

# Segmentation of Tumor in Digital Mammograms Using Wavelet Transform Modulus Maxima on a Low Cost Parallel Computing System

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**Abstract**— Parallel Computing System (PCS) is currently used widely in many applications of complex problems involving high computations. This is because it has the capability to process computations efficiently using a parallel scheme. ARS cluster is a low-cost PCS developed to implement processing of full-field digital mammograms. In this system eight processors are used to communicate via the Ethernet network using LINUX which is Fedora 7 as the operating system and Matlab Distributed Computing Server (MDCS) as a platform to process the digital mammograms. In this paper the Wavelet Transforms Modulus Maxima (WTMM) method is used to detect the edge of tumor in digital mammogram implemented on the ARS cluster. The study involved 80 digitized mammographic images obtained from the Malaysian National Cancer Center (NCC). The performance of the PCS in detecting the edge of tumors in digital mammograms using WTMM on the ARS cluster is reported. The experimental results showed that the speedup of the PCS improves when the number of processors is increased.

**Keywords**— Breast Tumor, Digital Mammograms, Edge Detection, Segmentation, Matlab Distributed Computing Server, Parallel Processing, Wavelet Transform Modulus Maxima.

## I. INTRODUCTION

Parallel Computing System (PCS) is a system based on parallel processing conception that uses multiple processors which run simultaneously and operate independently. In the system each processor has its own private Internet Protocol (IP) address, memory and space to store data. The data is shared via a communication network. The performance of a PCS depends on the specification of each processor and the memory capacity available in the system.

A Full Field Digital (FFD) mammogram is an image that consists a huge data in matrix form that represent the resolution, brightness and contrast of the image. Hence image processing of FFD mammograms require a system with high computational capability.

The ARS cluster is a low cost PCS that consists of eight workers that uses the Matlab Distributed Computing System (MDCS) and the open source LINUX Fedora 7 as an interface

between the user and the system. This system can be used to solve problems involving high complex computations.

In this paper the improvement in time processing, speedup and effectiveness of the ARS PCS in segmenting tumors in FFD images is reported.

## II. MATERIALS AND METHODS

In this work a multiscale edge detection that is based on the wavelet transform modulus maxima (WTMM) is used to segment tumors in FFD mammograms. The ARS PCS with MDCS is developed and used as a platform to process the segmentation. Parallel technique and computation used in processing the mammograms adopted work done by Mylonas [5] and Srivinasan [4].

Figure 1 below displays the framework of the parallel technique used.

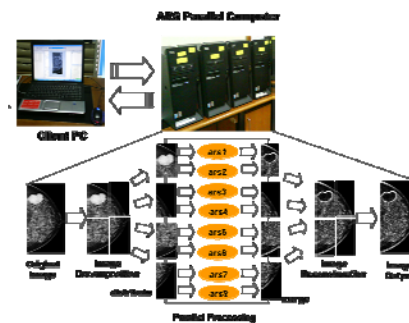


Fig. 1 Parallel Framework of Edge Detection

Digital images have been produced by the digital mammography instrument is initially read by a client PC. The client PC submits the task to the Job Manager (JM) which in turn distributes the task to each worker in the system. Each worker processes the task given independently. When the task is accomplished the JM collects the output and returns it back to the client PC for the result to be displayed in the monitor. The ARS PCS is used on a set of 80 FFD images are acquired from the Malaysian National Cancer Center [6].

A local maximum is a value that is maximum within some specific neighborhood. The local maxima of a wavelet transform modulus is closely related with multiscale edge detection that concerns about contours or boundaries of objects. From the multiscale edges detected by the WTMM the original signal is reconstructed.

According to Mallat et.al (1992), a multiscale edge detection in two dimensions can be formalized through a wavelet transform defined respectively by the following wavelets

$$\psi^1(x, y) = \frac{\partial \theta(x, y)}{\partial x} \quad \text{and} \quad \psi^2(x, y) = \frac{\partial \theta(x, y)}{\partial y} \quad (1)$$

where  $\theta(x, y)$  is a two-dimensional smoothing function whose integral over  $x$  and  $y$  is equal to 1 and converges to 0 at infinity.

