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USING MATHEMATICAL MORPHOLOGY FOR CORRECTION OF MAGNETIC RESONANCE IMAGES

SUMMARY *The paper presents a morphological method for brightness correction of Magnetic Resonance (MR) images, which makes possible the use of watershed technique for image segmentation and extraction of objects. As an example of image correction, extraction of the mask of the gray matter from the image of the human spinal cord is given. The described image correction is based on the use of the White Top Hat (WTH) transform with a large structuring element. As a result of the correction, brightness in the image becomes more homogeneous, and one can merge the watershed regions included in the mask of the gray matter in a semi-automatic procedure. This is a significant improvement in comparison with uncorrected images, for which development of such a procedure proved to be very difficult. The current paper is a simplified and abbreviated version of [10].*

1. INTRODUCTION

Inhomogeneity of brightness in MR images was analyzed in the literature from the point of view of brain tissue classification. As a result of the inhomogeneity the brightness of a pixel belonging to the same tissue is different in various positions in the image, which makes pixel classification difficult. In principle, two

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approaches to this problem are possible. In the first, two-stage approach the inhomogeneity is corrected, and then the segmentation is carried out as though the image were uniform. In the second, one-stage approach pixels are classified simultaneously with correction of the inhomogeneity. The morphological method of image correction considered in this paper is an example of the first approach.

The two-stage approach is considered in several papers. In particular, it has been proved in [4] that the MR image can be simulated as a product of the original image and a slowly varying gain (or attenuation) field. In [4], manually chosen reference points are used for generating the correction surface by means of splines. In [7] correction of the image intensity is carried out by means of the homomorphic filter, which effectively removes slowly varying gain field component. [3] compares results obtained with several variants of homomorphic unsharp masking, which is a simplified version of the homomorphic filtering. It has been proved in [3] that the homomorphic filtering can deteriorate an image in some cases, instead of improving it. Inhomogeneity correction presented in [12] is based on the fact that the slowly varying gain field reduces the contents of high frequencies in the image. These frequencies are restored in an iterative process, in which the gain field is estimated in each iteration by means of the maximization of the contents of high frequencies.

In the following, an original morphological method of image correction is presented, which reduces brightness inhomogeneity and makes possible quasi-automatic segmentation of the spinal cord. The purpose of the spinal cord segmentation is extraction of the mask of the gray matter. The proposed method requires some human interaction, but certainly it is much less laborious than the manual pointing to all the regions belonging to the gray matter. Furthermore, because of its simplicity, this method is faster than other methods described in the literature.

For the general introduction to the mathematical morphology the reader is referred to [14], and for morphological analysis of biomedical images to [5].

2. WATERSHED SEGMENTATION OF UNCORRECTED IMAGES

The watershed is one of the most advanced morphological techniques offered by image processing for segmentation of images [13], [15]. This method is still being developed; nevertheless it has found many applications [14]. In order to speed up calculations it has been even adapted to the parallel computa-

tions ([2]). Without getting into lengthy discussion of the watershed method and its implementation, one can briefly describe it as follows. An image shows the brightness distribution over its region of definition. Brightness at an individual pixel can be regarded as the elevation above some reference level. In this way one can look at an image as some kind of a topographical map. In this map higher elevation corresponds to higher brightness. Having a topographical map, one can consider its watershed lines, which divide the whole terrain shown in the map into segments, or regions. Each drop of a rain falling onto this terrain flows down to some catchment basin. All pixels collecting water to a common basin form a watershed segment. The watershed lines are the boundaries between segments. For computational reasons, it is more convenient in the case of digital images to consider flooding the terrain starting from appropriate minima, instead of simulating downfall of water, but in principle the results are similar. In the case of flooding, the watershed lines are obtained as dams between individual basins; they are built in order to prevent the mixing of water from two basins.



Fig.1.

a) Original image of the spinal cord c23a. b) Reconstruction of the gradient of the image in figure (a). c) Superposition of the watershed lines and the original image.

