SAW) is a special walk along an *m*-dimensional lattice such that adjacent pairs of edges in the sequence share a common vertex of the lattice, but no vertex is visited more than once and in this way the trajectory never intersects itself. In other words SAW is a path on a lattice that does not pass through the same point twice. On the two-dimensional lattice (m=2) SAW is a finite sequence of distinct lattice points (x_0,y_0), (x_1,y_1), (x_2,y_2), ..., (x_n,y_n), which are in a neighbourhood relation and $(x_i, y_i) \neq (x_j,y_j)$ for all $i \neq j$ [3,5,7,9,12].

Let us introduce a virtual walking particle, which performs a SAW on a two-dimensional gray scale image lattice with eight-neighbourhood system and let the transition probabilities between points (x_0, y_0) and (x_1, y_1) in one step be described by

$$P\left[(x_0, y_0),(x_1, y_1)\right] = \frac{\exp\left\{-\beta \,|\, F\left(x_0, y_0\right) - F\left(x_1, y_1\right)|\right\}}{\sum\limits_{\left\{(x_0,y_0)\to(x_1,y_1)\right\}} \exp\left\{-\beta \,|\, F\left(x_0, y_0\right) - F\left(x_1, y_1\right)|\right\}} \tag{1}$$

where (x_0, y_0), (x_1, y_1) are two specific neighboring points, $F(x, y)$ is the gray scale value of (x, y) and $\left\{(x_{0,}y_0) \to (x_{1,}y_1)\right\}$ is a set of all neighbours of the pixel at position (x_0, y_0).

Let us now define a smoothing operator based on the self-avoiding walk model

$$J\left(x_{0,}y_0\right) = \sum_{\left\{(x_0,y_0)\to(x_n,y_n)\right\}} P\left[n,(x_{0,}y_0) \to (x_{n,}y_n)\right] F\left(x_{n,}y_n\right) \tag{2}$$

where the sum is taken over all pixels (x_n, y_n), which are connected by a trajectory of the walking particle starting at the point (x_0, y_0) and ending at (x_n, y_n); $\left\{(x_{0,}y_0) \to (x_{n,}y_n)\right\}$ denotes all trajectories leading from (x_0, y_0) to (x_n, y_n). Let the probability of a transition between points (x_0, y_0) to (x_n, y_n) be defined as

$$P\left[(x_{0,}y_0) \to (x_{n,}y_n)\right] = \frac{\exp\left\{-\beta\left[|\, F(x_0, y_0) - F(x_1, y_1)\,| + \cdots + |\, F(x_{n-1}, y_{n-1}) - F(x_n, y_n)\,|\right]\right\}}{\sum\limits_{\left\{(x_0,y_0)\to(x_n,y_n)\right\}} \exp\left\{-\beta \sum\limits_{\kappa=1}^{n} |\, F(x_{\kappa-1}, y_{\kappa-1}) - F(x_\kappa, y_\kappa)\,|\right\}} \tag{3}$$

then for $n = 1$ we obtain (1). In this way the operator J is defined as

$$J(x_0, y_0) = \frac{\exp\left\{-\beta\left[|\, F(x_0, y_0) - F(x_1, y_1)\,| + \cdots + |\, F(x_{n-1}, y_{n-1}) - F(x_n, y_n)\,|\right]\right\} F(x_n, y_n)}{\sum\limits_{\left\{(x_0,y_0)\to(x_n,y_n)\right\}} \exp\left\{-\beta \sum\limits_{\kappa=1}^{n} |\, F(x_{\kappa-1}, y_{\kappa-1}) - F(x_\kappa, y_\kappa)\,|\right\}} \tag{4}$$

If $\beta = 0$ then (4) defines the moving average and for $\beta \to \infty$ this operator assigns at (x_0, y_0) the value of $F(x_n, y_n)$ for which

$$(x_n, y_n) = \arg\,\min\left\{\sum_{\kappa=1}^{n} \left|F(x_{\kappa-1}, y_{\kappa-1}) - F(x_\kappa, y_\kappa)\right|\right\} \tag{5}$$

The new operator has the ability of image sharpening while preserving image edges. It also eliminates strong impulse noise and performed in an iterative manner can be viewed as a segmentation algorithm. To some extent the presented algorithm resembles the anisotropic diffusion, but it seems, that the new method solves many problems, which cannot be overcome by the classical models of diffusion.

In case of colour images, instead of the absolute value of the difference of the gray scale values of the neihbouring points, we take the norm of the difference of vectors representing the colour image pixels in a specific colour space. Thus we have

$$\mathbf{J}(x_0, y_0) = \frac{\exp\left\{-\beta\left[\left\|\mathbf{F}(x_0, y_0) - \mathbf{F}(x_1, y_1)\right\| + \cdots + \left\|\mathbf{F}(x_{n-1}, y_{n-1}) - \mathbf{F}(x_n, y_n)\right\|\right]\right\} \mathbf{F}(x_n, y_n)}{\sum_{\{(x_0, y_0) \to (x_n, y_n)\}} \exp\left\{-\beta \sum_{\kappa=1}^{n} \left\|\mathbf{F}(x_{\kappa-1}, y_{\kappa-1}) - \mathbf{F}(x_\kappa, y_\kappa)\right\|\right\}} \tag{6}$$

In this paper the ***RGB*** colour space and the *L1* metric was used while calculating (6) .

