MULTI-RESOLUTION LOCAL HISTOGRAM ANALYSIS FOR EDGE DETECTION

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ABSTRACT

The objectives of this paper is to present a novel multi-resolution 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. 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. It is shown that the proposed edge extraction algorithm provides the best trade off between noise rejection and accurate edge localisation and resolution.

Index Terms— Computer Vision, Edge Detection

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 [5-6]. The attractive feature of this technique is that, it incorporates two noise removal mechanisms namely adaptive quantization and local histogram smoothing that can be tuned and controlled depending on the noise level of the image. However, in the presence of noise and even with adaptive quantization, local histogram smoothing is still required prior to local threshold computation in order to reduce the effect of noise. The amount of smoothing required depends on the level of noise in the image and is controlled by the size of the local histogram smoothing operator. Nevertheless, choosing the size of one local histogram smoothing filter that will work well in the whole image is often critical to establish.

A possible solution that attempts to alleviate the difficulties faced by the adaptive local histogram analysis (ALHA) method in the presence of noise is the application of multi-resolution Local histogram analysis techniques proposed in this paper. The Multi-resolution local histogram analysis involves applying the ALHA concept at different resolutions, extracting edge maps at each resolution and combining the recovered edge information to form a more complete picture of the actual edge representation. Two different multi-resolution techniques are proposed here aiming to reduce the misclassification rate faced by the ALHA method. The proposed technique involves applying the ALHA method at different local histogram smoothing scales, extract edges at each scale and combining the recovered edge information to form the final edge map

2. EDGE EXTRACTION USING LOCAL HISTOGRAM ANALYSIS

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. 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.

Recently an adaptive local histogram analysis (AHLA) method has been proposed by the authors [6] to answer this problem. It follows on from our previous work [5], and Voorhees and Poggio [3] work on modelling the gradient magnitudes arising from noise. In the ALHA 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.

3. MULTI-RESOLUTION ALHA FOR EDGE DETECTION

The first stage of the edge detection algorithm performs the smoothing and the edge enhancement on the image [5-6]. The output of this stage is a thinned gradient magnitude image which is then processed by the ALHA 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. 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.

In [6] it is shown that the ALHA based edge detector provides the best trade-off between noise rejection and edge resolution. However, noise in complex real images may have relatively distinct local features, and by using the local histogram of the gradient magnitude alone and the lack of any built-in knowledge of what constitutes a good edge segment within a local block, limit ability to distinguish between significant edges and spurious isolated noisy pixels.