With  $s$  serves as the dilation factor let

$$\psi_s^1(x, y) = \frac{1}{s^2} \psi^1\left(\frac{x}{s}, \frac{y}{s}\right) \quad \text{and} \quad \psi_s^2(x, y) = \frac{1}{s^2} \psi^2\left(\frac{x}{s}, \frac{y}{s}\right) \quad (2)$$

This allows the wavelet transform of a function  $f(x, y) \in L^2(\mathbb{R}^2)$  at the scale  $s$  with the respective wavelets to produce two components defined as

$$W_s^1 f(x, y) = f * \psi_s^1(x, y) \quad (3)$$

$$W_s^2 f(x, y) = f * \psi_s^2(x, y) \quad (4)$$

Theoretically the multiscale sharp variation points can be obtained when Equations (1) are satisfied. Consequently the wavelet components above can be rewritten as

$$\begin{pmatrix} W_s^1 f(x, y) \\ W_s^2 f(x, y) \end{pmatrix} = s \begin{pmatrix} \frac{\partial}{\partial x} (f * \theta_s)(x, y) \\ \frac{\partial}{\partial y} (f * \theta_s)(x, y) \end{pmatrix} = s \vec{\nabla} (f * \theta_s)(x, y) \quad (5)$$

The two wavelet transform components are proportional to the two components of the gradient vector  $\vec{\nabla} (f * \theta_s)(x, y)$ . At any scale  $s$ , the wavelet transform modulus of  $f(x, y)$  is defined as

$$M_s f(x, y) = \sqrt{|W_s^1 f(x, y)|^2 + |W_s^2 f(x, y)|^2} \quad (6)$$

where the angle of the gradient vector with the horizontal direction is governed by

$$A_s f(x, y) = \tan^{-1} \left( \frac{W_s^2 f(x, y)}{W_s^1 f(x, y)} \right) \quad (7)$$

The sharp variation points of  $(f * \theta_s)(x, y)$  are the set of points  $(x, y)$  where the modulus  $M_s f(x, y)$  has local

maxima in the direction of the gradient given by  $A_s f(x, y)$ . The line formed by the  $(x, y)$  along this direction represents the edge.

### III. WTMM ALGORITHM EDGE DETECTION OF TUMOR ON MAMMOGRAM IMAGE

The WTMM algorithm of edge detection of tumor on mammogram image is based on the A`Trous Algorithm [9]. The algorithm involves three convolution kernels namely the low-pass filter  $H$ , the high-pass filter  $G$  and the direct filter  $D$  [1]. In this work the kernels used are shown in the Table 1.

Table 1 Convolution Kernel

H	G	D
0.125	0	1
0.125	0.5	0
0.125	-0.5	0
0.125	0	0

The following algorithm computes the WTMM of the digital mammogram.

$j=0;$   
while  $j < J$

$$I_{2^{j+1}}(x, y) = I_{2^j}(x, y) * (H_j, H_j)$$

$$W_{2^{j+1}}^1 I(x, y) = I_{2^j}(x, y) * (D, G_j)$$

$$W_{2^{j+1}}^2 I(x, y) = I_{2^j}(x, y) * (G_j, D)$$

$$M_{2^{j+1}} I(x, y) = \sqrt{|W_{2^{j+1}}^1 I(x, y)|^2 + |W_{2^{j+1}}^2 I(x, y)|^2}$$

$j=j+1$   
end of while.

This algorithm is implemented on the digital mammogram using ARS PCS with Matlab R2009a software.

### IV. PARALLEL IMAGE PROCESSING APPLICATION

The parallel implementation of WTMM on digital mammograms adopted the technique by Mylonas [5] where the original image is decomposed into several sub-images.

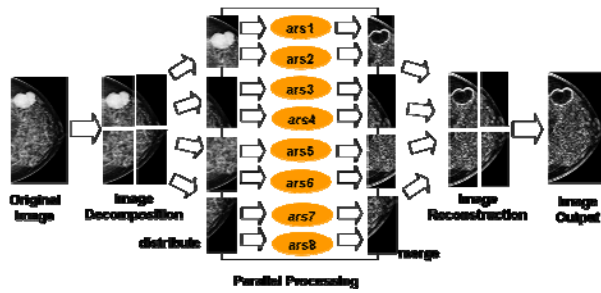


Fig. 2 Physical Parallel Algorithm

Figure 2 illustrates the physical parallel algorithm that decomposes the original image into four sub-images. Each sub-image is distributed into two processors. Hence each of the 4 sub-images undergoes the WTMM computation in a parallel manner. The output images are then united and displayed as one whole image. Consequently the edges detected by the eight workers merge to form one closed contour. Based on several experiments, the time taken for the iterations to complete sequentially and parallel is recorded. The performance of the PCS in terms of time processing, speedup and efficiency are analyzed.

