Signal Compression using variable frames and Wavelets

S.Khatta, Deepti Garg
Student M.M.U.Mullana
Er.S.Mondal
Lect.EIEC Mullana
Er.GeetanjaliPuri
Lect.M.M.Mullana

simpy1354@gmail.com

Abstract- Speech compression is one area of digital signal processing that focusing on reducing the bit rate of the speech signal for transmission or storage without significant loss of quality. Speech signals are non-stationary processes in nature. To represent the non-stationary, time-frequency analysis techniques are suitable tools since they represent signals simultaneously in both time and frequency. In recent years a new technique called wavelet transform has been proposed for signal analysis. In this paper signal is compressed by changing the threshold value the signal manually. Firstly the decomposed signal is divided into segments. Then we set the different threshold values to the voiced and unvoiced segments.

Introduction

Signal will be polluted in the process of generation, transmission and acceptance, In order to extract useful information from raw data, a robust de-noising method is often required. Different methods arising from scientific investigation for removing noise have been introduced. As a new time-frequency analysis method, wavelet de-noising can characterize accurately the local features of signals. So it is also a powerful tool for noise reduction. Wavelet thresholding de-noising is based on the idea that the energy of the signal to be defined concentrates on some wavelet coefficients, while the energy of noise spreads throughout all wavelet coefficients. Similarity between the basic wavelet and the signal to be defined plays a very important role, making it possible for the signal to concentrate on fewer coefficients. The components of the impulse should be made as prominent as possible so as to improve the performance of impulse isolation. Wavelet threshold de-noising is a very efficient method, the purpose of which is to remove independent and identically distributed Gaussian noise.

Let \( x(t) = \{x_1(t), x_2(t), \ldots, x_n(t)\} \) be the signal series acquired by means of a sensor. This signal series consists of impulses and noise \( x(t) \) can be expressed as follows:

\[ x(t) = p(t) + n(t) \quad \ldots \ldots 1 \]

where \( p(t) = \{p_1(t), p_2(t) \ldots p_n(t)\} \) indicates the impulses to be determined, whereas \( n(t) = \{n_1(t), n_2(t) \ldots n_n(t)\} \) indicates identically distributed and independent Gaussian noise with mean zero and standard deviation \( \sigma \). The wavelet threshold de-noising procedure has the following steps:

1. Transform signal \( x(t) \) to the time-scale plane by means of a wavelet transform. It is possible to acquire the results of the wavelet coefficients on different scales.
2. Assess the threshold \( \lambda \) and, in accordance with the established rules, shrink the wavelet coefficients. Thresholding is one of the important steps to remove noise. Thresholding function in this study covers hard thresholding and soft thresholding. Thresholding function is the wavelet shrinkage function which determines how the threshold is applied to wavelet coefficients.

Wavelets, unlike more traditional filtering methodologies, have the ability to preserves the temporal locality of sharp transitions within time domain signals. This property is important with in a fault detection context since sharp transitions are likely indicators of fault conditions and, hence, any utilized filtering methodology should not perturb the location of their occurrence. The basic idea behind signal processing with wavelets is that, like in Fourier analysis, a signal can be decomposed into its component elements through the use of basis functions. In the case, of Fourier the basis functions are sine and cosine waves. In the case of wavelet analysis, the basis functions consist of the wavelet scale function and scaled and shifted versions of the mother wavelet function. The scale function in wavelets is used to capture the general (or low detail information) about the signal, while different mother wavelet scales are used to capture the details of the signal, with each successive scale capturing (describing) finer and finer levels of detail. At low scale levels, time resolution is traded off for better frequency resolution thereby allowing low frequency events to be analyzed very accurately with respect to
their frequency content but not with respect to their location in time. At high scale levels frequency resolution is traded off for time resolution. The location of high frequency events is accurately marked in time, but their actual frequency content is poorly resolved.

**Wavelet Transform**

Wavelets are mathematical functions that satisfy certain requirements. From a mathematical point of view, the wavelet is described as a function that should integrate to zero and it has a waveform that has a limited duration. The wavelet is also finite of length which means that it is compactly supported. Wavelet analyze a signal using different scales. This approach towards signal processing is called multi-resolution analysis. The scale is similar to the window function in STFT. However the signal is not segmented or divided equally by using a fixed window length. Multi-Resolution Analysis (MRA) analyze the frequency components of the signal with different resolutions. This approach especially makes sense for non-periodic signal such as the voice signal which has low-frequency components dominating for long durations and short durations of high-frequency components. A large scale can be interpreted as a “large” window. Using a large scale to analyze the signal, the gross features of a signal can be obtained. Vice versa, a small scale is interpreted as a “narrow” window and the small scale is used to detect the fine details of the signal. This property of wavelet analysis makes it very powerful and useful in detecting or revealing hidden aspects of data and since wavelet transform provides a different perspective in analyzing a signal, compression or denoising a signal can be carried out without much signal degradation. Local features of a signal can be detected with far better accuracy with wavelet transform.

**Discrete Wavelet Transform**

Discrete Wavelet Transform (DWT) is a revised version of Continuous Wavelet Transform (CWT). The DWT compensates for the huge amount of data generated by the CWT. The basic operation principles of DWT are similar to the CWT however the scales used by the wavelet and their positions are based upon powers of two. This is called the dyadic scales and positions as the term dyadic stands for the factor of two. As in many real world applications, most of the important features of a signal lie in the low frequency section. For voice signals, the low frequency content is the section or the part of the signal that gives the signal its identity whereas the high frequency content can be considered as the part of the signal that gives nuance to the signal. This is similar to imparting flavor to the signal. For a voice signal, if the high frequency content is removed, the voice will sound different but the message can still be heard or conveyed. This is not true if the low frequency content of the signal is removed as what is being spoken cannot be heard except only for some random noise. The basic operation of the DWT is that the signal is passed through a series of high pass and low pass filter to obtain the high frequency and low frequency contents of the signal. The low frequency contents of the signal are called the approximations. This means the approximations are obtained by using the high scale wavelets which corresponds to the low frequency. The high frequency components of the signal called the details are obtained by using the low scale wavelets which corresponds to the high frequency.