An example of the spinal cord cross-section obtained between the second and third cervical vertebrae (c23a) is shown in Fig.1a. The gray matter takes the center of the image and has the shape of a letter H or of a butterfly. The gray matter is brighter than the white matter, which surrounds it, and it would be very interesting for medical professionals to recover the shape of the gray matter in successive cross-sections. Such information might be used in studies of various diseases of the nervous system, for example Alzheimer's and multiple sclerosis. The image in Fig.1a, as well as the following ones are of size 230×178 pixels and have 256 brightness levels.

It can be demonstrated that the watershed of the original image does not give expected segmentation results, and instead it is necessary to carry out watershed segmentation of an image that shows the contours of the objects, for example the gradient image. In this case a morphological gradient was used, according to the equation

$$\text{grad}(f) = \delta(f) - \varepsilon(f) \quad (1)$$

where $\delta(f)$ and $\varepsilon(f)$ denote the dilation and erosion of the original image f , respectively. The dilation and erosion were carried out by means of a small flat structuring element of size 3×3 .

The gradient of the image in Fig.1a is not shown since the respective image would be completely dark. However, multiplying brightness of each pixel by 3 and complementing the result, one obtains an image that is very similar to the one shown in Fig.1b. In principle, the gradient image could be used by the watershed segmentation as it is. However, both the original image, and the gradient are quite noisy. There are many local minima and maxima of brightness that do not convey any useful information but rather are representation of noise in the image. Referring to the topographical surface once more, one could say that there are many small hills and shallow basins, which should be removed from the image without distorting significant larger hills and basins.

Local maxima and minima are removed by means of the reconstruction by erosion [14], [16]. The reconstruction by erosion can be briefly described as follows. Two images are necessary for this operation, that is a mask g and a marker f . The mask and the marker should have the same region of definition, and should satisfy the condition $g \leq f$, that is brightness at every pixel of the marker should be higher than brightness at the same pixel in the mask. The reconstruction by erosion is defined by the equation

$$R_g(f) = \varepsilon_g^{(i)}(f), \quad (2)$$

where i denotes a successive iteration of the geodesic erosion $\varepsilon_g^{(i)}(f)$, and $\varepsilon_g^{(i)}(f)$ satisfies the condition $\varepsilon_g^{(i)}(f) = \varepsilon_g^{(i+1)}(f)$. The geodesic erosions are defined by the equations

$$\begin{aligned} \varepsilon_g^{(1)}(f) &= \varepsilon^{(1)}(f) \vee g \\ \varepsilon_g^{(n)}(f) &= \varepsilon_g^{(1)}[\varepsilon_g^{(n-1)}(f)] \quad \text{with} \quad \varepsilon_g^{(0)}(f) = f. \end{aligned} \quad (3)$$

$\varepsilon^1(f)$ in the above equations denotes a usual erosion of size 1 of f . The structuring element used in this erosion in the experiments described herein was a 3×3 square. In theory, the reconstruction by erosion may be carried out by iterating up to infinity. However, the result of erosion at any pixel of the image is not allowed to become less than the value in the mask at the same pixel. Since a digital image has a finite number of pixels and a finite number of brightness values, it follows that the iteratively eroded image comes to stability in a finite number of steps and does not change any more in subsequent iterations.

In the case considered, the original gradient image was used as a mask, and the marker was obtained by adding a small integer to the brightness at each pixel in the mask. In the experiments the value of 2 was used. It was observed that the value of 3 would also give satisfactory results, but higher values would excessively reduce the number of segments and some of them would tend to look nonuniform, which is contrary to human intuition.

The reconstructed gradient is characterized by smaller variability in comparison with the original gradient. Fig.1b depicts the reconstructed gradient of the image in Fig.1a. Similar results can also be obtained by reconstruction by dilation.

The watershed segmentation of the reconstructed gradient image in Fig.1b is shown in Fig.1c. The major trouble with the image in the latter figure is that it exhibits a very high over-segmentation, as there are still 1152 regions.

One of the advantages of the watershed segmentation is that one can immediately see whether the obtained regions coincide with the expected boundaries of the objects. Once this condition is satisfied, the next problem is that of region merging, or aggregating small segments into larger, meaningful regions. Some early attempts at extracting the mask of gray matter are described in [6] and [11], but the results have been only partially satisfactory.

