Increasing the contrast of mammograms containing breast cancer regions on the background of fat involution using wavelet transformations

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Abstract. According to the International Agency for Research on Cancer, in 2018, Russia ranks fifth in cancer mortality. Every sixth woman was diagnosed with breast cancer. The only way to diagnose this disease is the timely passage of professional examinations. For women older than 40 years, a mammary gland examination with mammography is provided. Most of the state medical institutions are equipped with outdated mammographic systems, which often do not allow obtaining images of the required quality. The presence of any type of mastopathy also complicates the diagnosis, as a result of which, on the screening mammogram, it is easy to skip the nucleation of an oncological tumor. The paper proposes the use of wavelet transforms to increase the contrast of mammographic images both against the background of fat involution, and against the background of fibrocystic disease and adenosis. The aim of the work is to study the approach to increasing the contrast of mammograms containing breast cancer on the background of fat involution, based on wavelet transforms. The results of experimental studies have shown the possibility of using this algorithm in mammography screening.

1. Introduction

Mammography is the most effective method for the early diagnosis of breast cancer and other breast diseases. According to international studies [1, 2], every 6 Russian women in 2018 were again diagnosed with breast cancer, every 11 women live with this diagnosis until the end of their lives. If an oncological tumor is detected at an early stage, then a complete cure of the patient can be achieved, thereby improving and increasing its duration and quality of life. The complexity of the early diagnosis of breast diseases lies in the structure of the gland tissue, the quality of the image, as well as in the professionalism and experience of the radiologist.

The mammary gland consists of three types of tissue visible on the mammogram: fibrous, glandular and adipose. Fibrous and glandular tissues have approximately the same radiographic density and cannot be adequately distinguished on the mammogram. Adipose tissue better transmits x-rays, which leads to an increase in the contrast of images. Since soft tissues differ only slightly in X-ray absorption coefficients, the image has low contrast, therefore, the detection of minor changes in tissues in the early stages of the disease and the detection of small tumors are difficult. When projecting an image of the mammary gland on an x-ray, various sections of tissues overlap each other, which also distorts the overall picture of the changes occurring in the tissues.

Contrast is one of the main characteristics of the image, directly related to the brightness of pixels, which are sources of information about objects in the image. By contrast, we mean the difference between the average brightness of the observed object and the surrounding background. The contrast calculation is performed according to the Vorobel method [3]:

$$K = \frac{B_1 - B_2}{B_{\max}}, \tag{1}$$

where K is contrast, B_1 is average brightness of an object, B_2 is average background brightness, $B_{\max}$ is maximum image brightness.

$$K = \begin{cases} 0, & no \quad contrast \\ (0,0.3) & low \quad contrast \\ [0.3,0.5) & medium \quad contrast \\ [0.5,1] & high \quad contrast \end{cases}. \tag{2}$$

Changing the contrast of a mammogram allows you to increase the clarity of image perception, highlight the boundaries of tumors, as well as the effectiveness of its subsequent processing. So, with increasing image contrast, the light areas become even lighter, and the darkened ones are even darker. As a result, pixels are redistributed due to the mid-tone range. With a decrease in image contrast, on the contrary, the mid-tone range is expanded. Dark pixels become lighter, while lighter pixels are darker and partially go into midtones.

Thus, increasing the contrast of the image allows you to make the individual details of the image more distinguishable, which is important for medical images.

2. Algorithm of enhancement of mammogram

Various methods can be used to contrast mammographic images, among which can be distinguished [4-8]: alignment of the histogram of brightness values, equalization, nonlinear stretching of the dynamic range of brightness values of the image, the use of various filter masks, fuzzy masking. The disadvantage of these methods is the possible loss of some contrasting details present in the original signal, which could be of interest to the radiologist.

In modern science, the processing of signals and images actively uses signals of a special kind - wavelets [9-11]. They showed their effectiveness both in spectral analysis and in signal compression.

Image processing using wavelets is divided into two approaches: 1) work with wavelet coefficients, which allows you to remove noise, increase the contrast of images, and 2) multiscale processing, which allows you to segment the image, highlight the contours, and so on. This article will consider the first approach.

