Visualization Using Rational Morphology and Zonal Magnitude-Reduction

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1 ABSTRACT

Morphological filters are investigated and employed for detecting and visualizing objects within an image. The techniques developed here will be employed on NASA's Earth Observing System (EOS) satellite data products for the purpose of anomaly detection. Previous efforts have shown the phase information in the spectral domain to be more significant than the magnitude information in representing the location of objects in an image. The magnitude information does provide some useful information for object location, but it is also sensitive to image illumination, blurring, and magnification variations, all of which influence the performance of object detection algorithms. Magnitude reduction techniques in the spectral domain can dramatically improve subsequent object detection methods by causing them to rely less on the magnitude and more on the phase information of the image. However, magnitude reduction enhances the high-frequency noise within an image, often causing unwanted noise to be interpreted as image objects.

We propose three new techniques for improved object detection and noise reduction. Our first method employs varying magnitude reductions within radially concentric zones, using increasingly greater reductions in higher frequency zones. By employing this zonal magnitude-reduction technique, we manage to attenuate the high-frequency noise component while still maintaining the improved visualization performance of the magnitude reduction method. Our second technique operates by utilizing several magnitude reductions of varying scale, performing object detection on each magnitude-reduced image, and combining the results for improved accuracy. This result-averaging method allows us to further reduce our false-alarm rate from high-frequency noise while increasing visualization performance. Our third method is a new technique which is based on the ratios of morphological filters. By combining classical morphological filters in this way, we are able to produce more robust results which can yield useful information as to the location of image objects.

Keywords: rational morphology, morphological filters, magnitude-reduction, alpha-rooting, object detection, object visualization, orthogonal transforms

2 INTRODUCTION

Visualization is the process of locating and enhancing objects within an image. Visualization is an excellent tool in preparing an image for further processing with techniques such as image segmentation, where an image is partitioned into its various regions or objects. Changes in the visualization algorithm also affect the quality of the image segmentation process. [1]

Morphological filters, a type of order-statistic filter, have been shown to be very useful in many image and signal processing applications.[1,2,9,10] These filters yield useful information as to the location of regions of interest (ROI's) within an image while maintaining low computational complexity.[3,10] For these reasons, we examine these filters for use in our visualization algorithms.

In order to classify image features for object detection and visualization, one should first seek a dimensionless measure which is invariant to image illumination and magnification.[4] If this measure is found, it can then be applied to any image without concern for brightness or scale. Gradient-based edge detection techniques[5,6,7] are sensitive to illumination and magnification, which means any threshold will need to be modified for each image. This technique is difficult because, in general, one does not know the brightness and magnification statistics of an image in advance.

Previous efforts in this area have shown that magnitude reduction techniques applied to the entire image can dramatically improve subsequent feature detection.[8] Since the magnitude is being reduced before visualization, any thresholding will be less effected by magnitude variations such as illumination and magnification. At the same time, magnitude reduction serves to enhance an image by increasing its high frequency components, thereby improving later efforts in visualization.

As an improvement to the magnitude reduction algorithm, we propose employing varying magnitude reductions within radially concentric zones. This zonal magnitude-reduction technique gives us much more flexibility in choosing the scale of our magnitude reductions in different regions within the frequency domain. By using increasingly greater reductions in higher frequency zones, we manage to attenuate the high-frequency noise component of an image. At the same time, we also maintain the enhancing effects of the magnitude reduction algorithm.

We propose an additional improvement to the visualization algorithm, which utilizes several magnitude reductions of varying scale. This technique performs object detection on each magnitude-reduced image and combines the results for improved accuracy. In each magnitude-reduced image, we detect many regions of interest as well as several noisy regions, which are confused for image objects. Since we will pick up different noisy regions in each image based on the amount of magnitude reduction, the noise components should average out over several images, leaving only true object features. This result-averaging method allows us to reduce our noise detection while increasing visualization performance.

As an extension of classical morphological filters, we propose various combinations of morphological filters, such as opening and closing[9,10]. These combinations can yield more robust and useful filters for finding ROI's. In this paper, we investigate Rational Morphological Transforms (RMT's) and employ them for detecting and visualizing objects.

