Informational and Spectral Techniques in Boundary Detection

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Abstract: *The paper reports the results of the research focused on the developement of a suitable methodology in solving boundary detection problems. The feature extraction attempts in image processing are based on using different picture information measures (PIM). The algorithm BDPIM presented in the second section of the paper is formulated in terms of the NPIM and DM measures. A new technique, combining the information measure NPIM and the spectral power, yields to the algorithm DBSP-PIM presented in the third section. The experimental results and conclusive remarks are provided in the final section.*
Keywords: *spectral power, picture information measure, histogram, DFT.*

Introduction

Boundary detection techniques work based on the fact that there are gray level changes around boundary points. Because of problems such as illumination, the reflectance of object surface, the degradation of image quality due to noise in image acquisition, and so on, modeling those gray level changes is difficult. Researchers have developed many boundary detection techniques based on different models, such as the edge detection by resolution pyramid, the Hough transform for boundary detection, the relaxation methods for edge detection, the contour following technique, boundary detection based on graph searching methods and so on.
Edge detection by resolution pyramid is a hierarchical method, witch combines crude edge detection and extended edge detection at different levels. The relaxation method makes use of contextual information by introducing consistence function and dynamically adjusting edge confidences. Contour following produces a list of boundary points.
Frequently, the feature extraction process in image processing is essential based on picture information measures. Since the classical Shannon entropy proved inadequate enouth in capturing the image spatial structure, some special tailored measures have been proposed instead. Information measures of this type, usually referred as PIM take into account the minimum number of gray level changes needed to transform the image into another one of given histogram. The algorithm BDPIM presented in the second section of the paper is formulated in terms of the PIM and some dissimilarity measure based on the local gray level values. It is known that low values correspond to the pixels belonging to the background and the pixels belonging either to the boundary or representing noise have larger values of the spectral power. A new technique, combining the information measure NPIM and the spectral power, yields to the algorithm DBSP-PIM presented in the third section.

2. The DBPIM algorithm

Let $X \in M_{M\times N}(L)$ be an image, where L represents the set of grey levels, and M, N are the number of rows and respectively columns of the matrix representation X. We denote by h the histogram of the image X. The picture information measure (*PIM*) is defined as, [Cha, 89]

$$PIM(X)=\sum_{j=0}^{L-1}h(j)-\max_{j=0,L-1}h(j).$$

The normalized PIM denoted by NPIM is given by,

$$NPIM(X)=\frac{PIM(X)}{N(X)},$$

where $N(X)$ stands for the total number of image pixels.

The preprocessing of the input image is performed by segmenting it in windows of size five, two windows are taken as neighbours if and only if they have four colums or four rows in common. We assign the following information measures to the central pixel of any window F,

$$NPIM(X/F) = \frac{\sum_{i\in IM(X/F)} h(i) - \max_{i\in IM(X/F)} h(i)}{9}$$

$$DM(F_k) = \sum_{\substack{(i,j)\neq(2,2)\\(i,j)\in F}} \left|(X/F)(2,2) - (X/F)(i,j)\right|$$

.

The central pixel of the window is considered as a boundary pixel if at least one of the conditions holds,

1. $NPIM(X/F) < T$ and *DM(F)>DM1*;
2. $NPIM(X/F) > T$ and *DM(F)<DM2,*

where *T, DM1, DM2* are convenable threshold values.

The procedure is given by the algorithm *BDPIM.*

INPUT: The image X and the resulted windows $F_k, k = \overline{1,NF}$.

Step 1. *BPL=Æ*

Step 2.

2.1. For each $k = \overline{1,NF}$, compute

$$NPIM(X/F_k) = \frac{\sum_{i\in IM(X/F)} h(i) - \max_{i\in IM(X/F)} h(i)}{9}$$

$$DM(F_k) = \sum_{\substack{(i,j)\neq(2,2)\\(i,j)\in F_k}} \left|(X/F_k)(2,2) - (X/F_k)(i,j)\right| .$$

2.2 If $(NPIM(X/F_k) > T)$ *and* $(DM(F_k) < DM1)$ or $(NPIM(X/F_k) < T)$ *and* $(DM(F_k) > DM2)$,

then $BPL = BPL + ((X/F_k)(2,2))$.

OUTPUT: The set *BPL* of boundary pixels.

Using the computed set *BPL*, we obtain the transformed image *Y*, $Y(k,l) = \begin{cases} 0, (k,l)\in BPL \\ L-1, otherwise \end{cases}$, for each pixel (k,l) of the initial image.

