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CONTRAST OPTIMIZATION BY ADAPTIVE FILTERS IN COMPUTER TOMOGRAPHY IMAGING

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Abstract

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The aim of the presented work was processing of a computer tomography image in such a way that all of its information could be presented in a single, visually balanced image. This was accomplished by the use of adaptive filters performing the image histogram equalization according to its local properties. The experiment, carried out on a tomography image of a head (340x340 pixels) and 12-bit range of image data, proved the method to be functional and correct. Resulting images were characterized by very high contrast. However, due to the high contrast, the brightness information had been suppressed. Two techniques were used to reintroduce that information into the image. In the first method, the images were subjected to arithmetic operations involving normalized addition of the original image with linearly maximized contrast and the adaptive filter-processed image. In the other method, image colouration by means of bicolour semi-equalisation was used. The final colour image was a result of a transformation of the filtered image and the original one with linearly maximized contrast, where one colour element was added to the original image, and another colour element to the filtered image. These two images were subsequently combined into a single colour image. Both methods of brightness information enhancement proved to be very effective. Although somewhat reduced, the overall contrast remained relatively high.

Computer tomograph, image processing, contrast, adaptive equalization

Imaging of internal parts of the human body by computer tomography (CT) plays an irreplaceable role in contemporary medicine. Very high information value of these images enables a relatively accurate determination of the size, shape and position of individual organs, bones, blood vessels and other parts of the body. This information are very useful not only in diagnostics but also in planning and execution of medical interventions.

CT images carry information in several levels of brightness within the entire range. A histogram of such an image has several local maxima (Fig. 1b) which represent the mean brigthness values of different tissues. Mean brightness of individual tissues can differ a great deal and high quality imaging of all tissues is therefore impossible. In practice, this means that individual tissues have to be represented by several images derived from the original one in the following manner: First, a section of values bracketing the maximum associated with the selected tissue is identified. This section is then expanded to cover the entire range of brightness. The tissue thus acquires its optimum brightness and contrast. The same procedure is then applied to all tissues that require high-quality imaging.

The disadvantages of this procedure include a reduction in information content compared to the original image, a division of one image into a number of several images, and difficulty in defining the limits for the individual areas.

Adaptive filters thus offer the possibility of depicting all tissues at their optimum brigthness and contrast within a single image (Kotek et al. 1980).

Materials and Methods

The research work was done with images from ELSCINT axial computer tomograph ELECT 2000 obtained from Radiological Clinic of the Teaching Hospital of St. Anna in Brno. Data processing was done on a PC 486/90 MHz computer with the author's original software running in Microsoft Windows for Workgroups, version 3.11.

Both brightness and contrast of CT images were optimized by local equalization with an adaptive filter (Media Cybernetics 1993). The filter was used to process a completed digital image by assigning a new value to every picture element (henceforth called pixel) according to a predetermined algorithm (Murray and Ryper 1993).

In performing local histogram equalization, adaptive filters calculate histograms of pixels processed using their variable surroundings (Venetsanopoulos 1985). The shape and size of the area depend on local properties of the image.

There are two methods for determining the variable surroundings by means of rank statistical methods (Jaroslavskij and Bajla 1989). Both are based on a predefined surroundings of the pixel processed. It is a square-shaped area with the pixel processed located centrally within the square. It will be referred to as $S_w(x,y)$, where w is an odd integer from interval <3,101> and it represents the side of the square in pixels.

The first approach used in defining the variable surroundings (henceforth subsurroundings) is referred to as „cluster area" in literature (Druckmüller and Heriban 1992). Let $A_{k,w}$ be such a subsurroundings made up of a cluster with a pre-determined maximum number of pixels, whose values deviate the least from that of the pixel processed. In the classical definition (Druckmüller and Heriban 1992), the subsurroundings have exactly k pixels. It is, however, clear that this definition cannot be used to describe a continuous area of pixels of approximately the same value. I therefore resorted to the definition below.

Subsurroundings $A_{k,w}$ of pixel (x,y) is the set $M_{k,w}$ (x,y) defined as follows:

1) $M_{k,w}$ (x,y) is a continuous subset of a square surroundings $S_w(x,y)$ with the side w pixels long and pixel (x,y) in the centre of the square of the area, while condition $abs(a_{x,y} - a_{i,j}) \leq E$ is true [where $a_{i,j}$ is a member of the continuous subset $M_{k,w}$ (x,y)].

2) k is the maximum number of pixels in surroundings $A_{k,w}$

3) $a_{x,y}$ is the value of the processed pixel (x,y)

4) h(i) is the histogram of surrounding $S_w(x,y)$, where the i interval is <0, 4095> i.e. the image data range.

5) E is the number which maximizes expression $\Sigma(h(j))$ for
$j = <a_{x,y} - E, a_{x,y} + E>$ without exceeding k.

