Contrast as a Method of Image Processing in Increasing Diagnostic Efficiency When Studying Liver Fatty Tissue Levels

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***Abstract*—The paper discusses various problematic issues in the analysis of digital medical images. Examples of identifying and studying the level of fatty liver tissue are presented. For these purposes, a technique was used to contrast the input image in order to improve the perception of transition zones that limit the foci of fatty lesions. For contrast, the classic histogram equalization procedure was used. This ensures an even distribution of brightness levels. The quality assessment of the processed image is based on such indicators as entropy, niqe and brisque. Various strategies for contrasting the original image are considered based on individual values of quality indicators or their combination. This made it possible to improve the identification of transition zones of fatty lesions. The results obtained are presented for real digital images of fatty liver lesions.**

Keywords—contrast, diagnostics, liver, image processing, microscopic imaging, adipose tissue level

I. Introduction

Digital image is one of information sources that helps to make informed and effective decisions. Such a source plays an important role in various research fields [1]-[5]. Using the information presented in the image, it is possible to obtain so-called primary information. Processing results provide additional information. This is an important point in digital image analysis. At the same time, the information content of additional data is largely determined by image processing procedures that are applied to certain types of digital images.

The study of digital images is of particular importance in the diagnosis and analysis of various diseases [5], [6]. This makes it possible to justify the necessary decisions based on studying the human microcosm using images of its organs, tissues and cells. In this case, as a rule, unnecessary surgical intervention necessary to preserve the health of the person is avoided.

One of the areas of diseases diagnosis and analysis based on images examination taken under a microscope is the study of the level of fatty liver tissue. This disease has various forms and is dangerous for humans [6]-[9]. Therefore, its early detection is a condition for prescribing an effective course of treatment. The solution to this problem is to detect fatty liver lesions and calculate the area of lesions, both individually and as a whole.

The complexity and routineness of the process of detecting and determining the area of the lesion necessitates its automation. This can be done using image processing techniques [9].

Many authors also highlight various approaches that make it possible to most effectively solve individual stages of such a problem. For example, K. Mala, V. Sadasivam and S. Alagappan consider texture analysis for the study of obesity and liver cirrhosis [10]. The study [11] addresses the classification of fatty liver disease using supervised learning and a genetic algorithm. The article [12] explores various problematic issues in the study of effective imaging and image analysis in fatty liver disease. The work [13] explores the possibility of determining the stage of liver fibrosis based on contrast enhancement of the original image. J. Singh, P. Thakral and R. Kaur focus on identifying fatty liver disease using machine learning [14]. At the same time, in each of the above papers, methods of source images pre-processing are used, where special attention is paid to contrast.

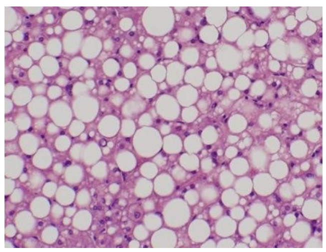
However, luminance nonlinearity occurring in many medical imaging devices often affects the performance of medical image processing techniques. At the same time, the coloring methods used may impair the perception of transition areas that limit the foci of fatty lesions [4], [12].

Thus, an important issue is the most accurate determination of the contours of fatty liver lesions [9]. Such accuracy may be considered in terms of improved visualization of such heterogeneities or in view of more efficient determination of the area of fatty lesions. It is also necessary to take into account in this aspect the possibility of automating the general procedure for identifying and determining the area of fatty liver lesions. This suggests that the main goal of our study is to consider the contrast of the original image based on certain parameters (indicators) that can improve the detection of lesions in the future. However, no special attention is paid to contrasting methods. The main task is to justify the procedure for increasing the contrast of the input image. Although in general it should be emphasized that a certain contrast approach may impose certain restrictions on such a procedure for improving the resulting image. It should also be noted that other methods of image preprocessing may also influence the efficiency of identifying lesions. For example, this is noise suppression or removal of non-classical objects (objects not typical for a given area of research). However, such cases are not considered. The focus is on automating the overall contrast procedure.

