Human Visual System Based Mammogram Enhancement and Analysis

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***Abstract*—This paper introduces a new mammogram enhancement algorithm using the human visual system (HVS) based image decomposition. A new enhancement measure based on the second derivative is also introduced to measure and assess the enhancement performance. Experimental results show that the presented algorithm can improve the visual quality of fine details in mammograms. The HVS-based image decomposition can segment the regions/objects from their surroundings. It offers the users flexibility to enhance either sub-images containing only significant illumination information or all the sub-images of the original mammograms. The algorithm can be used in the computer-aided diagnosis systems for breast cancer detection.**

***Keywords*—Mammogram enhancement, HVS-based image decomposition, nonlinear filtering, breast cancer detection.**

I. INTRODUCTION

Breast cancer is the leading cause of death in women. The National Cancer Institute estimates that one out of eight women in the United States will develop breast cancer at some point during her lifetime [1]. Early detection of breast cancer is an effective method to reduce mortality since treatments of breast cancer in the early stages are more successful. Mammography is the most common and reliable technique for radiologists to detect and diagnose breast cancer [2].

However, due to the limitations of the X-ray hardware systems, screened mammograms may present poor characteristics such as poor resolution or low contrast. The difference between the malignant diseases and the benign glandular tissue is not readily discernable and makes accurate diagnosis extremely difficult. Image enhancement is an effective technique to improve the visual quality of mammograms without affecting the acquisition process or increasing the hardware costs. This allows a more confident interpretation of difficult cases without resorting to follow-up patient examinations and secondary procedures, as well as allowing faster diagnoses of routine cases [3].

Many enhancement algorithms for mammograms have been developed by utilizing different image enhancement technologies such as wavelet enhancement [4, 5] in the frequency domain, and contrast limited adaptive histogram equalization (CLAHE) [6] as well as adaptive neighborhood contrast enhancement (ANCE) [3] in the spatial domain. These methods have their own limitations such as over-enhancement of brightness, or presence of noises or/and artifacts.

The human visual system (HVS) based image decomposition has been used for image enhancement [7, 8] and edge detection [9]. In this paper, we investigate its applications in mammogram enhancement and analysis. A new algorithm for enhancing mammograms is introduced by integrating the HVS-based image decomposition and nonlinear filtering such that the new algorithm has ability of enhancing mammograms while reducing noises. The concept of the second derivative is also used for the new enhancement measure and quality assessment. The HVS-based image decomposition is also used in object segmentation for mammogram analysis.

The rest of this paper is organized as followed. Section II modifies the HVS-based image decomposition in [9] and then introduces the new algorithm for mammogram enhancement. Section III introduces the new SDME measure. Section IV provides some simulation results for mammogram enhancement and a performance comparison. Section V reaches a conclusion.

II. NEW ENHANCEMENT ALGORITHM

In this section, we discuss the modified HVS-based image decomposition. Then, a new mammogram enhancement algorithm is introduced by combining the HVS-based image decomposition and the enhancement techniques.

A. HVS-based image decomposition

HVS-based image decomposition separates images by using the background intensity and the rate of information change. It divides an image into four sub-images based on four defined regions with different background intensities: (1) the saturation region for over-illuminated areas; (2) the Weber region for properly illuminated areas; (3) the Devries–Rose region for under-illuminated areas; (4) the fourth region for all pixels underneath the curve containing the least informative pixels [9].

The background intensity in the HVS is defined as a weighted local mean,

$$B(m,n) = a_0 X(m,n) + a_1 Y_1 + a_2 Y_2 \tag{1}$$

where, $B(m,n)$ is the background intensity at each pixel with value $X(m,n)$, and

$$\begin{aligned} Y_1 &= b_{11}X(m-1,n) + b_{12}X(m+1,n) + b_{13}X(m,n-1) + b_{14}X(m,n+1) \\ Y_2 &= b_{21}X(m-1,n-1) + b_{22}X(m+1,n-1) + b_{23}X(m-1,n+1) \\ &\quad + b_{24}X(m+1,n+1) \end{aligned}$$

where $a_0, a_1, a_2, b_{11}, b_{12}, b_{13}, b_{21}, b_{22}, b_{23}$ are weight coefficients.