The second approach to subsurroundings delineation is mentioned in literature as „Cluster Value" (Druckmüller and Heriban 1992). This subsurrounding is formed by a cluster of pixels with values differing from that of the processed pixel by no more than d. Let that subsurroundings be denoted $V_{d,w}$. Then subsurroundings $V_{d,w}$ of pixel (x,y) will be set $N_{d,w}(x,y)$ for which the following statement is true:

$N_{d,w}(x,y)$ is a continuous subset of a square-shaped surrounding $S_w(x,y)$ with w pixels long sides and pixel (x,y) located in its centre, while condition $abs(_{x,y} - a_{i,j}) \leq d$ is true, where $a_{i,j}$ is an element of the continuous subset $N_{d,w}(x,y)$.

The continuity of sets $M_{k,w}$ and $N_{d,w}$ may be jointly defined as follows (Žára 1992): pixel (i,j) having a value of $a_{i,j}$ belongs to square-shape surroundings S_w. This pixel is an element of the $M_{k,w}$ or, rather, the $N_{d,w}$, subset if $abs(a_{x,y} - a_{i,j}) \leq E$ or $abs(a_{x,y} - a_{i,j}) \leq d$, respectively, and if there exists a continuous curve starting from pixel (i,j) and ending in pixel (x,y), and if all the pixels it passes through meet the condition that $abs(a_{x,y} - a_{i,j}) \leq E$ or $abs(a_{x,y} - a_{i,j}) \leq d$. Also, such a curve must not intersect any corner of any square-shaped pixel.

In the final phase, the filter calculates a continuous subarea for each pixel (x,y) of an image in the square-shaped surroundings Sw(x, y). The size of the surrounding area w is a parameter which must be set. The other parameter is either k or d, depending on the approach to the subsurroundings formation used.

For the calculated subsurroundings, a cumulative histogram is computed, which is a transformation function for the calculation of a new value of the pixel processed. That function is $f(a_{x,y}) = 4095.c(a_{x,y})$, where $c(a_{x,y})$ is a relative cummulative frequency of $a_{x,y}$ values (the number of pixels whose value is lower than, or equal to $a_{x,y}$) divided by the number of all pixels in the subsurroundings.

Setting of w and k (or d) values directly affects the result of filtration. The w parameter determines the local adaptiveness of equalization. Low w values result in high local adaptiveness when, consequently, fine structures of images are enhanced. The appropriate setting is w>2g, where g is the maximum from the horizontal and the vertical dimension of the object that we consider the most interesting in the picture. The k parameter gives the number of pixels of the smallest object to be equalized independently of its surroundings. The d parameter should satisfy the condition that $d_1 < d < d_2$, where d_1 is the maximum of the absolute value of the difference between values of pixels of the object to be equalized independently of the background, d_2 is the minimum of the absolute value of the difference between pixels of the object and of the background.

The use of adaptive filters for local equalization in image processing helps maximize CT image contrast. However, with contrast maximization, the brightness differences between individual objects are suppressed. In order to re-introduce the brightness information to images, two methods were used.

One of the methods to enhance brightness information was an arithmetic addition of the resulting image and the original one where linear contrast maximization had been performed using the transformation $g_{x,y} = k \,.\, a_{x,y} + lp_{x,y}$. K and l are positive constants satisfying the condition of $k + l = 1$, $a_{x,y}$ is the value of the filtered image pixel, and $p_{x,y}$ is the value of the original image pixel with linearly maximized contrast. The x and y parameters correspond to image lines or columns. This operation produces a weighted mean of the original and the filtered images.

The other method, called „bicolour semiequilization" in literature (Druckmüller and Heriban 1992), is based on the combination of the filtered image and the original image with linear contrast maximization by different colours. It constitutes a synthesis of two black-and-white images into one coloured image. In coloured digital images, each pixel is represented by three colour components, which can be mixed to produce any colour. The most frequently used standard is based on the utilisation of the red, green and blue for the colour pixel representation, the so-called RGB standard. In the case of bi-colour semiequalization, the values of pixels of the original image with linearly maximized contrast correspond to the values of, for instance, the red component of the pixels of the colour image, while the values of pixels of the filtered image correspond to the values, for instance, green component of the pixels image. The blue component of the colour image pixels may remain equal to zero, or it may be allocated the value of pixels of one of the black-and-white images being semiequalized. This is one of the best techniques for enhancing image structures without any major loss of other information.

The linear contrast maximization in the original image was performed by the following transformation of each of its pixels: $p_{x,y} = (P_{x,y} - H_1).4096 / (H_2 - H_1)$, where $P_{x,y}$ is the original image pixel, H_1 is a minimum value of a pixel of whole image and H_2 is a maximum value of a pixel of whole image.

