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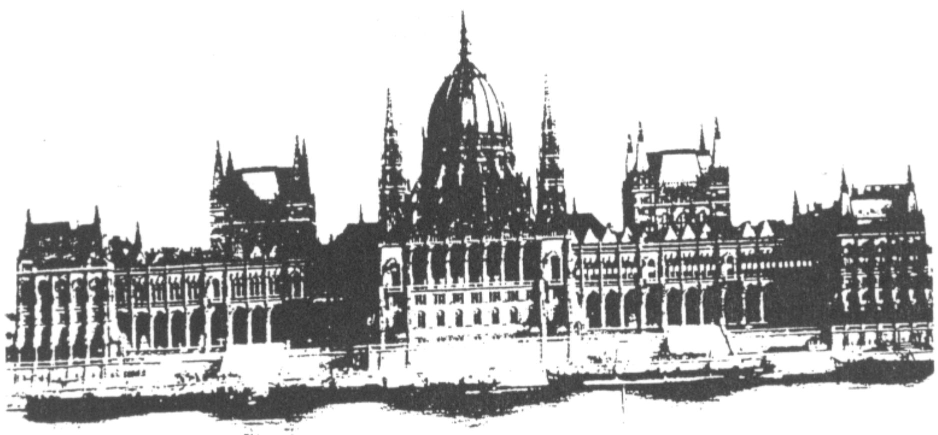


PROCEEDINGS

Prior Knowledge for Improved Image Estimation from Raw MRI Data

Iraklis M. Spiliotis[1], Dirk van Ormondt[2] and Basil G. Mertzios[1]

[1]*Department of Electrical and Computer Engineering, Democritus University of Thrace, 67 100 Xanthi, Hellas*
[2]*Applied Physics Department, Delft University of Technology, Delft, The Netherlands*

Abstract - In this paper is presented a method for the accurate estimation of the image boundary from incomplete raw MRI data. This is necessary for the phase correction and the image reconstruction from incomplete Cartesian or Radial scans using MR techniques and therefore for the reduction of MRI scan time. The exact estimation method comprises the binarization of the low resolution image, the fast separation of the displayed objects using image block representation and the extraction of the external and of all the interior edges which can be used as prior information for the phase correction and the image reconstruction.

I. INTRODUCTION

This contribution concerns accurate estimation of the boundaries of an object from a small subset of *raw* MRI data. These boundaries are subsequently used in the estimation of a high-resolution image from *incomplete* raw MRI data. This procedure can be used for reduction of the MRI scan time.

The raw data obtained from an MRI scanner are made up of complex-valued numbers sampled in the inverse Fourier domain of an image. Typically, a 2-D scan comprises 256x256 samples. In MRI, the positions of the samples are specified in the so-called k-space. Most often, a Cartesian grid is used, *i.e.* $k_x = -128, -127, \ldots, 127$ and $k_y = -128, -127, \ldots, 127$. An image is obtained from raw Cartesian samples by applying 2-D FFT and subsequently by converting the absolute values of the resulting numbers into gray values.

The conventional way to reduce scan time is to simply truncate the acquisition in the k_y-space as indicated in Fig. 1 (a) [1]. The omitted data can be estimated by linear prediction methods, after which 2-D DFT is applied as mentioned above. More promising scan time reduction schemes are shown in Fig. 1 (b), (c) and (d).

The sampling scheme of Fig. 1 (b) takes advantage of the symmetry that is present in (ideal) MRI data: After applying 1-D FFT in the k_x-space, the data possess Hermitian symmetry with respect to reflection about k_y=0 [1]. This implies that an ideal scanner needs to provide only a 'one-sided' scan. However, since real-world scans are corrupted by phase errors, complete omission of one side is impossible. In actual fact, some 16 to 32 scan lines of the otherwise empty half are required to correct for the mentioned phase errors [2].

The sampling scheme of Fig. 1 (c) is non-uniform [3]. Consequently, estimation of omitted samples amounts to interpolation rather than extrapolation. Since interpolation is more stable than extrapolation, the resulting estimation is significantly better [3]. In addition, the positions of the omitted samples can be optimized using general information criteria. A Bayesian estimation procedure capable of handling both interpolation and extrapolation is described in [4]. Important prior knowledge used in this procedure is, among other things, that the image intensity outside the boundary of the scanned object be as low as that of the noise. For this purpose, one requires an accurate prior estimate of the object boundary from only a limited number of samples in the center of the k_y-space. This latter aspect is addressed here. For completeness we point at the sampling scheme of Fig. 1 (d) which combines one-sided sampling and non-uniform scanning. This combination further reduces the scan time.

Fig. 2 shows some cases of limited number of samples from (a) 64 lines, (b) 32 lines, (c) a 64x64 window and (d) a 32x32 window at the center of the k-space. These cases are used in this contribution for the estimation of the object boundaries. The last two schemes of Fig. 2 (c) and (d), may also be used for not grid based scans, such as the radial and the spiral scan.

