# WAVELET BASED EXTRACTION OF BLOOD VESSELS

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Abstract: An algorithm for the segmentation of blood vessels based on the correlation of different wavelet scales is presented. First the wavelet coefficients are computed for a defined number of scales and then the correlation between the corresponding coefficients of two consecutive scales is computed. The normalized product is used as a reference threshold for retaining original wavelet coefficients. If the normalized product is greater than the corresponding original wavelet coefficient, the original coefficient is retained for image reconstruction by inverse wavelet transform, otherwise the coefficient is changed with zero value. Low frequency wavelet coefficients matrix is not used in image reconstruction process as we want only the edge information. The proposed algorithm is quite general and can be used for the extraction of any type of blood vessels and provides very promising results.

## 1 INTRODUCTION

Blood vessel identification and extraction in medical images is an important step in many medical image analysis applications e.g. diagnosis of the vessel stenosis, development of models to analyze different medical conditions, multimodal image registration etc. Many vessel extraction techniques have been proposed in the past. Cemil and Francis (Cemil and Francis, 2004) presented a very good review of many such techniques developed in the recent past. Some of the techniques are suitable for a particular type of blood vessel extraction e.g. retinal blood vessels, abdominal blood vessels etc. This limits the use of these approaches to a particular type of application only. The vessel segmentation algorithms developed so far may be broadly categorized into six main categories (Cemil and Francis, 2004): 1) pattern recognition techniques, 2) model-based approaches, 3) tracking based approaches, 4) artificial intelligence based approaches 5) neural network based approaches, 6) tube-like object detection approaches. More details of these approaches can be found in (Cemil and Francis, 2004). The blood vessel segmentation approach presented here is based on correlation of wavelet coefficients and is based on the idea presented by Xu (Xu et al., 1994). The approach is quite general and can be applied to any type of blood vessels quite confidently.

## 2 METHODOLOGY

Wavelets constitute a tool to decompose, analyze and synthesize functions with an emphasis on time-frequency localization (Omer et al.). Wavelets are families of functions generated from a single base wavelet by dilations and translations. The wavelet coefficient at scale j and time k is calculated as:

$$We(j,k) = \int_{-\infty}^{+\infty} e(u)\psi_j(k-u)du \qquad \text{(Eq.1)}$$

where $\psi_j$ is the wavelet at scale j.

The wavelet transform W(s,t) gives us a scale-space decomposition of signals and with simple modifications, images. They help in breaking complicated signals into simpler components and can be used in the analysis of complex signals, in the segmentation or detection of particular features, and in compression as well as de-noising images. Infact, wavelets decompose a signal into different resolution scales.

In a one-level Fast Wavelet Transform (FWT), a signal $C_i$ is split into an approximation part $C_{i+1}$ and a detail part $D_{i+1}$. In a multilevel FWT, each subsequent $C_i$ is split into an approximation $C_{i+1}$ and detail Di+1. For 2-D images, each $C_i$ is split into an approximation C i+1 and three detail channels $D^1_{i+1}$, $D^2_{i+1}$, $D^3_{i+1}$ for horizontally, vertically and diagonally oriented details of the image,



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respectively. Figure 1 is an illustration of this process. The inverse FWT (IFWT) reconstructs each $C_i$ from $C_{i+1}$ and $D_{i+1}$. This transform and its inverse are called the Fast Wavelet Decomposition (FWD) and Fast Wavelet Reconstruction (FWR), respectively, see (Westenberg and Roderdink, 2000) for more details.

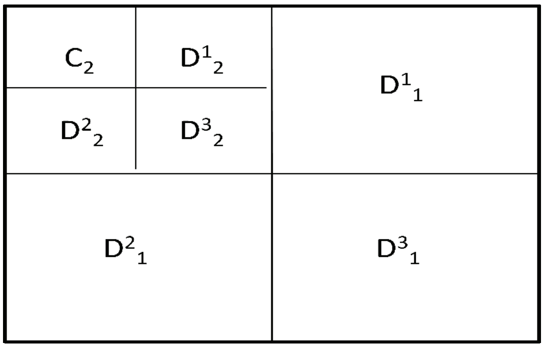


Figure 1: Ordering of the approximation and detail coefficients of a two-level 2-D non standard FWT.