Results

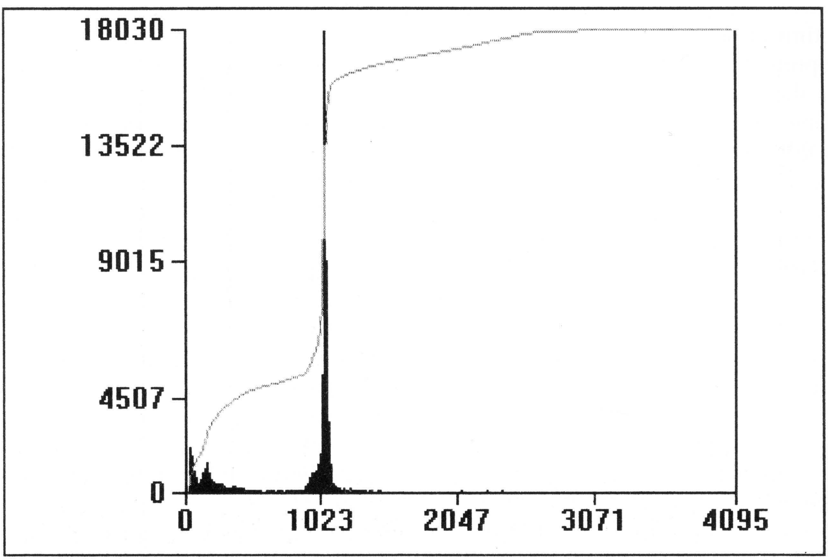
Contrast optimization by adaptive filter equalization is based on an assumption that pixel values of an optimum image will be regularly distributed over the <0,4095> interval.

This means that all colours of the spectrum occupy the same area in the image. In a corresponding histogram, values are distributed almost regularly and the curve of a cumulative histogram approximates a straight line. This means that the shape of a histogram and a cumulative histogram are objective parameters for the evaluation of contrast optimization. For that reason, all images presented in this paper are therefore shown together with their histograms and cumulative histograms.

CT images are characterized by large areas where pixels have a zero value. Image processing does not change the situation and their histograms will consequently show an enormous frequency of zero value pixels. Compared to that zero, other values are so small that the whole histogram is almost undeciphrable. For that reason, the zero value in histograms and cumulative histograms presented here has been eliminated.

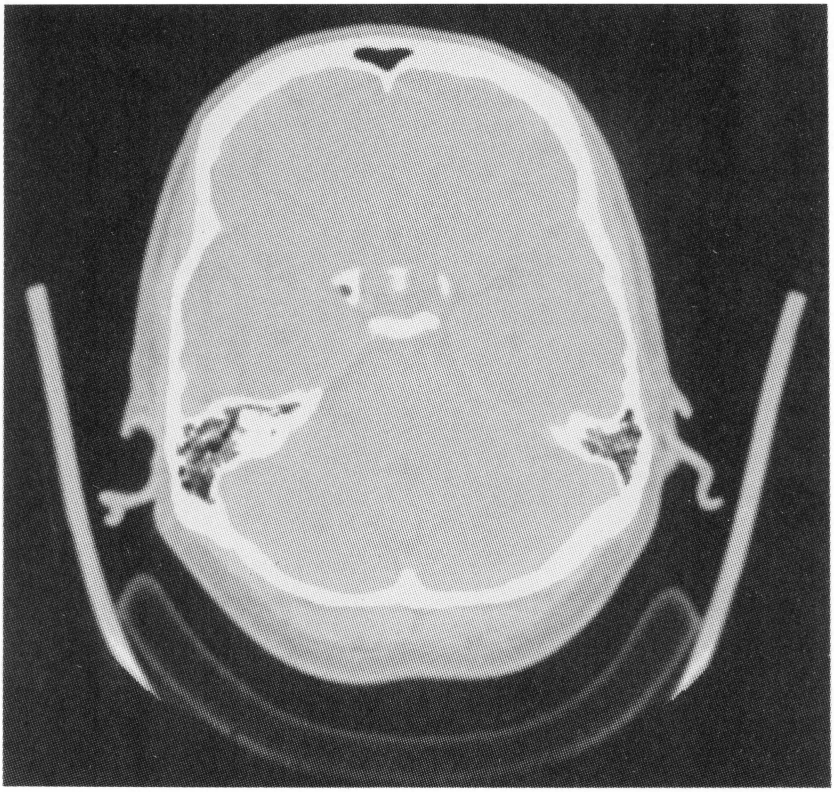
Fig. 1a shows an original CT image of the head. In this image, only the skull is visible, moreover, with only poor contrast. Fig. 1b shows a corresponding histogram (bar graph, in black) and a cumulative histogram (a grey curve). The cumulative histogram shows quite clearly why the image contrast is so poor: most pixels (over 75%) lie in the first quarter of the brightness range (values from 0 to 1023) of the image, while there are practically no pixels in the last quarter of the range (values from 3071 to 4095). Numbered identically as their corresponding images, figures of histograms and cumulative histograms are differentiated by the letter b added to the number.