3. IMAGE BRIGHTNESS CORRECTION

The idea of image correction is simple. One wants to modify brightness distribution in the image in such a way that those fragments of watershed lines that represent the contour of the gray matter stay intact. At the same time the differences in the average brightness of individual segments should reveal not the magnetic field distribution, but rather the anatomical structure of the investigated object.

The correction of the image is based on the use of the WTH transform [14]. This transform is defined as a difference of the original image f and its opening $\gamma_B(f)$

$$\text{WTH}(f) = f - \gamma_B(f). \quad (4)$$

The following example illustrates the operation of WTH transform in the 1-dimensional case with the structuring element $B = \{-1, 0, 1\}$ consisting of three pixels

Image	2	2	10	3	3	8	1	2	2	6	6	1	1	9	2	7	7
Opening	2	2	3	3	3	3	1	2	2	2	2	1	1	2	2	7	7
WTH Transform	0	0	7	0	0	5	0	0	0	4	4	0	0	7	0	0	0

The opening is an anti-extensive operation, that is $\gamma_B(f) \leq f$, and as a consequence the result of the WTH transform at every pixel is greater than or equal to 0. It can be observed that the WTH transform detects local peaks of brightness, independently of the absolute brightness level. This stays in contrast with thresholding, which detects all cases where brightness exceeds a certain level established for the whole image. The opening $\gamma_B(f)$ removes local peaks of brightness, such as a gray matter, on condition that their dimensions are not greater than the structuring element. Assuming that the inhomogeneity of brightness is characterized by spatial frequencies lower than the frequencies of the gray matter, and calculating the difference between the original image and its opening, one obtains the image of the gray matter. For the WTH to be effective, the structuring element used for the opening has to be of considerable size. For example, the images of the background, shown in Figs.2b and 3b were obtained by opening with the structuring element B of size 25×25 pixels. The operations using such a large structuring element would be time-consuming. In order to speed up computations, the 25×25 square element was decomposed into two linear elements: B_{hor} and B_{ver} , each containing 25 pixels positioned horizontally, or vertically. In this case, one executes composite operations, which give intermediate results, for example

$$f_1 = \varepsilon_{B_{hor}}(f), \quad (5)$$

and then

$$f_2 = \varepsilon_{B_{ver}}(f_1), \quad (6)$$

where f denotes the input image, and f_2 the final result of erosion by 25×25 square element. Similar equations can be written for dilation. The result of the opening is then the composition of erosion and dilation.

One can note in Fig.2b that the maximum of brightness takes place in the upper right corner of the image, whereas in Fig.3b on the right side. Brightness in Figs.2b and 3b does not change quite smoothly, and in fact one can recognize the shapes reminding of the structuring element. This is not a major obstacle, however. Subtracting the image in Fig.2b from that in Fig.2a, one obtains, in accordance with Eq. (4) the corrected image shown in Fig.2c, (and similarly in 3c). Strictly speaking, the images of the WTH transform are complemented, but this was done solely for better visibility.

The most important thing is, as one can notice comparing the upper arms of the letter H in Figs.2a and c, that the left and right arms of the corrected image have roughly the same brightness, whereas the right arm in the uncorrected image is significantly brighter than the left one. The watershed segmentation of the corrected images is carried out similarly to that of uncorrected ones, as was demonstrated in Fig.1, that is by finding the morphological gradient, reconstructing the gradient by erosion, and finding the watershed lines for the reconstructed gradient. Figs.2d and 3d below show the watershed lines obtained, respectively, for two examples of the spinal cord cross-section. The superposition of the watershed lines on the respective corrected images is included in Figs.2e and 3e. A more careful comparison of Figs.1c and 2e reveals that the correction of the brightness distribution results in some change of watershed lines. Nevertheless, relevant fragments of watershed lines correctly represent the contours of the gray matter in both cases. The change of shape of some segments took place inside the areas of the white matter or gray matter taken separately. This side effect is rather unimportant from the point of view of the extraction of the mask of the gray matter.

4. WATERSHED SEGMENTATION AND REGION MERGING FOR CORRECTED IMAGES

The idea of merging regions obtained by watershed segmentation into meaningful masks of objects was considered in a quite limited number of papers.