3 RATIONAL MORPHOLOGICAL FILTERS

3.1 Morphological Filters

Morphology is one of the most active research areas of non-linear image processing. Its goal is to develop quantitative descriptions of geometrical structures. In recent years, significant advances have been made in the development of non-linear image processing techniques. Such techniques are used in digital image filtering, image enhancement, and edge detection.[11] One of the most important families of non-linear image filters is based on order statistics.[3] The widely used median filter is the best known filter of this family. Nonlinear filters based on order statistics are not greatly influenced by extreme data values, which helps them to perform well in the presence of impulsive noise. They tend to preserve edge information, which is very important to human perception. Their computation is also relatively easy and fast compared with some linear filters.

Morphological filters are a class of non-linear filters which respond based on the structure and topology of the input data.[12] In general, these filters work by passing a *structural element*[11] over the image and performing a particular operation on all pixels covered by the structural element. The basic binary morphological transformations are erosion and dilation. Erosion is the process of removing all boundary points of an object within an image, thereby shrinking the object. Dilation is the process of adding neighboring points to an object in an image, causing the object to expand.

The dilation of a set, **X**, by a structural element, **B**, is defined by:

$$X \oplus B = \bigcup_{b \in B} X_b$$

whereas the erosion of a set, **X**, by a structural element, **B**, is defined by:

$$X \ominus B = \bigcap_{b \in B} X_b$$

These binary morphological transforms can also be expanded to operate on gray-scale images. The 100th percentile order statistic filter, or maximum filter, performed on a gray-scale image is analogous to the binary dilation operation. Similarly, the 0th percentile order statistic filter, or minimum filter, in the gray-scale case is analogous to binary erosion. By utilizing these Max and Min operations, we are able to derive useful topological information from any gray-scale image.

Morphological filters operate by moving a structural element over an image, and performing the specified morphological operation on the pixels covered by that structural element. The central pixel of the structural element is then replaced by the result of the morphological operation.

In this paper, we investigate the ratios of morphological filtering operations in order to better understand and visualize the structure of objects within an image.

3.2 Rational Morphological Filters for Image Enhancement and Detection

Although the basic morphological operations are simple, they can be combined to produce more robust results. We present new filters which, are rational functions of the ratio of two morphological filters (for example, MF_1 – dilation and MF_2 – erosion).

$$R = \frac{\sum_{i=1}^{m} a^i \left(\frac{MF_1}{MF_2} \right)^i}{\sum_{j=0}^{n} b^j \left(\frac{MF_1}{MF_2} \right)^j}$$

Where a and b are constant. We will investigate the case where m=1 and n=0, which simplifies to:

$$R = \frac{a_1}{b_0} \left(\frac{MF_1}{MF_2} \right)$$

Finding the ratio of these two operations yields useful information about the location of object features in an image. In this article, we will use only the 3x3 case for the structural element (Figure 1). Note, the structural element size and shape can be varied based upon the application. Smaller structural elements are better for picking up fine details within an image. Larger structural elements are better at detecting bigger trends within an image, thereby eliminating any localized noise contained in a small region which might be inconsistent with the rest of the image.

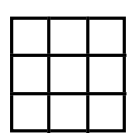

Figure 1. 3x3 Structural Element.

Now that we have defined the structure of the rational morphological filter, the problem becomes the selection of the ideal filter for our particular application. The basic problem is to determine what ratio of morphological operations to use, as well as which structural element will perform optimally.

3.3 Elementary Rational Morphological Filters

The MAX/MIN Filter

The rational morphological operation, MAX/MIN, or dilation/erosion, was investigated. Since both of these operations manipulate the edges of objects within an image, the proper ratio of these two quantities can yield useful information about the location of object edges. Intuitively, when the maximum and minimum values within a structural element vary greatly, the element is located above an area of great change, most likely an edge. In these areas, the MAX/MIN calculation will produce a much greater value than in areas of relatively little change. Thus, we have a useful tool for determining the boundaries of objects within an image.

