Evaluation and Selection of Wavelet Filters for De-noising Medical Images Using Stationary Wavelet Transform (SWT)

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Abstract

Image processing techniques in medical imaging are used to analyze the symptoms of the patients with ease. Often images get noise during acquisition process. Traditionally, statistical methods are used to estimate the noises. Many researchers have successfully applied and proved the advantages of the Discrete Wavelet Transform for image denoising [1][2]. DWT in image denoising has limitation due to its non-invariance in time/space. The time invariant property of SWT is useful in denoising the image. In this paper we have analysed and chosen the best wavelet filter for de-noising the medical images using SWT, because there is no filter that performs the best for all images [3]. Daubechies, Symlet, Haar, Coiflet and biorthogonal wavelet transforms applied through different orders at level 1 to 5 on the MRI images and evaluated through structural distortion measurement i.e. universal quality index instead of error measurement. Our results show that the sym6 give the better results at level 5. The application of this method would improve the accuracy of MRI Image, and therefore easily identify the diseased in MRI image for diagnosing critical diseases.

Keywords Image De-noising, Medical Imaging, SWT, Universal Quality Index, and Wavelet Filter.

1. Introduction

Image processing technology in medical field made the doctors to see the interior portions of the body for easy diagnosis. And it also helps to make keyhole surgeries for reaching the interior part without really opening too much of the body. CT scanner, X-ray imaging, ultrasound etc. are making the doctors to look at the bodies elusive of 3D. Many image-processing techniques have been developed for analyzing the output of medical imaging systems to get the advantage to analyze the symptoms of the patients with ease.

Paper Identification Number: CI-8.1

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MRI images often consist of random noise that does not come from the tissues but from other sources in the electronic instrumentation and its environment during acquisition. The noise of an image gives it a grey appearance and mainly the noise is evenly spread and more uniform. To extract the features such as the edges of tumour needs desirable process to enhance the visibility condition of the image. Image denoising techniques are used to improve an image both objectively (e.g. increases the signal to noise ratio) and Subjectively (e.g. make certain features easier to see by modifying the colour or intensities). Basically image-denoising techniques are fall into two basic categories namely spatial domain and frequency domain. Wavelet Transform (WT) is one of the frequency domain technique emerged as very powerful tool and provide a vehicle for digital image processing applications. Because it has a ability to take into account of Human Visual System (HVS) characteristics, good energy compaction capabilities, under transmission and decoding. It is also more robust under transmission and decoding error. With standard DWT, signal has same data size in transform domain and therefore it is a non-redundant transform. Standard DWT can be implemented through simple filter bank structure of recursive FIR filters. A very important property of DWT is Multiresoluiton Analysis (MRA) allows DWT to view and process different signals at various resolution levels [4]. The advantage of non-redundancy over a Continuous Wavelet Transform (CWT) helps to implement fast and simple with a digital filter. And MRA capability populated with DWT in many signals and image processing applications since last 10-15 years. Many researchers have successfully applied and proved the advantages of DWT for signal and image denoising and also in compression in number of diverse fields [5]-[10].

As DWT is a powerful tool for signal and image processing applications; but it has three serious disadvantages. First, is shift sensitive: because input signal shift generate unpredictable changes in DWT coefficients. Second, it suffers from poor directionality: because DWT coefficients reveal only three spatial coefficients i.e. Diagonal (D), Horizontal (H) and Vertical (V). And the third is, it lacks the phase information that accurately describes non-stationary signal behaviour. And the use of larger DWT basis function or wavelet filters produces blurring and ringing noise near edge regions image or video form and larger compression time. These disadvantages severely restrict its scope for certain signal and image processing applications [11,12]. The Stationary Wavelet Transform (SWT) has overcome the non-invariance property of Discrete Wavelet Transform (DWT). In this paper, we have applied SWT on medical images and evaluated through universal image quality index measure for performance evaluation. The results, which we have achieved, are more useful for the general medical practitioners for easy analysis, which in turn saves the processing time

2. Methodologies

2.1 Overview of Stationary Wavelet Transform (SWT)

Wavelet Transform is superior approach to other time-frequency analysis tools like Fourier Transform (FT) and Short Term Fourier Transform (STFT) because its time scale width of the window can be restricted to match the original signal especially in image processing applications. This makes that it is particularly useful for non-stationary signal analysis such as noises and transients. For discrete signal, DWT is a Multiresoluiton Analysis (MRA) and it is a non-redundant decomposition. The drawback of non-redundant transform is their non-variance in time [4]. The stationary wavelet transform (SWT) was introduced in 1996 to make the wavelet decomposition time invariant [13,14]. In order to preserve the invariance by translation, the downsampling operations must suppressed and the decomposition obtained is redundant and is called stationary wavelet transform, which is as shown in figure 1.

