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Hardware Architecture for Variational Mode Decomposition for Breast Cancer Feature Extraction on Ultrasound Images

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Abstract

Ultrasound (US) imaging proved to be less harmful than the traditional mammography is used for diagnosing breast cancer and this has helped reduce the number of unnecessary biopsies.The most important feature of malignant breast lesion is its infiltrative nature in US images.This infiltrative nature having composed of the frequency components that are adjacent to the lower frequency band contains the local variances that are characterized by Variational Mode Decomposition (VMD).On comparison with the existing decomposition models such as Empirical Mode Decomposition (EMD) and Wavelet Transform (WT) which are known for their limitations like sensitivity to noise and sampling which could only partially be addressed by more mathematical attempts to this decomposition problem, like synchrosqueezing, empirical wavelets or recursive variational decomposition.To overcome these limitations, a non-recursive VMD was selected.In this paper, we have presented an algorithmbased on VMD and a suitable architectureto obtain the infiltrative nature of the malignant breast lesion from the US image.

Keywords: Breast cancer feature extraction, Segment Accumulation Algorithm, Variational Mode Decomposition

1. Introduction

Breast cancer is considered as one of the most aggressive diseases among women and is diagnosed by means of a mammography.Mammography is a distinct type of imaging that uses low-energy x-rays to examine the human breast [14].There is a minimum possibility of 10% for acquiring a false negative information in this type of imaging [1].US type of imaging is considered to be an alternative to overcome this deficiency of mammography [15].Since, the US images are noisy in the real time,there are many computer-aided diagnosis (CAD) algorithms to analyze them [11].These algorithms help even the inexperienced physicians to differentiate between malignant and benign breast lesions [1].It is interesting to note from the lesion boundary delineation on US image, malignant breast lesion is highly infiltrative in nature.However, characterizing the infiltrative nature with highly efficacious and computationally inexpensive features is crucial for CAD [2].

Lee et al. found thatthe infiltrative nature of the lesion had causedan irregular local variance in 1-D representation [2].This local variance is found to be characterized by a few high octave energies in the 1-D discrete periodized wavelet transform (DPWT) [1].This motivated an algorithm to analyze US images of breast lesion using the octave energies derived using a reversible round-off 1-D non recursive discrete periodic wavelet transform (RRO-NRDPWT) [3].But there is alimitation in the wavelets approach, that the basis functions are fixed, and thus do not necessarily match all real signals[7]-[12].However an improved algorithm for 1-D signal was proposed by Huang et al. [10]andthe difficulty of pre determination of the basis function is resolved by a signal decomposition method called Empirical mode decomposition (EMD).

EMD is used for analyzing data from non-stationary and non-linear processes [13].This method has fully data driven approach.The basis function which can be obtained from the signal,is considered as the main benefit of using EMD. This makes the analysis to be adaptive as compared to the conventional methods.The decomposition in EMD is based on the direct extraction of the energy associated with various intrinsic time scales [10].Sifting is the algorithm used to decompose the signal and obtain the intrinsic oscillatory components called Intrinsic Mode Functions (IMF) [7].Using the previously filtered IMFs the signal is reconstructed.The highest frequency oscillation is selected using EMD from the input signal, as result IMF will contain only the lower frequency oscillations.However, EMD is also found to suffer from some drawbacks in robustness in extremal point finding, interpolation of envelopes, and stopping criteria.With the intention of overcoming the limitations of EMD, KonstantinDragomiretskiy and Dominique Zosso used a new technique known as VMD which sparsely decomposes images in a mathematically well-founded manner [16].Also Lahmiri and Boukadoumhave concluded that VMD approach outperforms the existing techniques of decomposition in their work of biomedical image analysis [10].We are thus motivated to use VMD for the diagnosis of malignant breast lesion and to identify a suitable VLSI architecture.

