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IMAGE RESTORATION VIA N-NEAREST NEIGHBOUR CLASSIFICATION

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ABSTRACT

A novel and powerful perspective on image reconstruction and restoration is to regard the computational objective as the classification of corrupt (= unclassified) pixels using the classification of the nearest uncorrupt (classified) pixels. In N-nearest neighbour (NNN) restoration, the distance transform is used to determine the set of N-or-more classified pixels which are as close, or closer, than the Nth nearest to each corrupt pixel. NNN classification includes classic restoration algorithms, but new algorithms are implied, especially for color and gray-scale images that are very sparse or highly corrupt. We present experimental results for an NNN restoration algorithm, for N=1using for nearest set classification the median of the one-or-more nearest 'good' neighbours. At low corruption levels this algorithm is equivalent to classic median filtering; for images with random pixel loss of 50% to 90%, satisfactory restoration has been achieved for both gray-scale and colour images.

1. INTRODUCTION

The prime objective of this paper is to present a new perspectiive on image restoration based on the notion of classification. In classic image restoration algorithms attention is confined to an image window of fixed size surrounding each pixel, and all pixel values within that window are used for restoration. Here, in contrast, we propose the use of the N nearest good pixel values for the restoration of a corrupt pixel.

As more than one uncorrupted neighbour may be equidistant in the image, the set of good pixels that are as close, or closer, than the Nth closest, contains at least N good pixels,
but possibly more.

The term restoration is used here in a very broad, sense to encompass both extremes as the repair of images subject to a minor amount of shot noise, and to the activity that mostly goes under the phrase "image reconstruction".

The classic restoration methods based on averaging and median filtering, replace significantly corrupt pixels by values closer to the statistical average within the filter window. Thus the classifier concept may be considered to be also implicit in the-traditional restoration methods. However the general methods to be introduced have a wider gamut

Image reconstruction is mostly concerned to devise methods of 'completing' or ‘reconstructing' an image that is incomplete or irregularly sampled. Data may be incomplete due to sensor and transmission problems, or because of inadequacies of earlier processing stages. Examples include: drop-outs as by range sensors, corruption in transmission by shot noise, local disparity between two images, local image flow not being estimable over locally smooth regions.

The image reconstruction algorithms based on the use of splines and membranes, notably those of Blake and Zisserman[1], essentially focussed on the use of 'good' pixel values within a window to supply the missing (or corrupted) values using a window function. A modest generalisation of that approach is to maintain unchanged those pixel value that are known to be good (uncorrupted).

In this paper we confine attention to the restoration of images where over some definite range of pixel values, pixels are (possibly) corrupt, but over other ranges the pixels can be considered valid, or "good". In the examples presented, purely Poisson salt or pepper noise has been applied to corrupt the image. Conventional median, or general rank filters, have poor capability when applied to images where some 50% or more of image data has been lost. [3][4]. However a small number of recent papers [5 and references therein][6] have been concerned primarily with gray-scale interpolation,

NNN image restoration involves the use of a distance trasnform to determine the N'th nearest 'good' pixel to every corrupt pixel. In the next section we review the DT. Explicit use of the DT was made by Borgefors[10] to eliminate crevices and peninsulas from the boundary of binary regions Combettes[7] has presented an elaborate set theoretic approach to restoration, which, however, was applied to the restoration of essentially binary images (characters) blurred with non-negative white noise,

In section 3 we give a formal specification of NNN restoration. In the subsequent section we present experimental results for the lowest order NNN restoration of gray-scale and coloured images.

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2.0 DT OPERATIONS

Rosenfeld and Pfaltz, [8][9] introduced the sequential algorithm for the computation of the distance transform using the following masks:

Chess-board Distance Masks

Forward Mask	Backward Mask
I I I	* 1
I *	I I I

Manhattan Distance Masks

Forward Mask	Backward Mask
∞ 1 ∞	* 1
1 *	∞ 1 ∞

Chamfer Distance Masks

Forward Mask	Backward Mask
4 3 4	* 3
3 *	4 3 4

Fig I DT masks. An asterisk (*) is used to denote the mask centre, ∞ is taken as the largest number in the number set used.