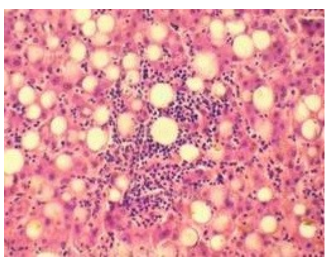
II. Some Aspects of the Implementation of a General Procedure for Contrasting Images of Liver Tissue with Foci of Fatty Lesions

A. *Image of liver lesions as an object of study*

To implement a generalized procedure for identifying fatty liver lesions, it is necessary, first of all, to understand the essence of the object of study. Fig. 1a and Fig. 1b show some relevant images.



(a)

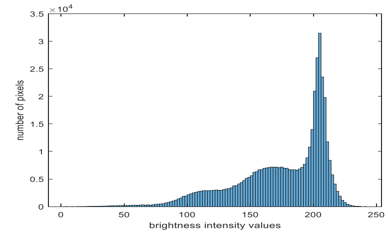


(b)

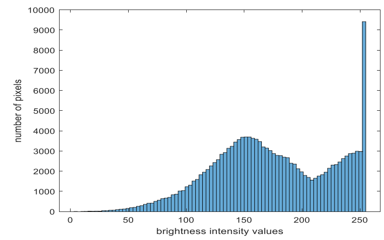
Fig. 1: Example image of fatty liver lesions: example 1 (a), example 2 (b)

It should be noted that the examples of digital images presented differ from each other. At the same time, these examples reflect some problematic aspects in solving the problem. First of all, this is the use of various staining methods when examining foci of fatty lesions. It should also be noted that there is a difference in the texture of the background where such lesions are located. Fig. 1a has a less complex background than Fig. 1b. Please note that some formations have blurred edges, which makes it difficult to clearly identify them and calculate the affected area. At the same time, it should be emphasized that fatty lesions have a pronounced shape, close to a circle. In this case, the lesions differ from the background. This allows the use of simple methods for identifying them based on a certain threshold.

When considering examples of the above images, one should emphasize their individuality, which is reflected in one way or another in the corresponding brightness distribution histograms for each example. Fig. 2 shows brightness distribution histograms for the images in Fig. 1.



(a)



(b)

Fig. 2: Histograms of brightness distribution for the original data: example 1 (a), example 2 (b) (respectively)

There are very different brightness level distributions here, which can affect contrast results.

B. *Changing the histogram as a way to contrast the image*

The basis for contrasting a digital image is the methods of changing the histogram of the distribution of brightness levels of such an image. This is based on the definition of contrast according to Weber or Michelson [15]-[18]. At the same time, contrast characterizes the perception of an image and the ability to distinguish individual details in it. This, in turn, is associated with the spatial quality of the image and its naturalness of perception.

One of the simplest approaches is based on transforming the original image so that the histogram of the transformed image is close to a uniform distribution. In this case, a certain variable (n) is used, which correlates with the number of gradations of brightness levels of the original image (*Iimage*). Then, the smaller n, the more uniform the histogram of the resulting image is. By changing n, it is necessary to view the various images obtained and analyze them from the point of view of solving the problem.

At the same time, in this aspect, the choice of contrasting procedure is not important. It is important to show the possibility of such an application to build a generalized automation procedure in the diagnosis of fatty liver disease.

C. *Measures for assessing changes in image contrast*

It is natural to choose to assess changes in image contrast measures that correspond to this definition according to Weber or Michelson. But it is also necessary to take into account the natural visual sensitivity of the resulting image and its spatial quality. It should be borne in mind that contrast is necessary to more accurately determine the boundaries of fatty liver lesions. Based on this, it is proposed to use:

niqe model as an assessment of naturalness image quality [19]. The lower the niqe value, the better the quality of perception;

brisque model as an assessment of spatial quality [20]. The lower the brisque value, the better the perceptual quality;

entropy as a measure that shows the change in uncertainty [21]. In this aspect, a higher entropy value indicates the presence of a large number of details on the image.

Then the purpose of contrasting the input image is to select a number of parameters to obtain the resulting image – *Rimage*, taking into account its further processing to identify lesions using a certain procedure (*pro*):

$$Rimage = Iimage_{pro}(n, niqe, brisque, entropy). \qquad (1)$$

D. Highlighting areas of fatty liver lesions in the image

The final stage of this study is the identification of liver lesions. For these purposes can use various edge selection methods.

At the same time, given the fact that fatty liver lesions have a pronounced brightness value, it is advisable to use the simplest method for identifying lesions. This method is based on cutting off unnecessary information based on a certain threshold. This threshold can be determined based on the histogram, where liver lesions are the brightest and, accordingly, have the highest brightness values.