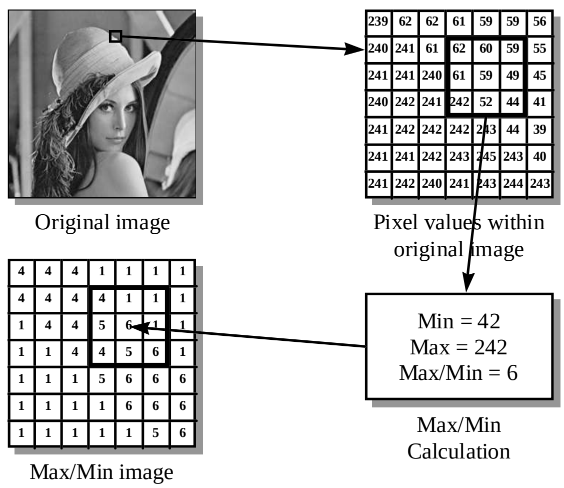

Figure 2. MAX/MIN Filtering.

The MIN/MAX Filter

The MAX/MIN filter succeeded in amplifying the borders of objects, but it also amplified much of the background noise contained within the image. Because of this noise, the edge determination was obscured and inaccurate. In order to circumvent this obstacle, we employed the MIN/MAX filter. The same methods used in the MAX/MIN filter were implemented in this filter, except that the central pixel of the moving sub-window was replaced with the minimum value divided by the maximum value. This filter suppressed the edges of the image rather than enhancing them. The experiments have shown that the MIN/MAX filter performed better at edge determination and avoided much of the noise enhancement problems of the MAX/MIN filter.

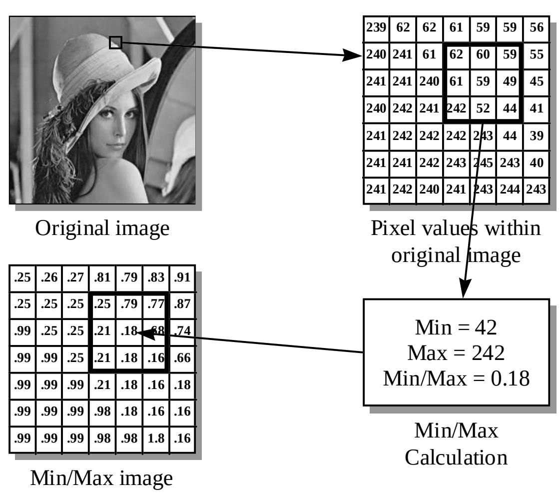

Figure 3. MIN/MAX Filtering.

The log MAX / log MIN Filter

The MAX/MIN and the MIN/MAX filters both work well in finding strong edges within an image, but neither are good at picking up more subtle edges. In order to accomplish this task, the higher values must be scaled down so as not to overshadow the smaller values. The log MAX/log MIN function solves this problem and allows us to make edge determinations on bold and subtle edges with the same filter.

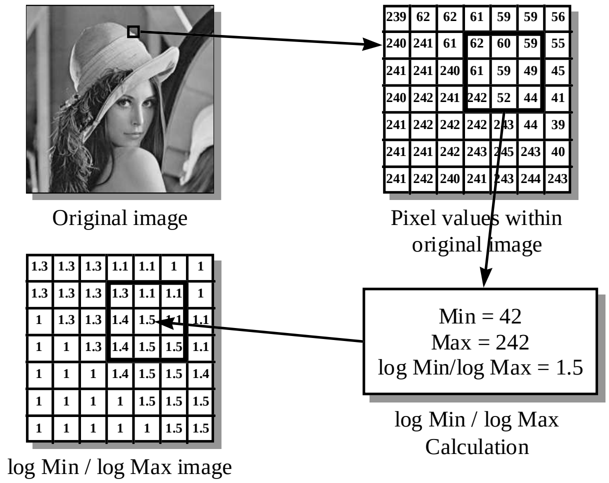

Figure 4. log MAX / log MIN Filtering.

The result of the log Max / log Min filter is shown below. As you can see, the borders of the image objects are enhanced while most of the background is suppressed. Very little noise is picked up as image features, as you can see in the thresholded image. Subtle edges are not overshadowed by stronger ones as a result of the log operation. The following algorithm for the determination of image features will be our standard upon which all subsequent improvements will be compared.

