ALGORITHMS FOR IMPLEMENTING HILBERT HUANG TRANSFORM FOR THROUGH WALL HUMAN ACTIVITY DETECTION

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ABSTRACT

The Hilbert Huang Transform (HHT) is a recent nnovation, developed by N.E. Huang, et al. (1998) for the analysis of non-stationary and non-linear signals. HHT has significant advantages over the existing methods of time-frequency analysis such as short time Fourier transform (STFT) and wavelet analysis because of its adaptive and nonlinear nature. Preliminary results make a strong case for using the HHT algorithm for through wall sensing not only of arm and leg movement but also of respiration. Due to the empirical and adaptive nature of the algorithm, there are a number of challenges in implementing the HHT through wall system. We identify some of the challenges and present possible methods to overcome them. We study the behavior the algorithm on different types of signals. We believe that the development of the HHT algorithm has potential for application in several fields, as diverse as shock and vibration analysis of structures, blind source separation, analysis of gravitational waves, image compression, tsunami detection, etc

1. INTRODUCTION

One of the important problems in technology enhanced law-enforcing is through-wall surveillance and detection of human activities. Current technologies use short pulse radar techniques which employ short pulses of single tone waveforms at microwave frequencies. The disadvantage of such a system is that these pulses can be intercepted by adversary and simple suitable counter measures can be employed by them to jam the signal. In our research group we have been working on covert through-wall detection schemes. We propose to use ultra-wideband noise-like waveforms in [2] to overcome this problem. The transmit signal in such a system is ultra-wideband noise which covers a range of frequency. Within the band of this noise waveform we hide a single tone waveform which is used to detect Doppler signatures.

A critical component of the system is the analysis of the returned signal to extract Doppler signatures. The motion of humans is complicated and can be considered to be composed of motions happening at different scales. For instance a single tone waveform incident on a walking human will be modulated by various motions such as the movement of the torso, swinging of the arms and expansion and contraction of the chest cavity. Each of these movements produces a Doppler signature that may be uniform or non-uniform. Thus, it is a formidable challenge to detect and characterize human movement. To compound the problem, the waveform of choice is a highly noisy sinusoid waveform. Due to the low signal-to-noise ratio of the transmitted signal, the Doppler signatures in the reflected waveform will be buried in considerable noise. It is hence important to develop an algorithm suitable for such an application. In this paper, we outline our approach to the signal analysis and develop the necessary algorithms. We justify the use of the Hilbert-Huang Transform (HHT) algorithm and present some interesting preliminary results related to adapting the HHT algorithm for detection of faint Doppler signatures.

2. HHT FOR THROUGH WALL DETECTION

2.1. Time-frequency analysis of human activity Doppler

The signals encountered in non-unuform radar Doppler applications, such as human activities are non-stationary in nature, i.e the statistics of the signal varies over time. For simple, uniform Doppler applications, the Doppler effect would just manifest as an additional frequency shifted component whose frequency is given by the Doppler shift equation $f_r - f_o = f_o \times v/c$. In our application, we intend to analyze non-uniform Doppler for detection and characterization of human activity. When you consider a human walking or performing various actions, say the waving of hands, the Doppler shift is not constant and changes according to the motion of the human target. The eventual goal of the project, as stated earlier, is to detect a stationary human by capturing the Doppler signatures caused by an involuntary, critical activity such as breathing. The equation for such non-uniform Doppler would be of the form $f_r(t) - f_o = f_o \times v(t)/c$. Human activity consists of various components as mentioned earlier. The

Doppler frequencies can be considered to result from movement of the torso, movement of the arms and legs, swinging of the arms and legs, expansion and contraction of the chest cavity, and the changes in the position of the arms and legs. Human activity can be considered as a combination of these movements. Each of these movements occurs at a different amplitude and time scale. Thus, the return signal from the human target consists of the noise embedding the signal, in addition to various non-stationary components arising from the various movements that make up human activity. It is also reasonable to assume that there is no way of knowing about the specifics of the human activity a-priori, in the most general case. Based on this reasoning, the criteria we choose to decide on the time-frequency transform are- *frequency resolution, ability to resolve time-frequency components of low amplitude, non-linearity of transformation and adaptive selection of time-scales.*

