EDGE DETECTION USING ADAPTIVE LOCAL HISTOGRAM ANALYSIS

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ABSTRACT

The objectives of this paper is to present a novel adaptive edge extraction algorithm, based on processing of the local histograms of small non-overlapping blocks of the output of the first derivative of a narrow 2D Gaussian filter. It is shown that the proposed edge extraction algorithm provides the best trade off between noise rejection and accurate edge localisation and resolution. The proposed edge detection algorithm starts by convolving the image with a narrow 2D Gaussian smoothing filter to minimise the edge displacement, and increase the resolution and detectability. Processing of the local histogram of small non-overlapping blocks of the edge map is carried out to perform an additional noise rejection operation and automatically determine the local thresholds.

1. INTRODUCTION

Edge detection is one of the most important areas in lower level computer vision. The main problem existing in many edge detection approaches is that they are sensitive to noise. To achieve usable results, the process of edge detection is usually preceded by the application of a 2D Gaussian smoothing filter. There is a conflict between the precision of edge detection and the effect of the noise removal. Another problem encountered with gradient based edge detectors is the difficulty to define appropriate threshold values to the gradient image [1]. In fact, automatic edge thresholding is a series drawback of the gradient based edge detection methods. Only a few works deal with automatically setting the threshold parameters [2, 3, and 4]. Limitations of global thresholds are typically due to poor quality of the source material, existence of multiple object classes of varying contrast, and non-uniform illumination. A possible solution that provides a good trade off between edge localization and noise rejection based on local histogram analysis has been proposed [5]. In this method the edge localization is maintained through the use of the smallest possible Gaussian filter, and noise rejection is achieved by performing smoothing on the local histogram prior to local threshold calculation using a 1D Gaussian filter with standard deviation σ =1. This method was further improved in terms of threshold calculation speed using the method named as Differential Local Histogram Analysis [6]. The Local histogram analysis method extracts edges through the processing of a 4x4 non overlapping blocks of the output of the first derivative of a narrow 2D Gaussian filter. The method starts by convolving the image with a narrow 2D Gaussian filter with standard deviation =0.5 in order to minimise the edge displacement. The gradient magnitude is then computed using the Prewitt operator. Processing of the local histogram of small non overlapping blocks of the thinned gradient magnitude is carried out to perform an additional noise rejection and automatically determine the local threshold for each block. In this method non uniform quantization technique [7] was employed on the thinned gradient magnitude prior to the processing of the local blocks. This quantization step is necessary in order to be able to conduct the processing on such small block. This is due to the fact that the number of gray levels of the local histogram is greater than the number of pixel in a block, which means that, the statistics of the individual local histograms become insignificant. The quantization step provides a robust representation of the local histogram without any loss of information. Experiment results showed that this method can provide the best trade off between edge localization and noise rejection compared with the canny edge detector [5]. However, a problem associated with this method is at the quantization step. The non uniform quantizer is applied on an ad hoc basis to all pixels of the thinned gradient magnitude image. Therefore, and in the presence of noise this leads to the need of larger local histogram smoothing filter in order to minimize the effect of noise at the thresholding stage. This will result in greater computations and the risk of eliminating edge pixels due to the large smoothing applied to the local histogram.

The work presented in this paper attempts to answer this problem. It is called Adaptive Differential Local histogram Analysis (ADLHA), and follows on from our previous work [6], and Voorhees and Poggio [3] work on modelling the gradient magnitudes arising from noise. In the proposed method the gradient magnitude quantization is made adaptive based on the noise estimation of the filtered gradient magnitude. Using the adaptive quantization not only produces a more robust representation of the local histogram, it also acts as a noise suppression process. Furthermore, computation is reduced as only smaller 1D Gaussian filters are used for local histogram smoothing and the method will work better for a larger range of signal to noise ratio.

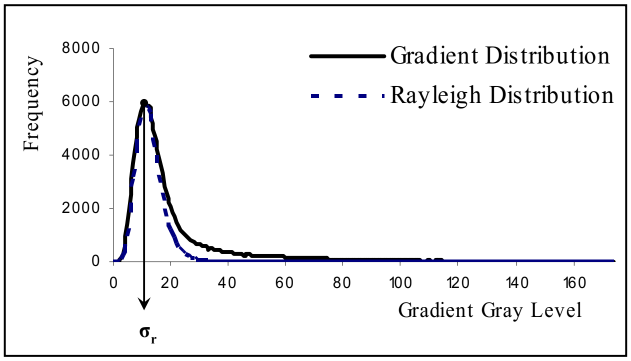

Figure 1: Thinned gradient magnitude histogram

2. ADAPTIVE DIFFERENTIAL LOCAL HISTOGRAM ANALYSIS.

The first stage of the edge detection algorithm performs the smoothing and the edge enhancement on the image [6]. The output of this stage is a thinned gradient magnitude image which is then processed by the ADLHA method in order to extract the edge pixel from the noise. Prior to local histogram processing, the quantization is performed on the thinned gradient magnitude based on the noise estimated from it as discussed bellow.