However, one of the most important, ubiquitous and intermediate step in all image analysis is segmentation.We use Chan-Vese algorithm to segment the diagnostically relevant feature from the US image which is lesion in our case.We found from literature survey that this is the predominant image segmentation algorithm in medical image analysis.

The rest of this paper is organized as follows. The Image Segmentation is reviewed in Section 2.VMD is explained in Section 3. We give the details of our work of image segmentation and VMD in Section 4.The VLSI architecture for the above image analysis is discussed in Section 5.We draw conclusions in Section 6.

2. Image Segmentation

Segmentation is the process of partitioning an image into a set of distinct regions to discoverboundaries of the desired region in the images.The Chan and Vese model is used to locate objects whose boundaries are not necessarily defined by the gradient.Here the main idea is to consider the information inside the regions along with its edge information [6].This is the model with minimized energy is seen as a peculiar case of minimal partition problem.There are some objects whose boundaries are not well defined through the gradient.The smeared boundaries and boundaries of large objects are defined by grouping smaller ones.

Chan and Vese introduced a new contour model, called “without edges“ [4].The main idea is to consider the information inside the regions in addition to edge information.Chan and Vese define the following energy,

$$E(u, c_1, C_2) = \mu\int_{\Omega} \delta(u) \mid \nabla u \mid dxdy + v\int_{\Omega} H(u)dxdy + \lambda_1\int_{\Omega} \mid f - c_1 \mid^2 H(u)dxdy + \lambda_2\int_{\Omega} \mid f - c_2 \mid^2 (1 - H(u))dxdy \tag{1}$$

where$f$ is the original image and c_1 and c_2 are constants representing average pixel value inside ad outside of the curve C.H (u) is given by

$$H(u) = \begin{cases} 1, if u \geq 0 \\ 0, if u < 0 \end{cases} \tag{2}$$

This model looks for the best approximation of image f as a set of regions with only two different intensities (c_1 and c_2). One of the regions represents the objects to be detected (inside of C), and the other region corresponds to the background (outside of C). The snake C will be the boundary between these two regions. In equation (1), the last two terms are fitting terms which guide the curve to the boundaries of the object.The fitting term E_1 (C) and E_2 (C) are minimised only at the object boundary. The first fitting term E_1 (C) gives error resulting from approximating the original image inside C with c_1 and the second fitting term E_2 (C) gives the error resulting from approximating the original image outside C with c_2. The solution can be obtained by approximating H (u) and δ (u) and by solving the following three equations

$$c_1 = \frac{\int_{\Omega} f(x,y)H(u)dxdy}{\int_{\Omega} H(u)dxdy} \tag{3}$$

$$c_2 = \frac{\int_{\Omega} f(x,y)\,(1 - H(\phi))dxdy}{\int_{\Omega} (1 - H\,(\phi))dxdy} \tag{4}$$

Chan Vese model is related in spirit to the Mumford-shah functional [4], which can be given as

$$E_{MS}\,(\mathrm{C, u}) = \mu\ \text{length (C)} + \upsilon\ \text{area (inside C)} + \int_{\Omega} |\ u - f\ |^2\ dxdy \tag{5}$$

For implementing using levelset theory, we replace (U) by $|\nabla \mathrm{U}|$. So the levelset evolution becomes

$$\frac{\partial u}{\partial t} = |\ \nabla u\ |\ \left(\mu div\left(\frac{\nabla u}{|\ \nabla u\ |}\right) - |\ f - c_1\ |^2 - |\ f - c_2\ |^2\right) \tag{6}$$

3. Variational Mode Decomposition

VMD is a non-recursive, fully intrinsic and adaptive, variational method, the minimization of which leads to decomposition of a signal, into its principal modes [5].VMD characterizes the local variances obtained from the infiltrative US images.This process is carried on by splitting the finest local mode from the data based only on the characteristic time scales.Connecting the local maxima and minima of the original signal through cubic splines, upper and lower envelopesare formed.The average of the two envelopes is then subtracted from the original data.Usually the process is reciprocatediteratively until various modes are extracted.The extraction of local extrema and their interpolation for envelope forming is substituted by more robust constraint optimization techniques.Here, the candidate modes are extracted variationaly. The signal is recursively decomposed into an IMF.