In particular, in [9] region merging was used for obtaining masks of extended defects of ferrite cores. These defects are brighter than the surroundings, and a region classifier merges regions having similar average brightness levels. The construction of the mask of a defect starts with a kernel, which is

obtained independently from the watershed segmentation. This kernel consists of pixels around which brightness changes sufficiently irregularly so that one can be sure that they represent a defect. Every pixel of a kernel belongs to a certain region. On this basis, a list is found of regions included in the starting mask. Merging neighboring regions whose average brightness satisfies certain logical conditions subsequently increases the mask.

In [17] an algorithm is presented for merging watershed regions for the purpose of recognition of the macula of a human eye. The area to be identified is characterized by lack of blood vessels, whereas the area around the macula contains a large number of vessels. Unfortunately, blood vessels are hard to recognize, and the relatively dark area of the macula is nonuniform. The algorithm begins with choosing the segment with the lowest brightness as a starting region. The contour of the macula is found by merging subsequent neighboring regions in accordance with a procedure consisting of morphological operations and of decision criteria. Skipping rather involved details, one can say that, similarly to the case of the aforementioned ferrite cores, the region merging procedure is precisely adapted to the class of images under consideration.

In [1] a watershed segmentation and region merging based on rules are presented for the case of 3-dimensional histopathological images. The method described aims at extraction of individual cells. For this purpose the dark background has its brightness changed to zero, and the cell area has brightness 255. In this way a binary image is obtained. Segmentation of the cell area is carried out using the notion of the distance function together with basin growing, the basins being initialized at those pixels which are the most distant from the background. In the ideal case there is only one basin for one cell. In practice, however, there may be several basins covering the area of one cell, and furthermore the cells do touch one another so that the situation becomes even more complicated. The region merging is carried out according to several rules. First of all, all regions with areas below a certain level are considered as noise and have to be merged to some native cell. The rules for merging with a native cell are the following. If a given region has an area smaller than the threshold and smaller than the area of its neighbor, then this region is merged with its neighbor. If a given region has two neighbors with an area larger than the threshold, then this region is merged with the neighbor with whom it shares a longer boundary. In the case when a given region has several neighbors, but none of these regions has an area larger than the threshold, then all of the regions under consideration are merged into a single region. If this larger region has the area larger than the threshold, then it is classified as a cell. Otherwise, the region is assumed to represent local noise and removed. It can be observed that also in this case the rules for region merging are strictly adjusted to the class of images under consideration.

The above survey of the methods of region merging clearly shows that these methods are strongly case-dependent. Similarly, the method proposed for the extraction of the mask of the gray matter in the spinal core is rather specific. Its main idea is illustrated by Figs.2 and 3, where Fig.2a is a repetition of Fig.1a, and Fig.3 shows the image c4, representing a cross-section in the area of the fourth cervical vertebra.

The watershed lines, such as in Figs.1c, 2d, 2e, etc. have width of one pixel. It does happen sometimes, that the watershed line can take a wider area, which might look like a region obtained from the watershed segmentation. A rule was assumed that, whenever possible, a pixel of the watershed line is assigned to the neighboring region, which may be above it, below, to the left, or to the right, whatever the case. Having the watershed lines, one generates an array A, in which for each (or almost each) pixel the label (ordinal number) of the region is given, to which this pixel is assigned. Subsequently, another array B is generated, which contains region statistics, in particular the area and the average brightness of each region. The array B is sorted in accordance with increasing brightness. After generation of these auxiliary arrays, the region merging is carried out as described in the following.