Signals and noise behave very differently in wavelet transform domain. Singularities are more regular than noise(Xu et al., 1994). The evolution of singularities and noise across wavelet scales were analyzed by Mallat et al (Mallat and Hwang, 1992), (Mallat and Zhong, 1992) and reiterated by Paul Bao et al (Bao and Zhang, 2003).

As shown in the Figure 2, the edges in a signal (or image) are represented by large wavelet coefficients at the corresponding spatial locations and tend to propagate through the scales. Using a simple low pass filter would introduce heavy blurring due to the cutoff of useful components at the finer scales (at higher frequencies). To retain the useful high frequency image features as well, it is very important to distinguish between the high frequency contributions from the actual signal and those from the noise. Infact, most of the signal features contributing to high frequencies also contribute to low frequencies at the same spatial locations. Hence there will be correlation between wavelet coefficients of the useful image signal (such as edges and spikes) at different scales. In the case of noise, the correlation is much smaller. For this reason, the correlation across scales is used to distinguish between noise contribution and signal features at high frequencies.

So, wavelets are used for subband decomposition of a signal (or image). The approach has been to detect edges directly on the wavelet transform data algorithm, such as those introduced in (Witkin, 1983), (Fu et al., 2008). Xu(Xu et al., 1994) adopted the direct multiplication of wavelet transform data (sub-band decompositions of an image) at adjacent scales to distinguish important edges from noise and accomplish the task of removing noise from signals. In practice, it is sufficient to implement the multiplication at two adjacent scales. So, the DWT scale products can be calculated as:

$$P_j f(x)=W_j f(x).W_{j+1} f(x) \qquad \text{(Eq.2)}$$

Similarly, for 2D images, the multiscale products have two components:

$$P^x_j f(x,y)=W^x_j f(x,y)\ W^x_{j+1} f(x,y) \qquad \text{(Eq.3)}$$

$$P^y_j f(x,y)=W^y_j f(x,y)\ .\ W^y_{j+1} f(x,y) \qquad \text{(Eq.4)}$$

Figure 3 shows the DWT and multi-scale products of a noisy test signal f where

$$f = g + \epsilon \qquad \text{(Eq.5)}$$

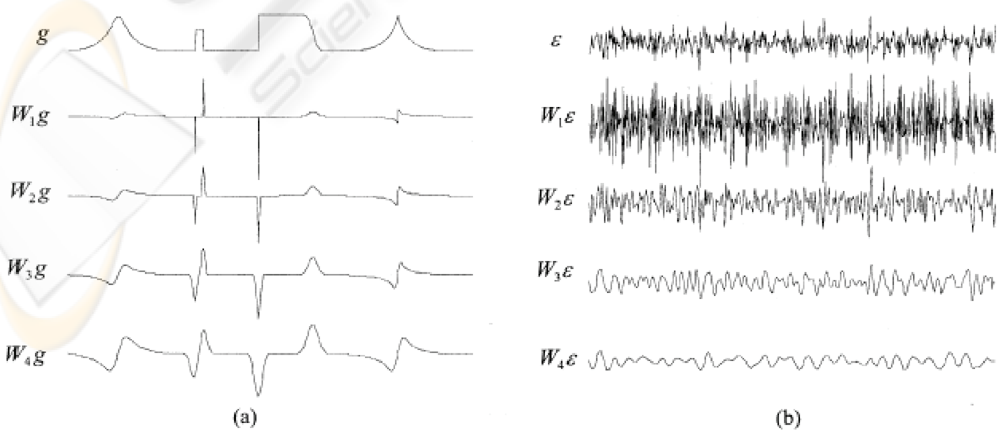


Figure 2: a) DWT of a test signal g at the first four scales. b) The DWT of a sequence of Gaussian white noise at the first four scales (Bao and Zhang, 2003).