VMD decomposes an input signal into a discrete number of sub-signals (modes), where each mode has limited bandwidth in spectral domain.Each mode is compact around a center pulsation $\overrightarrow{\omega_k}$, which is to be determined along with the decomposition. In order to assess the bandwidth of a mode, the following scheme is proposed by Konstantin Dragomiretskiy and Dominique Zosso [5]: 1) for each mode u_k, compute the associated analytic signal by means of the Hilbert transform in order to obtain a unilateral frequency spectrum. 2) for each mode, shift the mode's frequency spectrum to "baseband", by mixing with an exponential tuned to the respective estimated center frequency. 3) The bandwidth is now estimated through the H_1 smoothness of the demodulated signal, i.e. the squared L_2- norm of the gradient.

In 2D one half-plane of the frequency domain must be set to zero; it is chosen relative to a vector, in our case to $\overrightarrow{\omega_k}$. Thus the 2D analytic signal of interest can first be defined in the frequency domain:

$$u_{AS,k}(\vec{x}) = \begin{cases} 2\,\widehat{u_k}(\omega), if\,\vec{\omega}.\vec{\omega}_k > 0 \\ \widehat{u_k}(\omega), if\,\vec{\omega}.\vec{\omega}_k = 0 \\ 0, \vec{\omega}.\vec{\omega}_k < 0 \end{cases}$$

$$= (1+ \text{sgn}\,(\vec{\omega}.\vec{\omega}_k))\,(\widehat{u_k}(\vec{\omega})$$

(7)

The analytic signal with Fourier property:

$$u_{AS,k}(\vec{x}) * \left(\delta\,(\langle\vec{x},\overrightarrow{\omega_k}\rangle + \frac{j}{\pi\langle\vec{x},\overrightarrow{\omega_k}\rangle}\right)\delta\,(\langle\vec{x},\overrightarrow{\omega_{k,}}\rangle)$$

(8)

where * denotes convolution and the transform is separable.

Here, the analytic signal is calculated line-wise along the direction of reference $\overrightarrow{\omega_k}$.

2-D VMD Functional

The functional to be minimized, stemming from this definition of 2D analytic signal, is:

$$\min_{u_k,\vec{\omega}_k}\{\textstyle\sum_k \Box\,\nabla[u_{AS,k}(\vec{x})e^{-j\langle\vec{x},\overrightarrow{\omega_k}\rangle}]_2^2\}\text{s.t.}\textstyle\sum_k u_k = f$$

(9)

Minimization w.r.t. the modes u_k

With this definition of the 2D analytic signal, optimization for uk and $\omega_k$analogously to the 1D counterpart. Since L^2-norms are dealt with, the functional including the augmented Lagrangian can be written in Fourier domain:

$$\hat{u}_k^{n+1} = \underset{\widehat{u_k}}{\arg\min}\left\{\alpha\Box j\,(\vec{\omega} \;\; - \vec{\omega}_k)[1 + sgn\big((\vec{\omega}.\vec{\omega}_k)\big)(\widehat{u_k}(\vec{\omega})]_2^2 + \;\Box\hat{f}(\vec{\omega}) - \textstyle\sum_k \hat{u}_\iota\,(\vec{\omega}) + \frac{\widehat{\lambda(\vec{\omega})}}{2}\Box_2^2\right\}$$

(10)

which yields the following Wiener-filter result:

$$\hat{u}_k^{n+1}(\vec{\omega}) = \;(\hat{f}(\vec{\omega}) - \sum_{i\neq k}\hat{u}_i(\vec{\omega}) + \frac{\hat{\lambda}(\vec{\omega})}{2}\left(\frac{1}{1 + 2\alpha\,|\,\vec{\omega} \;\; - \vec{\omega}_k\,|^2}\right)$$

(11)

$$\forall\vec{\omega}\epsilon\Omega_k\text{: }\Omega_k = \{\,\vec{\omega}\mid\vec{\omega}.\omega_k \geq 0\,\}$$

Minimization w.r.t. the center frequencies

Optimizing for $\vec{\omega}_k$for a 2-D, considering the domains to be the half-planes, and that there are two components.