<table>
<thead>
<tr>
<th>Mother wavelet</th>
<th>Order</th>
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<tbody>
<tr>
<td>Daubechies</td>
<td>4,6,8,10,12,14,16,18,20</td>
</tr>
<tr>
<td>Symmlet</td>
<td>4,5,6,7,8,9,10</td>
</tr>
<tr>
<td>Coiflet</td>
<td>1,2,3,4,5</td>
</tr>
</tbody>
</table>
Figure 1 demonstrates the single level filtering using DWT. First the signal is fed into the wavelet filters. These wavelet filters comprises of both the high-pass and low-pass filter. Then, these filters will separate the high frequency content and low frequency content of the signal. However, with DWT the numbers of samples are reduced according to dyadic scale. This process is called the sub-sampling. Sub-sampling means reducing the samples by a given factor. Due to the disadvantages imposed by CWT which requires high processing power the DWT is chosen due its simplicity and ease of operation in handling complex signals such as the voice signal.

**Wavelet Energy**
Whenever a signal is being decomposed using the wavelet decomposition method, there is a certain amount or percentage of energy being retained by both the approximation and the detail. This energy can be obtained from the wavelet bookkeeping vector and the wavelet decomposition vector. The energy calculated is a ratio as it compares the original signal and the decomposed signal.

**Wavelet Denoising**
Wavelet de-noising is done by transforming the data to the wavelet domain, then zeroing all the wavelet coefficients below a given threshold, and then inverse transforming back to the time domain. Several issues therefore must be addressed in order to obtain “good” denoising results: first, an appropriate mother wavelet function must be chosen, second a suitable methodology must be identified to select the denoising threshold, thirdly, a suitable thresholding methodology must be employed.

Tested mother wavelet functions:
The complete set of 325 combinations of the 21 mother wavelet functions given in Table 1 were utilized in combination with the 5 threshold determination methodologies given in Table 2, and the 3 thresholding functions of Table 3 were evaluated.

### Table 2 Tested threshold determination methodologies

<table>
<thead>
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<th>Threshold determination Methodologies</th>
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<tbody>
<tr>
<td>Universal Threshold</td>
</tr>
<tr>
<td>SURE Threshold</td>
</tr>
<tr>
<td>Hybrid Threshold</td>
</tr>
<tr>
<td>MinMax Threshold</td>
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<tr>
<td>Cross Validation Threshold</td>
</tr>
</tbody>
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Obviously, in order to compare the possible denoising approaches some objective cost function was required. This cost function was obtained by generating an independent estimate of the underlying sensor signal $x$.

### Table 111: Tested thresholding functions

<table>
<thead>
<tr>
<th>Threshold Methodologies</th>
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</thead>
<tbody>
<tr>
<td>Hard Thresholding</td>
</tr>
<tr>
<td>Soft Thresholding</td>
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According to the characteristic of signal and noise, noise immunization process using wavelet analytical method as follows: firstly decomposing signal with wavelet (three-layer decomposing as shown), noise signal is usually contained in $cD_1, cD_2, cD_3$ and processing the wavelet coefficient with threshold value, then reorganization the signal to suppress noise.

The multi-resolution analysis (MRA) of wavelet analysis can decompose signal in time domain effectively. However, because its scale change is based on binary, the resolution in high frequency band is low. Wavelet packet analysis method has successfully solved the problem.
packet analysis can divide bandwidth finer and further decompose the high frequency that hasn’t been subsection, thereby increasing the frequency resolution of signal processing.

3. Simulation
The experimental results are derived with the help of two wavelets i.e. wavelet Packets and wavelet 1-D. In wavelet packets signal is decomposed into different segments and by level thresholding is possible but in case of wavelet packets only global thresholding is possible.

3.1. Wavelet analysis simulation
One experimental signal is presented to test the proposed method of the signal model based on the wavelet transform. The simulation accelerative signal is shown in Fig. The absolute values of a, b coefficients are also shown in Fig. and the Continuous wavelet transform representation is shown as follows:

![Original Signal](image1.png)

**Fig.1 original signal**

This signal is decomposed into approximation and detailed coefficients by choosing particular wavelet and level

![Decomposed Signal](image2.png)

**Fig.2 decomposed signal**

The decomposed signal is divided into segments to set the different threshold values for compression as:

![Thresholding](image3.png)

**Fig.3 Adjust the threshold for different segments and then compress.**

The compressed signal is shown in the fig. The adjusted threshold valued signal is compressed by any of the two methods i.e. (a) Global threshold (b) By level threshold

By level threshold is in Wavelet 1-D. Wavelet packets gives us information about energy of each node. The retained energy is computed in various methods and is compared also.

![Global Thresholding](image4.png)

**Fig.4 Global Thresholding**

The original and compressed signals are shown in the fig.4 in case of global thresholding. In this the retained energy is 16.72%
4. Conclusion:
Here both thresholding methods are applied one by one and the result is compared. In by level thresholding voice is more clear but with less compression. In global thresholding the signal is compressed more but somewhat less clarity.

5. References
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