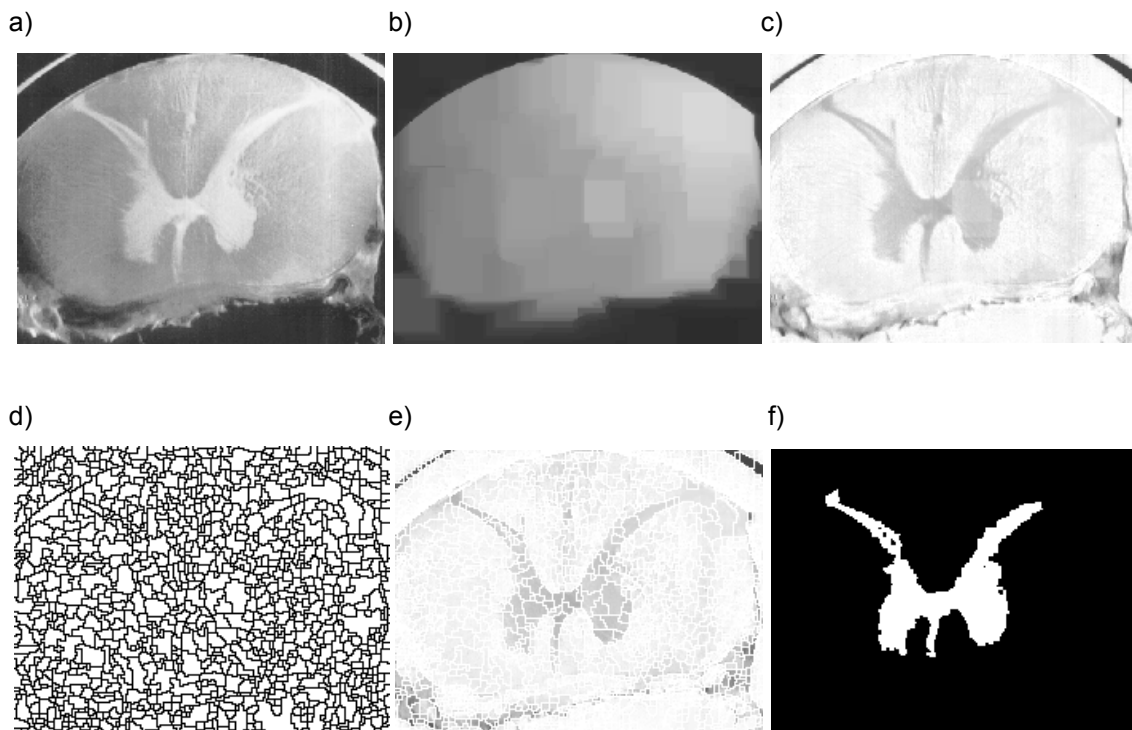


Fig.2.

a) Original image c23a from the previous figure. b) Opening of the image from figure (a). c) Top Hat Transform. d) Watershed lines. e) Superposition of watershed lines and the image from figure (c). (f) Mask of the gray matter.

The algorithm begins calculations with the starting region indicated by the user. The starting region for an image such as in Fig.2d should be as dark as possible. In the examples shown in Figs.2 and 3 this is the region lying at the center of the letter H, which is at the point of connection of all four arms. Selection of the starting region follows by indicating arbitrary pixel belonging to this region.

In the first iteration, with the known label of the starting region and using the array A the program generates another auxiliary array containing the labels of all neighbors of this region. This new array is sorted according to increasing average brightness of the neighbors of the starting region. The program then chooses the darkest region and merges it with the starting region by changing the label of all the pixels of that region to the label of the starting region. In addition, the program updates the array B by removing the region being joined to the starting region and changing the statistics for the starting region. Subsequently the program executes the next iteration – with a modified (increased) starting region. The number of iterations can be arbitrarily set in the program. As a rough estimate, an expected value of the number of the regions in the mask of the gray matter can be used.

The choice of the darkest region for the start is not critical, because the algorithm always looks for a neighbor with the lowest brightness level. Whenever the darkest region has been skipped, the algorithm will find the missing darker neighbor anyway.