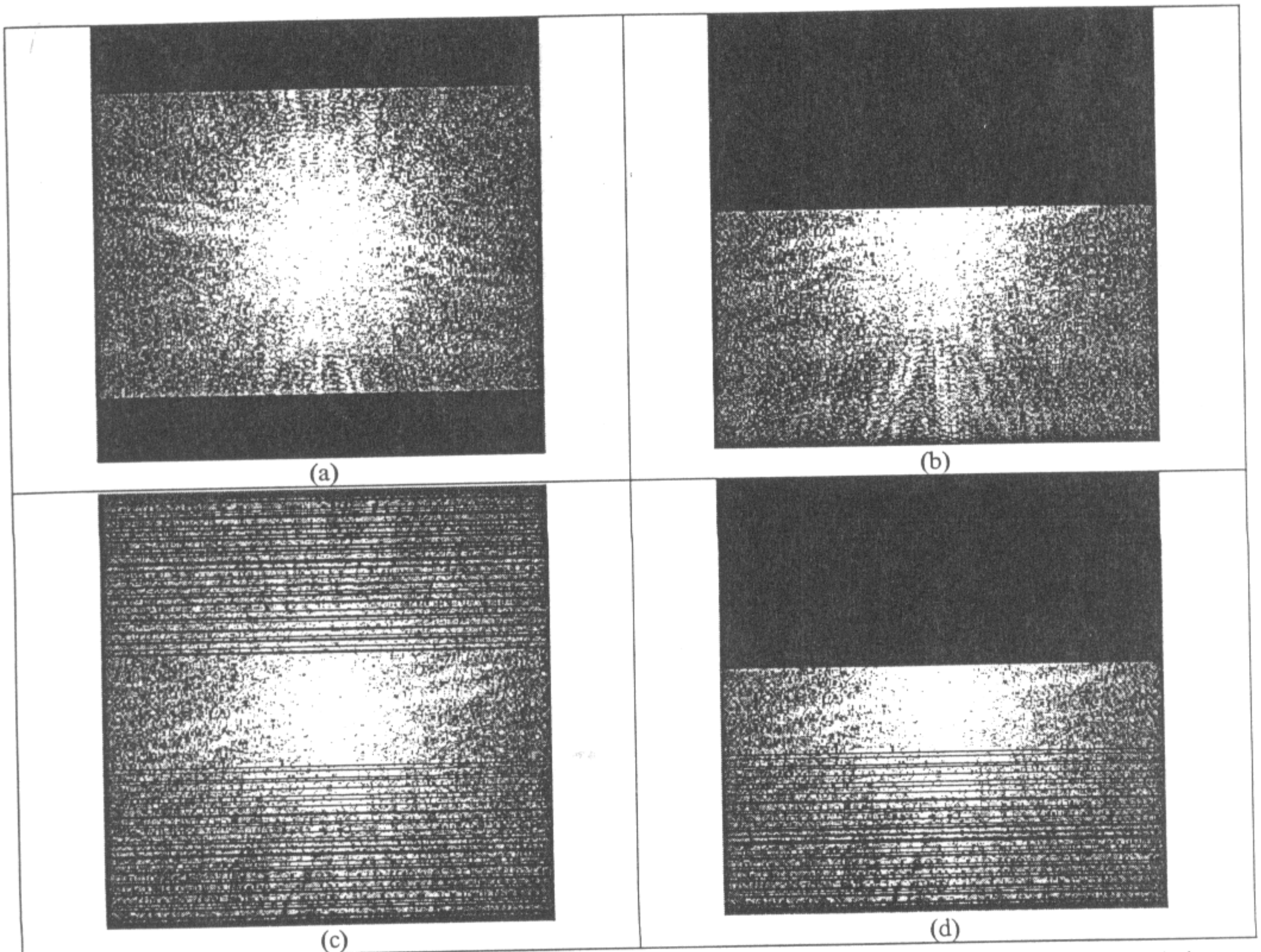


Figure 1. Incomplete raw MRI data at the *k*-space. (a). Truncated scan with 30% reduction. (b). One-sided scan with 44% reduction. (c). Nonuniform symmetric scan with 30% reduction. (d). One-sided and nonuniform scan with 59% reduction.

This paper is organized as follows: In Section II the image thresholding procedure is presented. In Section III a fast procedure for the extraction of the main object and in Section IV the interior and the external edge extraction procedure are presented.

II. IMAGE THRESHOLDING

In the image thresholding process the task is to obtain a binary image, corresponding to the objects of the gray image. This task is achieved by considering the histogram [5] of the gray level image and finding an appropriate point for thresholding. A well known method for this is the peak-picking algorithm, which finds two peaks of the histogram curve and then finds the minimum between them. Alternatively, the minimum value of the histogram curve located after the first maximum may be found. This latter approach is used in this work, which is equivalent to the peak-picking algorithm, due to the histogram distribution: In the histogram of the gray level image there exist two peaks, the first of which is located at the lower gray values corresponding to the image background while the second peak is located at the medium of high gray values corresponding to the image objects. In Fig. 3 (a), (b), (c) the original image, the resulted binary image, the histogram of the gray image are shown, respectively.