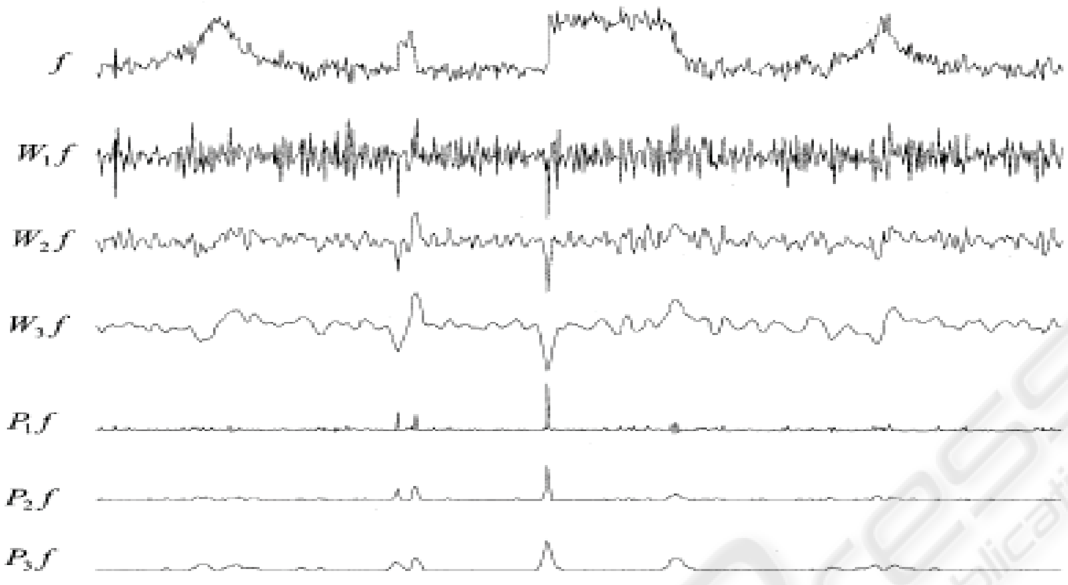


Figure 3: The DWT and multi-scale products of a noisy test signal at the first three scales (Bao and Zhang, 2003).

Although the wavelet transform coefficients of the original signal 'g' are immersed into noise 'ε' at fine scales, they are enhanced in the scale products $P_j f$. The significant features of 'g' are more distinguishable in $P_j f$ than in $W_j f$ (Bao and Zhang, 2003).

We calculate the correlation of the wavelet coefficient across consecutive scales starting from the first scale to the last. Since there is no down sampling, the $j^{th}$ scale has the same number of coefficients as the first scale. We also estimate the noise power at each level by observing the wavelet transform of a small region of interest corresponding to background signal. We assume the background signal contains the same noise components as the image. The position at which $Corr_2$ is smaller or equal to that relative to the estimated noise (taken as threshold value), the coefficient is changed to zero.

Thus the filtering process consists of, first, calculating the wavelet decomposition and correlation between different levels and then, if the correlation value is lower than a threshold value, the wavelet coefficient to which it refers is assigned a value of zero, otherwise it is left unchanged (Bao and Zhang, 2003). The technique can be considered as a spatially dependant filter (it can be demonstrated as a spatially dependant mask); it spatially selects which part of the data is to be kept (the edges) and which part of the data to eliminate (noise); the signal is passed where the wavelet transform is highly correlated across scales and suppressed elsewhere. (Xu et al., 1994)

The absence of edges or other significant features in a localized region of the signal allows the noisy background to be removed. The thresholding in wavelet domain over several scales sharpens the image which results in enhancement of major edges while suppressing noise. This also improves the accuracy of locating important edges in images. This method is simple and performs well on MRA images of the head.

## 3 ALGORITHM

The proposed algorithm is based on the identification of important vessel edges by correlation between different scales of Wavelets. The flow chart of the algorithm is shown in Figure 4 and can be discussed in the following steps:

1) The size of the input image is computed.