The rate of information change is defined as a gradient, $X^{'}(m,n)$, which is calculated by,

$$X'(m,n) = \frac{1}{2}\left(\left|X(m,n) - X(m,n+1)\right| + \left|X(m,n) - X(m+1,n)\right|\right) \tag{2}$$

Let B_1, B_2, B_3 denote the background illumination thresholds, K_1, K_2, K_3 denote the gradient thresholds at X_1, X_2, X_3, and $X_{\max}$, $X_{\min}$ are the maximum and minimum values of the image respectively, then [9],

$$\begin{cases} B_T = X_{\max} - X_{\min} \quad B_1 = \alpha_1 B_T \quad B_2 = \alpha_2 B_T \quad B_3 = \alpha_3 B_T \\ K_1 = \dfrac{\beta}{100} \max\left(\dfrac{X^{'}(m,n)}{B(m,n)}\right) \quad K_2 = K_1\sqrt{B_2} \quad K_3 = \dfrac{K_1}{B_3} \end{cases} \tag{3}$$

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where $\alpha_1, \alpha_2, \alpha_3, \beta$ are coefficients based on the response characteristics of the human eyes for different regions.

The four sub-images for each HVS-based region can be defined by,

$$\begin{cases} R_1 = X(m,n) & \text{for } B(m,n) \geq B_3 \ \& \ \dfrac{X'(m,n)}{B^2(m,n)} \geq K_3 \\ R_2 = X(m,n) & \text{for } B_3 \geq B(m,n) \geq B_2 \ \& \ \dfrac{X'(m,n)}{B(m,n)} \geq K_2 \\ R_3 = X(m,n) & \text{for } B_2 \geq B(m,n) \geq B_1 \ \& \ \dfrac{X'(m,n)}{\sqrt{B(m,n)}} \geq K_1 \\ R_4 = X(m,n) & Otherwise \end{cases} \tag{4}$$

where R_1, R_2, R_3, and R_4 are four sub-images for the four regions, respectively. For example, R_1 is the sub-image of the first region.

The sub-images of region 2 and region 3 contain most of the illumination information of the original images. The less meaningful pixels are located in region 1 and region 4. This property is useful for image enhancement. Its applications are extended to mammogram visualization for breast cancer detection in this paper.

B. New mammogram enhancement algorithm

Since the four sub-images obtained by the HVS-based image decomposition contain different intensity information, the users can selectively enhance only sub-images of region 2 and region 3 while keeping sub-images of region 1 and region 4 unchangeable. As a result, mostly only illumination information in the original images is enhanced. This is accomplished without affecting other less meaningful information in the original image, thus minimizing artifacts in the enhanced images. Alternatively, all four sub-images can be enhanced individually and recombined to form a more visually pleasing output image.

Based on this concept, we introduce a new algorithm for mammogram enhancement using HVS-based image decomposition with the enhancement operation. It is called HVS-based Enhancement (HVSE). The algorithm is shown in Fig.1.

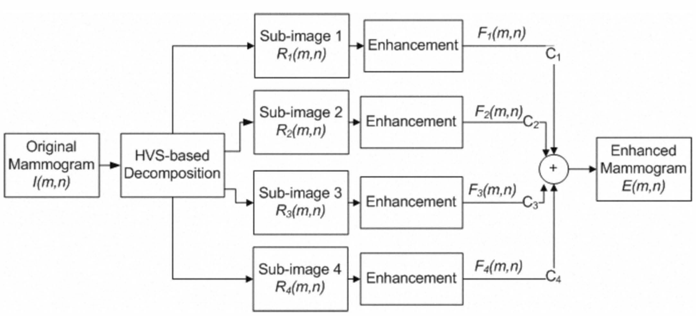


Fig. 1 The block diagram of the HVSE algorithm.

The HVSE separates the original mammogram into four sub-images, R_1, R_2, R_3, R_4 using the HVS-based image decomposition defined in equation (4). Each sub-image is enhanced by an enhancement process respectively. This enhancement process could be a filtering operator or any other enhancement algorithm. As an example, we propose a new nonlinear filtering method for the enhancement process in this paper. Finally, the resulting enhanced mammogram is obtained by combining all enhanced sub-images.