a

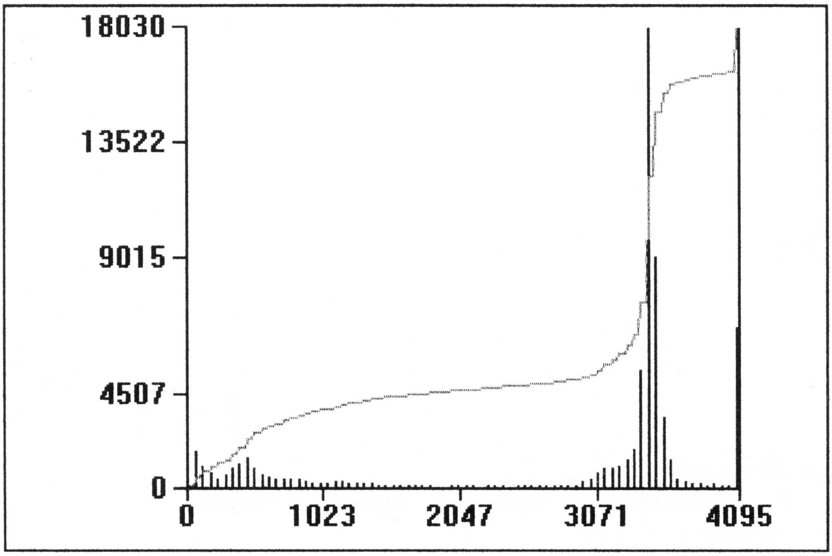


b

Fig.1 ab. CT image of the head

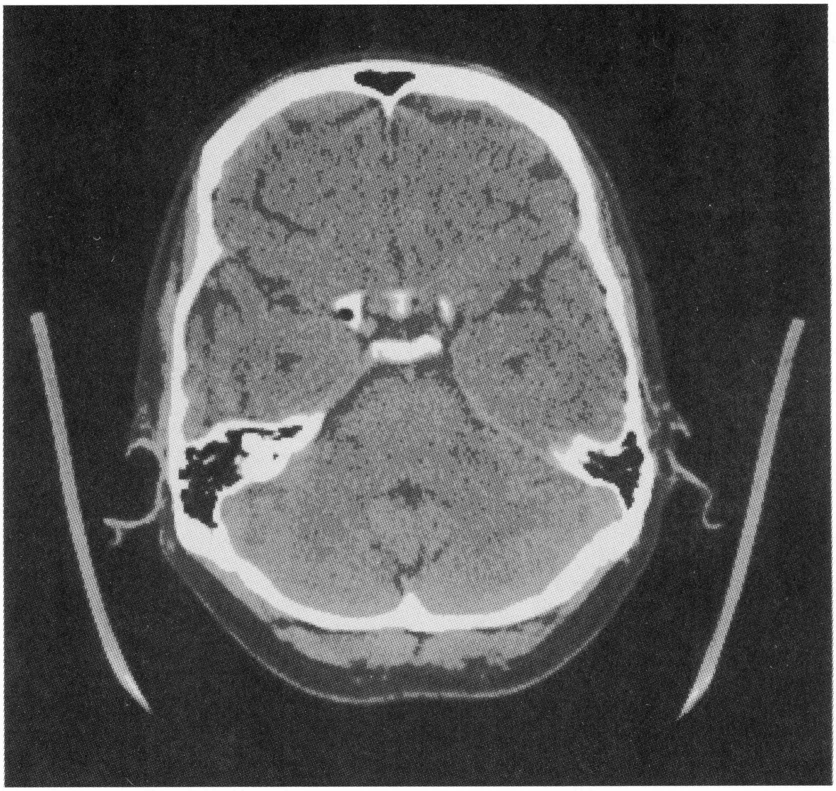


a

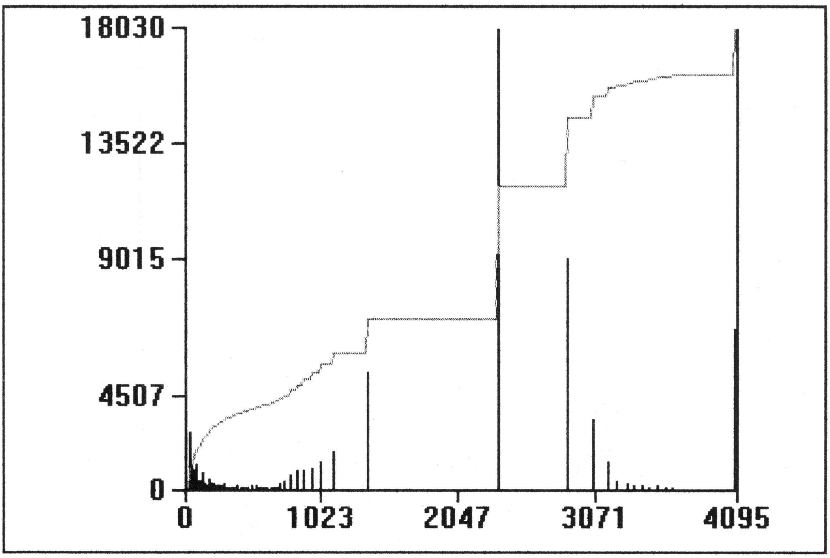


b

Fig.2 ab. CT image of the head after linear contrast enhancement