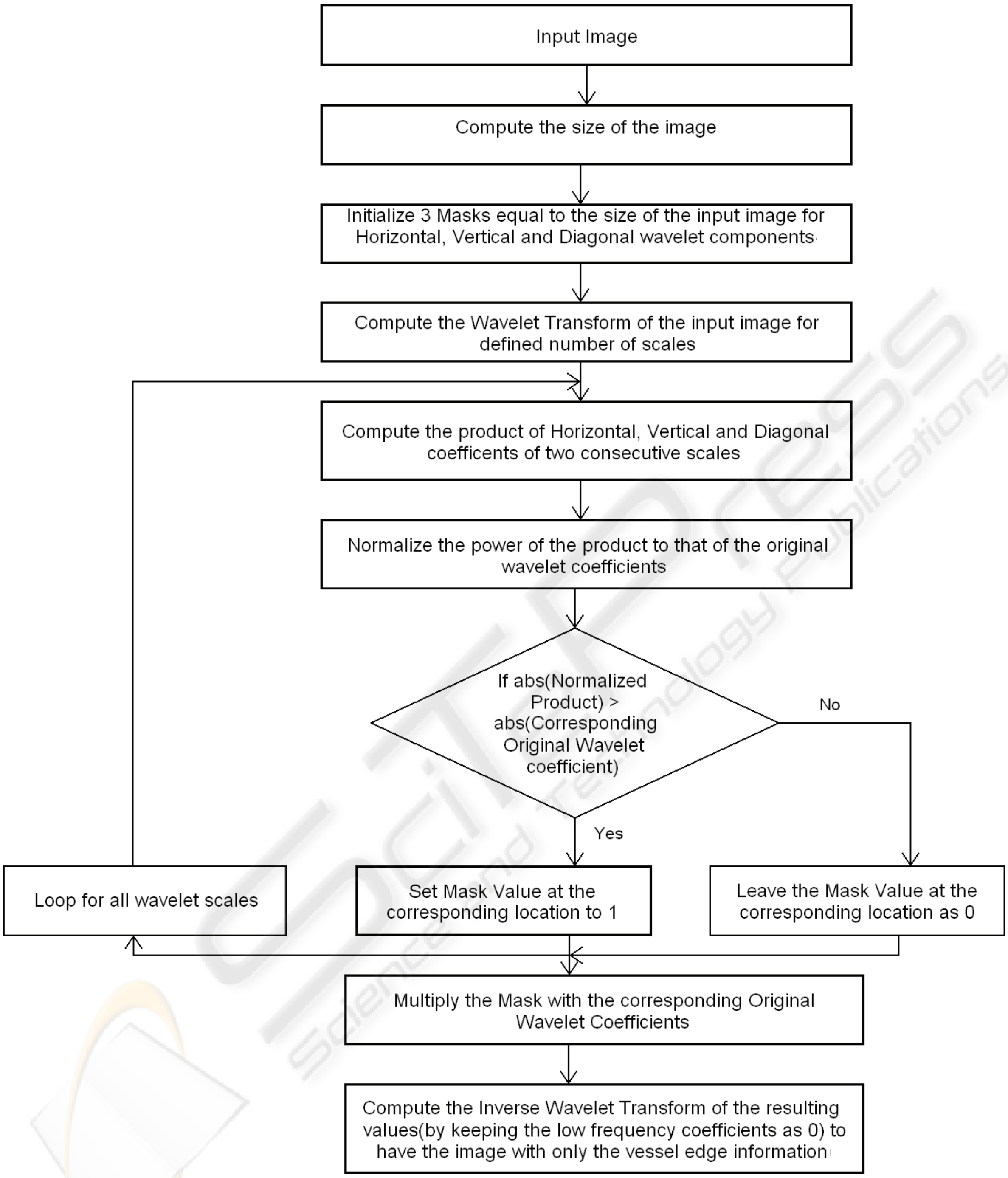


Figure 4: Flow-chart for proposed algorithm for Wavelet Based Vessel Edge Extraction.

2) Three masks are initialized with zero values. The size of the masks is equal to that of the original image.
3) The wavelet transform of the input image is computed for a defined number of scales. The output of this stage is a set of four matrices (Low Frequency coefficients, High Frequency Coefficients in horizontal direction, High Frequency coefficients in vertical direction and High Frequency coefficients in diagonal direction) for each scale.

