ENHANCEMENT OF VISUAL PERCEPTION THROUGH DYNAMIC CUES: AN APPLICATION TO MAMMOGRAMS

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ABSTRACT

Medical Images often contain very small and hardly detectable objects or patterns, which can be of grave importance for diagnosis. In this paper we present a new method for aiding medical doctors in diagnosis of such images by adding artificial movement to the static images, in order to utilize the motion sensitivity of the human visual system. This technique permits detection of lesions not just by intensity, structure and texture differences with its surroundings, but by motion as well. Statistical analysis of experimental tests with both radiologists and non-radiologists show improved detection rate of microcalcifications in mammograms, raising it on average by 20.8% for non-radiologists and by 8.4% for radiologists.

Index Terms— dynamic cues, visual perception, mammography

1. INTRODUCTION

The human vision system (HVS) is a very powerful tool for perception and image processing. Among its basic capabilities figure segmentation, registration and processing of still images. Nevertheless, there is a variety of cases in which for the HVS it is very complicated, if not impossible, to detect certain patterns or objects. This is often the case in medical images where it is necessary to spot objects in front of a background of a color or texture almost identical to the objects'.

A classical example of this kind of images are mammograms with microcalcifications. Microcalcifications are small deposits of calcium in breast tissue, that may indicate breast cancer if present in malignant clusters. Unfortunately mammograms tend to be of low contrast and microcalcifications of very small size, making it very difficult for the examining radiologist to detect them and make a correct diagnosis [1].

To overcome these problems the method described here uses two particular properties of the HVS, motion and flicker sensitivity. Amplitude sensitivity is what is used for viewing static scenes where differences of intensity or color can be interpreted as objects, textures, shadows, etc. Motion sensitivity on the other hand deals with detection of moving objects. In fact, most cortical cells of the HVS respond better to moving objects than stationary ones [2]. Flicker sensitivity is used for detection of temporally modulated stimuli.

By artificially introducing spatial or temporal movement into mammograms it is possible to use all three sensitivities in order to detect microcalcifications, instead of just amplitude sensitivity. This way, dynamic cues of locations of possible lesions are introduced into mammograms.

2. PROPOSED METHOD

There are several ways of introducing dynamic cues into images. They basically depend on two functions: The motion function f_{mov} and the observation function f_{obs}. The motion function specifies the type of movement or changes. The observation function sets the parameters for the motion.

2.1. Motion Function

From a single gray scale still image I_0 of $m \times n$ pixels it is possible to generate a sequence of $k = 0 \dots p$ images of $m \times n$ pixels, in which the intensity I of the pixel corresponding to the coordinates (i, j) of the k^{th} image can be expressed as in equation 1.

$$I_k(i,j) = f_{mov}(f_{obs}(I_0(i,j)), k) \tag{1}$$

$I_k(i,j)$ is a discrete sequence of $m \times n$ pixels dependent on the motion function $f_{mov}()$ which defines the movement of the pixels through the sequence of frames. This movement can be spatial or temporal, meaning that a pixel can vary its spatial location or its intensity in time.

A possible implementation of spatial movement is a sideways oscillation of every pixel at constant amplitude and a frequency that depends on the pixels original intensity. This way a light pixel may oscillate from one side to the other faster than a darker pixel.

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For temporal movement an example could be a sinusoidal variation of intensity for every pixel where frequency of variation depends on the pixels original intensity. That way an originally lighter pixels intensity would change faster than an originally darker one's. The equation for a possible implementation of this technique is given in equation 2.

$$I_k(i,j) = g(I_0(i,j)) + a \cdot \cos(2\pi f_0 k \cdot f_{obs}(I_0(i,j)) + \phi) \quad (2)$$

Here, $I_k(i,j)$ represents the intensity of the pixel of coordinates (i,j) in the k^{th} frame, $g()$ is an offset for every pixel, a is the amplitude of the sine wave, f_0 is its fundamental frequency, f_{obs} is the observation function and ϕ the phase shift.