3. The *BDSP-PIM* algorithm

The spectral power P_X corresponding to the pixel *(k, l)* is given by the amplitude of the bidimensional discrete Fourier transform,

$$P_X(k,l) = \frac{1}{(MN)^2}\left|\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} X_{u,v} e^{-2pi\left(\frac{uk}{M}+\frac{vl}{N}\right)}\right|^2 =$$

$$= \frac{1}{(MN)^2}\left|\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} X_{u,v}\cos\left(-2p\left(\frac{uk}{M}+\frac{vl}{N}\right)\right) + i\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} X_{u,v}\sin\left(-2p\left(\frac{uk}{M}+\frac{vl}{N}\right)\right)\right|^2 =$$

$$= \frac{1}{(MN)^2}\left[\left(\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} X_{u,v}\cos\left(2p\left(\frac{uk}{M}+\frac{vl}{N}\right)\right)\right)^2 + \left(\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} X_{u,v}\sin\left(2p\left(\frac{uk}{M}+\frac{vl}{N}\right)\right)\right)^2\right]$$

It is known that low values correspond to the pixels belonging to the background and the pixels belonging either to the boundary or representing noise have larger values of the spectral power. Using this property, we can transform the image in the following way. If the spectral power of the central pixel of a window is less than a given threshold then the pixel is taken as the background pixel and respectively as a boundary pixel otherwise. We conjecture that significant improvements could result in case the identification of boundary pixels would be performed by taking into account simultaneously the measures *NPIM*, *DM* and P_X. In such a case the pixel is decided as a boundary pixel if at least one of the considered measures "votes" it as being a boundary pixel. Being given the fact that the normalised pictorial information measure and the dissimilarity measure are global and P_X has a local character, we take as decision criteria P_X together with either *NPIM* or *DM*. Let $M(X/F_k)$ denote one of the global information measures and $C(M(X/F_k))$ the boundary pixel condition expressed in terms of $M(X/F_k)$.

$C(NPIM(X/F_k)) : NPIM(X/F_k) < T$

$C(DM(X/F_k)) : DM(X/F_k) > DM0$,

where T and $DM0$ are given thresholds. According to the previously mentioned developements, we arrive at the following algorithm.

Figure 1

The algorithm *BDSP-PIM*

INPUT: The image X and the resulted windows $F_k, k=\overline{1,NF}$.

Step 1. BPL=∅

Step 2.

2.1. For each $k=\overline{1,NF}$, compute $M(X/F_k)$ and $P_{X/F_K}(2,2)$

2.2. If $(C(M(X/F_k)))$ or $(P_{X/F_k}(2,2) > T)$, then $BPL = BPL + ((X/F_k)(2,2))$.

OUTPUT: The set BPL of boundary pixels.

4. Experimental results and concluding remarks

A series of tests on 256 grey levels images were performed and the experiments confirmed that the algorithms proved efficient in boundary detection. In order to obtain good computation times, the blocks were taken of small dimensions (5).

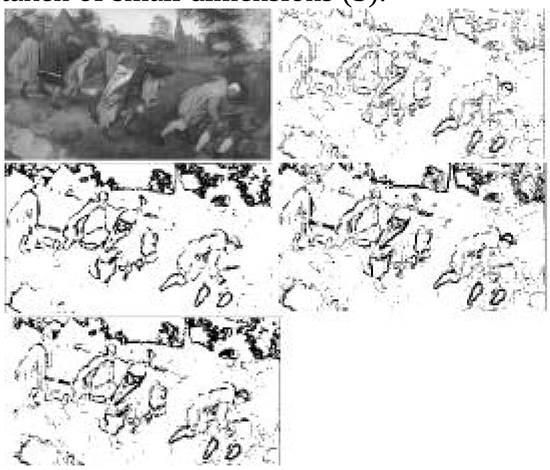

Figure 2

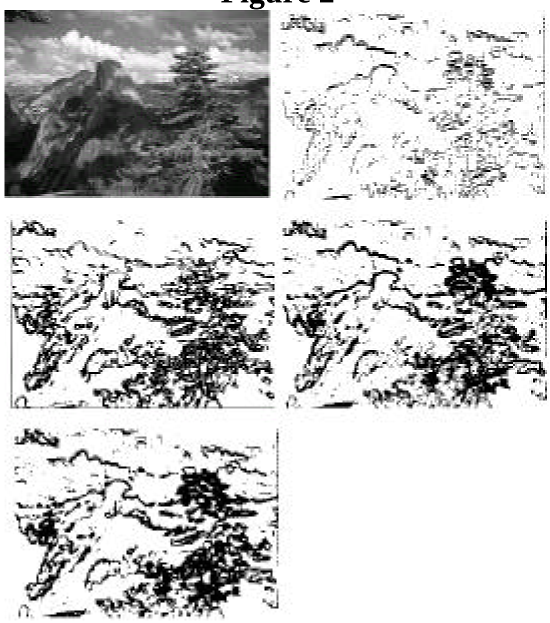

Figure 3

Some of the outputs obtained by the proposed algorithm are displayed in Fig. 1, Fig. 2 and Fig. 3. The depicted outputs were obtained by processing the initial image using the spectral power, DBNPIM and respectively both variants of the DBSP-PIM algorithm.

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