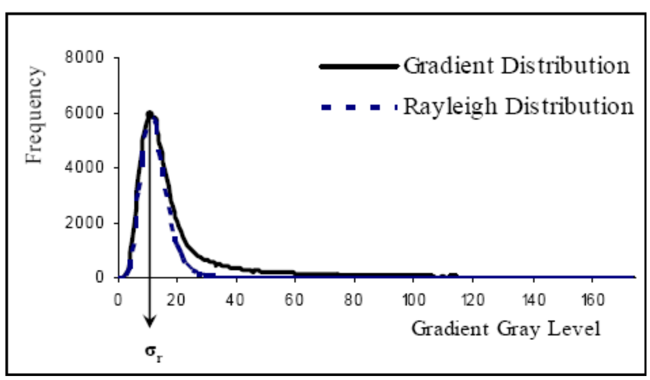


Figure 1: Thinned gradient magnitude histogram

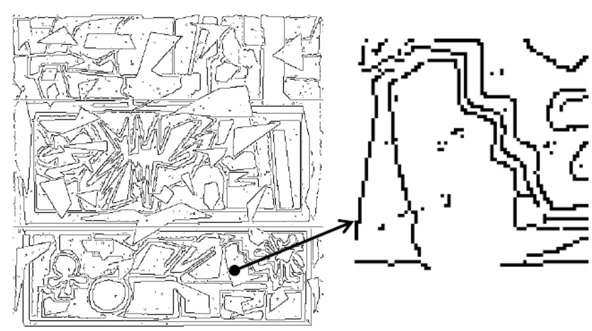
Although, increasing the size of the local histogram smoothing operator will eventually eliminate these isolated noisy pixels, it will also result in the misclassification of true edge pixels that have the same gradient magnitudes as those of the noisy pixels. The choice of the size of the local histogram smoothing operator is therefore an essential and important parameter that crucially influences the performance of the ALHA method. Choosing a large size smoothing operator to reduce the effect of noise may prevent smaller contrast edge pixels from being detected. On the other hand, the use of small size smoothing operators will be very sensitive to noise and will result in the detection of many false edges. These misclassifications will result in edge maps that have either disjointed contours or a cloud of blocks of noise especially around uniform background areas. Therefore, the basic conflict encountered here is the one of eliminating noise and insignificant edges without eliminating true edges.

This misclassification phenomenal can be visually illustrated with the aid of the binary images shown in figure 2. The edge maps shown in figure 2(a) and (b) are obtained by applying the Adaptive Local Histogram thresholding method to the thinned gradient magnitude of a noisy synthetic image using local histogram smoothing operators with sizes of W=3 and W= 7 respectively. Although blocks containing true edges have been reasonably thresholded by the ALHA method with W=3 operator, the noise effects produced by empty regions are clearly evident.

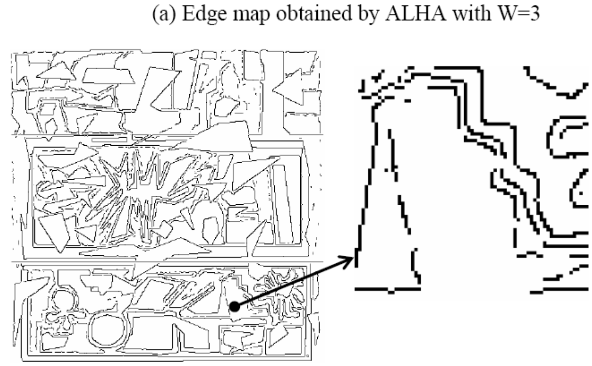
Since automatic adjustment of the local histogram operator size is difficult, using multiple scales and combining the results to recover the lost edge points should provide a reasonable answer. The proposed strategy thereby aims to combine the noise reducing aspect of the larger local histogram smoothing operator with the resolving power of the smaller local histogram operator in order to reduce noise and improve detection rate and edge connectivity. The main advantage of carrying out the smoothing on the local histogram is that, noise can be dramatically reduced or eliminated without moving the edge points from their actual position, and the only error that might occur is the elimination of true edge pixels. The proposed multi-resolution ALHA method consists of two main stages. The first involves the creation of multiple edge maps through the application of the ALHA method at different local histogram smoothing scales, and the second stage involves combining the recovered edge information by concatenating and linking the discontinuous edge segments obtained at a higher scale with those extracted from lower scale

In this paper, the local histogram of each block is computed and smoothed using the smallest possible a 1-D Gaussian kernel of width W=3. Each block is then classified as being a background block or a block which contains an edge segment depending on the shape of the smoothed local histogram. If the smoothed histogram is unimodal the block is considered to be a background block and all the pixels in the block are set to zero. The thresholded block is saved in to the lower scale edge map and eliminated from any further processing. Otherwise, the smoothed histogram is differentiated and the position of the first valley is taken as the threshold value for that block and all pixels with quantised gray level higher than the threshold value are classified as edge pixels and set to one. The thresholded block is saved in to the lower scale edge map. The same quantized block is smoothed again with a larger 1-D Gaussian filter and the quantized gray level corresponding to the position of the new valley is used to threshold the block and the result is saved into the larger scale edge map. Note that, the larger scale smoothing is only applied to those blocks that have been classified as being edge blocks by the smaller scale. After all the blocks have been processed, the edge combination process is applied to combine the two edge maps produced to form a single final edge map.