Voorhees and Poggio [3] showed that if the image noise consists of additive Gaussian noise then the filtered magnitude of the image has a Rayleigh distribution. According to [3] the background noise is at the low end of the gradient magnitude histogram which is characterized by the Rayleigh distribution. The standard deviation of the noise, σ_r, can be estimated by fitting the histogram of the filtered magnitude of the image to the Rayleigh distribution and simply measuring the location of the peak as shown in figure 1. This represents the thinned gradient magnitude of the Lena image shown in Figure 4.

Due to the non-maximal suppression, the histogram of the thinned gradient magnitude contains an enormous peak at gray level zero, and since it's a systematic effect this peak is eliminated and the histogram of Figure 1 starts from the next bin. In this work only a moderate estimation is required as it is only used for gradient magnitude quantization and no threshold decision is taken at this stage. We can assume that all pixels with gray levels less than or equal to (σ_r) are background noise and those above it are a combination of both significant edges and low noise ones. Therefore, the quantization will be performed by shifting the starting point of the quantizer from zero to the estimated value of σ_r. Here, the quantization is made adaptive and will depend on the noise in the image. In images with low noise the peak will be at or very near the gray level zero, and as noise is increased so will the peak position and all pixels with gradient magnitude less than (σ_r) will be quantized as zero, resulting in the elimination of all noisy gradients from any further processing that is carried out in the edge extraction method. The adaptive quantization not only produces a more robust representation of the local histogram, it also acts as a noise suppression process. The adaptive quantizer used in this paper is shown in figure 2.

Since the smoothing method is been applied to the quantized local histogram after the thinning process, the first peak is ensured to be around the quantized level (0) of the local histogram, and in the case of a bimodal histogram the quantized gray level value that corresponds to the position of the valley between the two peaks can be taken as the threshold value. The threshold value can be obtained by differentiating the smoothed histogram. As the derivation step occurs after histogram smoothing. By the derivative rule of convolution, histogram smoothing and differentiation can be done in one step by convolving the histogram wave form with the first derivative of the smoothing operator. The first valley can be determined as the first zero crossing of the differentiated histogram.

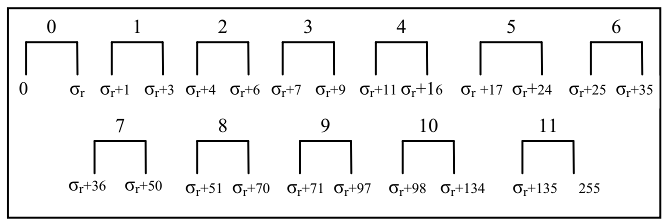

Figure 2: Adaptive 12-Level Nonuniform Quantizer

3. PERFORMANCE ANALYSIS

Real images and a synthetic image are used to investigate the performance of the proposed algorithm qualitatively and quantitatively. The proposed ADLHA method is compared with the previous LHA and the unimodal thresholding method [5]. The measure, Q, proposed in [8], which is the product of the proportions of correctly classified true edges and false edges, is used for the quantitative assessment. In order to calculate the measure Q, a synthetic image with its true edges known in advance is used. This image is composed of random shapes with different gray level values, overlaid with Gaussian noise with different standard deviation. Figure 3 shows the synthetic image and the resultant edge maps obtained from the different thresholding methods. The SNR of the image is ≈ 30, which is taken as the square of the ratio of the gray level difference with the highest probability of occurrence in the whole image over the noise standard deviation. Figure 3, shows that, better results are obtained using the adaptive quantization using a Gaussian filter with $\sigma = 0.8$, where, the results obtained using the existing method are under thresholded when the local histogram smoothing is carried out using a Gaussian filter with σ=1 and is a little over thresholded for the global unimodal threshold method, and the existing method when the filter standard deviation is increased to σ =1.5, which causes a loss of some of the week edges.

The same observation can be seen from the results obtained using natural images in figure 4. Furthermore, the figure of merits, Q, as a function of SNR, shown in figure 5 confirms the results and it's clearly seen that, the proposed method performs better over a larger range of noise level using smaller filter for histogram smoothing than the other methods.

4. CONCLUSION

In this paper, a more robust and improved edge detection method based on local histogram analysis which provides accurate edge localization while maintaining very good noise rejection is presented. This method not only has the ability to reject more noise through the adaptive quantization, but also reduce the computation required for smoothing, hence, increases the edge classification speed. Experiments show that the proposed method is more practical, effective and robust compared with the existing local histogram analysis method.