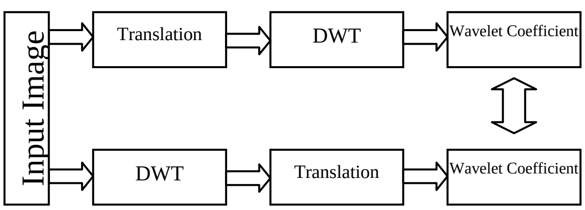

Figure 1: Stationary Wavelet Transform (SWT)

Therefore SWT has similar tree structured implementation without any sub-sampling. This balance of Perfect Reconstruction (PR) is preserved through level dependent zero padding interpolation of respective low pass and high pass filters in the filter bank structure. SWT has equal length of wavelet coefficients at each level. The computational complexity of SWT is O (n^2). The redundant representation of SWT makes shift-invariant and suitable for applications such as edge detection, de-noising and data fusion [12,15]. In stationary wavelet transform (SWT) instead of downsampling, an upsampling procedure is carried out before we separate the variables x and y like shown in the following wavelets

Vertical wavelet (LH): $\varphi^1(x,y) = \phi(x)\varphi(y)$

Horizontal Wavelet (HL): $\varphi^2(x,y) = \varphi(x)\phi(y)$

Diagonal Wavelet (HH): $\varphi^3(x,y) = \varphi(x)\varphi(y)$

…(1)

Where φ is the wavelet function and ϕ is the scaling function. The detailed signals contained in the three sub-images are as follows:

$$w^1_{j+1}(k_x,k_y) = \sum_{lx=-\infty}^{+\infty}\sum_{ly=-\infty}^{+\infty} g(lx)h(ly)c_{j,k+2^j}(lx,ly) \cdots (2)$$

$$w^2_{j+1}(k_x,k_y) = \sum_{lx=-\infty}^{+\infty}\sum_{ly=-\infty}^{+\infty} h(lx)g(ly)c_{j,k+2^j}(lx,ly) \ldots (3)$$

$$w^3_{j+1}(k_x,k_y) = \sum_{lx=-\infty}^{+\infty}\sum_{ly=-\infty}^{+\infty} g(lx)g(ly)c_{j,k+2^j}(lx,ly) \ldots (4)$$

2.2 SWT based Image De-noising

An image is often corrupted by a noise during acquition and transmission. Image de-noising is used to remove the additive noise while retaining as much as possible the important features. There are various techniques available for de-noising the signal and images. Wavelet thresholding is an effective method of de-noising noisy signals; which plays an important role in denoising the image and it is treated as widely investigated noise reduction method [7,8,16,17]. The wavelet de-noising is achieved via thresholding. Wavelet thresholding procedure removes noise by thresholding only the wavelet coefficient of the details coefficients, by keeping the low-resolution coefficients unaltered. There are two thresholding methods frequently used: soft thresholding and hard thresholding. A procedure keep or kill is called hard thresholding and alternative to this procedure is called soft thresholding. The soft thresholding is normally chosen over the hard thresholding yields more visually enhanced images over hard thresholding because the later is discontinues and yields abrupt artifacts in the recovered images, especially when the noise energy is significant.

2.3 Procedure for De-noising

The general procedure for de-noising through soft thresholding includes the following three steps.

a) Decomposition
b) Threshold detail coefficients (i.e. Diagonal, Horizontal and Vertical)
c) Reconstruct.

In the above three steps, firstly the image is decomposed by the wavelet transform, and then secondly the detail coefficients are thresholded by the SURE shrink thresholding algorithm [7]. After the thresholding, the new detail coefficients are obtained; using these new coefficients the image is reconstructed, which is the de-noised image by wavelet transform [18]-[21].

