Restorations of Aging Images Using Morphological Filters for Archiving

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Abstract

Old text images show many common signs of aging. These artifacts include noise, blurring, and fading. We will enhance these images to make these old texts readable so that we can archive the images and preserve our history.

Morphological filters have been successfully employed in edge and object detection algorithms. These filters possess computational advantages over traditional edge detection methods such as gradient-based edge detection algorithms, as they are less computationally complex and are less influenced by extreme data values.

In this paper, we propose new techniques for an improved morphological filter based object detection algorithm and image enhancement algorithm. We utilize components of image enhancement measures previously introduced by Agaian, Silver, and Panetta to focus on areas within an image that contain the most edge information. These algorithms are incorporated into our morphological filters as well as more complex pre- and post-processing methods.

Introduction

Morphological filters have been successfully employed for edge and object detection. They possess computational advantages over other traditional methods, such as improved time and computational complexities. These filters applied correctly and with proper pre- and post-processing techniques, can quickly and effectively locate edges and objects within the image. For these reasons, we investigate this type of filter for use with our edge and object detection algorithms.

We utilize our previously researched logarithmic AME and AMEE algorithms to help select the optimal filter parameters to achieve maximum performance. Using these methods, we are able to produce a more robust image enhancement algorithm. We also introduce new steps to improve the pre- and post-processing steps of the morphological algorithm, performed in conjunction with our measures.

We will demonstrate our new algorithm by using it to enhance several aging images from the 14^{th} Century. These text images show many common signs of aging. These artifacts include noise, blurring, and fading. We will enhance these images to make these old texts readable so that we can archive the images and preserve our history.

This paper is organized as follows: Section II presents necessary background information, including previously used edge and object detection algorithms. Section III presents our new methods for edge and object detection. Section IV shows experimental results comparing our methods to other methods. Section V is a discussion of results and some concluding comments are made.

Background

In this section, we present necessary background information, including previously used morphological filters and the logarithmic AME and AMEE.

Morphological Filters

Morphological filters are a class of non-linear filters which adapt based upon the structure and topology of the input data [1]. These filters generally work by passing a structural element [2] over the image and performing an operation on all the pixel intensities contained in the structural element. This structural element functions to look at a window surrounding a given pixel.

Several morphological filters which have been developed specifically for edge and object detection rely on the extreme cases of erosion and dilation, or minimum and maximum, respectively. These operate by selecting a 3x3 window around each pixel, computing the maximum and minimum in the window, and replacing the pixel with the max/min or min/max [3].

It has further been shown that it is possible to improve upon these results by using several methods of pre- and post-processing on the images and then averaging the results. One method that does this applies alpha rooting to the input image several times using several different values of alpha and applies the morphological filter to these images. To arrive at the output image, these results are averaged [3].

Measures of Image Enhancement

Many enhancement algorithms have operating parameters that help optimize the enhancement for the image to be enhanced. With these increasingly complex enhancement algorithms comes a need for an objective method of selecting optimal enhancement parameters. To solve this problem, several measures of image enhancement have been introduced.

These measures are based upon the Michelson Contrast Law, which is designed to measure the apparent contrast of a periodic pattern, such as a sinusoidal grating. Further, this information is processed using either Fechner's Law, which relates pixel intensity to brightness, or the Entropy Law, which measures the total information content in a signal. The measures are defined as follows:

$$\log AME_{k_1 k_2}(\Phi) = \frac{1}{k_1 k_2} \otimes \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} \frac{1}{20} \otimes \ln\left(\frac{I^w_{\max:k,l} \Theta I^w_{\min:k,l}}{I^w_{\max:k,l} \oplus I^w_{\min:k,l}} \right) \quad (1)$$

$$\log AMEE_{k_1 k_2}(\Phi) = \frac{1}{k_1 k_2} \otimes \sum_{i=1}^{k_1} \sum_{j=1}^{k_2} \frac{I^w_{\max:k,l} \Theta I^w_{\min:k,l}}{I^w_{\max:k,l} \oplus I^w_{\min:k,l}} \otimes \ln\left(\frac{I^w_{\max:k,l} \Theta I^w_{\min:k,l}}{I^w_{\max:k,l} \oplus I^w_{\min:k,l}} \right) \quad (2)$$

Where $I^w_{\max;k,l}$ and $I^w_{\min;k,l}$ are the local maximum and minimum intensity values in each block, respectively, and the image is divided up into blocks size $k_1 \times k_2$, and where all summations use logarithmic arithmetic [4].