Figure 3, shows the results of applying the edge combination algorithm to the two edge maps of the synthetic image which have been obtained by the ALHA with local histogram smoothing operators of size w=3 and w=7 shown in figure 3 above. Clearly, as can be seen from the enlarged sections of the image most of the weak edges lost due to the effect of the large local histogram smoothing operator are extracted by the edge combination process and a more robust, continuous and pleasant edge maps are produced.



(a) Edge map obtained by ALHA with W=3



(a) Edge map obtained by ALHA with W=7

Figure 2: Resultant Edge Maps Extracted Using ALHA Method With Different Histogram Smoothing Kernels.

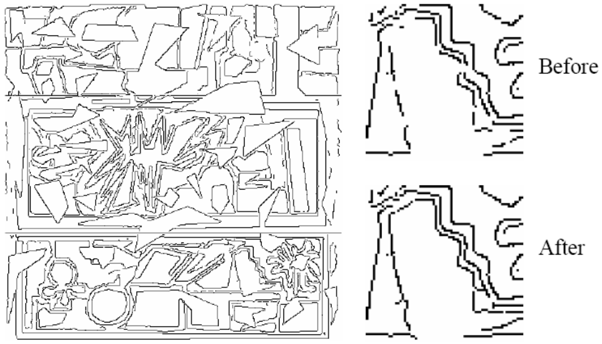


Figure 3: Result Of Combining Two Edge Maps Obtained By The ALHA Method With *W*=3 And *W*=7.

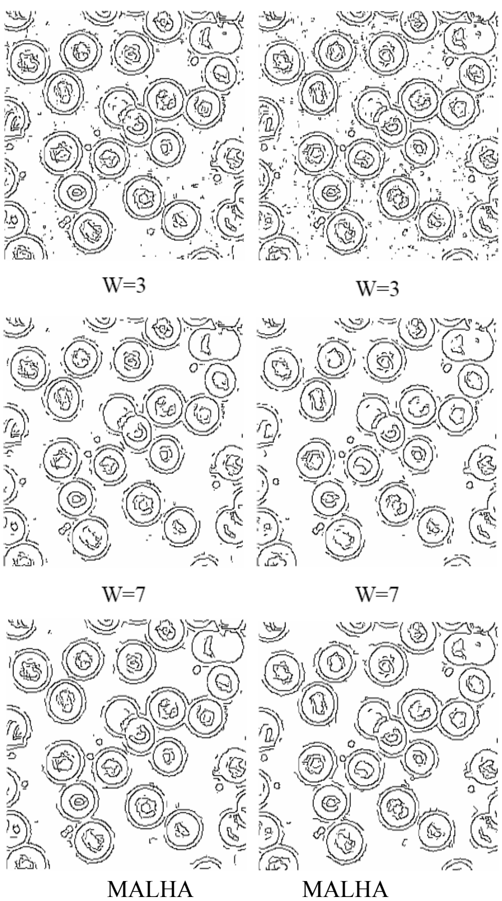


Figure 4: Edge maps obtained by the proposed MALHA and the ALHA algorithm with W=3 and W=7 for the blodd image corrupted with Gaussian noise of (a) σ = 12 (b) σ = 15

Figure 4 shows the improvements that can be achieved by applying the Multi-resolution ALHA algorithm to the blood cell image which have been contaminated by two different noise levels. Figure 4 (a) and (b) show the results obtained from the image that have been corrupted by a Gaussian noise with a standard deviation of 12 and 15 respectively. It can be seen that using different local histogram smoothing scales can be used to detect edges at different resolutions. However, as the SNR of the images decreases, results that have been obtained by the smallest scales appear to be quite noisy. It can also be seen that, the noise is drastically reduced as a consequence of increasing the scale of the local histogram smoothing operator result. Although this example shows that noise is successfully suppressed by increasing the scale of the local histogram smoothing operator, some of the week edges are also lost. The results of combining the two edge maps obtained at different scales are shown in the third column of figure 4. Comparing the combined resultant edge map with those obtained from using a single scale, it is clearly evident that, most of the edges that are lost due to the large local histogram smoothing operator are effectively recovered by the combination process.

4. CONCLUSION

In this paper, a more robust and improved automatic 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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