2.2. The Hilbert Huang Transform Algorithm

A good candidate satisfying these criteria is the Hilbert Huang Transform algorithm, introduced by Huang, et al. [1]. The algorithm consists of two parts, the *empirical mode decomposition* (EMD) algorithm followed by Hilbert spectrum analysis. The EMD algorithm decomposes the signal into "well-behaved" components for which one can define the Hilbert transform. It works by recursively removing components of different frequency modes, with the modes being described by the extrema of the signal. The resulting components are referred to as *intrinsic mode functions* (IMF). In the framework of the HHT algorithm, IMF's are defined as signals which have zero mean and as many zero crossings as extrema. This condition ensures that the IMF's are fit for yielding meaningful frequency information from Hilbert transform. Figure 1 shows the flowchart for the EMD algorithm. The first step of the algorithm is to identify and interpolate the maxima and then the minima of the input signal using a *good* interpolation algorithm. These maxima and minima envelopes are subtracted recursively until the we get an IMF, which has as many zero crossings as maxima or minima. This IMF is subtracted from the signal and the envelope extraction is continued recursively, yielding a number of IMF's until the signal is exhausted.

The objective of making the signal amenable to the Hilbert transform is to describe the frequency content of the signal using *instantaneous frequency*. The Hilbert transform is equivalent to convolving the signal with h(t) = 1/t. The process of Hilbert transformation converts a real signal into a complex analytical signal. Once we have the analytic signal of x(t), i.e $z(t) = x(t)+\mathcal{H}(x(t))$, we define the *instantaneous frequency* as $f(t) = d\,(\arctan(\mathcal{H}(x(t))/x(t))/dt$.

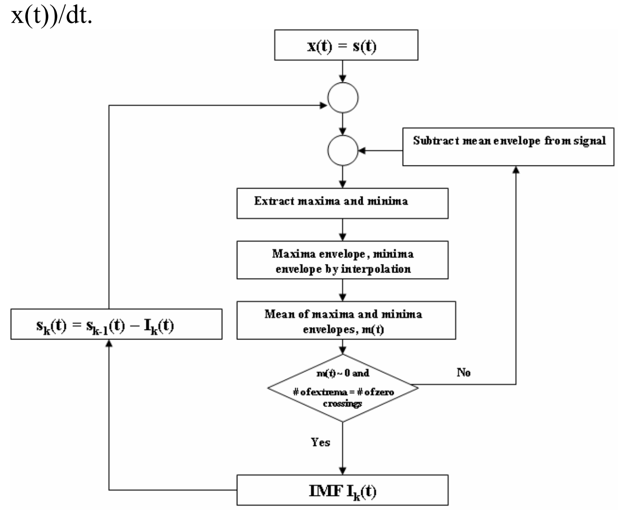

Figure 1: Flowchart describing the Empirical Mode Decomposition algorithm

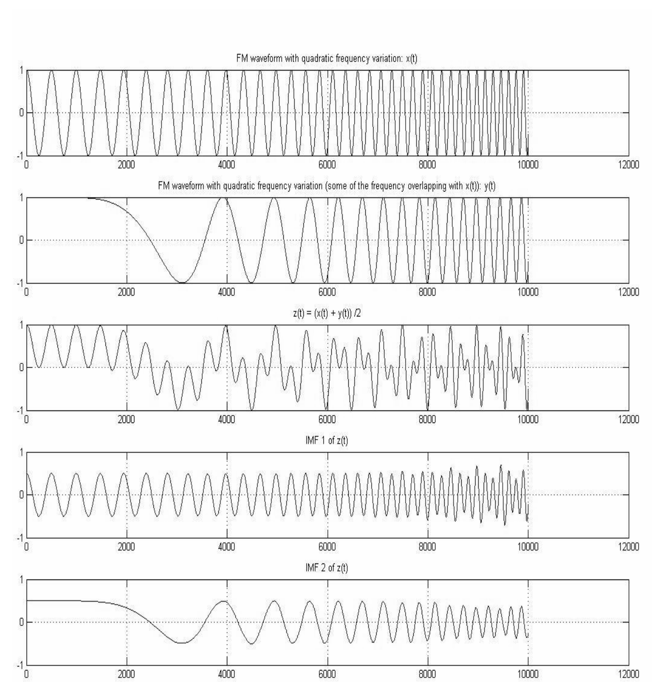

Figure 2: An example of EMD Decomposition, here we subject a signal which is the sum of the first two signals to EMD. The third signal from the top is the input, the bottom two are the decompositions. It is seen that the EMD algorithm effectively decomposed the signal into relevant time-frequency components

3. SOME USEFUL RESULTS ON HHT RELEVANT TO ITS APPLICATION TO THROUGH-WALL HUMAN DETECTION

The HHT algorithm is defined empirically and adaptively.