The logarithmic arithmetic, taken from Jourlin and Pinoli's Logarithmic Image Processing (LIP) model [5], is as follows:

$$a \oplus b = a + b - \frac{ab}{M}, \quad a\Theta b = M\,\frac{a-b}{M-g} \tag{3}$$

$$c \otimes a = M - M\left(1 - \frac{f}{M}\right)^c \tag{4}$$

Where a and b are any grey tone pixel values, M is the maximum value of the range, and c is a constant. In general, a and b correspond to the same pixel in two different images that are being summed.

Contrast Enhancement

In this section, we detail several contrast enhancement methods which can be used with our edge detection system.

Bi-Histogram Equalization with LIP

Histogram equalization is a common enhancement algorithm for enhancing low contrast images. Bi-histogram equalization is based upon standard histogram equalization but introduces a thresholding parameter to give better control over the enhancement and to obtain a better enhanced image [6]. Standard histogram equalization uses a cumulative density function to attempt to force a uniform probability density function for the image, according to the following formula:

$$f(x) = Y_{\min} + (Y_{\max} - Y_{\min}) \cdot P(x) \tag{5}$$

Where x is the input pixel intensity, $f(x)$ is the output pixel intensity, $Y_{\min}$ and $Y_{\max}$ are the minimum and maximum values for the desired output range, usually 0 and 255, and $P(x)$ is the probability distribution function, where $P(X_{\max}) = 1$.

In order to use this function for bi-histogram equalization, one performs the equalization twice, once for all pixel values below the threshold, and again for all those above the threshold. Finally, by introducing the LIP arithmetic based transfer function, we arrive at the equation:

$$f(x) = \begin{cases} Y_{\min} \oplus P(x) \otimes (Threshold - Y_{\min}) & x <= Threshold \\ Threshold \oplus P(x) \otimes (Y_{\max} - Threshold) & x > Threshold \end{cases} \tag{6}$$

Logarithmic Transform Shifting

Logarithmic transform shifting operates in the logarithmic domain. For logarithmic domain enhancements, an orthogonal transform of the image is performed to put the image into the transform domain. Next, the logarithmic transform is applied to these coefficients, according to the following formula:

$$\hat{X}(i,j) = \ln(|X(i,j)| + \lambda) \tag{7}$$

$$\theta(i,j) = \angle(X(i,j))$$

Where $X(i,j)$ is the 2-D orthogonal transform of the input image, $\hat{X}(i,j)$ is the logarithmic transform coefficients, λ is a shifting coefficient, usually set to 1, and $\theta(i,j)$ is the angle, required to perform the inverse transform. The inverse transform works as follows:

$$X'(i,j) = e^{\hat{X}(i,j)} \cdot e^{j\theta(i,j)}$$

Logarithmic transform shifting operates by taking the histogram of the logarithmic transform coefficients and applying a shift in the positive direction [7]. This shift in the logarithmic domain enhances the most important transform coefficients more than the least important, as the larger coefficients are shifted further in the linear domain than the smaller coefficients.

Methods

This section details our methods for restoring the aging images. The process is an iterative process, which employs edge enhancement and contrast enhancement.

Edge Enhancement

The edge enhancement stage can work with any suitable edge detection algorithm. It uses pre-processing steps to standardize image brightness throughout the image, and several post-processing steps to enhance the edges.

The first part of this algorithm works to affect a similar brightness level on the entire image. It is performed on each image pixel and is based on the local mean at each pixel. This step uses the following formula:

$$I(x,y) = \frac{2}{1 + e^{-2\tau(x,y)/\lambda(x,y)}} - 1 \tag{8}$$

Where $I(x,y)$ is the output image, $\tau(x,y)$ is either the V component of the image in HSV color space or the gray scale image, and λ is the local statistic of the image used to adjust the transfer function to the local mean. Finally, where λ is

$$\lambda(x,y) = C + (255 - C)\left(\frac{M(x,y)}{255}\right) \tag{9}$$

C is a user selected enhancement parameter, with effective range $0 \le C < 256$ and $M(x,y)$ is determined the local mean of the image, for example $M(x,y)$ may be determined by the Fourier transform DC coefficient, or by 2D convolution of the image by a Gaussian kernel normalized to sum to 1. Below, we select the optimal values for C using the measures (1), (2).