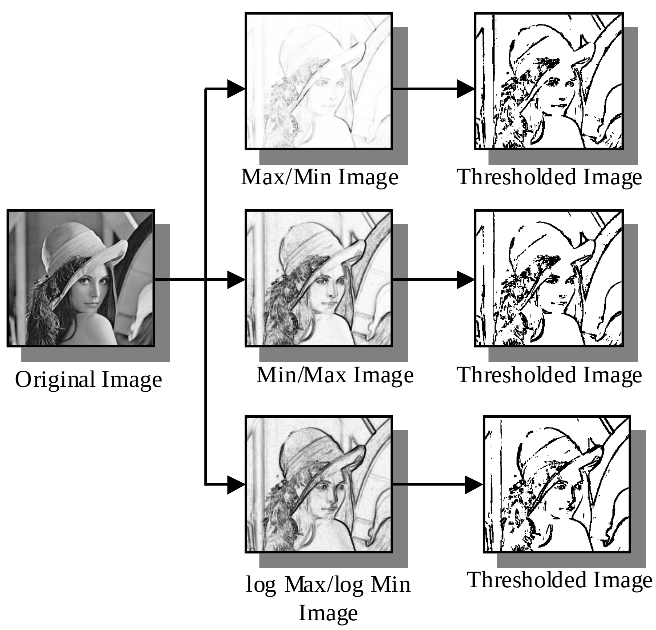

Figure 5. Thresholding of log Max / log Min Images.

4 FAST TRANSFORM AND IMAGE ENHANCEMENT

Orthogonal transforms play an important role in digital signal/image processing, such as filtering, coding, recognition, and restoration analysis.[13] Image transforms give spectral information about an image by decomposing the image into spectral coefficients that can be modified, linearly or non-linearly, for the purposes of enhancement and visualization.

4.1 Transform Image Enhancement Concept

Image enhancement involves processing an image to make it more satisfactory to the viewer. One class of image enhancement algorithms work within the frequency domain of an image by utilizing orthogonal transforms. These transforms allow us to view and manipulate the frequency composition of an image easily, without direct reliance on spatial information.

4.2 Magnitude Reduction (or Root Filtering) Method

In order to enhance our images before passing them through a visualization algorithm, we tried reducing the magnitude information of the image while leaving the phase information intact. Since the phase information is much more significant than the magnitude information in the determination of edges[4], reducing the magnitude produces better edge detection capabilities. This method also tends to reduce the low-frequency components more than the high-frequency ones. Since most edge information is contained in the high-frequency region of the spectrum, the edges are enhanced using this method. By varying the alpha level of the reduced image (α=1.0 is an image with full magnitude information, α=0.0 is an image with no magnitude information), we were able to enhance the quality of our images for visualization. If we analyze the existing Root Filtering and Magnitude Reduction methods, we can see there is a common algorithm for these two.

Algorithm:

We propose the following method as our enhanced visualization algorithm:

Step 1. Perform orthogonal transform.
Step 2. Multiplication of transform coefficients by some factor, C(n,m).
Step 3. Perform inverse orthogonal transform.

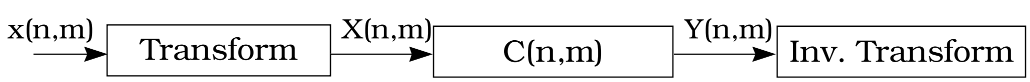

Figure 6. Enhanced Visualization via Magnitude Reduction.

Where:

$$Y(n,m) = X(n,m) \cdot C(n,m)$$

X(n,m) are our Fourier coefficients. Initially, we will choose C(n,m) to be constant.

$$\mathbf{1)}\ \ C(n,m) = \text{constant}$$

Note, C(n,m) must be a real number because we only wish to alter the magnitude information, not the phase information. Keeping C(n,m) real is our only restriction, which allows us to define several other possibilities for C(n,m) which can offer much more flexibility.