It is almost impossible to come up with a general theory concerning the behavior of the HHT algorithm applicable to all types of signals. The adaptive and empirical nature also precludes a statistical description of the algorithm. Various authors have attempted to describe the behavior of HHT for particular commonly occurring signals [3] [4] [5]. In our application, the returned signal consists of a number of chirp-like waveforms buried in noise. This defines the broad class of signals we studied to understand the behavior of the HHT waveform. We simulate waveforms which consist of a small amplitude chirp waveform embedded in noise. We later demonstrate the effectiveness of HHT in sorting time-frequency components of very low amplitude.

3.1. HHT and signals with low Signal to Noise ratio

We consider a waveform that consists of a signal buried in noise. The waveform model is x(t) = s(t)+a*n(t) where, considering the simplest case , s(t) = sin(2wt) for some frequency f much lesser than the sampling frequency, a is a scalar factor controlling the signal to noise ratio and n(t) is white Gaussian noise. As reported in [**6**] the EMD process almost behaves like a dyadic filter bank, with the cut-off frequency decaying exponentially. Thus when x(t) is predominantly noise, the trend in the frequency of the IMF's as represented by the number of zero crossings reduces exponentially. Extending this reasoning, we claim that the lesser the noise content in x(t) the lesser the frequency trend follows the exponential trend. Figure 3 shows this trend for various values of the parameter a. The lesser the parameter a, the more the deviation of the trend from exponential trend. Empirically, we found the exponential trend for noise varies approximately as $e^{-0.6n}$ where n is the number of the IMF. Thus a deviation from this quantity would mean that there is some sort of signal present in the waveform.

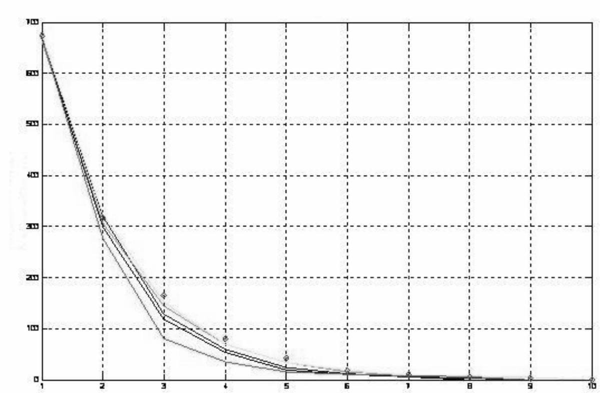

Figure 3: The number of zero-crossings (y-axis), representative of the average frequency is plotted against the IMF number (x-axis).

This suggests a method of extracting the signal from the noise. By identifying the IMF's which contain noise, based on some metric, it may be possible to extract the signal by selectively adding only those IMF's which are deemed to contain the signal. Such a signal as that described above is an imitation of the real scenario that arises when detecting a stationary human. Consider the transmit waveform is returned from a stationary human, hypothetically the only Doppler that is present in the returned waveform is due to the only considerable movement, the involuntary expansion and contraction of the chest cavity. Thus, a signal returned from a stationary human would contain faint Doppler signatures in the form of low amplitude chirp like waveforms whereas a signal that returns without Doppler would contain just the noise waveform. Hence a Yes/No decision about human prese nce can be made by indirectly observing the signal content of the returned signal. The advantage of such a technique is that we are trying to infer the signal contained in x(t) without any knowledge of the signal s(t) itself.

Another approach we have tried is to exploit the statistical trends occurring between different IMF's to classify the noise contained in a signal. White noise produces IMF's which are distributed identically to the original signal. Thus, an IMF that is more closely related to the distribution of white noise can be considered to result from the noise contained in the signal. This gives us a tool to denoise the signal by identifying IMF's that arise from noise, using classification techniques. Measuring statistical properties of successive IMF's is useful in identifying the Doppler signatures contained in our noise-like ultrawideband waveform. For instance Figure 3.1 shows the difference in distribution in the IMF's containing the changes due to Doppler from arm waving. A measure of this difference in distribution such as Bhattacharya distance can be used as a metric in an algorithm to decide the relevance of each IMF.

3.2. Resolution of low amplitude time-frequency components

Here, we consider the simple model x(t) = c1(t)+a X c2(t), where c1(t) and c2(t) are two chirp waveforms and a is a scalar. We demonstrate with an example how HHT spectrum resolves the signal into two time-frequency components whereas existing techniques like Choi-Williams, Psuedo-Wigner-Ville and Wigner-Ville distributions of frequency fail to resolve the signal into the two time-frequency components. Such a signal would occur in human activity Doppler due to the different components of motion that make up human activity. The Doppler returned from the moving of a hand will be of much lower amplitude than the Doppler returned from the movement of the torso, owing to the much lower area of cross section of the hand. Our implementation was able to resolve the two components up to about a = 0.05. The factor a can be considered as representative of the ratio of the areas of cross-section of the two moving components of the human body, say the hand and the torso, which can be assumed to be > 0.05.