5. REFERENCES

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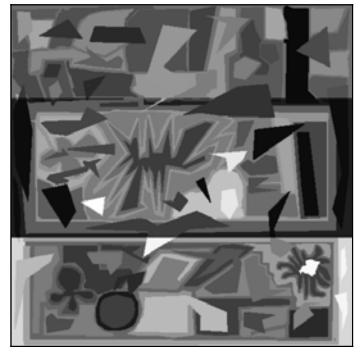
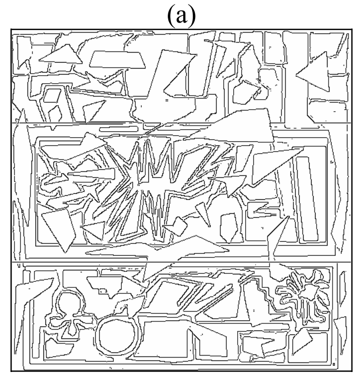
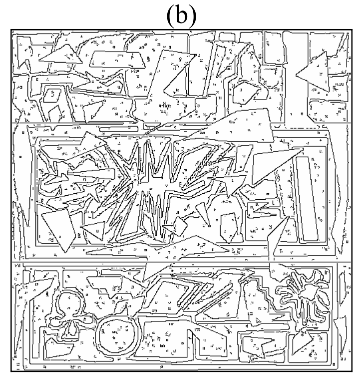


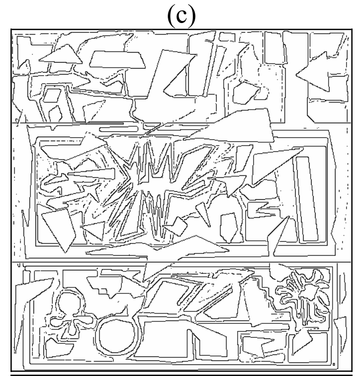
(a)



(b)



(c)



(d)

Figure 3: Results of edge detection on synthetic image (a) original image, (b) proposed method, (c) LHA σ =1 [5], (d) Unimodal algorithm in [2]

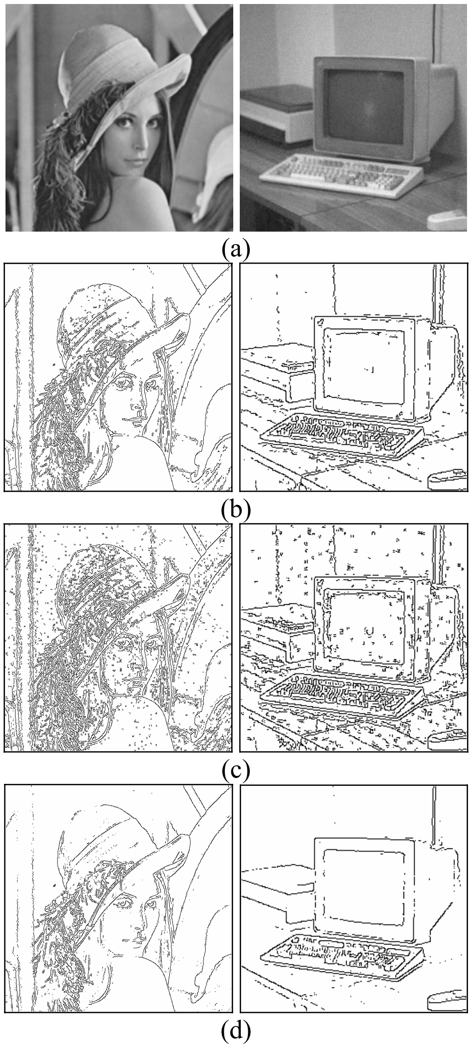


Figure 4: Results of edge detection on real images (a) Original image, (b) proposed method, (c) LHA σ =1 [5], (d) Unimodal algorithm in [2].

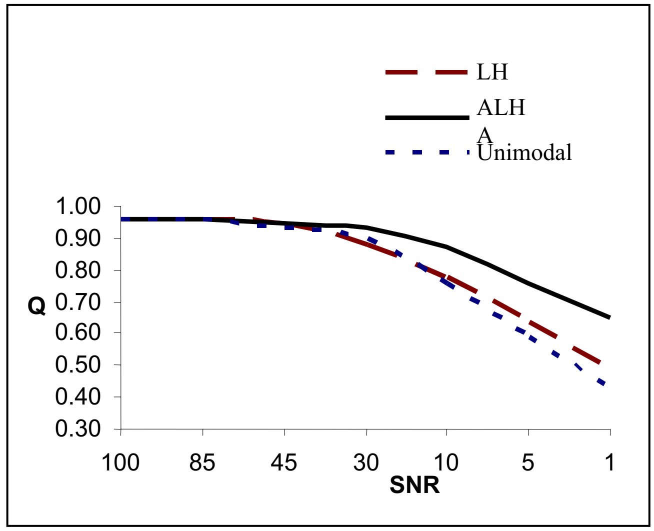


Figure 5: Figure of merit, Q against SNR