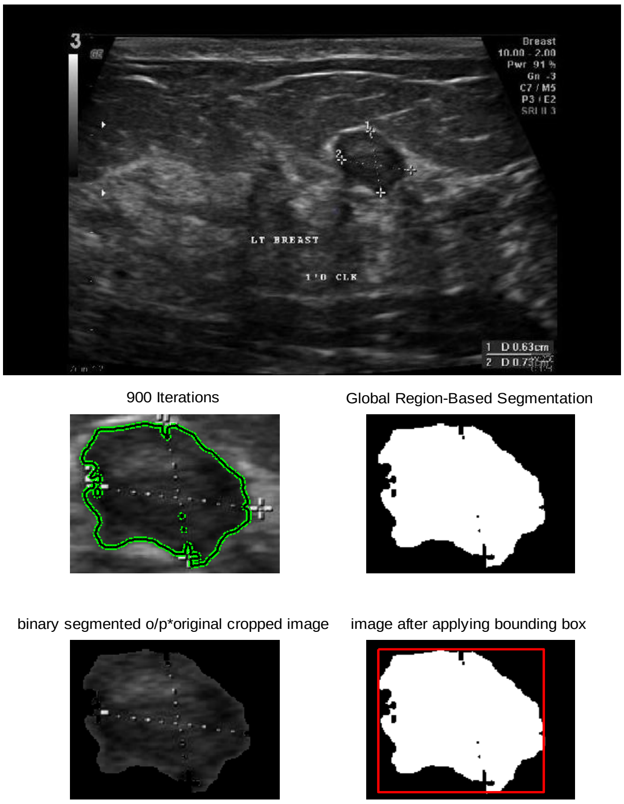
$$\hat{\omega}_k^{n+1}(\vec{\omega}) = \underset{\widehat{\omega_k}}{\arg min}\left\{\sum_k \|\nabla[u_{AS,k}\,(\vec{x})e^{-j\langle\vec{x},\overrightarrow{\omega_k}\rangle}]\|_2^2\right\} \tag{12}$$

In Fourier domain:

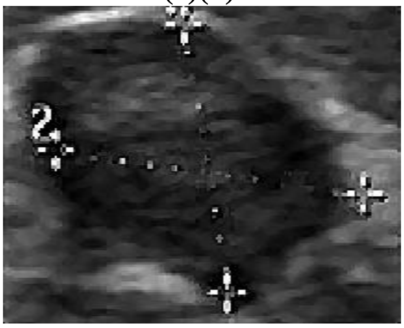
$$\overrightarrow{\omega_k} = \underset{\vec{\omega}_k}{\arg min}\left\{\alpha\|j\,(\vec{\omega}\;-\vec{\omega}_k)[1+sgn\big((\vec{\omega}.\vec{\omega}_k)\big)(\widehat{u_k}(\vec{\omega})]_2^2 + \|\hat{f}(\vec{\omega}) - \textstyle\sum_k \hat{u}_\iota\,(\vec{\omega}) + \frac{\widehat{\lambda(\vec{\omega})}}{2}\|_2^2\right\} \tag{13}$$

4. Proposed Work and Results

We start by letting the US image of the breast lesion to undergo image segmentation.Region based active contour segmentation method is used for this purpose. Fig. 1 shows the original image and the segmentation of the suspicious region of the image. We have implemented the segmentation work by using MATLAB.