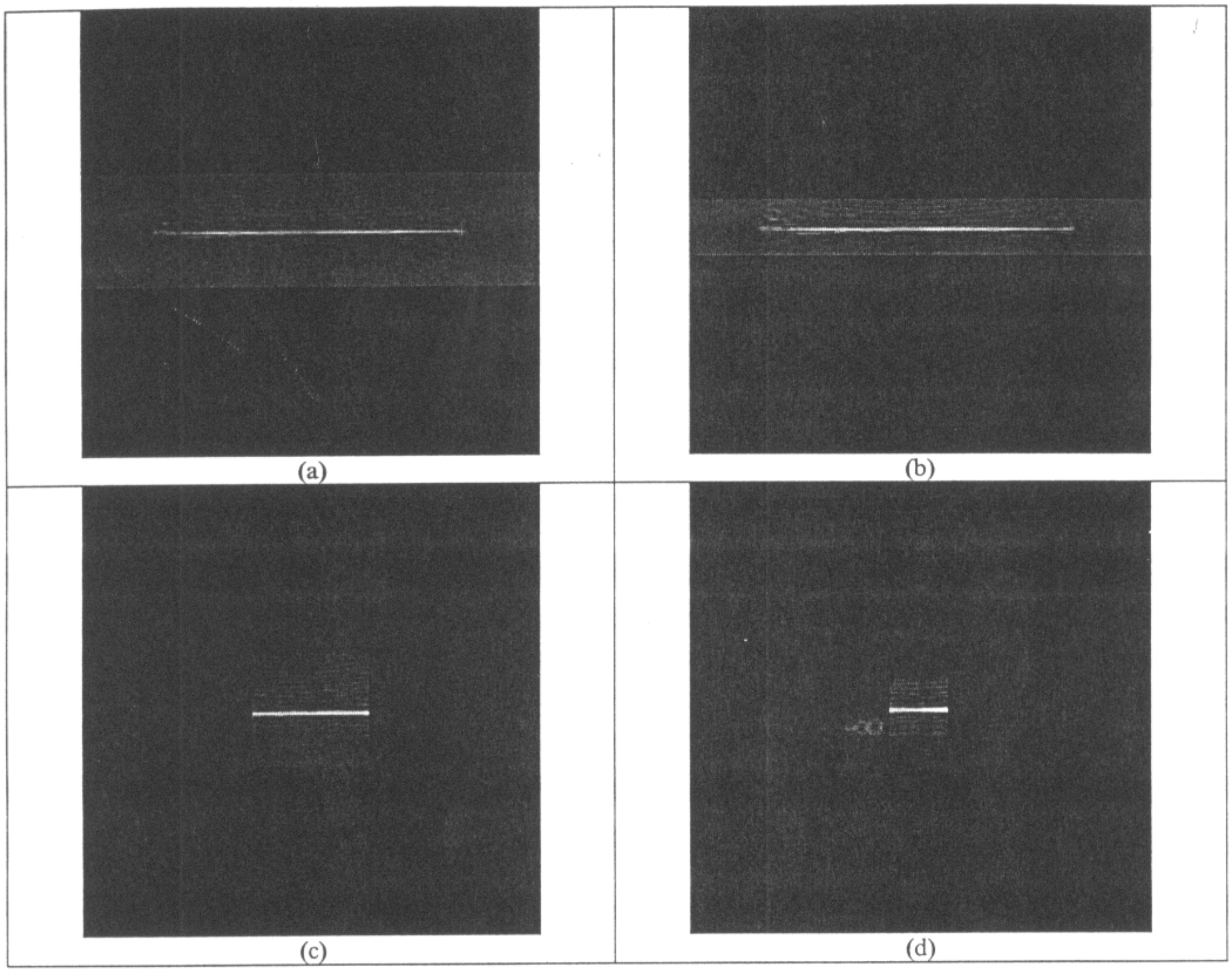
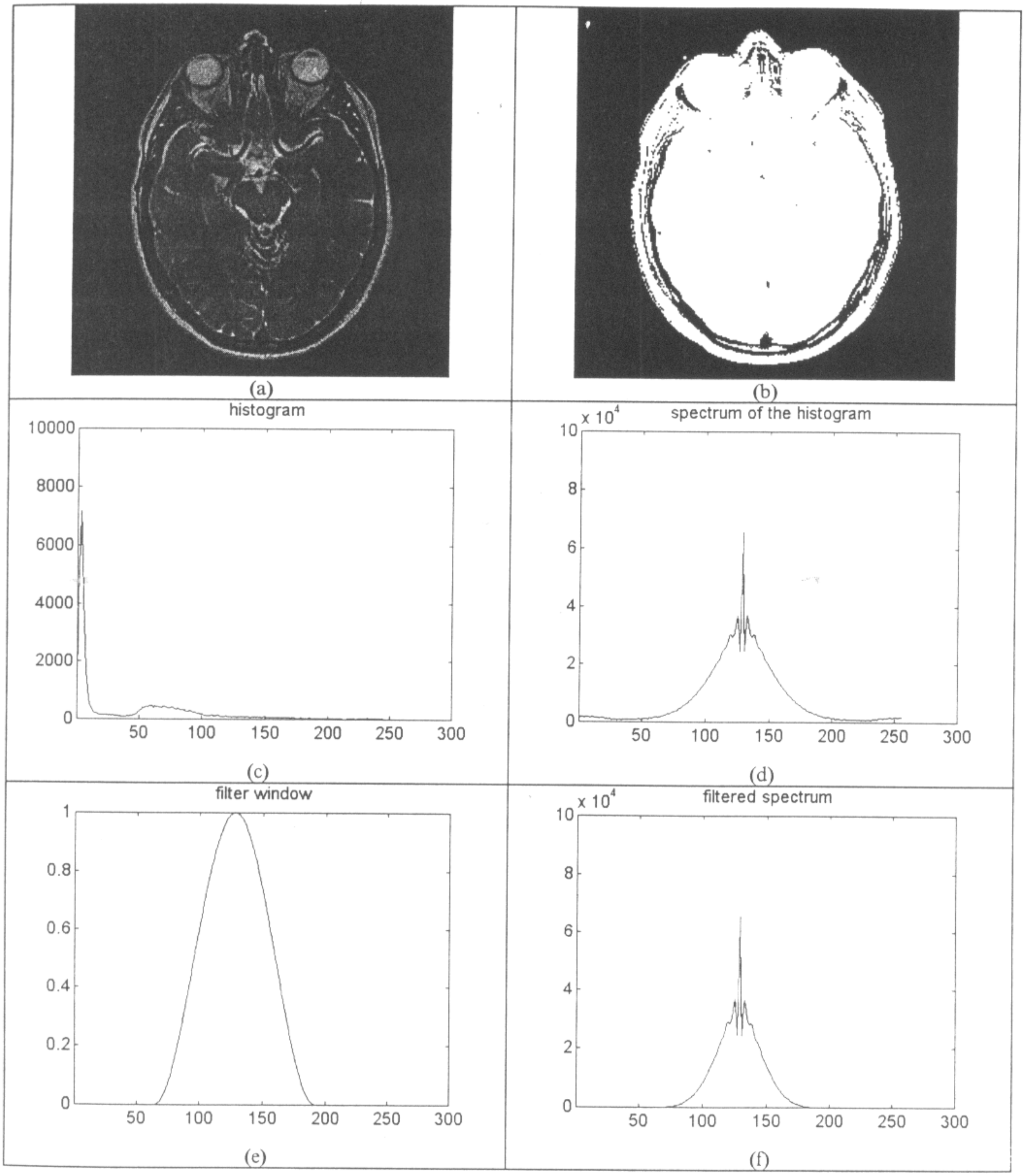