Each wavelet ψ allows any function $f(x) \in L^2(R)$ to be represented as a series obtained by multiplying the signal by the wavelet function of two parameters $f(x) = \sum d_{a,b}\psi_{a,b}(x)$. The basis of the functional space can be created by continuous scale transformations and wavelet transfers with arbitrary values of the basis parameters (scale factor a and shift parameter b):

$$\psi_{a,b}(x) = |a|^{-\frac{1}{2}}\psi\left(\frac{x-b}{a}\right) \qquad a,b \in R \qquad \psi \in L^2(R). \tag{3}$$

As a two-dimensional wavelet transform, we consider the extension of a one-dimensional signal to a two-dimensional one by the tensor product of one-dimensional functions. In this case, we obtain four generating functions: the scale function $\varphi\varphi(x, y)$ and three wavelets - $\varphi\psi(x, y)$, $\psi\varphi(x, y)$ and $\psi\psi(x, y)$ [8].

$$\varphi\varphi(x,y) = \varphi(x)\cdot\varphi(y), \tag{4}$$

$$\varphi\psi(x,y) = \varphi(x)\cdot\psi(y), \tag{5}$$

$$\psi\varphi(x,y) = \psi(x)\cdot\varphi(y), \tag{6}$$

$$\psi\psi(x,y) = \psi(x)\cdot\psi(y). \tag{7}$$

The direct wavelet transform is calculated by the formula [9]:

$$sv^i_{j,k} = \left\langle f(x,y) \middle| \varphi\psi^i_{j,k}(x,y)\right\rangle, \tag{8}$$

$$vs^i_{j,k} = \left\langle f(x,y) \middle| \psi\varphi^i_{j,k}(x,y) \right\rangle, \tag{9}$$

$$vv^i_{j,k} = \left\langle f(x,y) \middle| \psi\psi^i_{j,k}(x,y) \right\rangle, \qquad i,j \in Z \tag{10}$$

The inverse wavelet transform is calculated by the formula:

$$f(x,y) \sim \sum_{i=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} \left(sv^i_{j,k} \cdot \varphi\psi^i_{j,k}(x,y) + vs^i_{j,k} \cdot \psi\varphi^i_{j,k}(x,y) + vv^i_{j,k} \cdot \psi\psi^i_{j,k}(x,y) \right) \tag{11}$$

The Gabor filter [12, 13] was chosen as the basis, since in digital image processing it is used to highlight the boundaries of objects [13].

$$R(x,y) = \psi_{a,b}(x,y) \cdot g(x,y). \tag{12}$$

The formula for the Gabor function is as follows:

$$g(x,y) = s(x,y) \cdot w_r(x,y), \tag{13}$$

where $s(x,y)$ is the complex sinusoid, $w_r(x,y)$ is the Gaussian envelope for two-dimensional space. Let us dwell in more detail on these components of this filter.

The complex sinusoid is defined as:

$$s(x,y) = e^{j\cdot(2\pi(u_0 x + v_0 y) + P)}, \tag{14}$$

where (u_0, v_0) is spatial frequency of a sinusoid, P is sinusoid phase.

One can imagine a sinusoid as two real functions located in the real and imaginary parts of a complex function.

The real and imaginary parts of the sinusoid are:

$$\mathrm{Re}(s(x,y)) = \cos(2\pi(u_0 x + v_0 y) + P), \tag{15}$$

$$\mathrm{Im}(s(x,y)) = \sin(2\pi(u_0 x + v_0 y) + P). \tag{16}$$

The parameters (u_0, v_0) determine the frequency of the sine wave in Cartesian coordinates.

The envelope of Gauss has the form:

$$w_r(x,y) = K \cdot e^{-\pi(a^2(x-x_0)_r^2 + b^2(y-y_0)_r^2}, \tag{17}$$

where (x_0, y_0) is function peak coordinates, a and b are scalar parameters of Gaussian, r is an index denoting a rotation operation such that:

$$(x - x_0)_r = (x - x_0)\cos\Theta + (y - y_0)\sin\Theta, \tag{18}$$

$$(y - y_0)_r = -(x - x_0)\sin\Theta + (y - y_0)\cos\Theta. \tag{19}$$

The Gabor complex function is determined by the following 9 parameters:

– K is the Gaussian envelope weight coefficient;
– a, b are the envelope weights distributed along the axes;
– Θ is angle of rotation of the envelope of Gauss;
– (x_0, y_0) is coordinates of the peak of the envelope of Gauss;
– (u_0, v_0) is spatial frequencies of the complex sinusoid;
– P is the phase of the complex sinusoid.

Each complex Gabor function consists of two parts located in the real and imaginary parts of the function.

