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IMAGE NOISE REDUCTION USING MATHEMATICAL MORPHOLOGY SIZE DISTRIBUTIONS

A NEW IMAGE NOISE REDUCTION AND COMPRESSION ALGORITHM FOR GRAYSCALE IMAGES

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ABSTRACT

Morphological openings and closings are useful for the smoothing of grayscale images. However, their use for image noise reduction is limited by their tendency to remove important, thin features from an image along with the noise. This paper is a description and analysis of a new morphological image noise reduction and compression (INRC) that preserves thin features while removing noise. INRC is useful for grayscale images corrupted by dense, low-amplitude, random or patterned noise. Such noise is typical of scanned or still-video images. INRC differs from previous morphological noise filters in that it manipulates residual images – the differences between the original image and morphologically smoothed versions. It calculates residuals on a number of different scales via a morphological size distribution. It discards regions in the various residuals that it judges to contain noise. INRC creates a cleaned image by recombining the processed residual images with a smoothed version.

Keywords: *Morphological Openings, Smoothing of Grayscale Images, INRC, Noise Flter, Compression Algorithm*

1. INTRODUCTION

Many techniques for noise reduction replace each pixel with some function of the pixel's neighborhood. Because 1D features and 2D noise usually have common frequency components, they are not separable in the frequency domain. Hence, linear filters seldom can meet goals 1 and 2 simultaneously. Linear filters tend either to amplify the noise along with the 1D features, or to smooth out the noise and blur the 1D features. To minimize the conflict between goals 1 and 2 above, researchers have introduced a number of adaptive noise reduction algorithms

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2. PREVIOUS WORKS ON MORPHOLOGICAL SMOOTHING

Morphological filters are, perhaps, the most well-known nonlinear filters for image enhancement . These include erosions, dilations, openings, closings, and rank filters including the median filter. The action of a morphological filter depends on its structuring element, a small, quasi-image that defines the operational neighborhood of a pixel. The median filter is very good at removing some types of noise (notably shot noise or "salt and pepper" noise) while preserving some edges (perfect step edges). It is not so good, however, at removing dense noise, and it degrades thin lines and small features (smaller than half the area of its structuring element). Bovik provides a detailed analysis of the artifacts introduced by median filters.

Sternberg introduced the idea of image noise reduction through iterative application of openings and closings with successively larger structuring elements. This technique, called an "alternating sequential filter" (ASF) by Serra, is good for recovering some approximation of a structure that is nearly invisible in dense, high amplitude noise. It is inherently incapable of restoring image structures that are thinner than the largest structuring element used.

Song and Delp have devised a technique which they call the "generalized morphological filter". It takes linear combinations of the results of openings and closings with multiple structuring elements. This filter works well in the presence of impulsive noise. However, in the presence of dense noise there is a trade-off between noise smoothing and detail preservation. Moreover, there is no systematic approach for the exact specification of the structuring elements. Good results in different images probably depend on the choice of structuring elements.

The ASF and the Song-Delp algorithms remove noise from images because openings and closings annihilate image features whose support (i.e., area in the image) does not cover the structuring element. That is, they eliminate small features and thin features. On the other hand, these operations do preserve features that can contain the structuring element. Since features partition an image, opening and closing preserve those edges which are the boundaries between sufficiently large features. Edges that are boundaries between regions are preserved if they have zero width. That is, they are the visual result of one smooth region abutting another. The boundary itself has no support. The 1D features which are annihilated by opening and closing are thin features that do have support in the image, such as a dark line across a bright region.

3. ANALYSIS OF IMAGE PARAMETERS

There are a number of free parameters in the INRC algorithm.

- k, the number of size-bands to compute
- d_k, the sizes of the structuring elements;
- f, the residual threshold multiplication factor;
- s, the minimum number of non-isolated pixels in any 3 × 3 neighborhood of the cleaned up residuals;
- both f and s can be specified separately
- the structuring elements can be flat or hemispherical on top.

Experience gleaned from applying the algorithm to over 100 images (from about 2562 to 10002 in size) suggests that good default values are k = 3 with SE sizes 5, 9, and 17 f = 1 and s = 3. The values are good for images of up to about a million pixels in area to be viewed on a computer monitor screen.

4. THE INRC ALGORITHM

The fundamental idea behind the morphological image-cleaning algorithm is to segment into features and noise, the residual image that is the difference between an original image and a smoothed version. The features from the residual are added back to the smoothed image. Ideally, this results in an image whose edges and other one dimensional features are as sharp as the original yet has smooth regions between them. A rough sketch of the INRC algorithm follows:

Consider a noisy grayscale image I. Let S be the result of smoothing I with openings and closings. Assume S is noise free. Then the difference image, D = I − S contains all the noise in I. But, S cannot contain any features with nonzero support that are thinner than the structuring elements used to create it. Thus, D contains features as well as noise. If the noise in I has a smaller dynamic range than the thin features, then D will contain noise at lower amplitude levels and features at higher amplitudes. Experience with many scanned and still-video images has demonstrated that this is often the case (See section 4). If D is thresholded (actually, center-clipped since D is a signed image) at a value greater than the amplitude of the noise, the result is a support map or mask of the thin features in the image. The mask after further manipulation can be used to recombine the thin features in D with S while leaving the noise behind. The result is an image that is smoothly varying except for edges, thin lines and small spots. The algorithm described below is an elaboration of this idea using a morphological size distribution to isolate features from noise on different scales.