2.2. Observation Function

The observation function f_{obs} defines what exactly the movement is based upon. Whereas the motion function defines what is to be done with each pixel, the observation function defines the pixel itself, i.e. the original intensity of the pixel used to create the sequence. If $f_{obs}(I_0) = I_0$, meaning f_{obs} is the identity, we have the particular case that throughout the sequence the movement depends on the pixel intensities of the original image. When $f_{obs}(I_0) = \frac{d}{d\vec{x}}(I_0)$ movement varies according to the first derivative of the initial image. Other, more complex implementations are also possible as shown next:

$$f_{obs}(I_0) = \begin{cases} I_0 \\ \frac{d}{d\vec{x}}(I_0) \\ \text{Canny Filter of } I_0 \\ \text{Unsharp Mask of } I_0 \\ \text{Wavelet Transform of } I_0 \\ \dots \end{cases}$$

3. EXPERIMENTAL RESULTS

Let us consider the rather simple case of a sinusoidally changing pulsating intensity motion function and the identity matrix as observation function. The equation for such a sequence is $I_k(i,j) = \alpha I_0(i,j) + (1-\alpha)\cos(2\pi f_0 k \cdot I_0(i,j))$ for $k = 0 \dots p$ where the intensities of the pixels range from 0 (black) to 1 (white). The first frame is α times the original image since $k = 0$. The frames for $k = 1 \dots p$ yield a sequence of matrices in which each pixel sinusoidally changes its intensity proportionally to its original intensity.

By now seeing the whole array of images as a movie sequence it is possible to detect objects by the phase shift produced between two pixels with different original intensities. Even if these two adjacent pixels have relatively small differences in intensity in the original image, in time the phase shift will become clearly visible in the movie. An example of this is shown in figure 1, where using this proportional sinusoidal approach two pixels with a minimal intensity difference show a phase shift of 180° in a very short time.

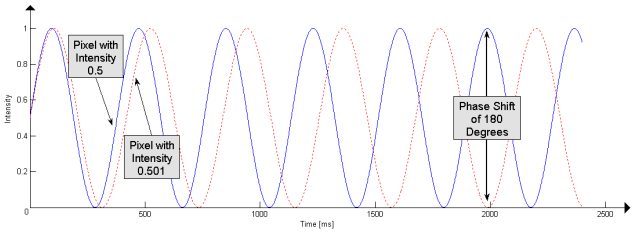
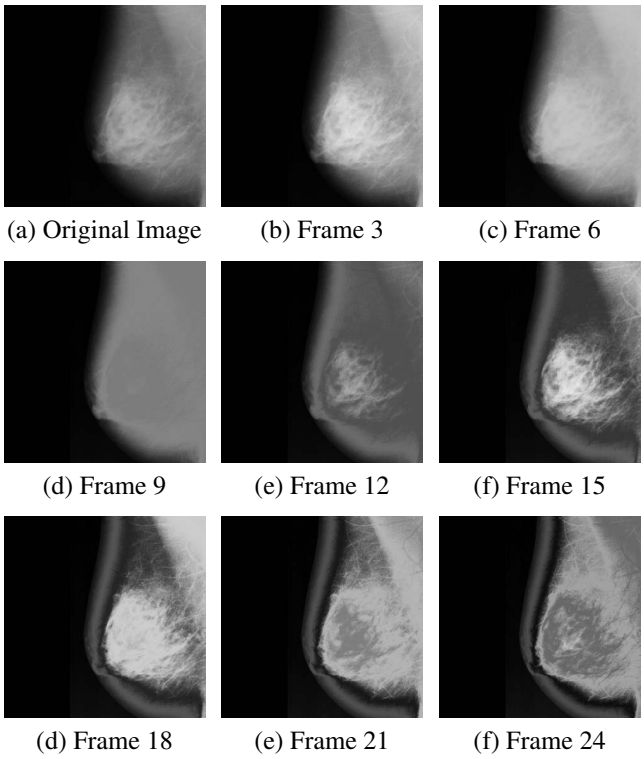


Fig. 1. Phase shift of two pixels with similar intensities



(a) Original Image (b) Frame 3 (c) Frame 6

(d) Frame 9 (e) Frame 12 (f) Frame 15

(d) Frame 18 (e) Frame 21 (f) Frame 24

Fig. 2. Sequence of frames

In some aspects this is similar to dynamically changing image contrast, which by itself is a frequently used tool in Medical Imaging. Here the viewer is presented with a sequence of the image with sinusoidally changing contrast.

To illustrate this effect on real images, figure 2 shows samples of a sequence of frames created from a static image. This sequence is comprised of 30 frames generated from a static digital mammogram using a sinusoidal intensity motion function and an Unsharp Mask observation function.

The mammogram presented here contains a malignant cluster of microcalcifications in the central right section barely visible in the original image (figure 2.a), but fairly visible in some of the subsequent frames. This holds especially true for frames 14 and 15. For comparison purposes the original image and Frame 15 are shown in figures 3 and 4 respectively.