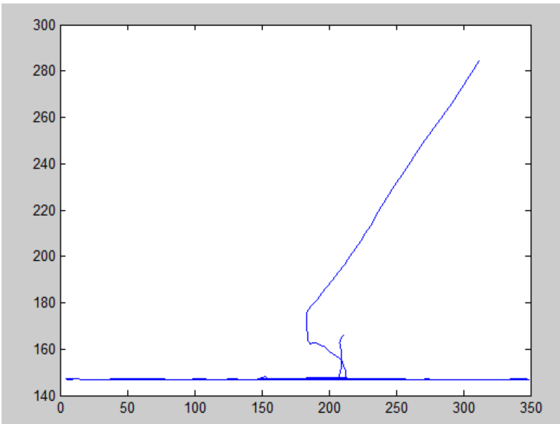
(a)(b)



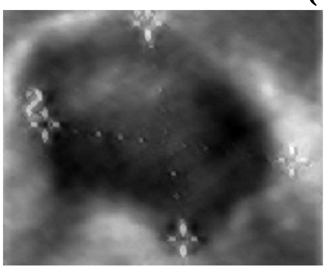
(c)

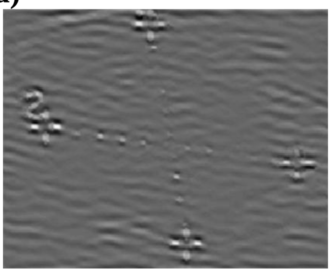
Fig.1 Segmentation of Ultrasound Image (a) Input UltraSound Image (b) Global Segmentation of the Image (c) Segmented image

We then apply the VMD algorithm to the segmented image.VMD decomposes the image into a given number of modes such that each individual mode has limited bandwidth. The VMD algorithm was run with parameters$\alpha = 5000$ (bandwidth constraint) and $K = 4$ (number of modes).The algorithm generates five constituent sub-images. The first four modes given in Fig. 2capture accurately the potential boundary of the desired region. It is very difficult to separate the possible region to even the experts manually. In fact, we implemented VMD also using MATLAB.

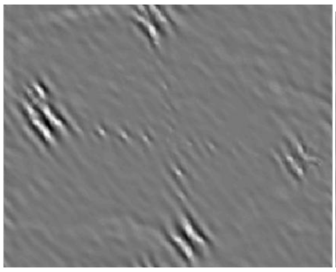


(a)

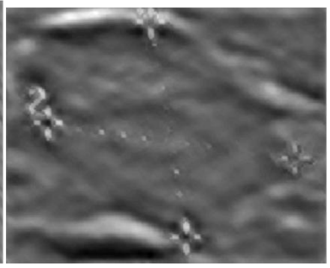




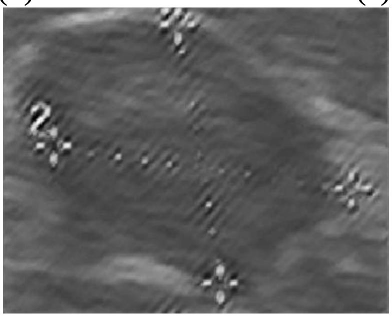
(b) **(c)**



(d)



(e)



(f)

Fig.2 VMD applied to the segmented image (a)Input Spectrum (b) Mode 1 (c) Mode 2 (d) Mode 3 (e) Mode 4 (f) Reconstructed Composite

5. Proposed VLSI Architecture Design

In this section, we give briefly discuss the architecture for the implementation of image segmentation by using Chan-Vese algorithm and VMD of this segmented image.

In fact, we obtain the sub-images which are called as modes arbitrarily from the segmented image.We denote them by u_{ik}, $k = 1, 2, 3 \ldots n$.For every $i = 1, 2, 3 \ldots N$, we expect the modes to satisfy

$$\sum_k u_{ik} = f \tag{14}$$

and, each mode should contain an unilateral frequency spectrum.Let, ω_{ik} for $i = 1, 2 \ldots N$ and $k = 1, 2 \ldots n$ giving central frequency of the modes.Now, we will calculate

$$S_i = \sum_k \left\| \partial_{x,y} [\left(\delta(x, y) + \frac{j}{\pi x y} \right) * u_{ik}(x, y) e^{-j\omega_{ik} x y} \right\|_2^2 \tag{15}$$

For every $i = 1, 2, \ldots N$.