Figure 2. Limited number of samples at the center of the k-space. (a). 64 lines. (b). 32 lines. (c). A 64x64 window. (d). A 32x32 window.

An important stage that precedes the threshold finding is the histogram smoothing. This stage is in the general case necessary in order to find a correct threshold under noisy or corrupted histogram conditions. Two techniques have been used for the histogram smoothing.

The first smoothing approach is the low pass histogram filtering. The histogram curve is transformed to the Fourier domain using 1-D FFT and the high frequencies are rejected. In order to avoid a Gibbs phenomenon a cosine window filter of width 128 is used. Fig. 3 (d), (e), (f), (g) and (h) show the spectrum of the histogram, the cosine filter window, the filtered spectrum, the smoothed histogram and the threshold position at the smoothed histogram, respectively.

The second approach is the smoothing at the histogram domain using a median filter of width 5. In Fig. 3 (i) the smoothed histogram is shown and in (j) the threshold position is shown. The two smoothing methods result to almost identical threshold positions and therefore to almost the same binary images. In the case of image of Fig. 3 (a), the threshold position is located at the level 20 for both histogram smoothing methods.


(a)
(b)
histogram
(c)
x 10^4
spectrum of the histogram
(d)
filter window
(e)
x 10^4
filtered spectrum
(f)