3	3	3	3	3	3	3
3	2	2	2	2	2	3
3	2	1	1	1	2	3
3	2	1	0	1	2	3
3	2	1	1	1	2	3
3	2	2	2	2	2	3
3	3	3	3	3	3	3

Chessboard distance

6	5	4	3	4	5	6
5	4	3	2	3	4	5
4	3	2	1	2	3	4
3	2	1	0	1	2	3
4	3	2	1	2	3	4
5	4	3	2	3	4	5
6	5	4	3	4	5	6

Manhattan distance

12	11	10	9	10	11	12
11	8	7	6	7	8	11
10	7	4	3	4	7	10
9	6	3	0	3	6	9
10	7	4	3	4	7	10
11	8	7	6	7	8	11
12	11	10	9	10	11	12

Chamfer Distance

Fig 2 Distribution of distance from an isolated pixel according to the three most useful DTs.

For the classic algorithm for binary images, the pixel value of the foreground is notionally zero. while the background is notionally. ∞*:* (conveniently represented by 0 and 255 for unsigned char) In the Rosenfeld-Pfaltz DT algorithm, the image is raster scanned, once forward, once backwards using masks as in Fig 1: if the pixel l[r][c] at the mask centre is 0. then it is unchanged, otherwise, it is given the value of the minimum under the mask M of M[i][j] + l[i+r][j+c]. subject to the rule oo+n = oo. The evolution of the algorithm is shown in Fig 3.

In applying the NNN restoration algorithm, one needs to be able to apply the reverse operation, determine all the pixels of the set that are at a given distance from any pixel outside the set. For this purpose, one needs to utilise the distance from an isolated pixel, as indicated in Fig 2.

3.0 NNN RESTORATION

The lowest level, N =l, NNN restoration algorithm, called NN restoration, precedes as follows:

Step 0 Produce a Distance Image D of the same size as the corrupted image 1. For (r,c) in image.
If l[r][c] is NOT corrupted
D[r][c] =0. else D[r][c] = ∞ (typically represented by 255 in unsigned char)

Step 2. Apply the DT of choice to determine the distance of every corrupt pixel from its nearest good pixel.

Step 3. For the pixel at (r,c) at a non-zero distance determine the set S(r.c) of good pixels at distance d from (r.c). (See Fig 2)

Step 4. Generate the restored image R:
If D[r][c] = 0, R[r][c] = l[r][c]
else R[r][c] = lazy median of S(r,c); for gray-scale images. the actual median if it exists, with random choice fixing selection otherwise. For the restoration of the indexed colour images, reported here. we have taken the lazy median of the index, with satisfactory results.

The most general NNN restoration Algorithm, is for neighbourhood classification containing at least the N=n >l closest neighbours.. The algorithm proceeds as per Step I and 2. Thence:

Step 3. For the pixel at (r.c) at a non-zero distance d. determine the set S(d, r.c) of good pixels at distance d from (r.c). Then determine S(d+l. r.c). S(d+2. r,c) ... until at least n good nearest neighbour pixels have been determined..

Step 4. Generate the restored image R:
lf D[r][c]=O, R[r][c] =l[r][c]
else R[r][c] = Classification Algorithm applied to the scalar valued gray-scale or vector-valued coloured pixels in the sets {S(d.r.c). S(d+l.r.c)...

4.0 EXPERIMENTAL RESULTS

Restoration data has been gathered in the range 50% - 90% corruption of the gray-scale Lena image and the 8-bit colour Clown images, and objectively measured in terms of the simple PSNR for gray-scale images, and the RGB-based PSNR for 8-bit indexed colour images. Better than 17 dB. and 12 dB enhancement for 85% corrupt Lena/Clown. Fig 4. and 5 show examples of rersration examples of restoration for Clown and Lena at 85% corrupt.

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5.0 CONCLUSIONS

A novel approach to image restoration has been presented, leading to the n Nearest Neighbour (NNN) restoration algorithm. The lowest order such algorithm, the NN Algorithm, involves replacing each pixel by the (lazy) median of the good pixels that are equally closest. Where the corrupted pixel is isolated and surrounded by good pixels, the Chessboard DT algorithm is very similar to median filtering. The experimental data, on both gray-scale and colour images, shows credible restoration, so this algorithm is remarkable in its range of application from images of minor corruption to images where as much as 90% image data has been lost. For practical application, the output of NN Restoration would clearly benefit from some smoothing operation. The acute reader will realise that a potential weakness of the NN algorithm is that an isolated valid pixel of locally exotic value, will tend to dominate the restoration of its immediate surroundings. This problem will be alleviated in the higher order NNN restoration algorithms, for which the distribution of pixels which are near, but not necessarily the closest to a corrupted pixel, can be used to determine the substitution value.