After this, a second step is performed to enhance the contrast. This is performed by first applying a high pass filter on the image, next enhance this image, then apply edge detection, resulting in the image we will call I_{EN}. Finally, the following formula gives the output-enhanced image:

$$I_{F,EN}(x,y) = \left(\left(I(x,y) + \mathrm{Im}age\_Edges * I_{EN}\right)^{\beta_1} \cdot I_{EN}^{\alpha_1}\right) \cdot A \tag{10}$$

Where $I_{F,EN}$ is the output image and A, α_1, β_1 are user defined operating parameters.

The presented algorithm may be executed as:

Input Image

Step 1: Find image statistics based upon local mean and k using equation 9

Step 2: Perform non-linear enhancement to correct for darker and brighter sections using equation 8

Step 3: Apply high pass filter

Step 4: Enhance image

Step 5: Apply edge detection

Step 6: Apply equation 10

Output Image

For step 4, most any common enhancement algorithm can be used, such as alpha rooting or logarithmic enhancement [4].

Morphological Filters

For the edge detection, we propose several new morphological filters. The previously discussed morphological filters used MAX/MIN and MIN/MAX. These can have results skewed by the local brightness of an image. We improve upon these by utilizing the sum and the difference of these local image statistics. This new filter is performed as follows:

$$Y(i, j) = \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}} \tag{11}$$

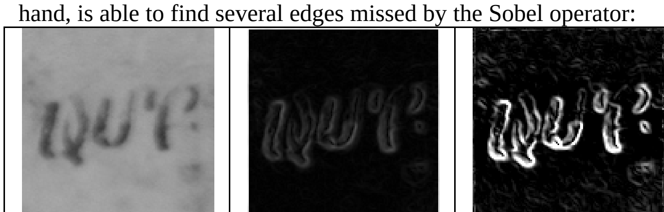
Where $Y(i, j)$ is the given pixel in the output image and max and min are the local maximum $I_{\max}$ and local minimum $I_{\min}$ respectively, in a small 3x3 window centered on the same pixel of the input image. This new filter can be improved upon by utilizing the logarithmic arithmetic, as follows:

$$Y(i, j) = \frac{I_{\max} \Theta I_{\min}}{I_{\max} \oplus I_{\min}}, \quad or \quad Y(i, j) = \frac{\log I_{\max} \Theta \log I_{\min}}{\log I_{\max} \oplus \log I_{\min}} \tag{12}$$

Computer Simulations

For our results, images were taken from a 14th Century text. The images show the common signs of aging; fading, blurring, and additive noise. For these images, a two step process was used. The first step was our edge enhancement step, and the second step was a contrast enhancement step.

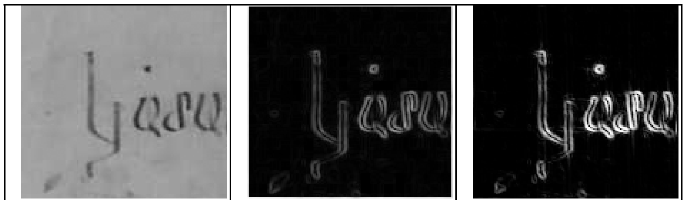
Figure 1 shows the results for our algorithm compared against the standard Sobel algorithm. Figure 1.a is the original image, figure 1.b is the output from the Sobel operator, and figure 1.c is the output from our algorithm. It shows that the Sobel operator is able to find the most obvious edges, however due to noise and fading the output is not clear. Also, portions of the second and third letters are missing. The proposed algorithm, on the other hand, is able to find several edges missed by the Sobel operator:



(a) (b) (c)

FIGURE 1: (a)Original image, (b)Output from Sobel Operator, (c)Output from proposed algorithm

Figure 2 shows the input image, output from the Sobel operator, and output from our algorithm. Again, the Sobel operator is able to find many of the edges, but the less obvious edges in the first letter are missed. The proposed algorithm finds more edges missed by the Sobel operator, such as the line one the bottom of the first letter and portions of the last letter.



(a) (b) (c)

Figure 2: (a)Original image, (b)Output from Sobel Operator, (c)Output from the proposed algorithm

Conclusion

In this paper we have presented new methods of enhancement and detection of edges and objects in images showing common signs of aging. It was shown that this algorithm performs better than the commonly used edge detection algorithms (for example Sobel algorithm). This algorithm can also be applied to problems outside of restoration, such as for enhancement of noisy or faded images.

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Author Biography

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