We compareS_i and we will find the specific value of i say i=j for which the L_2 norm becomes minimum.Then the collection ofthose modes u_{jk}will be the one decomposition that we will use for our purpose of diagnosing the malignant breast lesion.

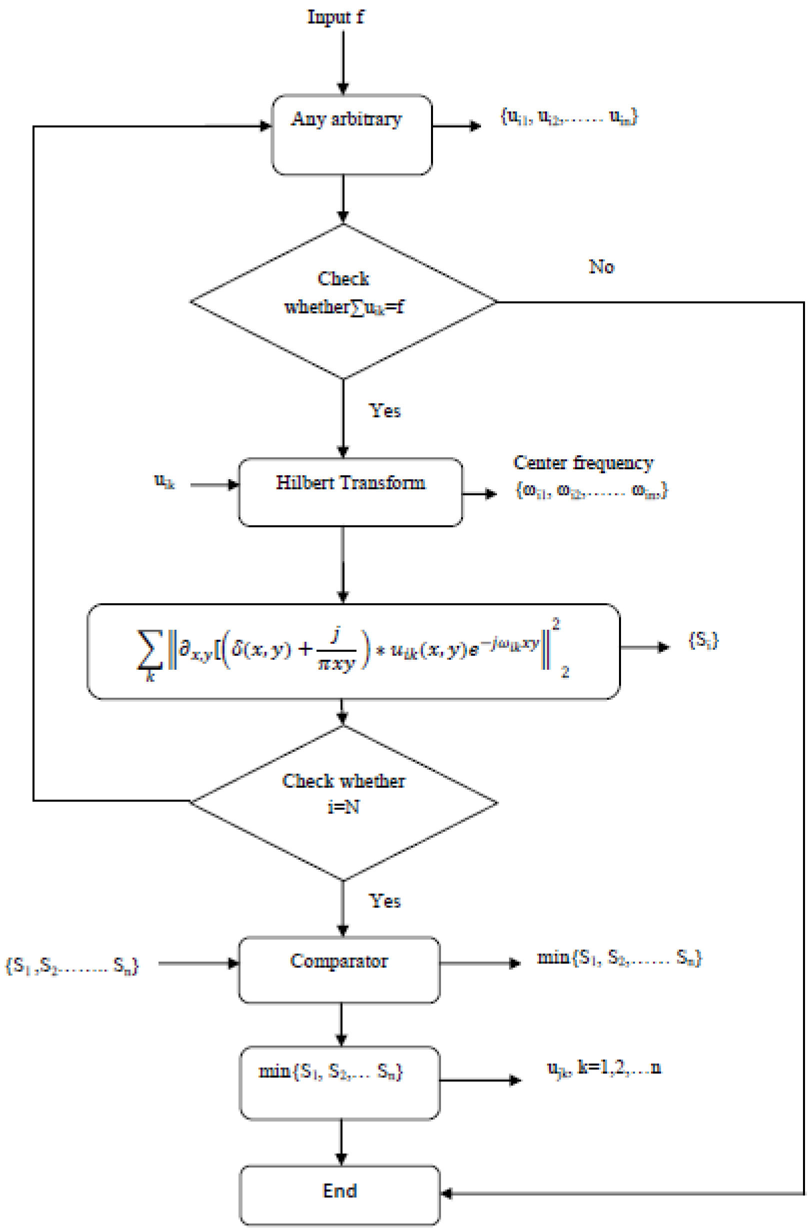


Fig. 3 Block diagram ofVMD approach.