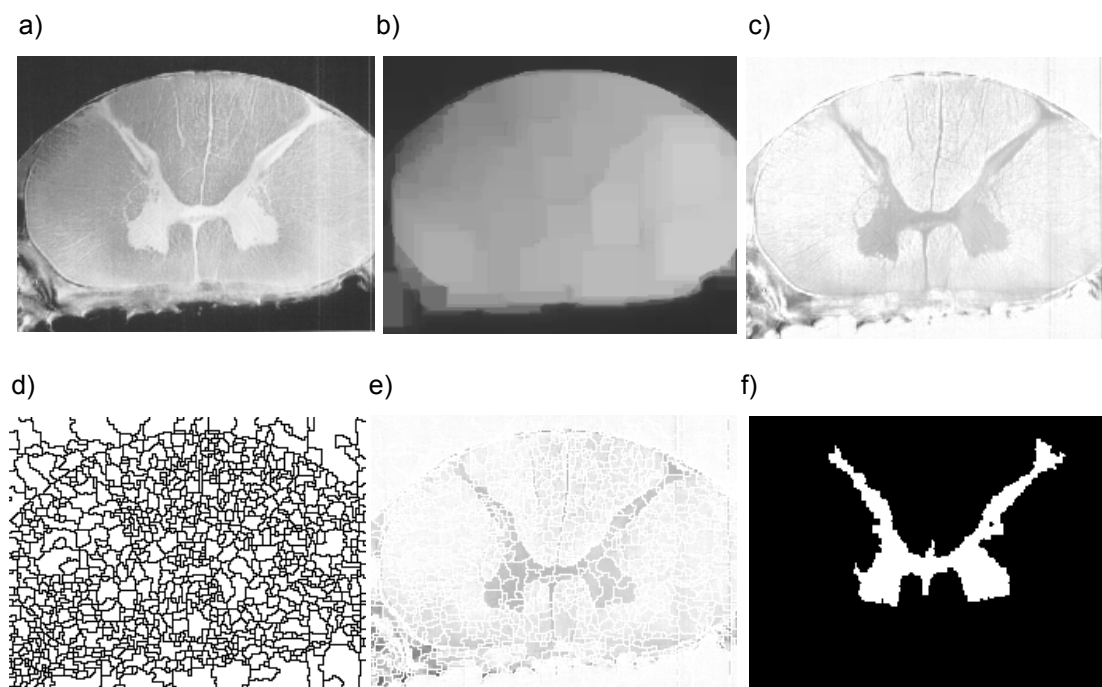


Fig.3.

a) Original image c4. b) Opening of the image from figure (a). c) WTH transform. d) Watershed lines. e) Superposition of the watershed lines and the image from figure (c). f) Mask of the gray matter.

In order to prevent the merging of regions with improbable brightness levels, three parameters were introduced, which are compared with the current counterparts, obtained in successive iterations:

Maximum total positive increase of brightness (MTPI). The MTPI determines how much the average brightness of the area representing the gray matter can increase with respect to the average brightness of the starting region. The calculations terminate whenever the MTPI is exceeded. The value MTPI=25 was used in experiments for the images shown.

Maximum total negative increase of brightness (MTNI). The MTNI determines how much the average brightness of the area representing the gray matter can decrease with respect to the average brightness of the starting region. The MTNI plays a similar role as the MTPI. The calculations terminate whenever the MTNI is exceeded. The value MTNI=25 was used in experiments for the images shown.

Maximum increment of brightness in a single iteration (MIB). The MIB determines what the maximum increment of the average brightness of merged region may be in comparison with the average brightness of regions already in the mask of the gray matter. The calculations terminate whenever MIB is exceeded. The value MIB=15 was used in experiments for the images shown.

The values of the parameters MTPI, MTNI, and MIB were found experimentally. However, they have only auxiliary meaning. In principle, the calculations are executed until the maximum number of iterations is reached. This number may turn out too small or too large. If it is too small, one can increase it and repeat the calculations. When it is too large, then the mask grows excessively and includes regions, which obviously do not represent the gray matter. In Fig.2f a mask is shown, obtained after 74 iterations. In this particular case there would be further growth of the upper left arm to the left, since this is the area of the regions with relatively lowest average brightness. In Fig.3f a mask obtained after 82 iterations is shown. In subsequent iterations the area near the end of the upper right arm would be included into the mask, because this is a relatively darkest area. Although the iteration terminating generation of the mask of the gray matter is chosen manually, the whole process of obtaining the mask is greatly accelerated in comparison with the manual pointing to all of the regions to be included in the mask.