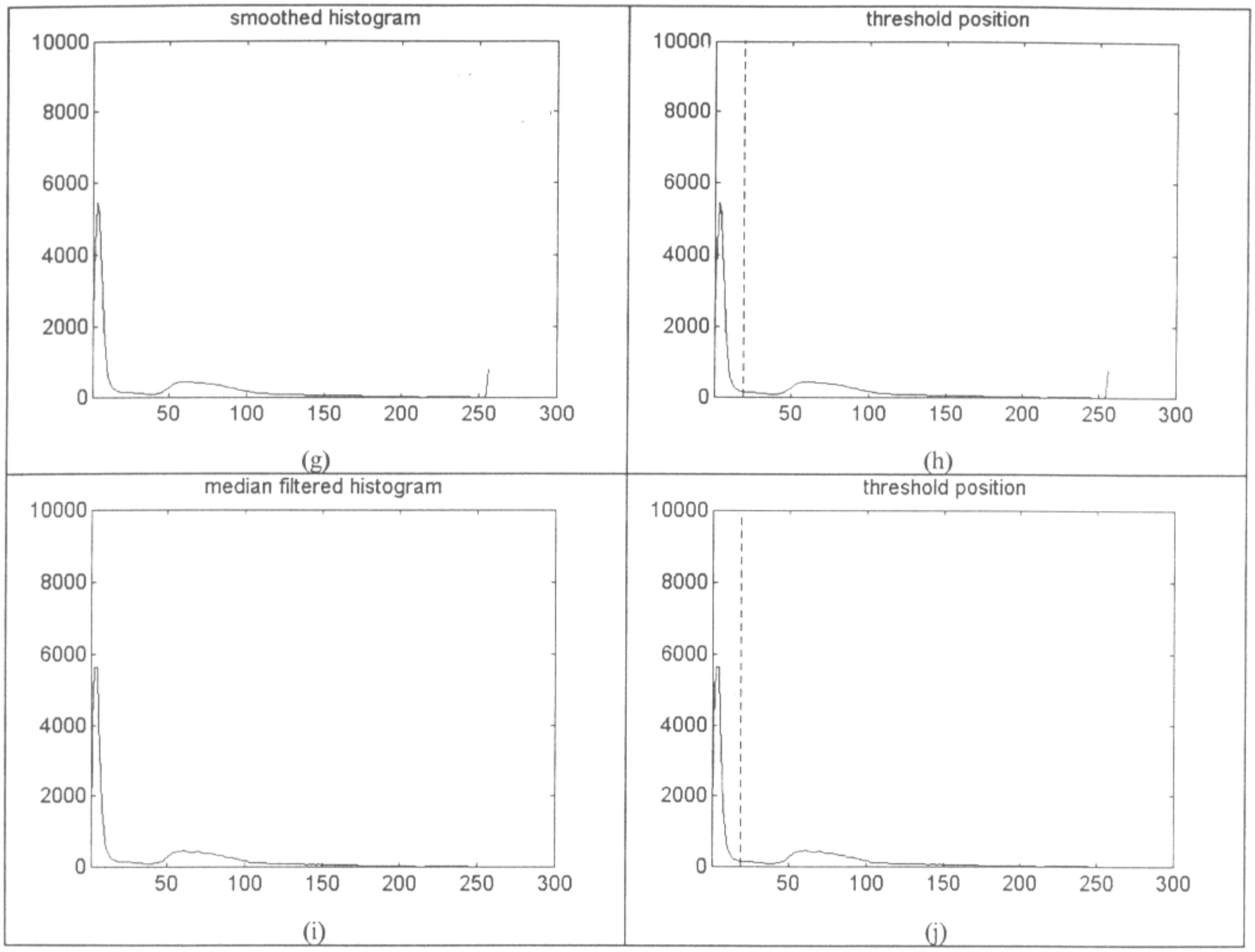


Figure 3. (a) The original image. (b) The thresholded image. (c) The histogram of (a). (d) The spectrum of (c). (e) The cosine filter window. (f) The spectrum of the filtered signal. (g) The smoothed histogram by the cosine filter. (h) The threshold position of (g). (i) The filtered histogram by the median filter. (j) The threshold position of (i).

III. EXTRACTION OF THE MAIN OBJECT

Due to the incomplete k-space data that are used for the formulation of the low resolution image using the 2-D DFT, a strong ringing (Gibbs) phenomenon is appeared in the image domain. As a result, after the binarization process, a number of small objects are contained in the binary image. The task in this stage is to extract the main object and to reject as noise all the small objects. A number of approaches may be used for this task. A fast one is the use of the Image Block Representation (IBR) for the representation of the binary image [6]-[9]. The fast connectivity checking and object extraction is permitted in block represented images. Also the fast external and internal edge detection and location is also permitted in block represented images, as described in the next Section.

A. Image Block Representation

A bilevel digital image is represented by a binary 2-D array. Without loss of generality, we suppose that the object pixels are assigned to level 1 and the background pixels to level 0. Due to this kind of representation, there are rectangular areas of object value 1, in each image. These rectangular areas have their edges parallel to the image axes and contain an integer number of image pixels. At the extreme case, one pixel is the minimum rectangular area of the image. These rectangulars are called *blocks* in the terminology of this paper.

Consider a set that contains as members all the nonoverlapping blocks of a specific binary image, in such a way that no other block can be extracted from the image (or equivalently each pixel with object level belongs to only one block). This set represents the image without loss of information. It is always feasible to represent a binary image with a set of all the nonoverlapping blocks with object level. This representation of the binary image is called *Image Block Representation (IBR)*.

The block representation concept leads to a simple and fast algorithm, which requires just one pass of the image and simple bookkeeping process. In fact, considering a $N_1 x N_2$ binary image $f(x,y)$, $x=0,1, .. , N_1-1$, $y=0,1, .. , N_2-1$, the block extraction process requires a pass from each line y of the image. In this pass all object level intervals are extracted and compared with the previous extracted blocks.

The image block representation is an information lossless representation of binary images. It is pointed out that, given a specific binary image, different sets of different blocks can be formed. Actually, the nonunique block representation does not have any implications on the implementation of any operation on a block represented image.

In the following, a uniquely determined image block representation algorithm, which is based on the row by row processing, is given by considering a specific scanning of the pixel grids.

Algorithm 1: *Image Block Representation.*
Step 1: Consider each line y of the image f and find the object level intervals in line y.
Step 2: Compare intervals and blocks that have pixels in line $y-1$.
Step 3: If an interval does not match with any block, this is the beginning of a new block.
Step 4: If a block matches with an interval, the end of the block is in the line y.

■

A block represented image is denoted as:

$$f(x,y) = \{b_i : i = 0,1,...,k-1\} \quad (1)$$

where k is the number of the blocks. Each block is described by the coordinates of two corner points and a list of its connected blocks, i.e.:

$$b_i = (x_{1,b_i}, x_{2,b_i}, y_{1,b_i}, y_{2,b_i}, nc, c_j) \quad (2)$$

where x_{1,b_i}, x_{2,b_i} are the coordinates of the i-th block according to the horizontal axis, y_{1,b_i}, y_{2,b_i} are the coordinates of the block according to the vertical axis, nc is the number of the connected blocks and c_j is a list of the connected blocks. For simplicity it is assumed that: $x_{1,b_i} \leq x_{2,b_i}$ and $y_{1,b_i} \leq y_{2,b_i}$.

