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X-RAY IMAGE ENHANCEMENT USING LOCAL STATISTICAL INFORMATION

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RESUME

L'utilisation des statistiques locales peut permettre de rehausser la visibilité des os et des tissus dans les images radiologiques. Les résultats d'un algorithme fondé sur la moyenne et l'écart-type locaux sont analysés. La performance de l'algorithme est évaluée en vue d'une réalisation matérielle.

SUMMARY

Local statistical information in X-ray images can be used to greatly enhance the visibility of bone and tissue structures. The results of an algorithm based on the local mean and standard deviation are evaluated. The algorithm itself is evaluated for its computational efficiency in view of a hardware implementation.

1. INTRODUCTION

X-ray images typically have a large overall contrast and a weak local contrast. The overall contrast is due to the difference between the patient and the background, and the local contrast is proportional to the difference of the X-ray absorption factor for the different tissues of the body. The strongest variations in the local contrast are caused by the presence and absence of bone tissue, but even these variations can be weak when the bones are superimposed on one another in the image or when the bones are relatively small. Local statistical image processing[1] can enhance these weak local contrasts so that the bones and another tissues can be more easily recognized.

2. ALGORITHM

In the X-ray image, we will consider each pixel (p) and the pixels in the local spatial neighborhood of that pixel. The images presented in this paper are all 512X512 pixel images with each pixel coded on 12 bits (Ø - 4095). We consider the mean (M) of a nxn square of pixels centered on the pixel, $p_{i,j}$ as :

$$(1)\quad M_{i,j,n} = \frac{1}{nxn} \sum_{r,s} p_{i+r,j+s}$$

where : $-n/2 < r < n/2$ $\qquad -n/2 < s < n/2$

We choose n as an odd integer to avoid ambiguity as to the center of the nxn square. After calculating the mean of the nxn square, we determine the variance of the region by the equation :

$$(2)\quad V_{i,j,n} = \frac{1}{nxn} \sum_{r,s} (p_{i+r,j+s} - M_{i,j,n})^2$$

with r and s as above.

The standard deviation (SD) is defined as the square root of the variance. Under the assumption that the standard deviation is a good measure of the local contrast variation, we can calculate a new value for the pixel at the center of this region to increase its difference from the mean. In expanding the difference of the pixel value from the calculated mean of its local neighborhood, the standard deviation of that same neighborhood in the newly calculated image increases, thus increasing the local contrast. We wish to increase the local contrast in a manner that emphasizes weak variations in the original image, thus the value of the new pixel is chosen to be proportional to the reciprocal of the calculated standard deviation.

$$(3)\quad p'_{i,j} = \frac{A}{SD_{i,j,n}}(p_{i,j} - M_{i,j,n}) + C$$

where A and C are constants.

A is a gain factor that corresponds to a desired standard deviation in the output image. C is a constant factor that corresponds to a desired mean in the output image.

Equation (3) has some disadvantages in that neighborhoods of uniform intensity cause the standard deviation term to approach zero which in turn causes an infinite gain. To avoid this problem, we add a "gain platform" term (GP) (see equation (4)). The other problem is that complete elimination of the original local mean information produces images that contain little low spatial frequency components and are thus too different from the original image. To avoid this second problem, we add in a component of the original local mean.

$$(4)\quad p'_{i,j} = \frac{A}{SD_{i,j,n} + GP}(p_{i,j} - M_{i,j,n}) + (x)C + (1-X)\,M_{i,j,n}$$

where $0 \leq X \leq 1$

For the images presented in this article, we have used :

A = 800 GP = .015 X = .95 C = 2150

n = 11,21,41,71,101

The values for A and C are dependent on the number of bits used to represent the pixel values. The useful range of the gain platform parameter is about .001 to 10, the ideal value depending on the image. The X parameter was found to be useful in the range .5 to 1, the ideal value again depending on the image. The most interesting parameter is the size of the nxn neighborhood as will be discussed in the next section.

3. RESULTS

Figures 1, 2 and 3 show the results of this algorithm (4) on three different images. The original images were digitized on a C.G.R. CE 10000 computer-aided Tomograph using the radiographic mode at a spatial resolution of 1024X1024 pixels. The "original" image in figures 1 and 2 are 512X512 pixel images where the value of each pixel is equal to arithmetic mean of the corresponding 2X2 pixel square in the unprocessed 1024x1024 image. Figure 3 is a 512X512 subsection from its original 1024x1024 form. The parameters for the algorithm are the same for all of the processed images (as defined in the previous section) with the exception of the size of the nxn neighborhood as noted. The overall brightness and contrast have been manipulated with a linear transformation to subjectively optimise their appearance.