Experiments with various cross-sections of the spinal cord have shown that it may be necessary to change the size of the structuring element for the WTH transform. An element as small as possible is needed for more accurate approximation of the background brightness (Fig.2b), which should be as smooth as possible. At the same time the structuring element should be large enough so that the gray matter would not disappear from the image as a result of applying the WTH transform. Obeying to these two contradictory conditions

may require a larger structural element, particularly in the case when the lower arms of the letter H have a significant area.

In the cases mentioned above, as well as depending on the particular brightness distribution in the image, it may turn out that the darkest region is not in the center of the letter H, as was the case in Figs.2c and 3c, but it may lie somewhere else. It may then be necessary to use the described algorithm several times, with different starting regions, and then to combine the partial masks into a single mask of the spinal cord [10]. However, even in this more complicated situation the algorithm speeds up finding the mask in comparison with the manual pointing of individual regions.

The presented algorithm keeps looking for regions with the lowest average brightness, tending to move steeply, as though along the gradient, without looking to the sides. This means that it is prone to skip some regions; although there is a feeling that they should be included. Such example is shown for the upper left arm in Fig.2f. Occasionally, missing single regions can be included manually.

5. SOFTWARE FOR SEGMENTATION

The software was developed mainly for experimentation. It consists of several parts that were written by the authors of [10], or were obtained commercially. Obviously they can be put together into a single package. The major functions of this software are the following: 1) Correction of the inhomogeneity by calculating the WTH transform, 2) Calculation of the gradient of the corrected image. 2) Reconstruction by erosion of the gradient. 3) Watershed segmentation of the reconstructed gradient. 4) Labeling of the watershed segments. 5) Generation of the mask of the gray matter. The main commercial component was the watershed algorithm. The program for labeling the segments was based on [8]. Because of the necessity of running several independent programs, it is difficult to specify the total execution time. However, the single most time-consuming program is that used for labeling. This is due to the fact that during the scanning of the image, the program stores the labels (ordinal numbers) of the segments in a large array. It happens quite often that the program assigns two or more different labels to the same segment, because it does not know in advance that it is processing the same segment. At a later stage, a more compact array is created, in which all multiple labels of the segments are removed.

6. CONCLUSIONS

The presented method of MR image correction facilitates extraction of the mask of the gray matter in the image of a cross-section of the spinal cord. Without correction it is very difficult to automatically select the regions which should belong to the mask, since local brightness depends more on the magnetic field and less on the anatomical structure of the spinal cord. As a result of the correction, semi-automatic method of selecting the regions for the mask of the spinal cord is possible.

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ZASTOSOWANIE MORFOLOGII MATEMATYCZNEJ DO KOREKCJI OBRAZÓW Z MAGNETYCZNEGO REZONANSU JĄDROWEGO

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STRESZCZENIE *Artykuł przedstawia morfologiczną metodę korekcji jasności w obrazach pochodzących z magnetycznego rezonansu jądrowego, pozwalającą na zastosowanie techniki wododziałowej do segmentacji obrazu i ekstrakcji obiektów. Jako przykład korekcji obrazu przedstawiono ekstrakcję materii szarej z obrazu rdzenia kręgowego człowieka. Opisana korekcja obrazu wykorzystuje transformatę White Top Hat (WTH) z dużym elementem strukturującym. W wyniku korekcji jasność w obrazie staje się bardziej równomierna i można przeprowadzić w sposób półautomatyczny łączenie obszarów powstałych w wyniku segmentacji wododziałowej i wchodzących do maski materii szarej. Stanowi to istotne ulepszenie w stosunku do obrazów bez korekcji, dla których opracowanie podobnej procedury okazało się bardzo trudne. Niniejszy artykuł stanowi uproszczoną i skróconą wersję [10].*

Prof. Mariusz Nieniewski is a professor in the Institute of Fundamental Technological Research of the Polish Academy of Sciences as well as in the Electrotechnical Institute. At one time he had a Fulbright scholarship and later worked for universities in the USA, Brazil, and Belgium. His current research interest includes digital image analysis and computer vision, in particular mathematical morphology. He is the author of about 75 publications, including journal papers, chapters in books, international conference contributions, and two books.

