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SPARSE COLOUR AND GREY SCALE IMAGE RESTORATION USING A MORPHOLOGICAL METHOD

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ABSTRACT

In an experimental study on colour and grey scale images coveting a range of corruption from 50 to 95%, good restoration was achieved using a new morphological method. The nearest good neighbour (NGN) morphological filter copies grey scale values from the 'good' pixels in a regular manner so that these pixels become seeds for the restoration during successive iterations. A complementary propagation method is also described. In this context, sparse data refers to an image in which a large fraction of the data has been replaced by impulsive noise. The impulse noise may have a high value or range or a zero or null value. Random loss of an image communication channel will result in a sparse image which may be restored by these methods. Range images or optic flow data may be processed by these methods also. On a face image which had lost 95% of its data, the restored image had a signal to noise ratio of 16dB and all features were clearly discernable. The filter had an 8 pixel neighbourhood and took about 0.5 second per iteration to filter the image on a 386 standard PC.

1.0. INTRODUCTION

Corrupted images, ie pictures that are subject to heavy impulsive noise degradation or loss of data, which have lost more than half their data have been effectively restored with a new morphological filter described here. Conventional filters which use smoothing or median values statistics are relatively ineffective when 50% or more of the image is lost.[3],[4] By using morphological filters which do not use average or median values, far better results are obtained for image restoration. These filters require that the range of the image corruption is known a priori. If the image is sparse in a conventional sense, corrupted pixels have a grey level of zero, tests may be made on the pixel neighbourhood to ascertain a better grey scale value for the restored image value. Clearly the original image will also contain of pixels in the same range as the interference. This will not matter if the range of corruption values is not too large. Satisfactory results have been obtained with interference ranges of up to half the image grey scale range. The success of the method relies on a normal level of correlation within the original image. Restoration of a truly random image is impossible whereas the improvement in more conventional images, a human face for example is quite marked. More sophisticated smoothing methods which minimise data errors and edge values [1] start to fail when image impulsive noise corruption rises above 90% due to the small support region of these methods. An earlier non-iterative method which gave much greater grey spatial dislocation and hence poorer results was reported in [2].

1.1. PRINCIPLE OF MORPHOLOGICAL FILTER

There are two ways the morphological filtering method may be performed. In the first, the nearest good neighbour (NGN) method, the value of the current image pixel is checked and if it is within the interference range, a data pixel from its nearest non-null valued neighbour is copied to it. A null value here means a pixel within the interference range. For example, if the image was simply sparse data, the null value is zero brightness and a non-zero value is copied to the current, zero valued pixel position. In the second method, termed the pixel propagation method, if the current pixel is a 'good' data value ie not a member of the null pixel set, it is propagated to its null values neighbours. If the current pixel is a null value, it is ignored. Eventually the pixel will be restored by a non-interference pixel value propagated to it from a nearby pixel. These methods differ from rank filtering in that no ranking of the pixel values is attempted and that the output depends on spatial relationships, not rank order. Restoration methods may use separate buffers or a single buffer for input and output. With iterative methods and a single buffer, care must be taken to avoid excessive streaking. In this study, the NGN method using a 3x3 neighbourhood was used for the colour image restoration and the results iterated until the SNR became essentially constant. For the grey scale images, the pixel replication method was used using a 2x2 pixel neighbourhood.

1.2. FORMAL DEFINITION OF NGN FILTER

A formal definition using set theory nomenclature for the NGN filter is as follows:

$$Sij(d) = \{ I(rs)|D(ij);(rs) = d|,\ I(rs) \notin C \}$$

Sij(d) is the set of good pixels at distance d from ij.

Sij(0) is the one element set containing Iij if lij is 'good' otherwise it is null. D is the integer distance measure function. Distance refers to the distance from the pixel output location to the nearest "good" pixel ie the distance from ij to rs. C is the set of noise impulses.

I(rs) is a good pixel adjacent to ij. The pixel replication method is essentially the complement of this definition.

1.3. PIXEL REGION CONSIDERATIONS

As the fraction of corrupted pixels increases, the size of the pixel neighbourhood can be increased in order to speed up the restoration, or in iterative methods a larger number of iterations can be made. For very high levels- of corruption, more and more null values will result in slow restoration due to zero propagation of interference pixels. For a 90% corrupted image, a 3x3 pixel block size gave good results. It is important to minimise the pixel neighbourhood replication area and to copy pixels in an omnidirectional way, ie to replicate the pixel that is truly closest to the current pixel position, to minimise spatial bias in the restored image.