The enhanced sub-images F_1, F_2, F_3, F_4 are obtained by the following filtering operation,

$$F(m,n) = w_0 S_0 + w_1 S_1 + w_2 S_2 \tag{5}$$

where

$$\begin{aligned} S_0 &= R^{2\alpha_0}(m,n) \\ S_1 &= R^{2\alpha_1}(m-1,n) + R^{2\alpha_1}(m+1,n) + R^{2\alpha_1}(m,n-1) + R^{2\alpha_1}(m,n+1) \\ S_2 &= R^{2\alpha_2}(m-1,n-1) + R^{2\alpha_2}(m+1,n-1) + R^{2\alpha_2}(m+1,n-1) + R^{2\alpha_2}(m+1,n+1) \end{aligned} \tag{6}$$

where constants w_0, w_1, w_2 are weight coefficients and $\alpha_0, \alpha_1, \alpha_2$ are exponential coefficients.

Then, the output enhanced mammogram is a combination of all enhanced sub-images as defined by,

$$E(m,n) = C_1 F_1(m,n) + C_2 F_2(m,n) + C_3 F_3(m,n) + C_4 F_4(m,n) \tag{7}$$

where constants C_1, C_2, C_3, C_4 are weight coefficients.

The nonlinear filter in equation (6) is type zero of Alpha Weighted Quadratic Filter (AWQF) [10]. Such type of the AWQF contains only the square term of each element. This is why the power of all elements in the equation (6) is $2\alpha_i$, $i = 0,1,2$. The AWQF has been shown to have ability of enhancing image while suppressing noise. One novelty of the HVSE is that the nonlinear filtering operator can be designed as a combination of two different types of filters. For example, the coefficients w_0, w_1, w_2 can be designed as a highpass filter and $\alpha_0, \alpha_1, \alpha_2$ can be chosen as a center weighted mean filter. In this case, the HVSE algorithm can suppress noise and keep sharp details unchanged while enhancing fine details in mammograms. This offers the HVSE algorithm more robust characteristics for different applications.

There are ten coefficients in the HVSE algorithm to be specified for practical applications. However, more coefficients offer the new HVSE more design flexibility to meet more specific and complex requirements in real world applications.

To simplify the HVSE design and reduce the number of its coefficients, the HVSE coefficients could be optimized by using an enhancement measure approach, obtaining the best enhanced result. In an alternative way, the HVSE can be designed by manually selecting its coefficients. However, this is a time-consuming process. The best enhancement results could be extremely difficult to be achieved due to lack of quantitative evaluation criterion.

III. New Enhancement Measure

Quantitatively measuring and evaluating enhancement performance of an algorithm is extremely difficult to determine because the improvement of the enhanced images is usually subjective. In this section, we introduce a new enhancement measure using an image contrast measure.

The new enhancement measure is based on the concept of the second derivative. It is called the second-derivative-like measure of enhancement (SDME) which is defined by,

$$SDME = -\frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} 20 \ln \left| \frac{I_{\max;k,l} - 2I_{center;k,l} + I_{\min;k,l}}{I_{\max;k,l} + 2I_{center;k,l} + I_{\min;k,l}} \right| \tag{8}$$

where an image is divided into $k_1 \times k_2$ blocks, α is constant. $I_{\max;k,l}$, $I_{\min;k,l}$ are the maximum and minimum values of the pixels in each block separately, and $I_{center;k,l}$ is the intensity of the center pixel in each block. Thus, the size of blocks should be odd number such as 3×3, 5×5, on many others.

IV. Results and analysis

The original mammograms in this paper are obtained from the mini-MIAS database of mammograms [11]. All mammograms are cropped into images with smaller sizes such that the resulting cropped images contain a minimal background. We denote each mammogram by the same name as that in the database.

A. Parameter design

The HVS-based decomposition process groups pixels into four sub-images based on different thresholdings. This decomposition may change the surrounding pixel values of a specific pixel. The filtered result for a filter applied to all sub-images in the presented algorithm is different than that of the same filter directly applied to the original image. Therefore, for simplicity, we used the same filter for all sub-images in the rest of this section.