Figure 1 shows a head X-ray and five processed images computed from the original (1-a). The decreasing size of the nxn neighborhood brings out increasingly finer details in the image. In the limit as n approaches the width of the image, the algorithm becomes a linear contrast strech. The image filtered with a 101x101 window (1b) is very similar to the original image. The edges of the bones and cartilage are enhanced, however, allowing the detail of the relationship of the neck vertebrae, for example,to be seen more clearly. In figure 1c, with a 71x71 window the nose and other soft tissues surrounding the skull become visible. The smaller windows in figures 1d, 1e and 1f show increasingly finer detail as well as enhancing noise in the image. The features brought out in figures 1e and 1f should be interpreted with caution and evaluated using expert knowledge on the structure of the skull and surrounding tissues. The ridges on the skull in the image, for example, could correspond to the cranial sutures on either the left or right side of the patient. The noise around the top and back of the skull could be caused by the support for the patient's head. The diagnostic value of these finer features must be considered in conjunction with the other images in the sequence to see if they do in fact correspond to structures in the patient's skull.

Another artifact of the algorithm is the over-enhancement of strong local contrasts already present in the original image. This can be seen as a saturation of the intensity of the fillings in the teeth (figure 1c) and the black zone surrounding the fillings.

Figure 2 shows another skull X-ray and the corresponding filtered (41x41 pixel neighborhood) image. Note the improvement in the definition of the vertebrae. The rectangular structure in the back of the skull is part of the support for the patient's head.

Figure 3 shows a thoracic X-ray and the corresponding filtered (41x41 pixel neighborhood) image. The algorithm brings out previously invisible information on either the blood vessels or the bronchi of the lungs. Contrasts between soft tissues such as these are usually not strong enough to be visisble in X-ray images. The filtered image, however, contains a sort of grainy noise in the center. The noise is more visible in this image because the original image is not an "averaged" image as explained at the beginning of this section. Unfortunately, the algorithm in its present form does not distinguish between this high-frequency noise and legitimate contrast variations.

4. COMPUTATIONAL EFFICIENCY

The information retrieved by this algorithm is most useful when viewed in the format of a sequence of images calculated with different window sizes as in figure 1. Thus, it would be desirable to have a fast calculating algorithm so that a doctor could use it to examine the sequence of images in real time. To obtain a high-speed algorithm, a hardware implementation would be necessary. Thus the algorithm has been viewed to see how well it lends itself to such implementations.

The calculation of the standard deviation is very "expensive" in hardware and time, so a substitue would be preferable. Other researchers[2] have found