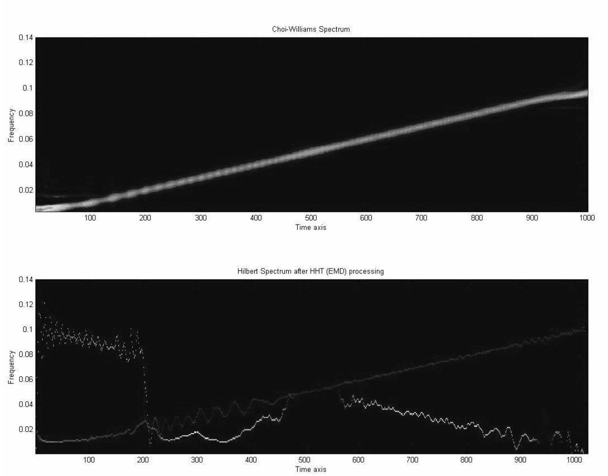

Figure 4: A signal consisting of two crossing linear chirps (chirp1(0-1000 sa/s) + 0.1*chirp(1000-0 sa/s)) resolved by HHT, where Choi-Williams transform fails. The second lower amplitude chirp component is not seen in the Choi Williams distribution.

3.3. Some experimental results

We conducted a variety of experiments with different types of human gait to characterize human movement in terms of Doppler signatures. The final outcome would be the development of a system using a 2GHz single tone waveform hidden in ultrawideband noise in the range of 1 to 2 GHz. For a simple model to extract human Doppler signatures, we use a single tone 2 GHz waveform as the transmit signal. Of special interest is the modeling of human body in conditions such as those that would arise in situations involving law enforcement. For instance through-wall radar, combined with mechanistic models of human movement, can be used to characterize movement of hostages and terrorists when hostages are held in an enclosed space. It would be dangerous for law enforcers to storm the room without a knowledge of the position and Such a model would in turn lead to a mathematical model of the Doppler effect and the signal. We hope that our experiments would lead to a mathematical model for the signal reflected from human motion.

With a knowledge of what to expect from the signal, it will be easier to develop the algorithm for time-frequency analysis. At this point we just model signals reflected from swinging arms, chest cavity expansions and contraction and similar simple harmonic motion as chirp waveforms with frequencies varying periodically with time. We designed experiments which mimic real scenarios. These included waving of arms in the direction of the radar line of sight(l-o-s) and perpendicular to the radar l-o-s, walking in the direction of and perpendicular to radar l-o-s, stationary human with chest cavity expansion in the direction of the radar and perpendicular to the radar. Some of these experiments were successful in producing satisfactory results to direct time-frequency analysis. We are working on the other experiments, on improving the experimental set up and developing the algorithm for picking out the signatures. For instance, Figure 5 shows the effectiveness of HHT in extracting the changes caused to the frequency by arm waving. In this experiment, a human placed about 1.5m from the antenna waved his arm about 14 times in 20 seconds. HHT analysis of the signal shows the 14 changes occurring to the frequency profile of the signal clearly showing up in the second IMF.

4. IMPLEMENTATION ISSUES

HHT is a very complex algorithm involving a number of iterations, with each iteration involving the interpolation of a number of points on extrema. For the extreme case of a white noise input, if the algorithm were allowed to run until the stoppage criteria are met, our experiments showed that on an average they take about 50 iterations to form each IMF for a data length of about 106 sample points. On an average, about 20 IMF's result from a data length of about 1 million, with the number of IMF's and iterations of IMF's increasing with the number of data points. At each IMF, there are half as many extrema as the previous IMF. Thus, the total number of interpolation operations would be of the order of O(N3). We intend to implement HHT on an FPGA based system, which requires us to reduce the number computations drastically. We experimented with a number of interpolation techniques including linear interpolation, Shannon, Gaussian, quadratic splines, cubic splines and b-splines. From our experiments we found that using simpler filters led to more iterations for IMF convergence and also result in more IMF's compared to less approximate interpolations. Considering these issues, we propose to use the cubic b-spline for interpolations, since fast algorithms exist for this method. Cubic b-splines are extensively used for interpolation in image and signal processing and quick implementations exist due to the orthogonal nature of the algorithm [7] [8].