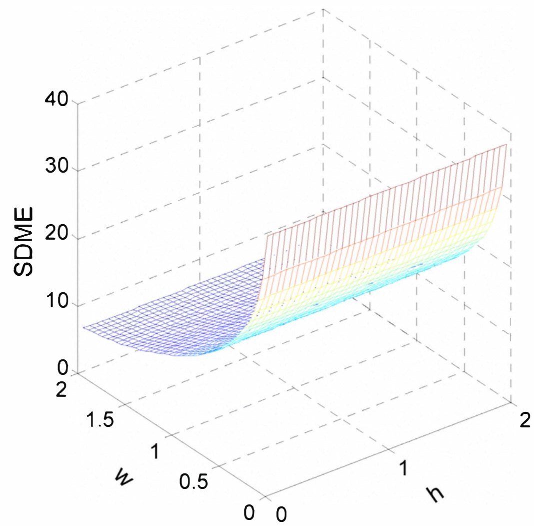
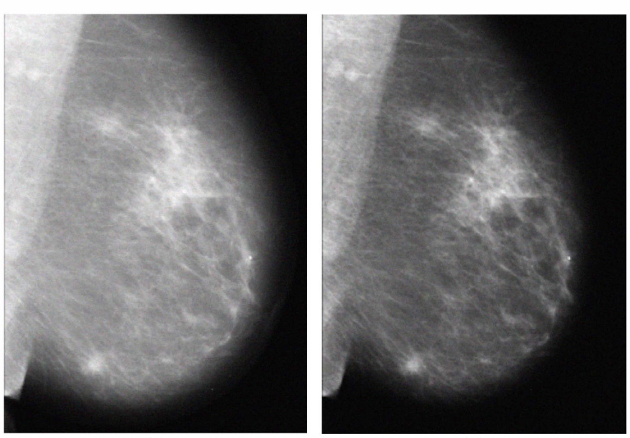


Fig. 2 Parameter optimization: SDME measure using the presented HVSE with different parameters



(a) (b)

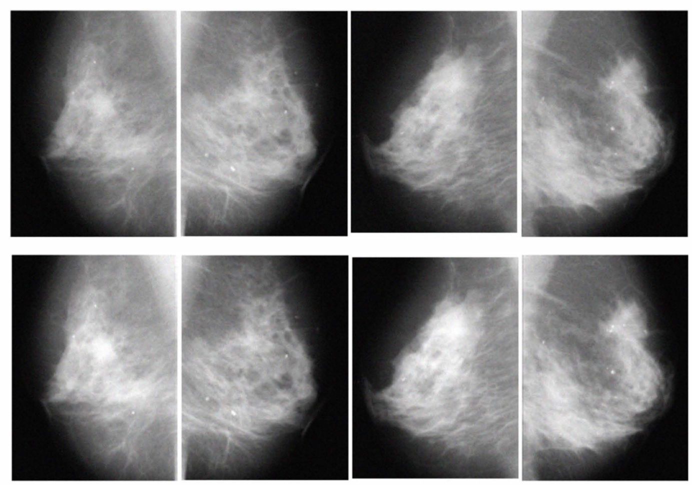
Fig. 3 Mammogram enhancement using parameters from Fig. 2. (a) Original mammogram, mdb206; (b) Enhanced mdb206.

To find the parameters for achieving a better enhanced image, we assume: $C_1 = C_2 = C_3 = C_4 = 1$, $\alpha_1 = \alpha_2 = h$, $\alpha_0 = 8h$, $w_1 = w_2 = -w$, $w_0 = 8w$ and $0 < h, w \le 1$. The mammogram referred as mdb206 in the database is enhanced by the presented HVSE and measured by the SDME when the parameters h and w change. Fig.2 plots the SDME measure results. The parameters h and w for the best enhanced result can be located at the point where the SDME curve reaches the first local extremum. Fig.3 shows the best enhanced results based on the measure results in Fig. 2.