2) $C_1(n,m) = |X(n,m)|^{\alpha-1},\ 0 \le \alpha < 1$

3) $C_2(n,m) = \log^{\beta}\left[|X(n,m)| + 1\right],\ 0 \le \beta$

4) $C_3(n,m) = C_1(n,m) \cdot C_2(n,m)$

The result, Y(n,m), is an enhanced image, which can now be passed through a visualization algorithm such as the morphological operations described above. The results of the visualization algorithms will be more accurate because they will be operating on these enhanced images. They will also be less dependent on magnitude variations based on magnification and blurring, so it will be much easier to set a thresholding constant.

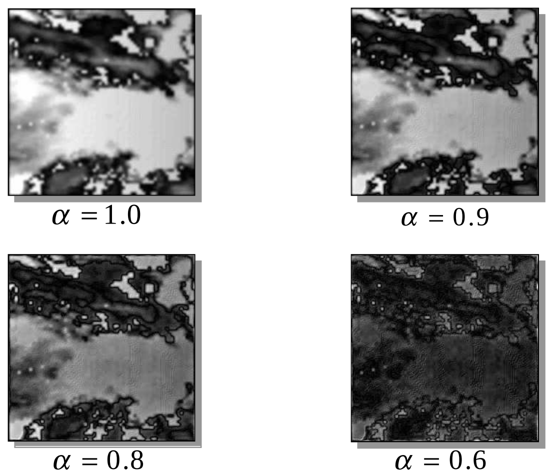

Figure 7. Result of Varying Magnitude Reductions on NASA EOS Cloud Data.

4.3 Zonal Magnitude Reduction Method

Classical magnitude reduction techniques are performed uniformly over the entire frequency spectrum. As an expansion of this technique, we propose employing varying magnitude reductions within radially concentric zones. By using this technique, we achieve much more flexibility and control over our magnitude reductions in different regions within the frequency domain. By using increasingly greater reductions in higher frequency zones, we manage to attenuate the high-frequency noise component of an image. At the same time, we also maintain the enhancing effects of the magnitude reduction algorithm.

In order to accomplish this zonal magnitude reduction, we first find the maximum and minimum values within the frequency domain data. Using these maximum and minimum points as end-markers, we then divide the frequency domain into regions based on each point's magnitude distance from the maximum and minimum. We set distance dividers between the maximum and minimum points, which divide the frequency domain into regions. Each region has a specified magnitude reduction value, α.

For the example image shown below, we must determine the four α values, as well as the three d (distance) values in order to specify our magnitude reductions. These values are determined empirically and are altered using trial and error methods until the desired results are attained.

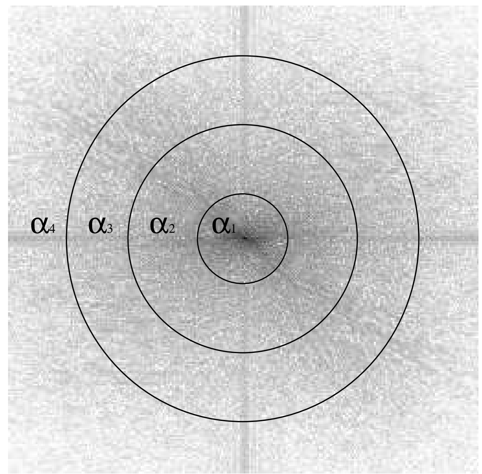

Figure 8. Zonal Magnitude Reduction Algorithm.

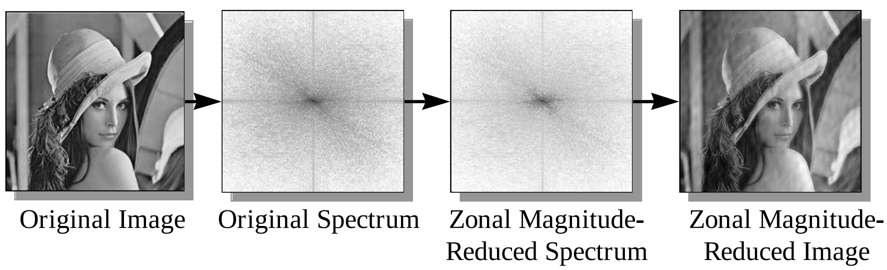

Figure 9. Zonal Magnitude Reduction.