The basic idea of this approach, is to treat the problem of restoration and image reconstruction as a classification problem, with missing and/or corrupted pixel value to be determined from the cohort of the N nearest neighbours. This approach has an attractive universality; it comprehends both classic restoration algorithms, as well as being unusually applicable to highly sparse images. Experimental studies have been limited so far to the lowest order of NNN; inspire confidence in the further development of this strategy.

ACKNOWLEDGEMENT

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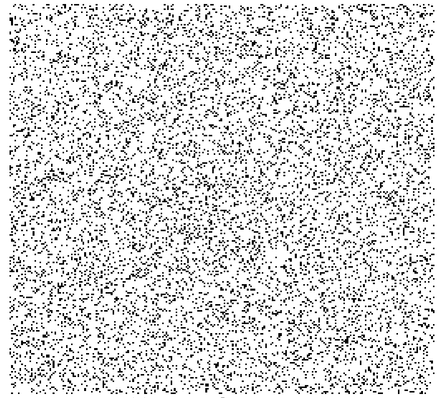
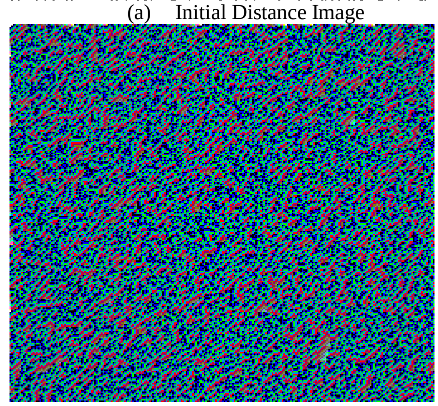
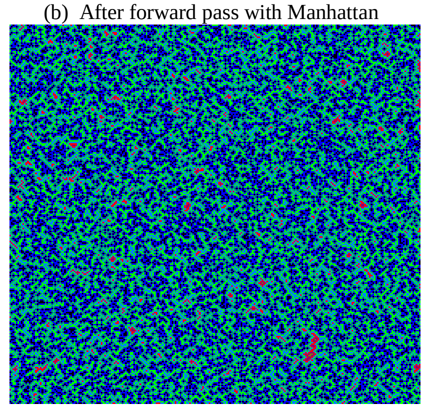


(a) Initial Distance Image



(b) After forward pass with Manhattan



(c)After the backward pass with Manhattan DT mask

(d) Colour-coding of the distance from the uncorrupted pixels from distance =0 to 15. Palette is periodic of period 16

Fig 3 Screen dumps showing the determination of distances from the good pixels in the Distance Image for the 85% corrupted Lena image of Fig 4 using colour coded distance

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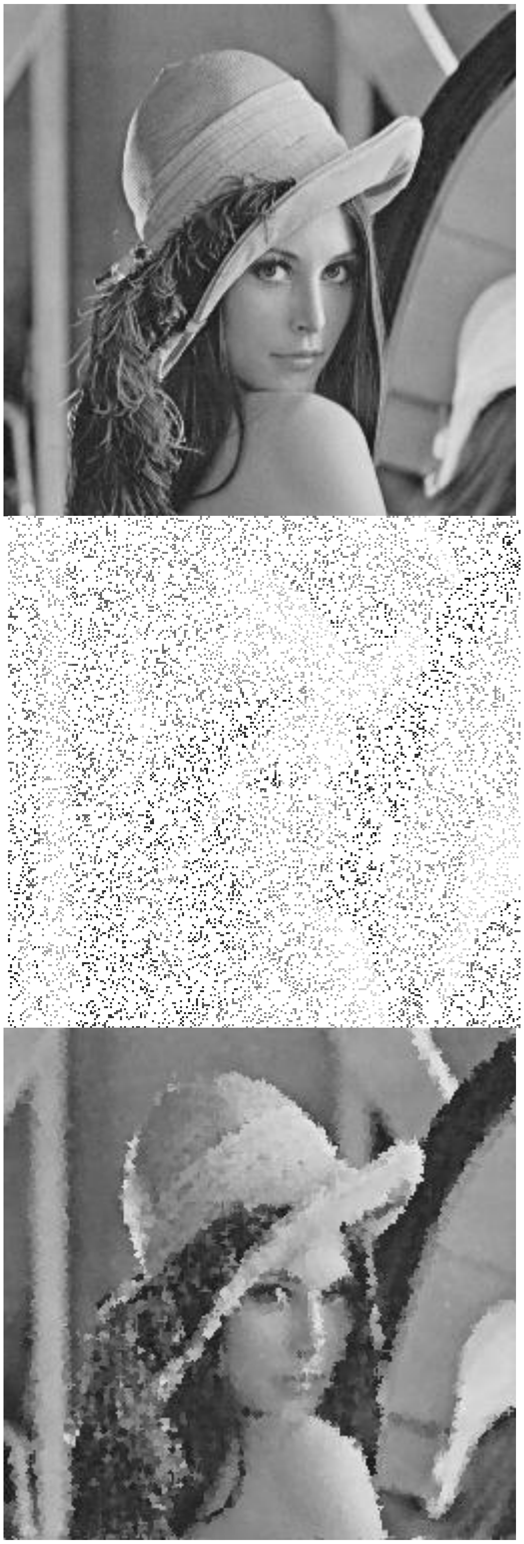