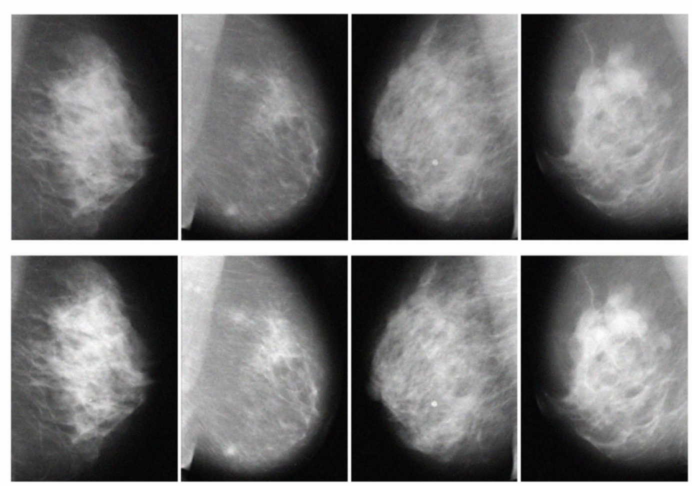
B. Performance measure

The presented HVSE has been applied to more than 44 mammograms from the mini-MIAS database. Fig. 4 shows several examples of the mammograms enhanced by the HVSE. The first row in Fig. 4(a)-(h) shows the original mammograms. Their second row shows the enhanced mammograms. These enhanced results show that the presented HVSE significantly improves the contrast of the original mammograms, especially for the abnormal regions which are potential tumor or cancer regions.

To provide better focus for the specific regions in the mammograms, we cropped the regions of interest from the original mammograms and their enhanced results in Fig. 4. The cropped regions are shown in Fig. 5. Similar to Fig. 4, the first and second rows in Fig. 5(a)-(h) are the cropped regions from the original and enhanced mammograms, respectively. The visual quality and contrast of specific objects in regions are greatly improved.

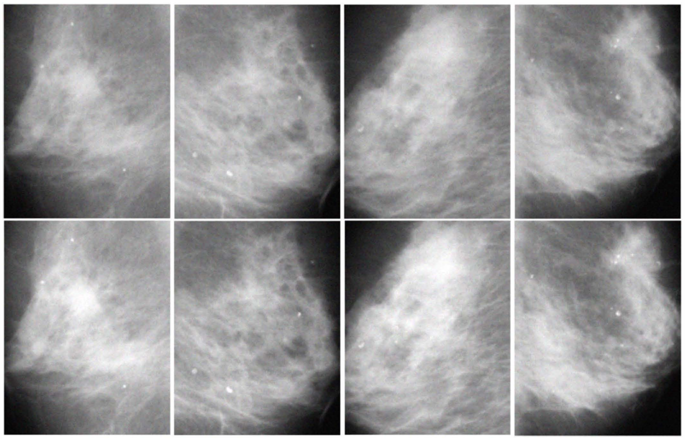


(a) mdb063 (b) mdb064 (c) mdb121 (d) mdb170

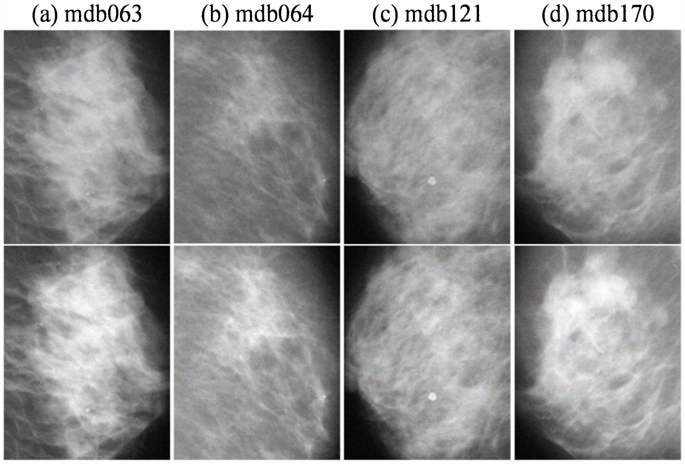


(e) mdb188 (f) mdb206 (g) mdb227 (h) mdb265

Fig. 4 Mammogram enhancement. (a)-(h) Top row: The original mammograms; Bottom row: The enhanced mammograms.



(a) mdb063 (b) mdb064 (c) mdb121 (d) mdb170



(e) mdb188 (f) mdb206 (g) mdb227 (h) mdb265

Fig. 5 Regions cropped from the mammograms in Fig. 4. (a)-(h) Top row: The regions cropped from the original mammograms; Bottom row: The regions cropped from the enhanced mammograms.

Table 1. SDME measure results for mammogram enhancement shown in Fig. 4 and Fig. 5.