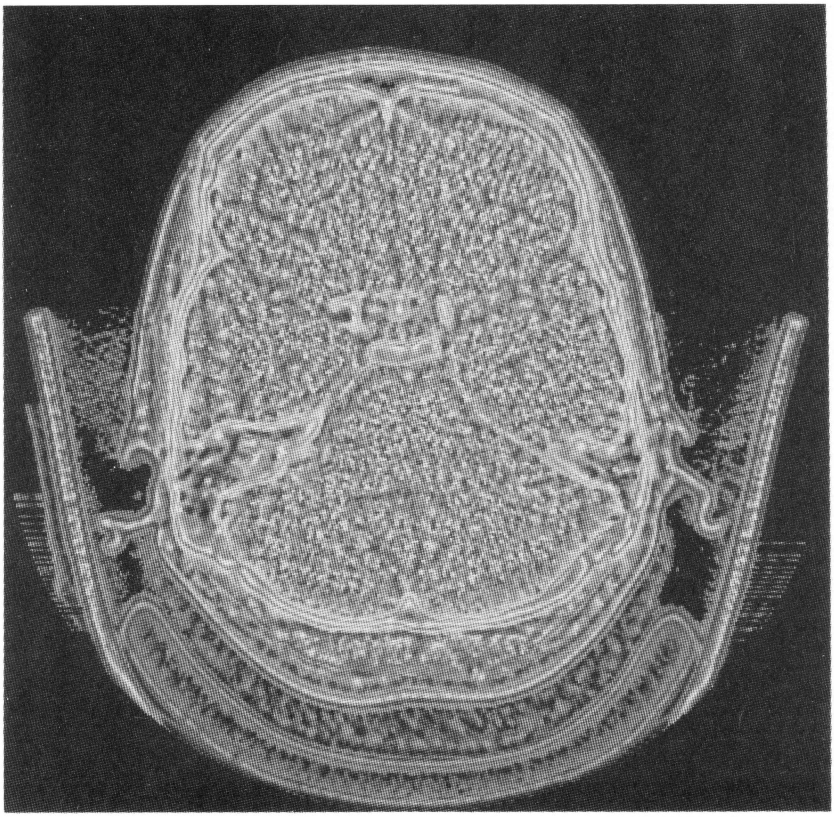


a

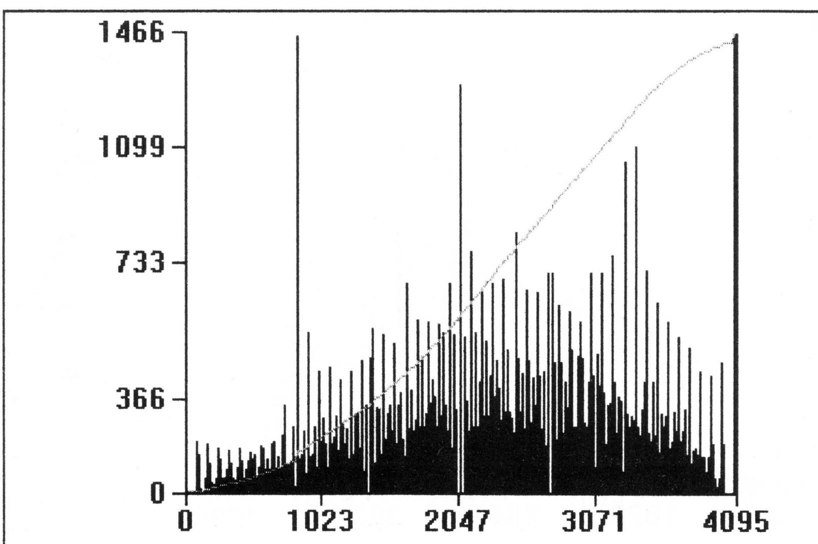


b

Fig.3 ab. CT image of the head after linear contrast enhancement and subsequent equalization on the basis of a cumulative histogram of the entire image