Thus, the essence of our analysis is to determine some scenarios for increasing the contrast of the input image based on the measures discussed above for assessing the change in image contrast or a combination of them.

It is now important to review the extraction of fatty liver lesions and determine the effectiveness of such detection of regions of interest. For these purposes, it is necessary to compare the results obtained with the original image and draw a conclusion based on expert assessment. As a result, some scenarios for contrasting the original image are determined.

III. Results and Discussion

Based on the fact that the choice of contrast parameters of the input image is based on a number of measures for assessing changes in such contrast and the histogram transformation parameter (n), their mutual dependence should be considered. By changing the parameter n, changes in such indicators as: *niqe, brisque, entropy*.

In Fig. 3 shows the change in *entropy* depending on the parameter n for the image shown in Fig. 1a. Here the ordinate axis shows changes in the *entropy* parameter, and the abscissa axis shows the changes in the n parameter. In this case, the values of the power of the parameter n in base 2 are considered.

Similarly, in Fig. 4 shows graphs for *niqe, brisque* depending on the change in the parameter n for the data Fig. 1a.

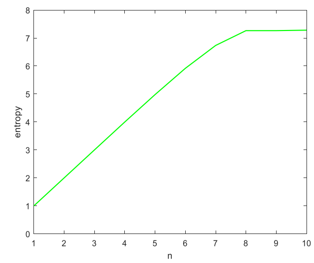


Fig. 3: Change of *entropy* depending on parameter n for the original image in example 1

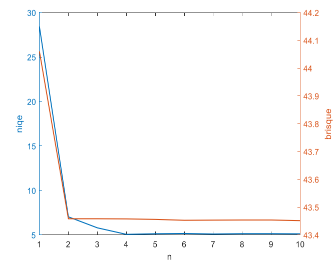


Fig. 4: Change of *niqe, brisque* depending on parameter n for the original image in example 1

Similar data are presented in Fig. 5 and Fig. 6 for image Fig. 1b.

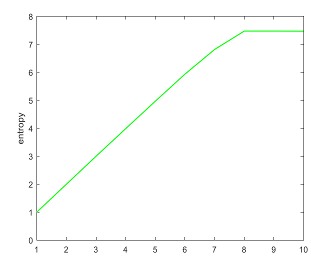


Fig. 5: Change of *entropy* depending on parameter n for the original image in example 2

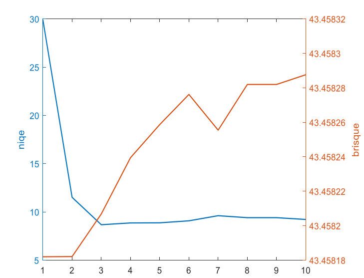


Fig. 6: Change of *niqe, brisque* depending on parameter n for the original image in example 2

At the same time, the *brisque* measure has multidirectional trends for the data in Fig. 1a and Fig. 1b. Growth of *brisque* measure values for data Fig. 1b is most likely due to the complexity of the background and its texture where liver lesions are represented. Based on this, it is advisable to represent the goal of contrasting the input image for this case in the following form:

$$Rimage = Iimage_{pro}(n, niqe, entropy). \quad (2)$$

It should also be noted that the uniformity of the histogram of the resulting image, in the first and second cases, is achieved when the degree values for the parameter *n* are equal to 3 and 4.

Then, taking into account the remaining values of the measures in the first case (for the data in Fig. 1a), the contrast goal has the following form:

$$Rimage = Iimage_{pro}(4, (4), (4)), \quad (3)$$

where the entry in brackets (…) means the parameter for assessing the change in contrast at a certain value of the parameter *n*.

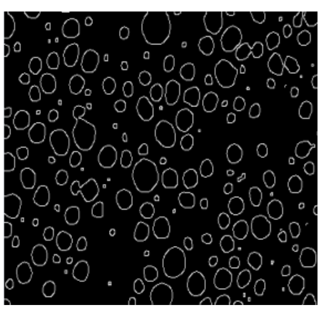
This choice is based on the fact that the evaluation measure *niqe* has the lowest value for $n=4$ (see Fig. 4). By increasing the *entropy* estimation parameter, unnecessary details appear in the resulting image.