Mammogram #	Name in database	original	enhanced
1	mdb063	38.3146	44.6766
2	mdb064	38.6223	40.1847
3	mdb121	41.2823	49.3953
4	mdb170	38.0557	41.3682
5	mdb188	39.7389	43.2786
6	mdb206	38.6094	45.0378
7	mdb227	37.2989	39.1545
8	mdb265	38.8355	42.8653

The improvement of the contrast and visual quality of specific regions and objects can be verified by the SDME measure results shown in Table 1 and the plotted curve shown in Fig. 6. These enhancement results are useful for computer-aided diagnosis systems to automatically segment the abnormal regions in mammograms with breast cancer.

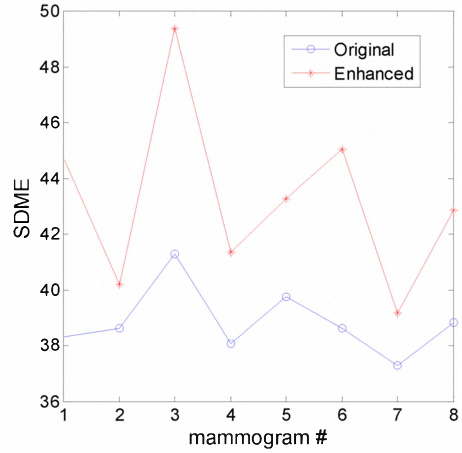
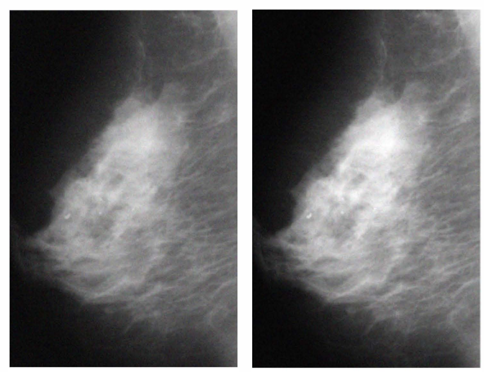


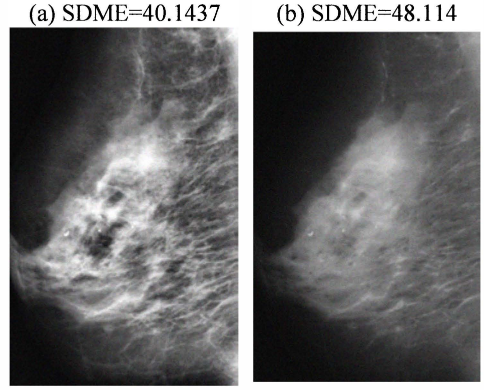
Fig. 6 Plot of the SDME measure results.

C. Performance comparison

We compare the enhancement performance of the presented HVSE with other well-known methods such as the CLAHE [6] and the ANCE [3]. An example is shown in Fig.7. The result enhanced by the presented HVSE in Fig. 7(b) shows better visual quality. The contrast of the microcalcifications and abnormal regions is significantly improved. The CLAHE over-enhances the abnormal regions in the mammogram shown in Fig. 7(c). There are many residual artifacts in the ANCE result shown in Fig. 7(d). Their performance is also verified by the SDME measure results as shown at the bottom of each image. The presented HVSE outperforms the other two methods.



(a) SDME=40.1437 (b) SDME=48.114



(c) SDME=34.326 (d) SDME=38.0198

Fig. 7 Performance comparison. (a) The original mammogram, mdb121; (b) The mammogram enhanced by the HVSE; (c) The mammogram enhanced by the CLAHE; (d) The mammogram enhanced by the ANCE.