To build a two-dimensional Gabor filter, the formula is used:

$$G(x,y) = \cos(2\pi\Theta x_\phi) e^{-\frac{1}{2}\left(\frac{x_\phi^2}{\delta_x^2} + \frac{y_\phi^2}{\delta_y^2}\right)}, \tag{20}$$

where $x_\phi = x \cdot \cos\phi + y \cdot \sin\phi$; $y_\phi = -x \cdot \sin\phi + y \cdot \cos\phi$; δ_x, δ_y are standard deviations of the Gaussian core along the axes, respectively, which determine the extension of the filter along the axes; Θ is filter frequency modulation; ϕ is spatial direction of the filter, which determines the orientation of the filter relative to the x and y axes.

The mammogram contrast enhancement algorithm can be divided into the following steps:

1. Translation of the image from color to gray (if required).
2. Selection of filter kernel parameters.
3. Calculation of Gabor filters for wavelet transform according to the selected parameters.
4. The Gabor wavelet transform for the image, which consists in a two-dimensional convolution of the image with the Gabor filter cores.
5. Displaying the results of the imaginary and real part of the wavelet transform.

Figure 1. Example of Gabor Filters.

3. Experimental results

For research, images of breast cancer tumors against a background of fat involution were selected from mammograms of the MIAS base [3].

Figures 2 (a, c, e) show initial low-contrast mammograms. Figures 2 (b, d, f) show the results of processing original images.

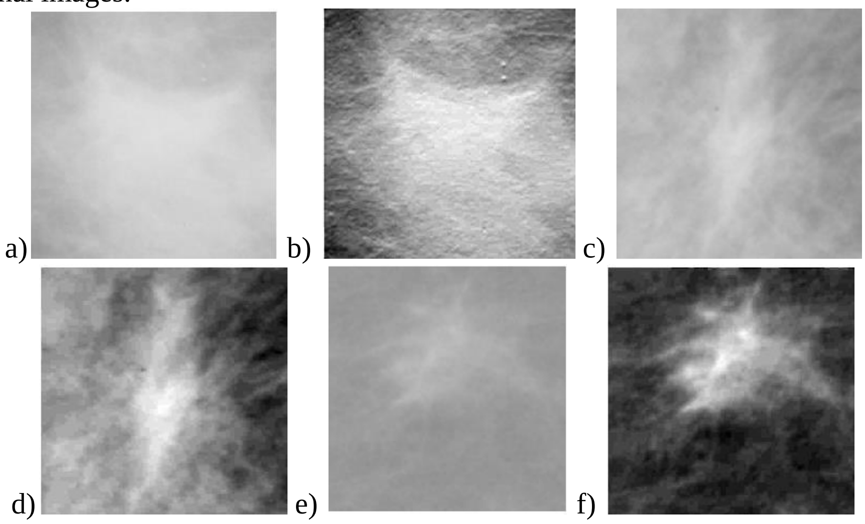

Figure 2. Examples of increasing the contrast of mammograms.

In experiments with increased contrasts of mammograms based on wavelet transforms, image characteristics such as:

k_{min} is the minimum value of the histogram of the image;

k_{max} is the maximum value of the histogram of the image;

k_{av} is the average value of the histogram of the image;

σ is standard deviation of the image;

K is the contrast of the image which calculated by formula 1, where the background and the object are separated by binarization according to the Otsu threshold.

All characteristics of the source and processed images for comparison were combined in table 1.

Analyzing the above characteristics, we can draw the following conclusions:

1) the brightness of the image points stretches over the entire range, for example, the brightness of the first test sample from the range [149, 225] was redistributed to [0, 255]. This enables the radiologist to visually examine those areas that were previously not visible to the human eye.

2) the distribution of brightness from the average value significantly changed in 1 and 3 samples, in 2 samples the brightness values are grouped around the average value.

3) the contrast value of the original images was in the low contrast range, after processing, the contrast values changed significantly: in 1 and 2 samples, the contrast increased to the average level, and in 3 samples - to the values of high contrast.

Table 1. Results of preprocessing.

Mammogram		k_{min}	k_{max}	k_{av}	σ	K
Test sample 1	Source	149	225	195	14.90	0.16
	Processed	0	255	131	42.50	**0.41**
Test sample 2	Source	129	221	174	18	0.12
	Processed	78	212	156	18.80	**0.45**
Test sample 3	Source	140	193	155	9.42	0.07
	Processed	11	228	64	26.20	**0.5**

4. Conclusion

The article examined the possibility of using wavelet transforms to increase the contrast of mammographic images.

Using such transformations, it is possible to significantly improve the quality of mammograms and bring it to the required for further processing, for example, to highlight areas of new formation both visually and automatically.

5. Acknowledgments

The reported study was funded by RFBR according to the research project №19-07-01215.

6. References

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