Evidently, the malignant cluster is far more visible in fig-

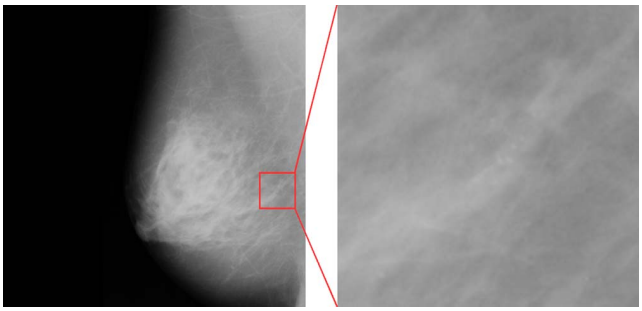


Fig. 3. Zoom of original mammogram

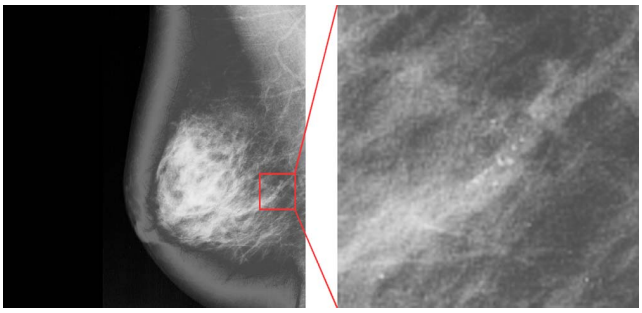


Fig. 4. Zoom of frame 15

ure 4. Additionally to the enhanced visibility, the fact that the cluster cycles rapidly from hardly visible to very visible gives it a blinking appearance. Obvious by common sense, something blinking is very likely to attract attention even if not directly looked at. The explanation lies in the use of motion and flicker sensitivity. Whereas amplitude sensitivity and foveal vision are used for concentrating on one specific point, motion and flicker sensitivity paired with peripheral vision give a broader view and are used primarily to detect moving or blinking objects. Once detected, foveal vision can be concentrated on these objects for detailed analysis. This approach is the basic idea behind dynamic cues.

4. STATISTICAL ANALYSIS

In order to compare diagnostics with and without dynamic cues we designed a test in which the observer is once presented with the set of static mammograms and once with the same set, but aided by dynamic cues. In both cases the observer has to give a diagnosis of presence of microcalcifications, ranging from *Category 1: Definitely not present* to *Category 5: Definitely present*, and their possible locations in each mammogram.

The results of these tests were analyzed using a Receiver Operating Characteristic (ROC) curve, which is widely recognized as a good statistical analysis method for diagnostic information [5]. In this method the True Positive Fraction (TPF) is plotted against the False Positive Fraction (FPF) sweeping through all categories of diagnosis. As a single measurement of diagnosis quality we used the Area Under the Curve (AUC), which lies between 0.5 for a random diagnosis a 1.0 for a perfect diagnosis. The higher the AUC, the better is the test.

We prepared a set of $n_y = 124$ mammograms with resolutions between 640×640 and 970×970 pixels and a gray-level resolution of 8 bits per pixel taken from the Mammographic Image Analysis Society (MIAS) mammographic database [3]. There are a total of 21 cases with microcalcification clusters and 103 normal cases. Since various degrees of visibility of microcalcifications are included in the set, this database is representative of clinical cases.

We tried our method with five radiologists and five non-radiologists. The resulting ROC curves and the associated AUC scores were computed using the ROCKIT program proposed in [4]. The AUC for tests with static images and dynamic cues for each person are shown in tables 1 and 2. These tables also show the pooled mean results for radiologists and non-radiologists, obtained by joining all the diagnoses of the 5 participants of the group and computing the resulting ROC curve as if it were one person analyzing $5 \times n_y = 620$ cases [5]. This method usually tends to underestimate the results, but since it underestimates both categories equally it is well suited for comparison purposes.

Table 1. AUC Scores for Non-Radiologists

Observer	AUC Static	AUC DynCues
1	0.830	0.977
2	0.858	0.909
3	0.888	0.985
4	0.886	0.959
5	0.888	0.919
Pooled Mean	0.806	0.910

Table 2. AUC Scores for Radiologists

Observer	AUC Static	AUC DynCues
6	0.899	0.921
7	0.970	0.970
8	0.913	0.929
9	0.964	0.966
10	0.862	0.934
Pooled Mean	0.900	0.942

As can be seen clearly, diagnosis aided by dynamic cues significantly raises the ROC curve for both groups. For non-radiologists the AUC is raised by 20.8%, while radiologists improve by 8.4%. Commonly, ROC scores for screening microcalcifications in mammography lie between 0.75 and 0.95

[6]. The scores obtained in our tests are well within these typical ranges. Moreover, they indicate a very good result for classification using dynamic cues in comparison to these general scores.