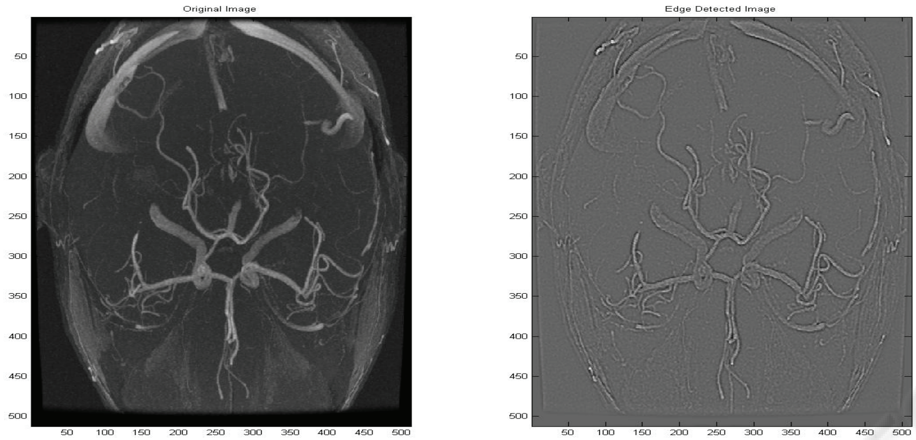


Figure 5: [Left] Time of Flight (TOF) MRA of the circle of Willis [Right] Edges enhanced image by the proposed algorithm.

4) These wavelet coefficients are saved for later retrieval.
5) The product of the two horizontal detail coefficient matrices in two consecutive scales is computed and the same process is repeated for the vertical as well as diagonal detail coefficients and for all resolution levels/scales.
6) The product (i.e. Energy) computed in the previous step is normalized to that of the original wavelet coefficients. It enables us to compare the power of the product to that of the original wavelet coefficients.
7) A comparison is made between the normalized product and the original wavelet coefficients. If the Normalized product is greater than the corresponding original wavelet coefficient, the mask value at the corresponding location is set to 1 otherwise it remains as zero.
8) The masks are multiplied with the original wavelet and thus only the coefficients related to edges are retained and others are lost.
9) The inverse wavelet transform is computed based on the processed wavelet coefficients. At this stage, we use only the processed detail coefficients (i.e. Horizontal, Vertical and Diagonal) and do not use the low frequency related wavelet coefficients.

# 4 RESULTS AND DISCUSSION

The above algorithm was applied on MRA images of Circle of Willis and the results obtained were very good with improved boundaries about blood vessel edges. The output image showed a clear suppression of the noisy parts of the image. One important observation was regarding the number of scales to be used to find inter-scale correlation which is a primary measure to identify which wavelet coefficients belong to the actual signal and which are representing noise. The use of more than two scales, causes the loss of much of the edge related information along with the noisy coefficients and the reconstructed image does not give very clear representation of the actual vessel edges. The best results are obtained with two scales used as almost all the edges are retained and are very clearly visible in the resulting image.

Another advantage of this approach is that the coefficients which are more likely related to noise are removed during this process of correlation and in this way, the result is containing noise free edge information. Figure 5 presents the results of this algorithm on an MRA image. The left hand side shows the original MRA image and the image on the right shows the enhanced image.

# 5 CONCLUSIONS

We propose a vessel extraction technique based on normalized inter-scale energy in wavelet domain which proves to be a very good tool to identify vessel edges. The noise level in the image is also reduced. The wavelet coefficients with small information at the higher scales are removed as they are more probably associated with noise. The image reconstruction involves the computation of inverse wavelet transformation of the processed detailed coefficients and suppressed low frequency coefficients. The resulting image contains only the contours of the blood vessels. This algorithm makes no assumption about the vessel shapes so it can be applied to the vessels of any part of the body. The future work may involve the optimization of the proposed algorithm. This algorithm is applied onto MIP (Maximum Intensity Projection) image of Time of Flight MRI image in which 3D data is mapped on a 2-D plane. During this process of image projection, some important information is lost. If this algorithm could be extended to 3D data, so that the algorithm would not be applied on 2D projection image but directly on the 3D image. It will improve the quality of the reconstructed image. Furthermore, since 3D involves huge quantity of data to be processed, introduction of some parallel approach may considerably reduce the computational time.

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