Fig 4 From top: 256x256 gray-scale Lena; corrupted by 85% white noise, PSNR = 5.916; restored using Manhattan Distance DT NN After restoration, PSNR = 22.673

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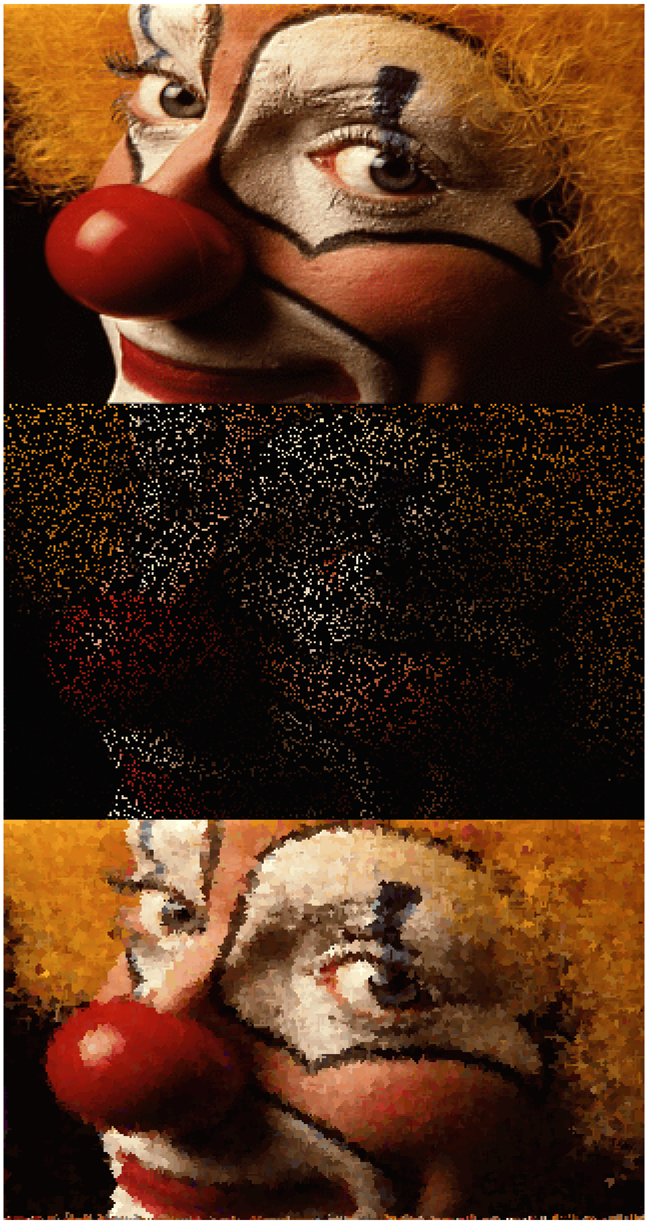

Fig 5 From left: 320x200 8-bit colour Clown; Clown corrupted by 85% black pepper noise, PSNR = 9.0452; restored using Manhattan Distance DT and NN restoration. PSNR - 21.6795

The colour images can be viewed on the author's home page http://homepage.cs.latrobe.edu.au/image/papers

NOTE IN PDF VERSION This paper was published in ICIP-96 Proceedings in gray-scale.