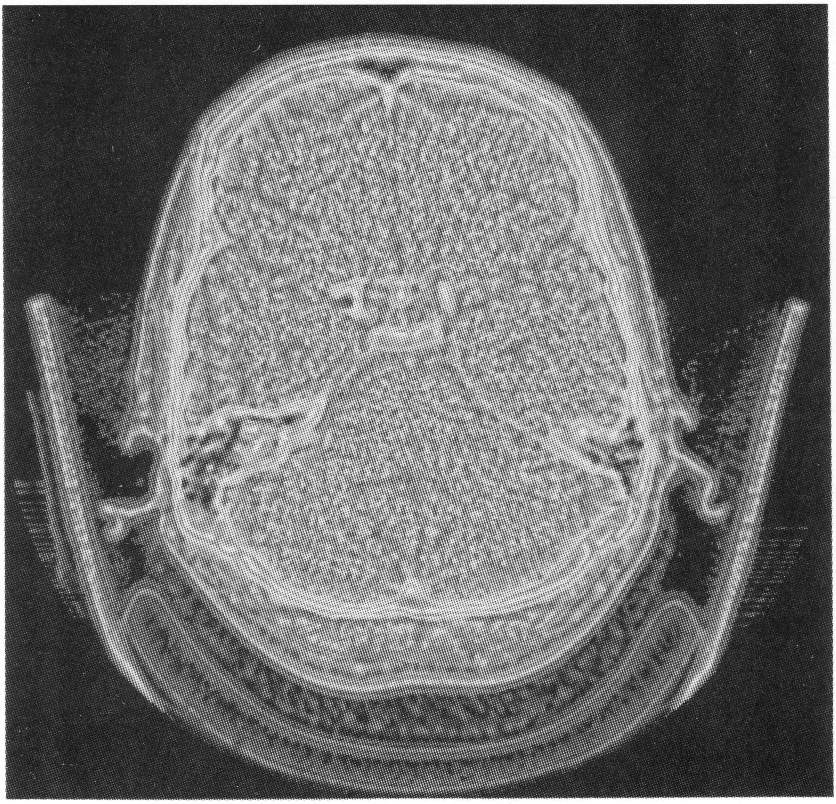


a

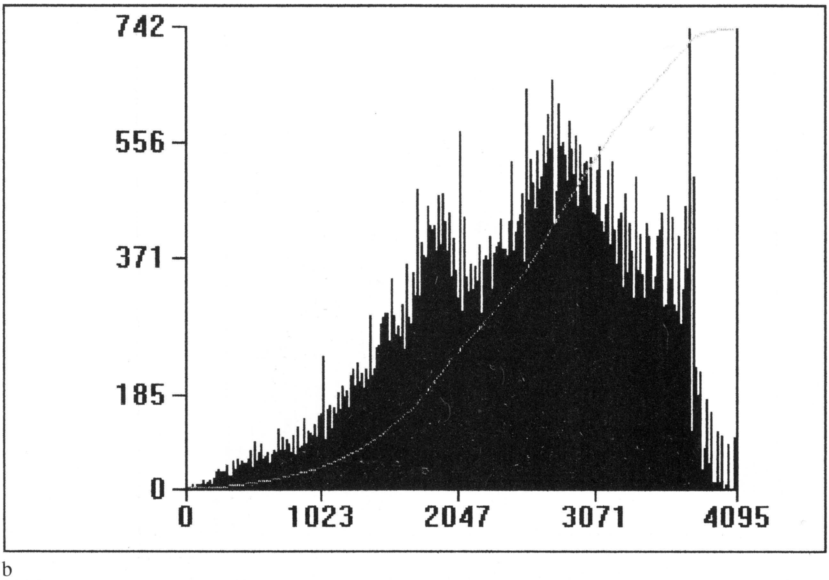


b

Fig.4 ab. CT image of the head after adaptive filter processing, „cluster area“ type of subsurroungings, w = 9, k = 50

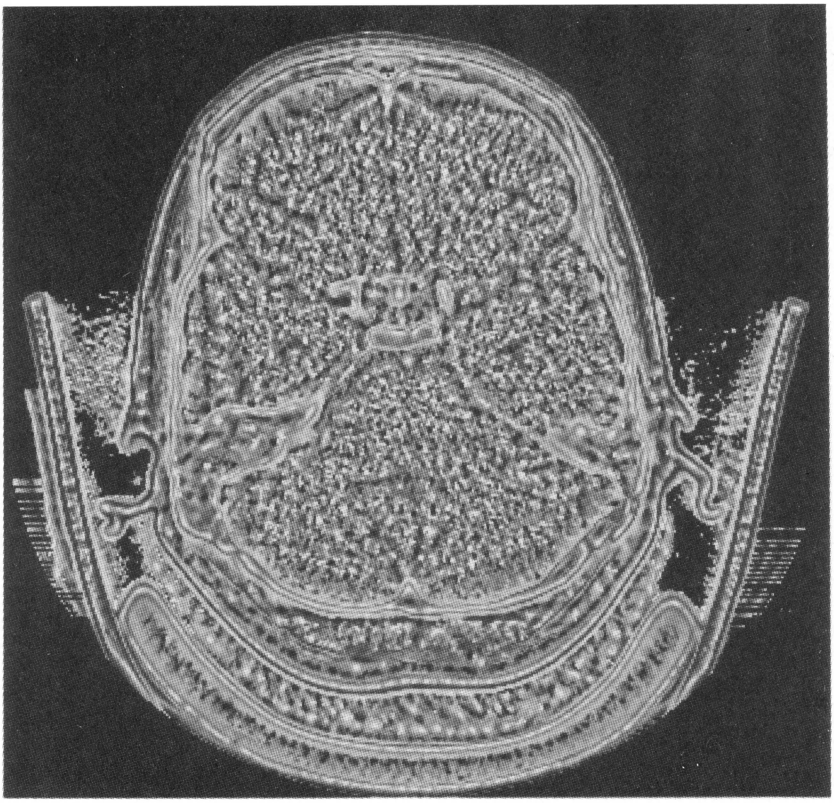


a

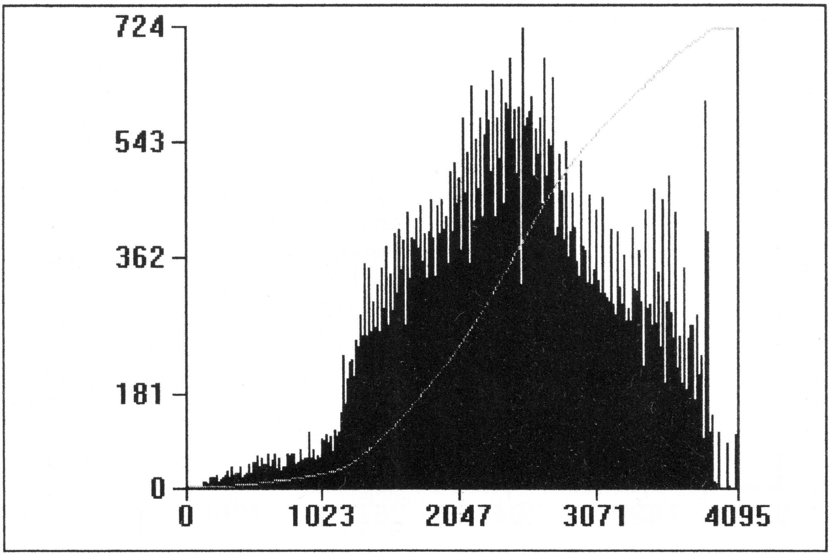


b

Fig.5 ab. CT image of the head as a result of arithmetic addition of Figs 2a and 4a