1.4. RESTORATION COLOUR ERRORS

The eye has lower sensitivity to chrominance (colour) errors compared with luminance errors and appear to be routed to independent neural channels, according to research into the psychophysical features of human vision.[51 Since straight morphological restoration will always replicate the data in the original image, there will be no new colours in the replicated data. Restored image points will replicate values in the sparse data. This will not always be correct when rapid changes in colour occur at different image neighbourhood boundaries for example. As data values become sparser, colour errors will occur more frequently and the requirement for further processing increases. Post-processing using median filtering of colour indexes will reduce splatter due to inter-mingling of colours at image regions of different colours or rapid changes in colour. Post-processing of the restored data will increase SNR by up to ldB using grey scale fidelity measures and is particularly necessary for the larger regions produced by the NGN filter when data is sparse. Smoothing filters can be used for post-processing filters for grey scale images but not for colour pictures. Median filters will reduce splatter due to colour intermingling at image region boundaries by rejecting outliers caused by replication of pixels from a different colour region, giving a small but significant improvement.

1.5. IMAGE RESTORATION MEASURES

The signal to noise ratio (SNR) of the original image to the restored image was used for an objective image quality measure. This measure is the sum of the original image pixel brightness values squared divided by the sum of the differences between the original and the restored image squared expressed in decibels. This is entirely conventional for grey scale images but for colour images, colour index values, were used to compute the SNR. This does correlate with restoration quality but not as well as for grey scale images. Another method which does not require the original image data is to count the comipt pixels remaining and to iterate until the number of corrupt pixels is normal, ie has a popularity similar to other pixels close to the corruption range.

1.6. COLOUR IMAGE RESULTS, NGN RESTORATION

A colour coastal scene was corrupted by null value impulses. at 50% and 90% data losses. The colour result while having appreciable artefacts was again much more pleasing than the corrupted image. Colour restorations will be shown at the conference presentation. Note SNR values are calculated using colour indexes rather than RGB colour values for convenience.

Colour Restoration Results

% Data Loss	SNR	Restored SNR
50	3.06	6.85 dB
90	0.43	3.96 dB

The restored images were generated using an iterated 3x3 pixel search block.

1.6.1. Discussion, Colour Restorations

A restored image was generated using the 50% data loss RGB picture using a 3x3 search block. Subjective examination of the restored image showed that the image was essentially identical to the original uncorrupted image. Closer examination showed a few colour spots which were different to the original. The restoration of the 90% data loss image gave a recognisable image but with considerable loss of fine detail, as the pictorial results show and splatter of adjacent areas into one another.

1.7. DISCUSSION AND GREY SCALE RESULTS

For the data presented here, Lena at corruption levels of 50%, 90% and 95% data loss were investigated. This was done by setting to zero the image pixels at random locations at the above percentages. Image data was in 8 bit grey scale format. Pictorial results are shown on the final page showing the 90 and 95% grey scale restorations. SNR results are tabulated as shown. Even at 99% data loss a face was obtained with all features recognisable with no post-processing. On grey scale images, after morphological restoration, smoothness based techniques can be used to improve the SNR by 0.5-2dB depending on the sparseness of the original data.

Picture Data loss	Original SNR dB	# of iterations. No
50%	26.08	5
90%	19.44	10
95%	17.41	15

1.8. CONCLUSION

A new method of morphologically restoring images that have been corrupted by impulse noise has been presented. It has been shown to perform satisfactorily on colour and grey scale images. Conventional order statistic filters which use the median or ranked values are relatively ineffective when 50% or more of the image is lost.[3],[4]. On a face image, rank filters gave a result some 7dB less than this method with much greater artefacts. The morphological restoration may use a nearest good neighbour method or a pixel replication technique. It should be noted that as images become more corrupted, pixels will be propagated for longer distances and larger spatial dislocation errors will occur giving poorer restoration results. Methods may use a single or dual buffer method for the restoration. Pictures with corruption of up to 95% of image pixels for grey scale images and up to 90% for a colour scene have been restored by these methods.

1.9. REFERENCES

[1] Blake A. Zisserrnan A. "Invariant Surface Reconstruction Using Weak Continuity Restraints" Proc. CVPR Conference CVPR-86 June 22-26 Miami Beach Florida 1986 pp62-67

[2] Harvey, A.L. Cohen, H.A. “Visual Reconstruction of Sparse Images using a Non-Linear Filter”. ISSPA 92, Gold Coast, Australia 1992 pp101-104

[3] Narendra, P.M. (1980) “A Separable Median Filter for image noise smoothing”. IEEE Trans PAMI 3 pp20-29

[4] Nodes, T.A. Galleger, N.C. (1982) “Median Filters: some modifications and their properties”, IEEE Trans ASSP 30 pp739-746.

[5] Lennie P., Eds: Spillman L & Werner J "Parallel Processing of Visual Information", Visual Perception, The Neurophysical Foundations”, J.Academic Press, 1990

[6] Press W.H, Flannery B.P,Teukolsk5,˙ S.A, Vetterling W.T. (1988) "Numerical Recipes in C", Cambridge University Press pp673-680.

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Clockwise from top left:

Figure 1. 90% Image Corruption
Figure 2. 90% Restoration
Figure 3. Lena Original
Figure 4. 95% Restoration