5. CONCLUSIONS

We propose the use of a Hilbert Huang Transform for detecting and characterizing human activity using a

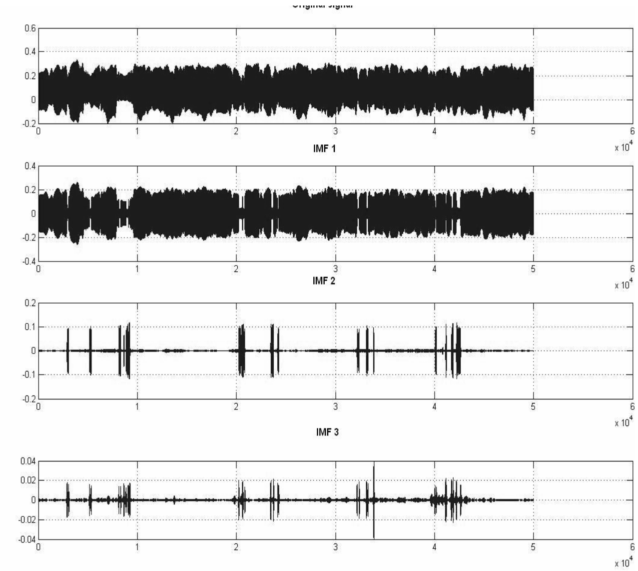

Figure 5. Different IMF's from a single tone transmit signal reflected from a human waving arms 14 times in the interval of the signal. The second IMF clearly shows a phenomenon occurring 14 times in 20s.

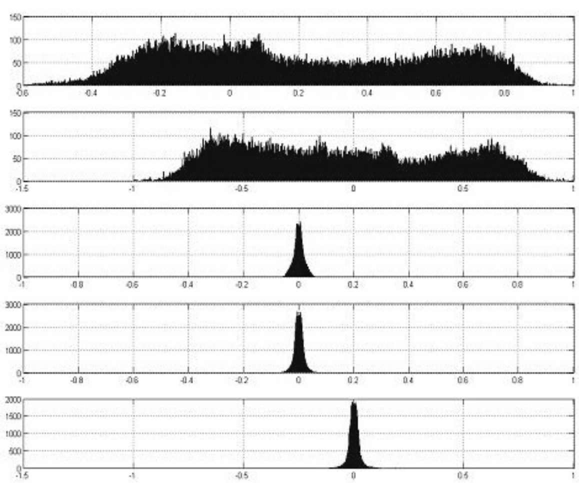

Figure 6. Distributions of the different IMF's a difference of which can be used to classify the relevant IMF's, for the arm waving Doppler signal.

wall ultra-wideband noise-like radar system. A through wall detection system which can reliably classify human activity is made possible by the advantages of HHT, which we described in this paper. We propose using statistical classification techniques combined with HHT to extract human Doppler signatures. We have started working on Implementation issues of HHT and have outlined approaches to developing the algorithm for implementation on a DSP-FPGA platform, a formidable task which has not been achieved so far. We believe that our work on the Hilbert Huang Transform, especially in developing an algorithm to characterize a signal's noise content without knowledge of the useful information in the signal will have wide applications for signals in which we are required to determine noise content with just an observation of the noisy signal.

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REFERENCES

[1] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.-C. Yen, C. C. Tung, H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of Royal Society A: Mathematical, Physical and Engineering Sciences*, Royal Society, London, pp. 903-995, March 8, 1998.

[2] C. P. Lai, Q. Ruan, R. M. Narayanan, "Hilbert-Huang Transform (HHT) Analysis of Human Activities Using Through-Wall Noise Radar", *Signals, Systems and Electronics, 2007. ISSSE '07. International Symposium on*, August 2, 2007.

[3] G. Rilling, P. Flandrin, "One or Two Components, EMD has the answer," *IEEE Transactions on Signal Processing*, 85-95, January 2008

[4] Z. H. Wu, N. E. Huang, "A study of the characteristics of white noise using the empirical mode decomposition method," *Proceedings Of The Royal Society Of London Series A-Mathematical Physical And Engineering Sciences*, Vol. 460 Issue 2046 1597-1611, 2004.

[5] P. Flandrin, P. Goncalves, G. Rilling, "Detrending And Denoising With Empirical Mode Decompositions," *Proceedings of EUSIPCO*, 2003.

[6] P. Flandrin, G. Rilling, P. Goncalves, "Empirical Mode Decomposition as a Filter Bank," *IEEE Signal Processing Letters,* Vol. 11, Issue 2 112-114, 2004.

[7] M. Unser, "Splines: A perfect fit for signal processing," *IEEE Signal Processing Magazine*, 22-38 November 1999.

[8] M. Unser, A. Aldroubi, M. Eden,. "Fast B-spline transforms for continuous image representation and interpolation," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, Vol. 13, Issue 3, 277-285, March 1991