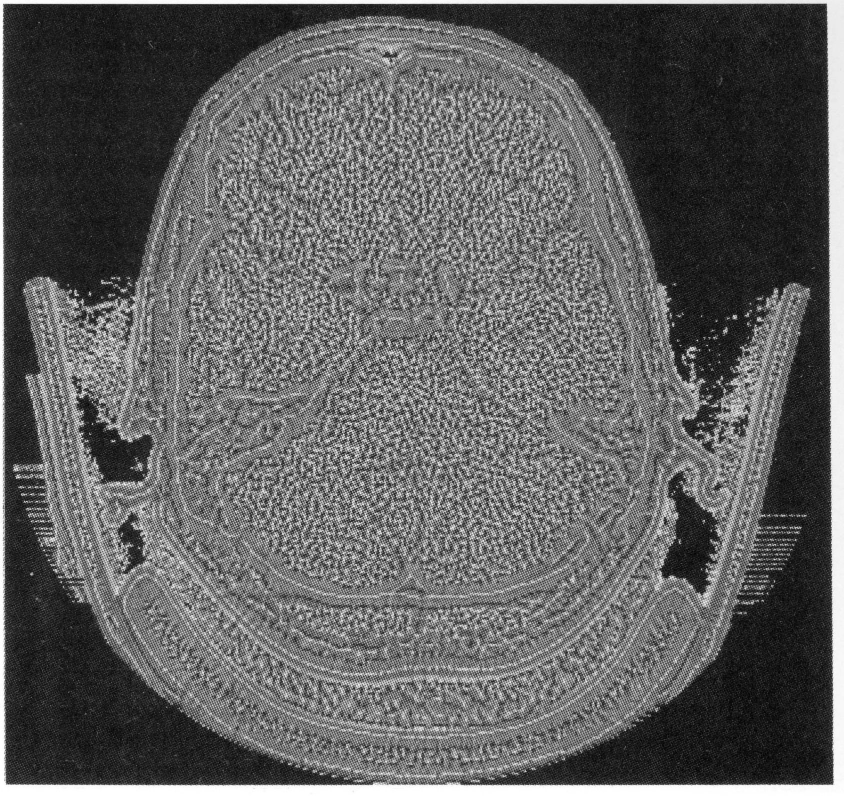


a

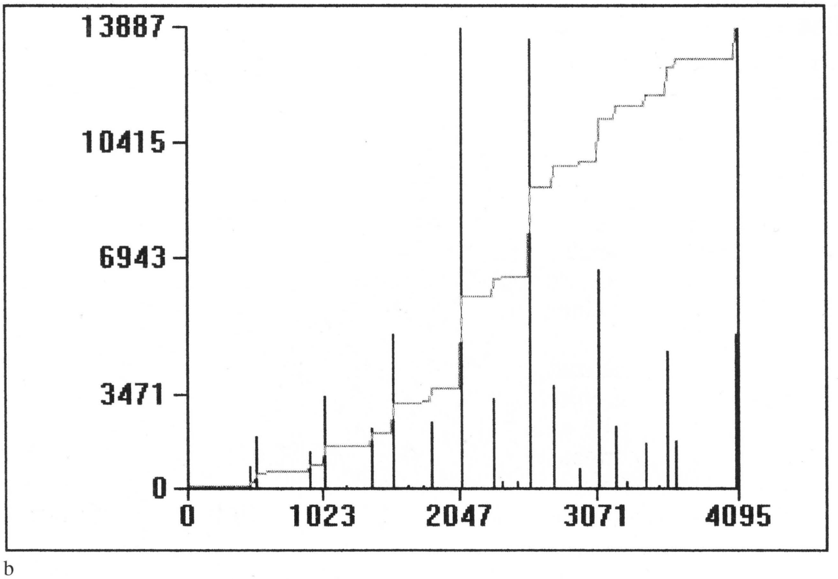


b

Fig.6 ab. A black-and-white showing of an image of the head resulting from bi-colour semiequalization, where Fig.4a was used as the green and blue components and Fig.2a as the red component



a



b

Fig.7 ab. Example of improper setting of adaptive filter parameters. A CT image of the head after processing by „cluster area“ adaptive filter (w = 3, k = 4)

Fig. 2a is an original CT image of the head after linear contrast enhancement. While some finer elements are already visualized, the contrast between individual tissues remains low. The principle of the linear contrast enhancement becomes clear when we compare the corresponding histograms, 1b and 2b.

Fig. 3a shows an image of the head with a linearly enhanced contrast and subsequent equalization according to the cumulative histogram of the entire image. The contrast is further enhanced, but it hardly constitutes a significant improvement. The 3b histogram shows the extent of non-linear changes in the image that were necessary to bring the histogram closer to an equal distribution. The approximation is evident from the cumulative histogram.