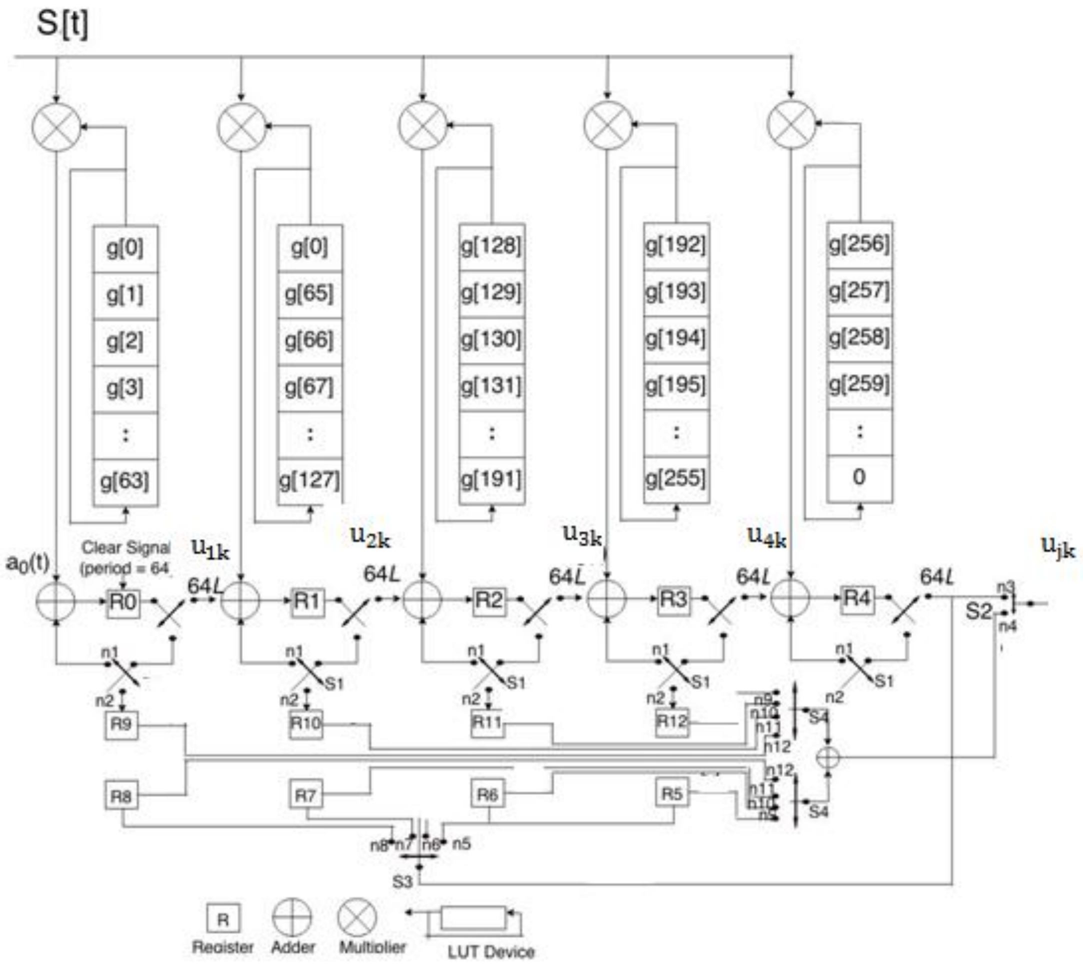


Fig.4 Architecture for VMD

6. Conclusion

In this paper, we have presented an algorithm based on VMD to obtain the infiltrative nature of the malignant breast lesion from the US image.Also we have presenteda suitable architecture to implement it.

Our proposed algorithm outperforms the existing wavelet based algorithm.In fact, on finding the drawbacks of wavelet transforms, (i.e.)representation of image using fixed basis function, we moved on to mode decomposition methods. VMD was found to be the most prevalent method among those available.It had a strong mathematical foundation.

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