By analogy, the contrast goal for the data in Fig. 1b has the following form:

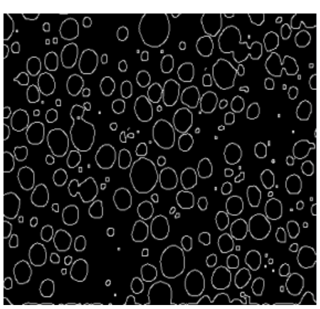
$$Rimage = Iimage_{pro}(3, (3), (3)). \quad (4)$$

Let's check our conclusions. To do this, consider the lesions. In Fig. 7 shows the results of identifying liver lesions for the initial image Fig. 1a (Fig. 7a) and the image after contrast (Fig. 7b).

There are some differences between the data here in Fig. 7a and Fig. 7b.



a) result for the original image



b) result after applying the contrast procedure

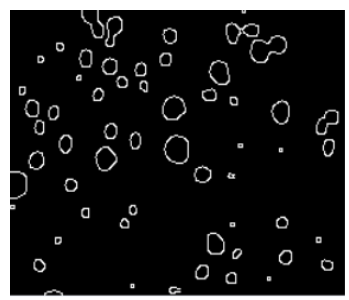
Fig. 7: Data processing result for example 1

At first glance, these differences seem insignificant. These differences relate to the identification of small areas of liver damage. However, in this aspect, all changes in fatty lesions of liver tissue are important. Therefore, it is important to take into account all lesions, even minor ones.

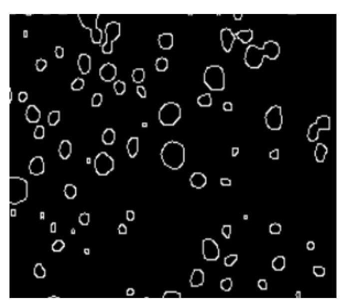
Knowing the clear boundaries of the lesions, it is easy to determine both the area of an individual lesion and the total area of fatty liver lesions.

According to the experts who were involved in assessing the results obtained, after contrast, the area of detected liver lesions increased by 5.7% in comparison with the original image. Further changes in contrast conditions result in an increase in the area of identified lesions by another 0.4%–0.52%. However, such an increase is typical only for the next three values of the parameter *n* (5, 6 and 7). Further increase in the affected area is not observed. Moreover, false areas are added as liver lesions. This makes the obtained result unreliable. With a significant increase in parameter *n*, there is a reduction in correctly identified areas of liver damage. The process of identifying such zones also becomes more complicated.

More complex is the process of identifying liver lesions for the data in Fig. 1b. In this case, even for the original image, according to experts, it is not possible to identify all fatty liver lesions. However, the result improves significantly after contrast (see Fig. 8).



a) result for the original image



b) result after applying the contrast procedure

Fig. 8: Data processing result for example 2

Comparing the data Fig. 8a and Fig. 8b, experts note a significant increase in the actual area of lesion identification by 9.3%. At the same time, about 2.2% of this area remains out of sight. Further changes in contrast conditions result in a slight increase in the area of identified lesions – 0.2%. Moreover, such an increase is no longer observed when the parameter value is $n=5$. In the future, the identification of liver lesions is also complicated. Moreover, the resulting images require additional processing.

In general, it should be noted that the results obtained are acceptable, based on the above. In this case, the generalized procedure for automating the process of identifying fatty liver lesions is to select the appropriate contrast parameters based on a comparison of their individual values. Next, the procedure for identifying the boundaries of such foci is applied and the total area of the lesion is calculated.

IV. Conclusion

The work examines key issues in the analysis of digital images, which represent areas of the liver affected by fatty disease. The importance of using a contrast procedure to more accurately identify fatty liver lesions was noted. For these purposes, various parameters are used both when changing the contrast of the original image and when evaluating the resulting image after contrasting. Experiments conducted on real images showed the effectiveness of the considered procedures in determining contrast conditions. In one case, the area of detection of liver lesions increased by 5.7%, in the other – by 9.3%. This contributes to the consideration of the possibilities of implementing an automated system for detecting fatty liver lesions based on the considered conditions for determining the contrast of the original image.

It should be noted that other parameters for assessing contrast quality can be used. This will help expand the contrast conditions of the original images.

Thus, the ability to change the contrast conditions and expand the conditions of the automation procedure is the strength of what was discussed above. However, this also imposes certain restrictions, which are determined by the complexity of the background against which such foci of liver damage are observed.

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