3. Image Quality Evaluation

After de-noising the image, it is often necessary to measure the quality of the original and de-noised images. Therefore, quality measures play an important role in image processing applications. Basically two kinds of quality measures are used to measure the quality of the images: Objective quality measures and Subjective quality measures [22]-[27]. Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) are the commonly used objective quality measures but they are widely criticized as well; not correlating well with perceived quality measurement. Universal quality index is one of new approach for measuring image quality distortion matrices, which is based on structural distortion measurement instead of error measurement. Universal means the quality measurement approach does not depend on the images being tested. And it is applicable in various image-processing applications and provides a meaningful comparison across the different types of image distortion; the universal quality index Q can be defined as:

$$Q = \frac{4\sigma_{xy}\ \bar{x}\cdot\bar{y}}{(\sigma_x^{\ 2}+\sigma_y^{\ 2})\,[(\bar{x})^2+(\bar{y})^2]} \quad \ldots(5)$$

Where,

$$\bar{x} = (1/N)\sum_{i=1}^{N} x_i,\ \ \bar{y} = (1/N)\sum_{i=1}^{N} y_i$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})^2$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i-\bar{y})^2$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})$$

The dynamic range of Q is lies in between [-1,1]. The best value of 1 is achieved if and only if $y_i = x_i$, for i=1,2,3…N. The lowest value of -1 occurs when $y_i = 2\bar{x} - x_i$ for all i=1,2…N. The quality of the index is combination of three different factors: loss of correlation, luminance distortion, and contrast distortion. Therefore the Q can be the product of these three components [20].

$$Q = \frac{\sigma_{xy}}{\sigma_x\sigma_y} * \frac{2\overline{xy}}{(\bar{x})^2+(\bar{y})^2} * \frac{2\sigma_x\sigma_y}{\sigma_x^{\ 2}+\sigma_y^{\ 2}} \quad \ldots(6)$$

The first component correlation coefficient, which measures the linear correlation between original and de-noised image, and which is lies in between [-1, 1]. The Second component luminance distortion, which measures the mean luminance between original and de-noised image, and which is lies between [0,1]. And the third component contrast distortion which measures how similar the contrast in between original and de-noised image, and which is lies in between [0,1].

4. Results and Discussion

In this paper we have applied different wavelets through SWT on MRI images [28] of size 256 x 256 to decompose the original image at level 1 to 5. At every level of decomposition we got three detail subimages (Diagonal, Horizontal and Vertical) as shown in figure 2 and one approximation image is produced. After the decomposition procedure the SURE shrink thresholding is applied on only details subimages, the noise source of detail images is eliminated at each level. After that, the de-noised detail and approximation image are reconstructed which is free from the noise as shown in Figure-3. We have applied db1 to db10, sym2 to sym8, haar, coif1 to coif5 and bior1.1 to bior2.4 and image quality of de-noised images is evaluated through the universal quality index. We got best results for db1 at level 4, haar at level 4 and bior1.1 at level 4 and sym6 at level 5. Among these sym6 give better results at level 5. If we increase the order of filter and the level of decomposition, which are leads to computational complexity and visual quality of de-noised image.

Therefore, we have decomposed the image up to level 5, and evaluated through above quality measures algorithm and the results are shown in Table1. And the effectiveness of each filter is dependent on the type of image and error criterion. In this experiment we have decomposed and reconstructed the image only up to 5^{th} level for decomposition because if we increase the level of decomposition the quality of the image will become very poor and get blurred. We have got less value of quality index since the image gets distorted; it means that the contrast distortion is increases. If the contrast distortion increases the luminance distortion also get increases.

We have also observed that if the contrast distortion is poor the negative correlation of the pixel values and the quality index of the de-noised image are very low. The observation of the applied wavelet types at decomposition level (DL) 1 to 5, the Quality Index, Loss of Correlation, Luminance Distortion and Contrast Distortion are predicted in table1 and it is also predicted through histogram in Figure 4 and graph in Figure 5. The histogram of resultant image after applying Haar, Db1 and Bior1.1 at level 4 is same. In this paper we have shown histogram of resultant image of Db1 at level 4. It is concluding that among these various types of transforms db1, bior1.1 and haar gives the betters results at level 4 than coif1 to coif5 at level 4. Whereas the sym6 at level 5 gives the drastic improvement in quality index. Therefore, the selection of appropriate wavelet filter plays a crucial role for de-noising the different noises affected on different images and also we observed that no one filter that performs best for all.