D. Mammogram Visualization and Analysis

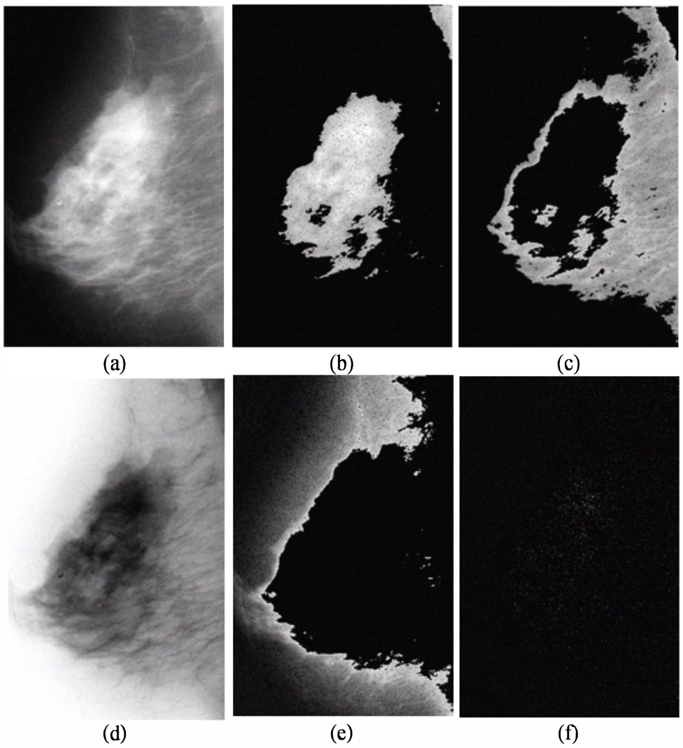


Fig. 8. HVS-based mammogram decomposition. (a) The enhanced mammogram in Fig. 7(b); (b) The first sub-image; (c) The second sub-image; (d) The negative photo of the mammogram in (a); (e) The third sub-image; (e) The fourth sub-image.

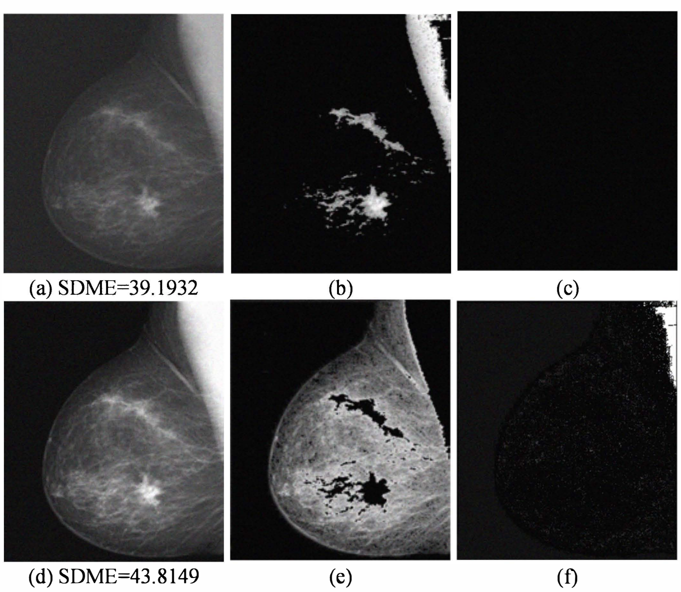


Fig. 9. HVS-based mammogram decomposition. (a) The original mammogram; (b) The first sub-image; (c) The second sub-image; (d) The mammogram enhanced by the presented HVSE; (e) The third sub-image; (e) The fourth sub-image.

Since the HVS-based image decomposition separates images based on the background intensity and the rate of information change, we extend its application to analyze the enhancement performance. Fig. 8 shows that an enhanced mammogram shown in Fig. 7(b) is separated by the HVS-based image decomposition. The interesting feature is that all abnormal regions are contained within a decomposed image as shown in Fig. 8(b). As shown in Fig. 8 (a) and (d), the abnormal regions in the enhanced image and its negative representation provide a good visualization to human eyes. This is very useful for radiologists to analyze and diagnose the breast cancer in mammograms.

Fig. 9 gives another example of the HVS-based mammogram decomposition. The results show that the abnormal regions are more visible in the enhanced mammogram in Fig. 9(d) compared with the original mammogram in Fig. 9(a). The enhancement process also helps the HVS-based decomposition to separate the abnormal regions or objects from the mammograms.

V. Conclusion

We have introduced a new enhancement algorithm for mammograms and a new SDME contrast measure for enhancement evaluation in this paper.

The performance measure and comparison have demonstrated that the presented algorithm shows better overall enhancement performance, especially in improving the contrast of specific regions, objects and fine details in mammograms without generating artifacts or over-enhancing the high illuminated regions.

We have demonstrated that the HVS-based image decomposition can be used for mammogram visualization and analysis. It can separate the abnormal regions such as cancer cells from the original mammogram and represent them in single sub-image without using any thresholding or segmentation algorithm. This feature is useful for automatic detecting and diagnosing breast cancer in the CAD systems.

Acknowledgment

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