4.4 Zonal log Magnitude Reduction Method

When using the zonal magnitude reduction technique, we found that the very large magnitudes of the sample would skew the distribution of points, causing an extremely uneven division of the points into the separate regions. As an improvement to the zonal magnitude reduction technique, we first compute the log of the frequency magnitude before dividing it into separate regions. This technique manages to scale down the extremely large magnitudes and provides for a more even distribution within the regions. From this point forward, when we refer to zonal magnitude reduction, we imply the inclusion of the log technique for improved zone classification.

4.5 Combinational Method

The visualization algorithms used earlier to determine regions of interest (ROI's) within an image run into the problem of picking up background noise as unwanted ROI's. As we increase our threshold to pick up more ROI's, we also are forced to pick up more background noise in the process. Magnitude reduction is a non-linear process which causes a visualization algorithm to make different determinations on ROI's in an image. We found that by reducing the magnitude of the same image by differing amounts, our visualization algorithm classifies different background noise as ROI's in each image. We found that by determining the ROI's in each of these magnitude-reduced images and then averaging the results, the varying noise component would average out while the desired image objects would be consistent from image to image. Therefore, this combinational method should allow us to pick up a great deal of image objects while avoiding much of the background noise.

Algorithm:

We propose the following method for combining the information in various magnitude-reduced images:

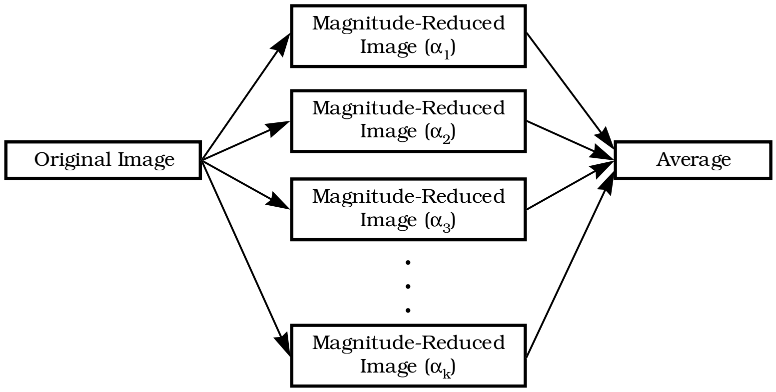

Figure 10. Algorithm for Combining Magnitude Reductions.

Increasing the number of magnitude reductions, k, will produce better results, but will also increase computation time. In the example below, we choose k=4, and α values of 0.9, 0.8, 0.7, and 0.6. We then make edge determinations on each of the log Max / log Min images. These thresholded images are then averaged and thresholded again in order to make the final edge determination. As you can see, our final image is a better determination of the edges than any of the initial four images. Using this technique, we manage to increase the visualization ability of our algorithm while reducing background noise.