3. SEGMENTATION OF COLOUR IMAGES USING THE NEW FILTERING TECHNIQUE

In [13] a new method for colour image segmentation has been presented. The algorithm is based on a region growing procedure and is using a homogeneity criteria for the distance between colour pixels in different colour spaces (RGB, YUV and IHS). Among tested homogeneity criteria, best results were obtained using the following HS-criterion with the Euclidean distance metric in the cylindrical coordinate system:

$$\sqrt{S^2 + \bar{S}^2 - 2S\,\bar{S}\cos\left(H - \bar{H}\right)} \le d \tag{7}$$

where *H* and *S* are current values of colour components of the tested pixel, $\bar{\mathrm{H}}$ and $\bar{\mathrm{S}}$ are mean values related to a region and *d* is tuning parameter, which determines the number of segments. The choice of a specific value of d is image dependent. The lower the value of d , the more segments are created and the risk of oversegmentation is growing. Very often the segmentation algorithm generates too many segments. It is possible to limit the number of segments by different additional pre-processing (filtration) and post-processing (elimination) procedures. Each filtration procedure (e.g. *Median Filter*, *Vector Median* etc.) decreases the number of regions in segmented image. Also, the elimination procedure can be used to avoid oversegmentation. The algorithm analyses the area of all segmented regions. The elimination procedure locates all regions smaller than a given value and eliminates these regions from the contour image.

Below, the segmentation result of the *LENA* image is shown for $d = 0.1$ (Fig.1.). If we decide to eliminate all regions, with area lower than 50 pixels, the region number decreases from the initial value of 5874 to 172. The results obtained using the PEPPERS image were similar, when the parameter $d = 0.35$ was taken (Fig.2.). The number of regions decreased from 231 to 31. It must mentioned however that small regions not always are caused by noise component and sometimes cannot be neglected. A good example of this effect are the pupils of Lena and that is why we prefer to do a good filtering of noise before the segmentation.

If the colour images are very noisy, then the number of the generated segments increases dramatically. If the *PEPPERS* image is contaminated by a Gaussian noise with $\sigma = 30$ and additional 4% impulsive noise, the number of regions reaches 1605. The elimination of small regions $d =$ 0.35 lowers their number to 42 (Fig. 3). As can be seen the noise component is responsible for generating of tiny segments which is the cause of the oversegmentation.

We compared the new filtering technique with the median applied to the RGB components and with the *Vector Median* as defined by Astola [14]. Filtering the noisy image with the scalar median, we obtained 224 regions and after the post-processing, taking $d = 0.35$ their number dropped to 73. Using the *Vector Median* we obtained 209 and then 55 regions. Filtering the image with the new noise reduction technique, the appropriate region numbers were 85 and 43 for one pass of the filter and 33, 23 for two filter iterations.

4. CONCLUSIONS

The new filtering technique has interesting properties. It has the ability of image smoothing while preserving the image edges. As can be observed, the number of regions obtained when applying the algorithm described in [13] to the noisy image filtered using the new technique is significantly lower when compared with the scalar and vector median. It is even lower than the number of regions created when using the original *PEPPERS* image (for two iterations of the new filter). Figure 4 shows three examples of the performance of the new colour image filtering technique.

5. REFERENCES

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Fig. 1. Segmentation results: the number of regions using the algorithm described in [13] applied to *LENA* image (left) was 5874 (middle), taking the parameter $d = 0.1$ it decreased to 172 (right).

Fig. 2. The results obtained using the *PEPPERS* image (left). When the parameter $d = 0.35$ was taken, the region number decreased from 231 (middle) to 31 (right).

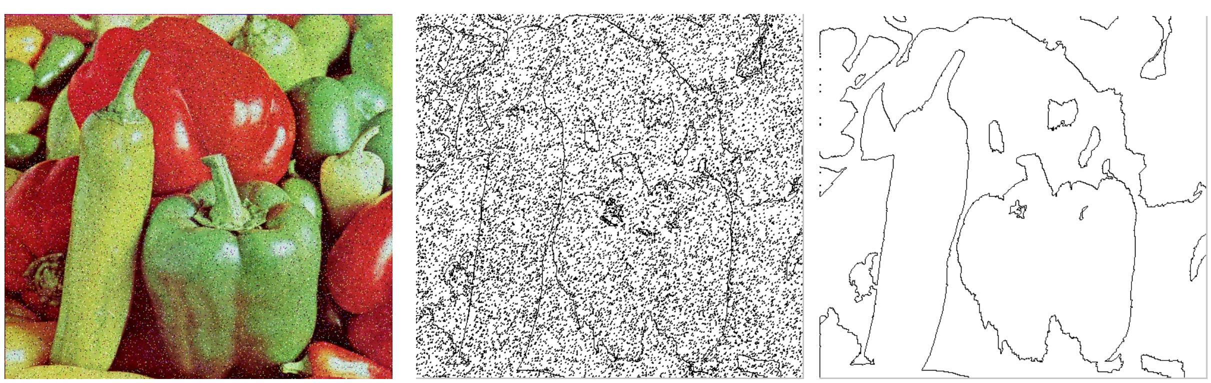

Fig. 3. Segmentation of the noisy image (*PEPPERS* contaminated with Gaussian noise $\sigma = 30$ and 4% impulsive noise, left) produced 1605 regions, this number decreased to 42 for $d = 0.35$. If the image was filtered two times with the new noise reduction algorithm, the region number was 33 without any postprocessing (right).

Fig. 4. Examples of the efficiency of the new filtering technique.