5. Conclusion

MRI images often consist of random noise and which are affected during acquisition and it spread over uniformly on the image. In such situation it is very difficult to diagnosis the particular disease. Therefore, it is necessary to de-noise the image. Denoising of MRI images through SWT in image processing method has noticeable advantage over DWT namely time invariance. This makes it particularly useful in recognizing and denoising MRI images. In this paper, we have applied different wavelets through SWT on MRI images at level 1 to 5. We have observed that out of db1 to db10, sym2 to sym8, coif1 to coif5 and bior1.1 to bior2.4; sym6 at level 5 of SWT gives better performance for denoising.

Through this work we have also observed that the choice of wavelet filters for de-noising the medical images would depends on the type of noise and type of transforms, which are used. This experimental analysis will improve the accuracy of MRI images for easy diagnosis. The results, which we have achieved, are more useful and it will more helpful for general medical practitioners to analyze the symptoms of the patients with ease and also which saves the processing time. Further this work can be extended to detect and de-noise with different types of noises with the help of Wavelet Packet and Complex Wavelets Transforms

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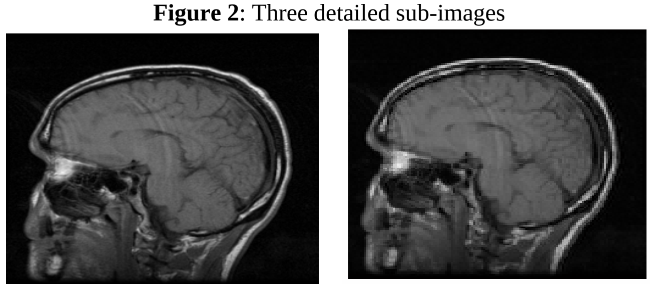
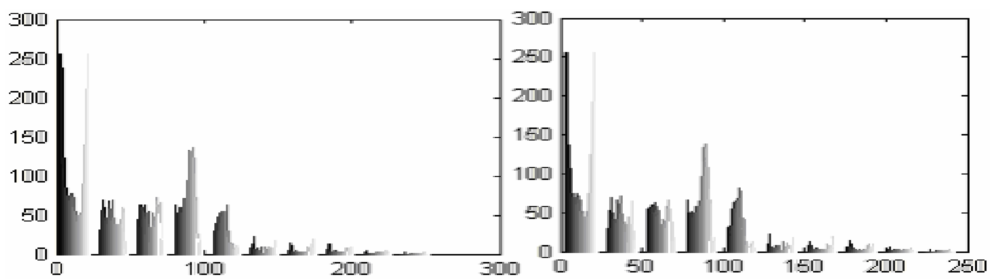
(a) Diagonal (b) Horizontal (c) Vertical

Figure 2: Three detailed sub-images

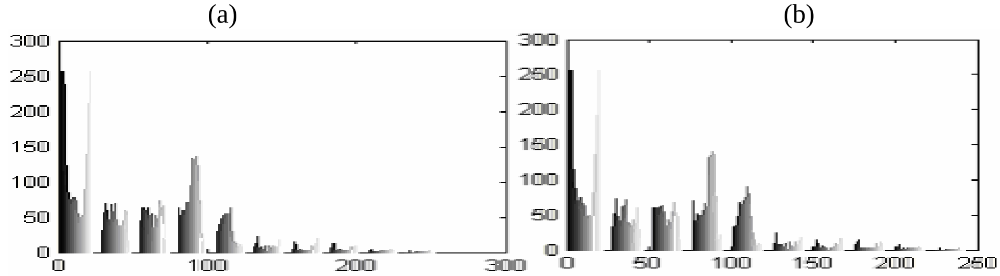


(a) Original (b) De-noised (SWT)

Figure 3: Original and de-noised MRI images.