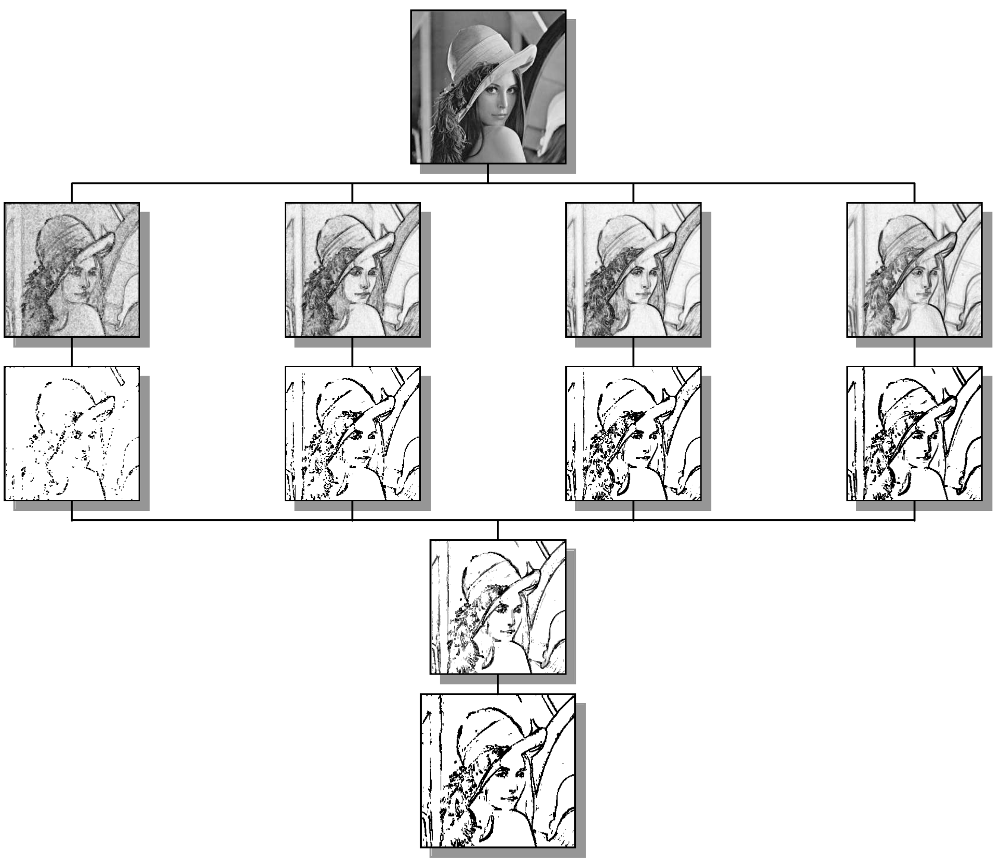

Figure 11. Combining Several Magnitude Reductions.

5 Image Enhancement and Visualization Using Rational Morphology and Zonal Magnitude Reduction

Combining the improved image enhancement technique of zonal magnitude reduction with the improved visualization performance of the log Max / log Min rational morphological filter dramatically increases our visualization accuracy. Using these techniques, we manage to detect most edges of image objects while avoiding most of the background noise content of the image. We show our technique in Figure 12. For this example, we set the α levels in regions 1 through 4 to 1.0, 0.9, 0.7, and 0.5 respectively, while the distances, d, were set to 0.5, 0.7, and 0.9. A value of 0.7 signifies that all points with magnitude values below the 70^{th} percentile fall below the divider, while all points with magnitude values above the 70^{th} percentile fall above the divider. These values were determined empirically through experimentation.

Original Spectrum | Zonal Magnitude-Reduced Spectrum | Zonal Magnitude-Reduced Image | log Max / log Min Image | Thresholded Image

Figure 12. Visualization Using Zonal Magnitude Reduction.

In Figure 13, we compare the three techniques we developed. The first technique uses the rational morphological filter, log Max / log Min, on the original image in order to make edge determinations. This technique makes a good determination of the edges, but still picks up a fair amount of background noise from the image. The second technique uses our result-averaging method, which combines several log Max / log Min calculations in order to reduce background noise. This technique results in better edge determination with less noise than rational morphology alone. Our third technique reduces the magnitude in zones, then computes the log Max / log Min filter on the enhanced image. This technique makes the best edge determination while picking up the least amount of background noise.

Original Technique (log Max / log Min) | Result-Averaging Technique | Zonal Magnitude Reduction Technique

Figure 13. Comparison of Results.

6 CONCLUSIONS

We have implemented rational morphological transforms and have successfully utilized them in order to achieve superior visualization. After comparing several rational morphological transforms, we found the log Max / log Min transform to be best at making edge determinations while avoiding much of the background noise contained within the image.

We have also developed two new techniques which improve upon rational morphological filters. Our first method, which combines the results of several magnitude-reduced rational morphological images, provided improved accuracy and noise reduction by averaging out background noise. This result-averaging method reduced our false-alarm rate from high-frequency noise and increased visualization performance.

Our second improvement enhances images before they are passed through a rational morphological filter. This method employs varying magnitude reductions within radially concentric zones, using increasingly greater reductions in higher frequency zones. By employing this zonal magnitude-reduction technique, we managed to attenuate the high-frequency noise component while still maintaining the improved visualization performance of the magnitude-reduced RMT.

7 ACKNOWLEDGEMENTS

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