B. Extraction of the main object

Using the scheme of connectivity among the blocks, the connectivity among different image regions and the detection of the objects appeared in the image may be checked. A simple way to perform this task is the formulation of chains of connected blocks. Each chain contains blocks that are connected among them in such a way that each block of the image belongs to a chain and a pair of connected blocks belongs to the same chain. Under these conditions each chain holds the blocks of a distinct image object. Each object is denoted as o_i, $i=0,1,...$ and is a list data type.

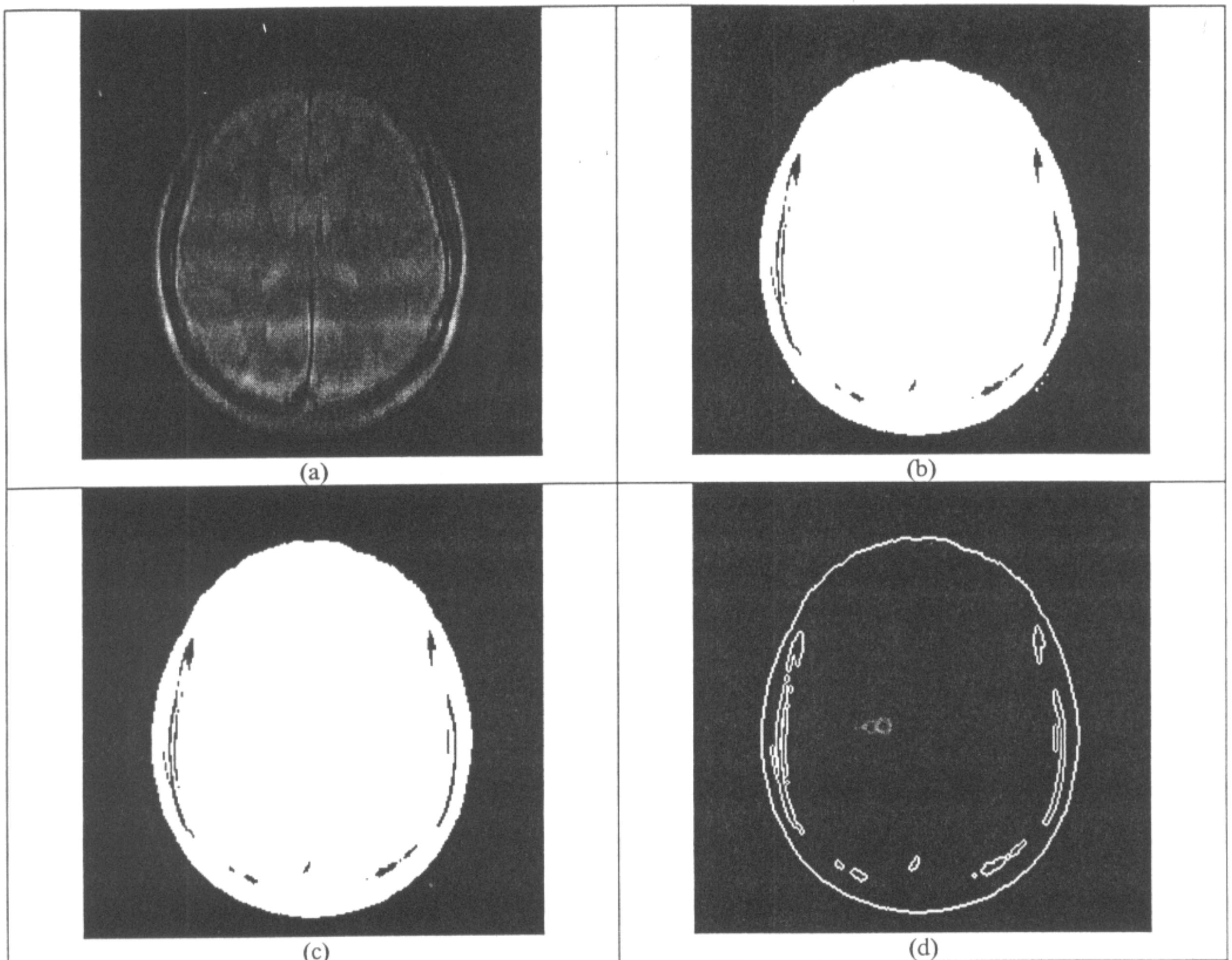


Figure 4. (a). The low resolution image from 32 lines at the center of the k-space. (b). The thresholded binary image. (c) The main object. (d). The edges of the main object.

The main object is the object having the largest area among the image objects. Since the image pixels with level 1 belong to the image blocks, the area A_i of the object is expressed as the summation of the areas of the blocks that constitute the object. Using the rectangular form appeared within the blocks, the area of an object is calculated as:

$$A_i = \sum_{j \in o_i} (x_{2,b_j} - x_{1,b_j} + 1)(y_{2,b_j} - y_{1,b_j} + 1) \tag{3}$$

The fast computation of the area A_i is achieved with the above simple and analytical formula (3). The area of an object can be expressed in terms of statistical moments as the moment of order (0, 0). Using similar analysis, the real-time computation of the statistical moments is also achieved in block represented binary images [6],[8].