5. NOISE AND IMAGE FIDELITY

The removal of the noise pattern requires some special treatment. Analysis of the individual size-bands showed that the pattern was completely contained in the band bounded by d = 9 and d = 17, where it was the dominant feature.The thresholds for this size-band were chosen very high at f = 2.5. However, the remaining size-bands were thresholded comparatively lower, at f = 1.25. Recombining all the thresholded residuals with a d = 33 OCCO smoothed version produced the image of panel (e). A straightforward application of INRC with f = 1.25 did not remove the noise pattern; using f = 2.5 removed most all the features along with the pattern. By thresholding the residuals at different levels INRC was able to remove the pattern.

To understand quantitatively the capabilities and limitations of a noise reduction algorithm one must analyze the algorithm under controlled conditions. To test INRC, a noise free image was found. A set of 15 images was created by adding noise of different variances to the original image. INRC was applied to the individual images. The images were median filtered for comparison. A low variance (nearly constant) area was selected in the original image. The noise was measured in the corresponding area in each of the noisy images before and after processing.

Two different measurements were made. The first was a measure of the noise standard deviation, σ, in a nearly constant 50 × 50 region of each image. The second was a comparison of each image with the original using a similarity metric. The metric is the energy of the difference between two images divided by the energy in one of them (the reference image).

6. EFFECT OF THE ALGORITHM

For larger standard deviations, the median filter produces better results. One can calculate the standard deviation of the features in the original, clean test image, I, by subtracting from it OCCO(I,17), the openclose - closeopen average computed with a structuring element diameter d = 17. The residual can be considered to contain features alone because I is noise free and d = 17 is the diameter of the largest SE used in the 4 cleanings above. This residual, hence the features, had σ = 10.6750. From this value and the perception that the INRC algorithm outperforms the median filter on the noisy test images for σ's up to about 6, one could state that INRC works well on images for which the the noise σ is no greater than one half of the feature σ.

A useful aspect of INRC is that it enhances JPEG compression. The image compression algorithm known as JPEG is a transform coding scheme. It partitions an image into blocks, computes the discrete cosine transform (DCT) of each block and codes each DCT component according to a quantization scheme as a function of the magnitude of the component. The compression is greatest for constant or slowly varying blocks since these can be described by just a few DCT components. If an image is noisy, even slightly, then all its constant or slowly varying regions are degraded. More DCT coefficients are necessary to code the block. This results in a larger compressed file. In effect, JPEG devotes a significant portion of the resulting file to coding the noise.

Clearly any procedure that will reduce the noise in an image is bound to improve the compression. To test INRC in this capacity, 36 scanned images were taken from the newsgroup. It is presumed that all of the images were scanned. None of them were images created directly by a computer. INRC processed the images with two size-bands, d = 5 and d = 9, and used s = 3. The algorithm was run twice; once with f = 1.0 and once with f = 1.5. With f = 1 INRC is very conservative; its noise reduction, although pronounced, is at a minimum. Under these conditions, the average reduction in file size was 12%.

7. CONCLUSION

This paper has presented a new algorithm, INRC, for image noise reduction based on morphological size distributions. INRC smoothes the image in a number of size-bands, subtracts these bands out of the image to create residual images, segments the residuals into features and noise, and adds the features back to the smoothed image. The algorithm was shown to be useful in removing noise and scanner artifacts in images where the standard deviation of the noise is not large. In a test case where it was possible to compute the relative standard deviations, it was shown that the standard deviation of the noise should not exceed one half of the standard deviation of the features in the residual. Such small noise levels are often the case in scanned and still video images.

Successful use of INRC requires a user to set three parameters, the number of size-bands, a residual segmentation threshold multiplication factor, and a segmentation neighborhood support size. Default values for these parameters were suggested, and the effects of parametric variations were reviewed. The results of the algorithm were compared to those of median filtering and the Song-Delp generalized morphological filter and shown to be superior when the noise conditions are met by the input imagery. A noise analysis was performed under controlled conditions of adding noise to a noise free test image. The algorithm was shown to useful for the preprocessing of images for JPEG compression where it resulted in an average size reduction of 12% when applied with its most conservative parameters.

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RESULS:

Original image test.jpeg

Result of the new algorithm applied to test.jpeg