V. RESULTS AND ANALYSIS

The edge of breast tumor has been detected using three scales of the multiscale edge detection using WTMM method. Each mammographic image shows the six images that have been processed based on scale of iteration. The last image shows the result of the edge detection of breast tumor that will be used by radiologist to analyze the tumor. Figure 3 shows the results obtained upon the implementation of the WTMM algorithm on a digital mammogram using the ARS PCS.

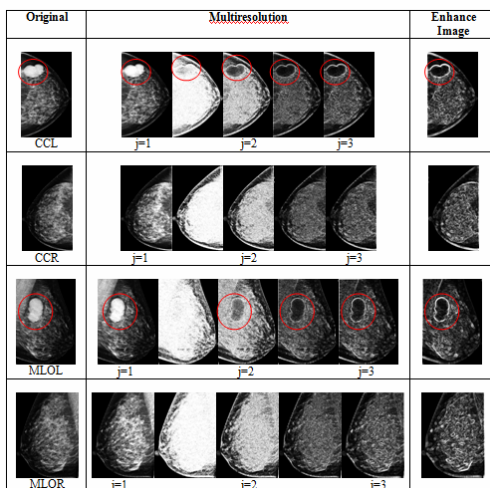


Fig. 3 Edge Detection Using WTMM

The performance of ARS PCS is based on Amdahl's law [7] in terms of the speedup and efficiency.

Figures 4-6 show the performances of the ARS PCS in detecting the tumor in digital mammogram using the WTMM method.

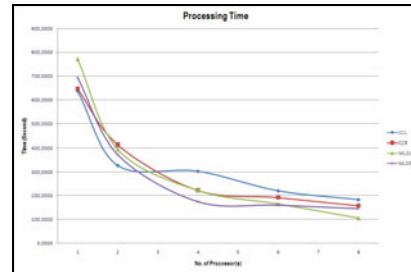


Fig. 4 Processing Time vs No. Worker(s)

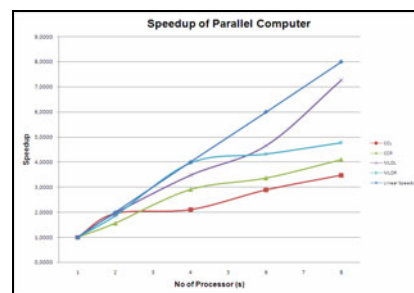


Fig. 5 Speedup vs No. Worker(s)

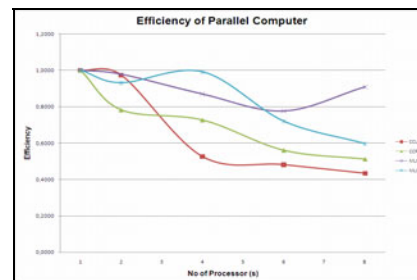


Fig. 6 Efficiency vs No. Worker(s)

In the Figure 4, the elapsed processing time of the WTMM tested on ARS PCS that consist of eight (8) IBM processors is depicted for four differences digital mammographic which are CCL, CCR, MLOL and MLOR. Each of it has their own size of the pixels. Based on the figure, the processing time decreased when the number of processors increased. In the Figure 5, it is shown the speedup of the ARS PCS is increasing slowly when the number of proces-sors increased. Based on the Kocak et.al. [10], the speedup of the large problem is better than the smaller problem. In

this case the size of the pixels of MLOR is large than the other digital mammographic. Hence, it gives the effect of the efficiency of ARS PCS that is shown in the Figure 6. From the figure, the efficiency of the ARS PCS is decreasing when the number of processors increased. It is shown that the utilization of the ARS PCS memory decreased when the processors increased. It depends on the size of the problems. If the efficiency reduced it shows that the PCS has a space to accept a more problem to solve. It is compared for one processor that solves the problem and the memory of processor is fully utilized and there is no space to accept more problems. Message Passing Interface (MPI) is used in ARS PCS as a communication tools between each processor. So, MPI is responsibilities to distribute the problem to each processor. In this experiment, the distribution of the problem is done by a Job Manager that indicated in the MDCS software [8].

## VI. CONCLUSION AND RECOMMENDATIONS

Based on the results obtained above, it shows that the ARS PCS is successful in improving the performance of the huge computations complexity in processing of FFD mammo-grams. This implies that the system can be benefited for image monitoring and visualizing in multidimensional problems.

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