(a) (b)



(c) (d)

Figure 4:(a) Histogram of Original MRI image (b) Histogram of Reconstructed MRI image using Haar or Db1 or Bior1.1 at level 4 (c) Histogram of Original MRI image (d) Histogram of Reconstructed MRI image using Sym6 at level 5

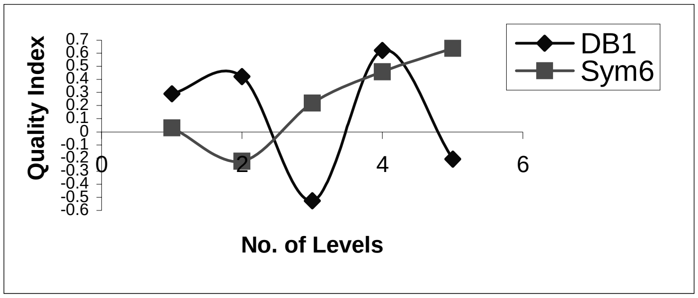


Figure 5: Shows the variation in quality index at different level
(The results of Db1, Haar and Bior1.1are same)

Table 1: Shows Quality Index, Loss of Correlation, Luminance and Contrast Distortion with Different Stationary Wavelet Transform (SWT**)**

Wavelet type	DL*	Quality Index (Q)	LOC**	Luminance Distortion	Contrast Distortion
Db1	1	0.291542	1	0.372472	0.782723
	2	0.422724	1	0.494259	0.855268
	3	-0.527095	-1	0.576416	0.914435
	4	**0.619953**	**1**	**0.622156**	**0.996458**
	5	-0.208544	-1	0.635923	0.327939
Db2	1	-0.0659571	-1	0.494259	0.241759
	2	0.262743	1	0.326771	0.80406
	3	-0.360399	-1	0.451909	0.797503
	4	0.36661	1	0.546225	0.671264
	5	-0.544247	-1	0.572826	0.950108
Db3	1	-0.0102563	-1	0.262102	0.0391309
	2	-0.212368	-1	0.365206	0.581503
	3	-0.50032	-1	0.502632	0.995399
	4	-0.473373	-1	0.622012	0.761034
	5	-0.189167	-1	0.645845	0.292891
Db4	1	-0.0289181	-1	0.260187	0.111143
	2	-0.004048	-1	0.314511	0.0128721
	3	-0.0979824	-1	0.484603	0.202191
	4	0.00613468	1	0.615528	0.00996653
	5	-0.190046	-1	0.63765	0.298041
Db5	1	-0.0753846	-1	0.260625	0.289246
	2	0.296623	1	0.296828	0.999309
	3	-0.433947	-1	0.468649	0.925953
	4	0.565786	1	0.59997	0.943023
	5	0.00174488	1	0.618996	0.00281888
Db6	1	-0.0171171	-1	0.260587	0.0656868
	2	-0.0900475	-1	0.297051	0.303138
	3	0.227507	1	0.475562	0.478395
	4	0.511241	1	0.607986	0.840876
	5	0.0899473	1	0.621298	0.144773
Db7	1	0.0120329	1	0.259974	0.0462849
	2	0.292668	1	0.293206	0.998165
	3	-0.458838	-1	0.474432	0.96713
	4	-0.470696	-1	0.60701	0.775433
	5	-0.61607	-1	0.616082	0.99998
Db8	1	0.0542676	1	0.260887	0.208012
	2	0.243719	1	0.287971	0.84633
	3	0.188046	1	0.472768	0.397754
	4	-0.595663	-1	0.599539	0.993536
	5	0.459828	1	0.605771	0.75908
Db9	1	-0.244965	-1	0.26088	0.938995
	2	-0.0631145	-1	0.28713	0.219811
	3	-0.405289	-1	0.461542	0.878119
	4	0.182387	1	0.58062	0.314017
	5	-0.526194	-1	0.587714	0.895324
Db10	1	0.0395764	1	0.259206	0.152683
	2	0.269041	1	0.280804	0.958109
	3	-0.0428344	-1	0.450966	0.949873
	4	0.394837	1	0.567917	0.695237
	5	0.244752	1	0.568124	0.430807
Sym2	1	-0.0659511	-1	0.272822	0.241759
	2	0.262743	1	0.326771	0.80406