The mean ROC curves for both groups are shown in figures 5 and 6.

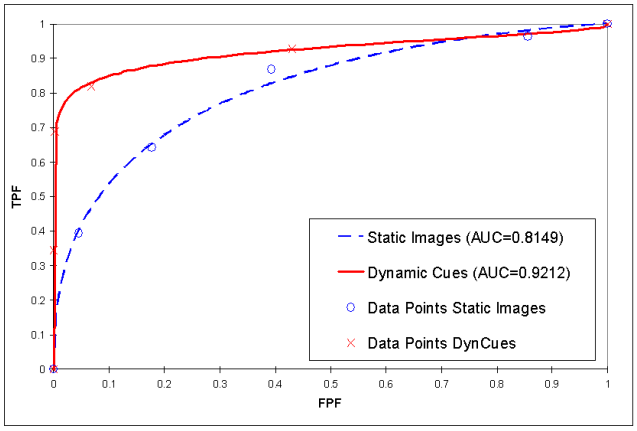


Fig. 5. Mean ROC Curves for Non-Radiologists.

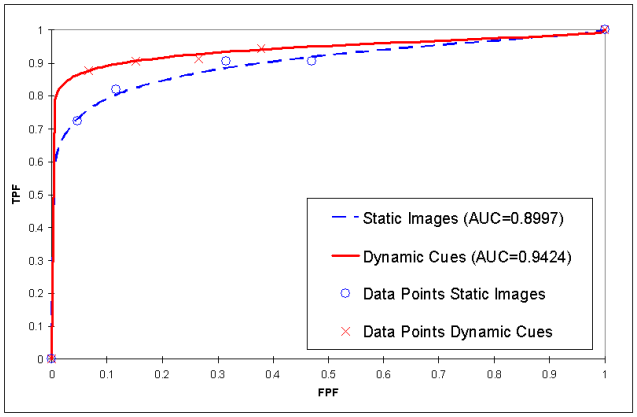


Fig. 6. Mean ROC Curves for Radiologists.

5. DISCUSSION

Results clearly show significant improvement in diagnosis for both groups. The 8.4% improvement for radiologists indicates vast possibilities of improvement if perfected and clinically implemented as a standard visualization tool for radiologists.

All five medical doctors involved in the tests agreed in their observations that this method has clinical potential if developed into a mature system embedded into standard medical imaging software used throughout hospitals and medical centers.

6. CONCLUSIONS AND FUTURE WORK

In this work we present a technique for aiding medical doctors in diagnosis of microcalcifications by introducing movement to static images. Unlike most previous studies this work does not rely on a dichotomic or cardinal classification by a computer, but leaves the decision to the human eye. Statistical tests show that our method significantly enhances detection and diagnosis capabilities in both experts and non-experts. Dynamic cues are also likely to give good results in detection of other abnormalities in medical images, such as lung nodules.

Further studies will investigate observation and motion functions most likely to yield even better results for detection of microcalcifications. Since dynamic cues involve rapidly flashing pictures, which can be straining on the eyes if looked at for prolonged periods of time, future work will also concentrate on determining a motion function that does not strain the eyes while still naturally directing attention to lesions.

7. REFERENCES

[1] Edward A. Sickles, "Breast calcifications: Mammographic evaluation," *Radiology*, vol. 160, no. 2, pp. 289–293, Aug. 1986.

[2] David H. Hubel, *Eye, Brain, and Vision*, Scientific American Library, Oxford, England, 1988.

[3] John Suckling et al., "The mammographic image analysis society digital mammogram database," in *Exerpta Medica*, 1994, number 1069 in International Congress, pp. 375–378.

[4] Charles E. Metz et al., "Statistical comparison of two roc-curve estimates obtained from partially-paired datasets," *Med. Decis. Making*, vol. 18, no. 1, pp. 110–121, Jan.-Mar. 1998.

[5] Vit Drga, *The Theory of Group Operating Characteristic Analysis in Discrimination Tasks*, Ph.D. thesis, Victoria University of Wellington, New Zealand, 1999.

[6] Xiao-Hua Zhou, Donna K. McClish, and Nancy A. Obuchowski, *Statistical Methods in Diagnostic Medicine*, Wiley Series in Probability and Statistics. Wiley, first edition, July 2002.