Fig. 4a shows an image of the head after treatment by an adaptive filter with a „cluster area" type of the subsurroundings, whose parameters have been set at the following values: w = 9, k = 50. The contrast enhancement is obvious at first sight. The curve of the cumulative diagram markedly approaches a straight line (see Fig. 4b). The differences in brightness between individual tissues evident in previous images are, however, completely obliterated here.

Fig. 5a shows a resulting image of an arithmetic addition of images 4a and 2a. Compared to the 4b histogram, the quality of its histogram and cumulative histogram is poorer from the optimum contrast point of view. The contrast is, admittedly, lower, but the image has recovered some of its brightness information value. Moreover, its contrast is much higher than that of the image in Fig. 3a, where the contrast has been normalized for the entire image. This marks a significant improvement which confirms that the use of adaptive filters for local image equalization is the right approach to contrast optimization in CT imaging.

Fig. 6a shows an image of the head after a semiequalization. The filtered image (Fig. 4a) was used as the green and blue components, and the original image with linearly enhanced contrast (Fig. 2a) as the red component. Because it is not possible to present the coloured image, it has been converted back to a black-and-white image. It is obvious that the reduction of the local contrast is smaller than in the previous image, which is also clear from the 6b histogram. Fig.7a shows the consequences of an improper setting of adaptive filter parameters. An image of the head with of the „cluster area" type of subsurroundings (w = 3, k = 4) was filtered.

Discussion

The use of adaptive filters for local equalization helps enhance the contrast of all tissues of CT images. Compared to traditional methods (Jaroslavskij and Bajla 1989) based on local equalization in a fixed surrounding area, there are no bands with low contrast in final images generated by this technique. Such bands occur when cummulative histograms are calculated not only from pixels belonging to the object in question but also from pixels outside it.

The drawback of the local equalization technique is the loss of brightness information which differentiates one group of objects in the image from another (Hlaváč and Šonka 1992), which means that originally clearly defined borderlines between objects may be completely obliterated. The enormous contrast enhancement in individual objects will reduce or completely eliminate the contrast between individual objects. This drawback can be corrected relatively easily by the above described methods of arithmetic addition or bi-colour semiequalization.

The approach to the subsurroundings definition depends on a number of factors. To put it very simply, the „cluster area" approach might be described as more flexible in the subsurroundings of the recalculated pixel. This technique, however, gives poor results if the noise level is very high, or if pixels that have very few pixels of the same tissue around them are being corrected. If, on the other hand, the level of noise is low (CT images are characterized by low noise levels), this approach can help filter some types of it. This technique is therefore suitable in the case of images where tissues exhibit comparable dynamic ranges of pixel values. Otherwise, the „cluster value" technique should be the method of choice. Its only disadvantage is lower efficiency when d is not set properly.

In the present study, the computer time necessary for adaptive filter image processing was about 10 minutes. Time optimization of the algorithm and the use of now common more powerful computers can significantly reduce that time.

Conclusions

The use of adaptive filters in contrast optimization by local equalization can help increase effectiveness of work with CT images. It is very probable that, for example in diagnostics, a complete image showing all tissues is far better than a set of images of individual tissues cut out of the original image.

Compared to classic - and still utilized - methods, the use of adaptive filters marks a new trend in CT image handling and processing (Oppenheim 1978; Pratt 1978; Říčný 1991), which is far from exhausted by the present paper. The use of adaptive filters may help resolve some problems related to noise in images, and the application of semiequilization can significantly improve the quality of CT images.

Optimalizace kontrastu v obrazech z počítačového tomografu užitím adaptivních filtrů

Cílem práce bylo zpracování obrazů z počítačového tomografu tak, aby poskytl všechny informace jež nese v jednom vizuálně vyváženém obrazu. Bylo využito adaptivních filtrů provádějících ekvalizaci histogramu obrazu v závislosti na jeho lokálních vlastnostech. Experiment se prováděl na tomografovém obrazu hlavy (o velikosti 340x340 pixelů) s 12-bitovým rozsahem obrazových dat. Ukázalo se, že metoda je funkční a správná. Výsledkem experimentu jsou obrazy s velmi vysokým kontrastem. V důsledku vysokého kontrastu však byla potlačena jasová informace. Tato informaci byla do obrazu doplněna dvěma způsoby.

V prvním se využilo aritmetických operací s obrazy. Bylo provedeno normalizované sečtení původního obrazu s lineárně maximalizovaným kontrastem a obrazu filtrovaného adaptivním filtrem. Druhý způsob využil kolorování obrazu metodou dvoubarevné semiekvalizace. Výsledný barevný obraz vznikl transformací filtrovaného a původního obrazu s lineárně maximalizovaným kontrastem tak, že původnímu obrazu se přiřadila jedna barevná složka a filtrovanému obrazu jiná barevná složka a tyto obrazy se složily v jeden barevný obraz. Oba způsoby přidání jasové informace se ukázaly jako vysoce efektivní. Přestože celkový kontrast poklesl, zůstal nadále dostatečně vysoký.

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