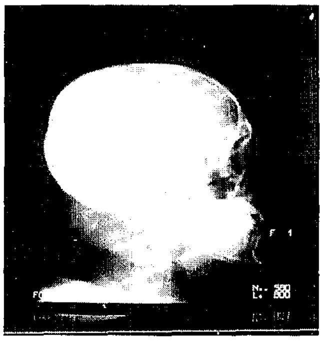

Figure 1a - ORIGINAL IMAGE

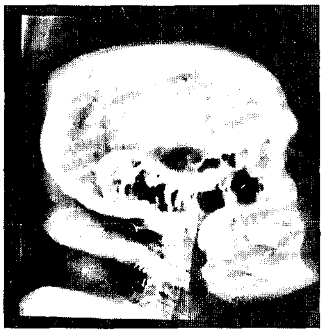

Figure 1b - FILTERED IMAGE, 101 x 101 window

Figure 1c - FILTERED IMAGE, 71 X 71 window

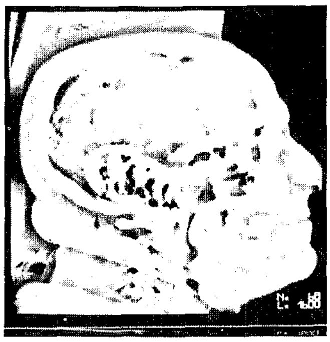

Figure 1d - FILTERED IMAGE, 41 X 41 window

Figure 1e - FILTERED IMAGE, 21 X 21 window

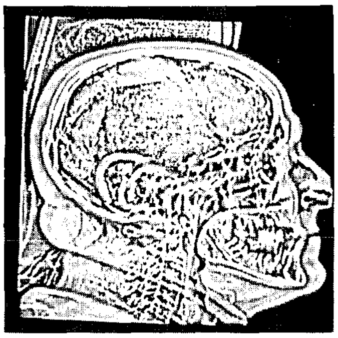

Figure 1f - FILTERED IMAGE, 11 X 11 window

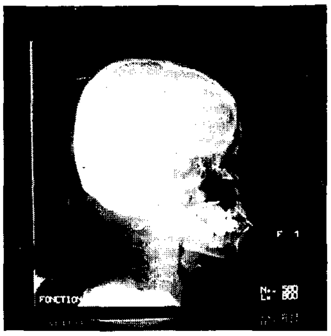

Figure 2a - ORIGINAL IMAGE

Figure 3a - ORIGINAL IMAGE, 2X magnification

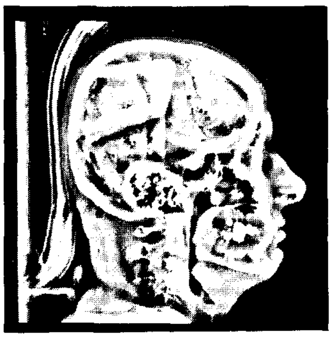

Figure 2b - FILTERED IMAGE, 41 X 41 window

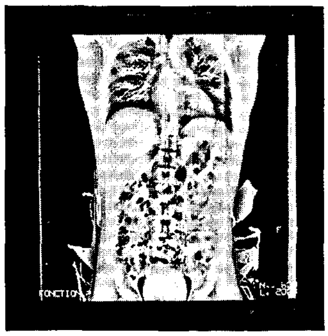

Figure 3b - FILTERED IMAGE, 41 X 41 window

the sum of the absolute differences between the pixel values in the local neighborhood and the local mean to be an acceptable substitute for the standard deviation.
Mathematically :

$$(5)\quad AD_{i,j,n} = \frac{1}{nxn} \quad |p_{i+r,j+s} - M_{i,j,n}|$$

This approximation avoids the square and square root calculation involved in the determination of the standard deviation.
The local means and standard deviations (or their substitutes) can be calculated using a "sliding window" where the mean and standard deviation for the pixel $p_{i,j}$ are calculated from the mean and standard deviation of the $p_{i-1,j}$ pixel by conserving the values from the region that is common to both neighborhoods. This cuts the calculation of the nxn factors into calculations on the order of n.

The constants of the algorithm can be chosen as powers of 2 (or powers of 2 minus 1) without much loss of generality. These changes allow for multiplications and divisions that correspond to bit shifts instead of complete multiplicative operations.

Finally, there is the division by the local standard deviation in equation (4). An alternative to a full division might be a look-up table calculation. This type of implementation might be useful in implementing nonlinear transformations more suited to avoiding over-amplification of already strong local contrasts in the images (by trimming the gain for regions of strong local standard deviation). The disadvantage of this method is the prohibitive number of bits that this table would require as input (the amount of memory used to store such a look up table is proportional to 2 to the power n where n is the number of input bits). Thus, with appropriate approximations and current digital electronic technology, the calculation could be done at video speeds (additions, subtractions, and division) in a time proportional to the number of pixels in the image, conceivebly in a few video frames. Such a calculation speed would allow a physician to examine the entire range of possible window sizes in a few minutes.

5. CONCLUSION

The local statistical image enhancement algorithm described above is a useful aid for extracting weak contrast variations in X-ray images. These weak variations contain the most important diagnostic information for the physician. The extracted features are best viewed in a range of filtered images using different window sizes. The algorithm can be approximated for a fast hardware implementation, thus permitting the generation of a sequence of filtered images in an acceptable amount of time.

ACKNOWLEDGEMENTS

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BIBLIOGRAPHY

1 W.K. PRATT
Digital Image Processing
Wiley and Sons, New York 1978

2 M. COCKLIN and G. KAYE
"Image enhancement of chest radiographs using local statistical information"
Proceedings - ISMII '82
IEEE Computer Society Press 1982