	3	-0.360399	-1	0.451909	0.797503
	4	0.366661	1	0.546225	0.671264
	5	-0.544247	-1	0.572826	0.950108
Sym3	1	-0.0102563	-1	0.262102	0.0391309
	2	-0.212368	-1	0.365206	0.581503
	3	-0.50032	-1	0.502632	0.995399
	4	-0.473373	-1	0.622012	0.761034
	5	-0.189167	-1	0.645845	0.292898
Sym4	1	0.0439323	1	0.260788	0.16846
	2	0.00552063	1	0.342301	0.016128
	3	0.244554	1	0.495232	0.493816
	4	-0.630962	-1	0.631226	0.99951
	5	-0.53077	-1	0.648123	0.818934
Sym5	1	0.0824339	1	0.26118	0.315621
	2	0.0949936	1	0.322798	0.294282
	3	-0.133432	-1	0.461344	0.289225
	4	0.435179	1	0.590985	0.736362
	5	0.343161	1	0.61017	0.562402
Sym6	1	0.0302662	1	0.260753	0.116027
	2	-0.225107	-1	0.319061	0.705531
	3	0.218478	1	0.485102	0.450376
	4	0.459693	1	0.627804	0.732224
	5	**0.635997**	**1**	**0.642905**	**0.989256**
Sym7	1	0.0978176	1	0.261381	0.374235
	2	-0.298313	-1	0.305708	0.975811
	3	0.0452516	1	0.468252	0.0966394
	4	-0.389464	-1	0.603221	0.645641
	5	-0.124235	-1	0.621368	0.199938
Sym8	1	0.249227	1	0.261155	0.954326
	2	0.0207302	1	0.305577	0.0678396
	3	0.236797	1	0.471927	0.501767
	4	0.243604	1	0.619294	0.3933357
	5	0.529017	1	0.633109	0.835587
Haar	1	0.291542	1	0.372472	0.782723
	2	0.422724	1	0.494259	0.855268
	3	-0.527095	-1	0.576416	0.914435
	4	**0.619953**	**1**	**0.622156**	**0.996458**
	5	-0.208544	-1	0.635923	0.327939
Coif1	1	-0.362908	-1	0.271787	0.1335226
	2	0.285177	1	0.354797	0.803777
	3	-0.102437	-1	0.448678	0.228309
	4	-0.257478	-1	0.536185	0.480203
	5	-0.393136	-1	0.561951	0.699593
Coif2	1	0.0147477	1	0.261289	0.0564422
	2	0.116756	1	0.333105	0.350509
	3	0.175019	1	0.487008	0.359376
	4	-0.273888	-1	0.62198	0.440349
	5	-0.62897	-1	0.6443	0.976207
Coif3	1	-0.151793	-1	0.261536	0.580393
	2	0.00503607	1	0.316688	0.0159023
	3	0.410617	1	0.486935	0.843268
	4	0.25015	1	0.626785	0.3991
	5	0.356355	1	0.647682	0.5502
Coif4	1	-0.134933	-1	0.261813	0.515377
	2	-0.158752	-1	0.305758	0.519208
	3	0.448128	1	0.481028	0.931604
	4	0.358217	1	0.624245	0.573841
	5	-0.28104	-1	0.643085	0.437019
Coif5	1	0.00612441	1	0.262054	0.233708
	2	0.165806	1	0.299599	0.553425
	3	-0.00435475	-1	0.477399	0.00912182
	4	0.0576469	1	0.621045	0.0928225
	5	-0.571211	-1	0.637141	0.896522
Bior1.1	1	0.291542	1	0.372472	0.782723
	2	0.422724	1	0.494259	0.855268
	3	-0.527095	-1	0.576416	0.914435
	4	**0.619953**	**1**	**0.622156**	**0.996458**
	5	-0.208544	-1	0.635923	0.327939
Bior1.3	1	-0.151407	-1	0.292056	0.518419
	2	0.0506863	1	0.355321	0.142649
	3	-0.0891363	-1	0.424008	0.210223
	4	-0.0283759	-1	0.484111	0.0586144
	5	0.199377	1	0.494285	0.403365
Bior1.5	1	-0.0508703	-1	0.28057	0.18131
	2	0.0714052	1	0.328939	0.217078

	3	0.0127754	1	0.388311	0.0328998
	4	-0.204629	-1	0.452974	0.451744
	5	0.456256	1	0.458487	0.995135
Bior2.2	1	-0.230697	-1	0.272009	0.84812
	2	0.274674	1	0.390634	0.703149
	3	0.508747	1	0.533569	0.953479
	4	-0.025187	-1	0.621192	0.0405462
	5	-0.564969	-1	0.642758	0.878976
Bior2.4	1	-0.0221159	-1	0.26262	0.0842123
	2	0.11141	1	0.340574	0.327123
	3	-0.235533	-1	0.473787	0.497127
	4	-0.153768	-1	0.569516	0.26998
	5	-0.479364	-1	0.58701	0.81662

* Decomposition Level **Loss of Correlation