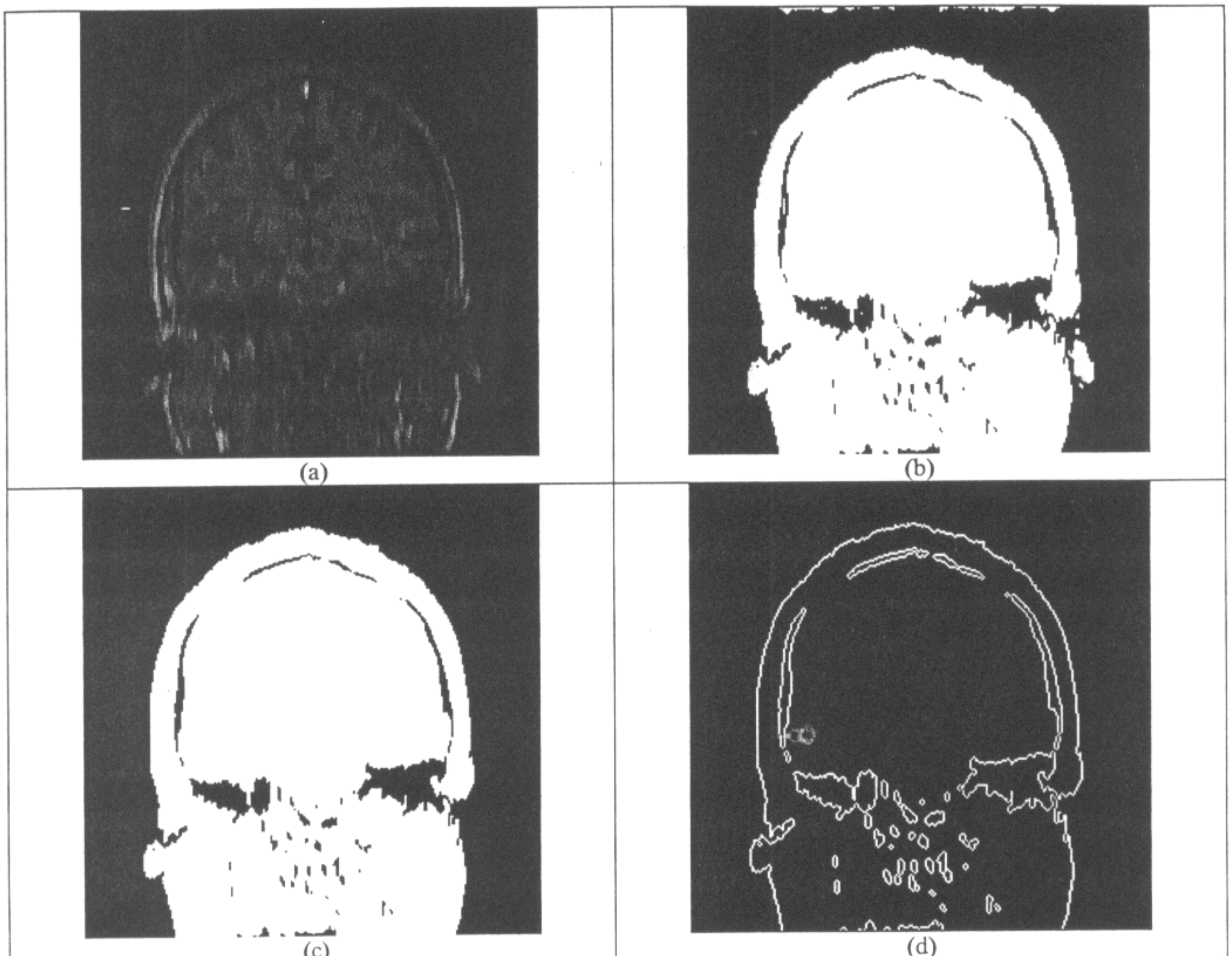


Figure 5. (a). The low resolution image from 32 lines at the center of the k-space. (b). The thresholded binary image. (c) The main object. (d). The edges of the main object.

IV. EDGE EXTRACTION

Each point of the binary image with object level and with at least one 4-connected neighbor with background level, belongs to an edge of the object and is called *edge point*. The edge extraction operation may be efficiently and fast performed using block represented binary images, provided that the information concerning the connections among the blocks is available.

Algorithm 2: Edge Extraction

Consider the block b, with coordinates $(x_{1,b}, x_{2,b}, y_{1,b}, y_{2,b})$, which is 4-connected with m blocks $b_j = (x_{1,b_j}, x_{2,b_j}, y_{1,b_j}, y_{2,b_j})$, $j=1, 2,..., m$. The contribution of the block b to the edge points of the whole object are all the boundary points of the block b, except of these boundary points that are 4-connected neighbors with the points of the m connected block b_j. Care should be taken if the block b has unity width, where a point is possible to be connected from the one side of the block but not connected from the other side of the block. In this latter case the specific point is retained as an edge point. The algorithm is implemented by the following steps:

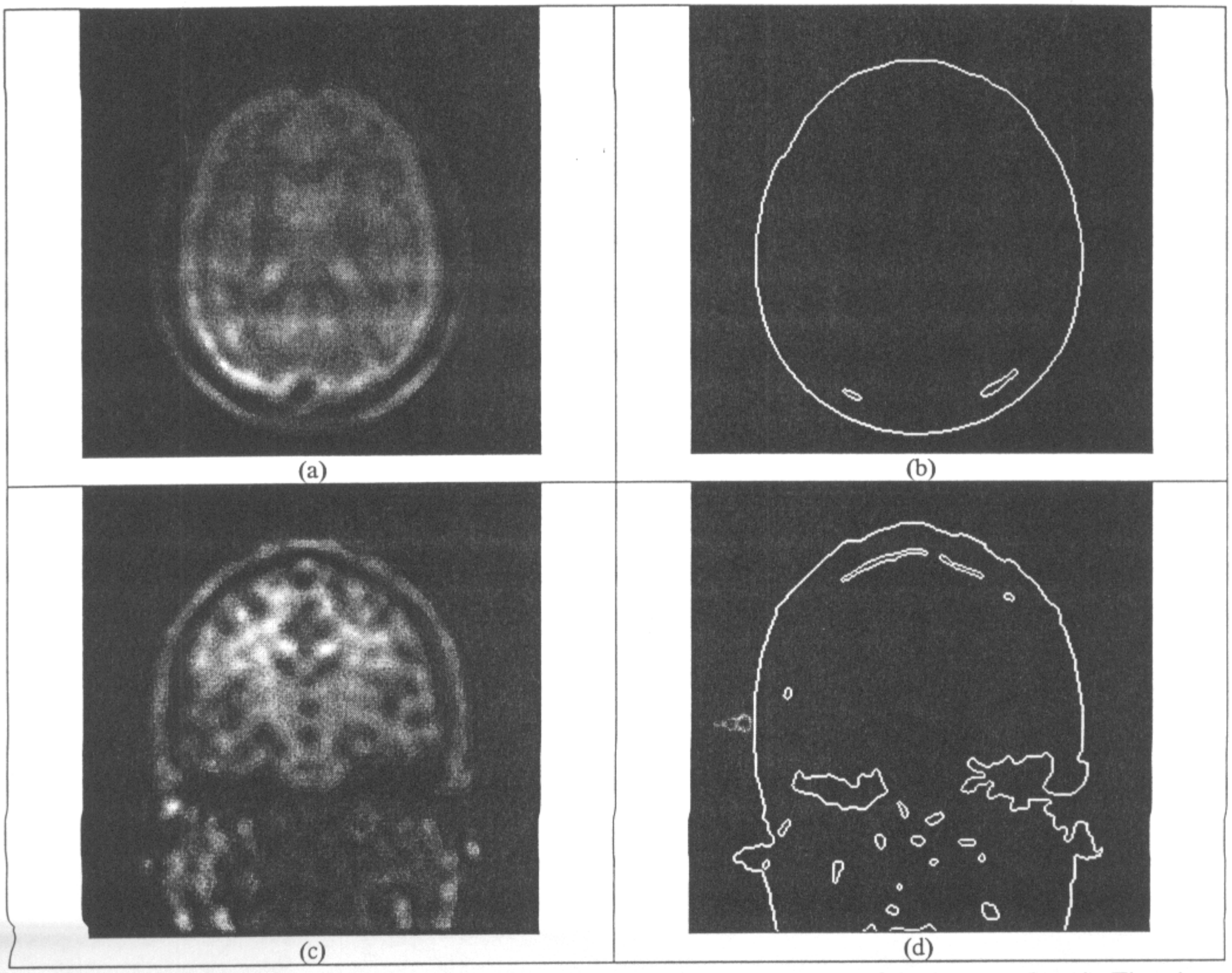


Figure 6. (a), (c). The low resolution images from a 32x32 window at the center of the k-space. (b), (d). The edges of the main object.

Step 1: Consider each block b_i, $i=0,1,...,k-1$.

Step 2: All the boundary points of the block b_i are labeled as edge points.

Step 3: Consider each block b_j, which is 4-connected with the block b_i.

Step 4: The boundary points of b_i, that are 4-connected with points of the block b_j, are removed from the set of the edge points.

■

The execution of the edge extraction operation, using the block representation based algorithm is faster in comparison with the edge extraction operation that is based on the checking of the four neighbors of each pixel with object level of the original image.

For the discrimination among the external edge and the interior edges, it is adequate to find a point of the external edge and then to trace and remove the external edge. The remaining points belong to an interior edge. In order to find a starting point of the external edge, it is adequate to perform a scan to the edge image from the left to the right and from the top to the bottom. The first white point which is found, is a point of the external edge. In Fig. 4 and 5, some results of the presentted method are shown. Both Fig. 4 and 5 show (a) the low resolution image, (b) the resulted binary image, (c) the main object is shown and (d) the edges of the main object. In both Fig. 4 and 5, the images are formed from 32 lines at the center of the k-space, as it is the case of Fig. 2 (b). The use of images formed from a window at the center of the k-space as it is the case of Fig. 2 (c) and (d) produces almost the same external edge, but due to the very low resolution the number of interior edges is significant less, as shown in Fig. 6.

V. CONCLUSIONS

In this paper an efficient method for the accurate estimation of the object edges from incomplete raw MRI data has been presented. This method yields to improved prior knowledge for Bayesian image reconstruction from incomplete raw data. The use of the image block representation and of the associated algorithms ensures the fast operation.

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