Comparative Analysis of Hilbert Huang and Discrete Wavelet Transform in Processing of Signals Obtained from the Cutting Process: An Intermittent Turning Example

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Nonstationary signal analysis is one of the greatest challenges in studying and control of dynamical processes. Cutting process is extremely dynamical process influenced by different phenomena such as chip formation, dynamical responses and conditions of machining system elements. The most commonly used Short Time Fourier Transform and spectrogram as its result have significant shortcomings in processing of signals acquired from dynamical systems. Two relatively new techniques that have notably better properties in the analysis of nonstationary signals are Hilbert Huang Transform (HHT) and Discrete Wavelet Transform (DWT). This paper gives comparative survey of HHT and DWT with the intention of giving the guidelines for deciding which of these techniques is the technique of choice for the analysis of signals obtained from cutting process, considering the desired outcomes of the analysis. Besides brief mathematical foundations of the transforms, the paper illustrates their utilization using two examples, one is numerical, and the other is experimental dealing with detection of cutting process stop during intermittent turning .

Keywords: *Cutting process monitoring, Hilbert Huang transform, discrete wavelet transform.*

1. INTRODUCTION

Cutting process is an extremely dynamical process. Besides phenomena related to the chip formation itself, cutting process dynamics is influenced by the dynamical responses and condition of machining system elements (machine, tool, workpiece). Thus, *in situ* cutting process monitoring can give valuable information not only about the condition of the cutting process itself, but also about the surface quality, the condition of the tool, and even the condition of the machine. This information can be utilized for enhancement of the machining process control. Cutting process monitoring systems are usually based on the measurements of cutting force, acceleration, acoustic emission or audible sound close to the cutting zone. A comparison of frequency contents of the signal that can be obtained using different sensors can be found in [1].

Different stages of material removal process: searing, ploughing, plastic deformation are related to the different frequency content in acquired signal. The presence of voids, inclusions, grain boundaries, etc. in material microstructure affects tool-workpiece interaction and can be observed at different frequency components [2,3]. Tool condition (wear or breakage) can also be identified from signals obtained from the cutting process. Using adequate signal processing techniques, a variety of useful information can be extracted.

Nevertheless, the information from the sensory system is useful for process and quality control only if it is available in due time. In order to detect tool condition, or to correlate machined surface quality or material microstructure with the chip formation mechanism, it is not enough to identify the presence of a certain frequency in the signal. It is necessary to localize this frequency in time/space.

For simultaneous time/frequency signal analysis different techniques can be utilized [4]. Short Time Fourier Transform (STFT) is commonly used. However, a huge limitation of this technique is that it has a constant resolution in time and in frequency, where the width of the windowing function defines the resolution [5].

Discrete Wavelet Transform (DWT), a technique suitable for time localization of frequency content of the signal, has drawn significant attention in the field, especially in tool condition monitoring (detailed reviews can be found in [4,6]) and in studying of other phenomena related to the chip formation process [3].

Hilbert Huang Transform (HHT) [7] is a recent technique for time/frequency analysis which simultaneously provides excellent resolution in time and frequency. HHT has been applied in the condition monitoring of rolling bearings [8,9]. Furthermore, some research has been carried out in the area of tool

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condition monitoring using HHT. In [10], the authors proposed an approach to flute breakage detection in end milling based on HHT. A tool wear correlation to HHT during end-milling was explored in [11], where the marginal Hilbert spectrum was considered.

Although it gives an excellent localization of the frequencies in time, HHT has not obtained nearly as much attention in the cutting process monitoring as DWT. One of the reasons is that HHT is for a decade newer technique than DWT.

This paper provides a comparative analysis of HHT and DWT regarding their application in detection of non-stationarities in the cutting process. A similar analysis of the HHT and Continuous Wavelet Transform (CWT) has been carried out in [17] for the application in fault diagnosis of rolling bearings. Nevertheless, recommendations from [17] are not very useful for machining monitoring since CWT is not suitable for the analysis of signals obtained from the cutting process, and it is very rarely, if ever, used in this area. Its main drawback is the computational cost and the lack of fast algorithms for real-time application. On the other hand, DWT offers a fast real time hierarchical algorithm and it is commonly used in research in the area of cutting process monitoring.

The objective of the comparative study presented in this paper is to point out the advantages and shortcomings of HHT and DWT in the analysis of signals from the cutting process. Besides a striking numerical case study, an experimental example of detection of cutting process stop instant in intermittent turning is given.

2. HILBERT HUANG TRANSFORM – A BRIEF INTRODUCTION

The frequency of the signals acquired from nonstationary systems changes in each time instant. Identification of the system and process condition implies time localization of frequency appearance, that is, the objective is to determine the instantaneous frequency of the signal, if possible.

The instantaneous frequency can be identified using Hilbert transform (HT). For monocomponent time series $f(t)$, HT is defined by:

$$y(t)=\frac{1}{\pi}\int_{-\infty}^{\infty}\frac{f(\tau)}{t-\tau}\mathrm{d}\tau \tag{1}$$

where $f(t)$ and $y(t)$ represent the complex conjugate pair that defines analytical signal $z(t)$ as:

$$z(t)=f(t)+\mathrm{j}\,y(t) \tag{2}$$

Relation (2) can be represented in polar coordinate system as:

$$z(t)=a(t)e^{\mathrm{j}\theta(t)} \tag{3}$$

where:

$$\begin{aligned} a(t)&=\sqrt{f(t)^2+y(t)^2}\\ \theta(t)&=\mathrm{arctg}\big(y(t)/f(t)\big) \end{aligned} \tag{4}$$

Here, $a(t)$ and $\theta(t)$ represent instantaneous amplitude and phase of the analytical signal. $a(t)$ and $\theta(t)$ give the best local fit of an amplitude and phase varying trigonometric function to $f(t)$. From the instantaneous phase, instantaneous frequency $\omega(t)$ can be derived as:

$$\omega(t)=\frac{\mathrm{d}\,\theta(t)}{\mathrm{d}\,t}=\frac{\dot{y}(t)f(t)-y(t)\dot{f}(t)}{f^2(t)+y^2(t)} \tag{5}$$

Instantaneous frequency $\omega(t)$ is physically meaningful only if $\theta(t)$ is monocomponent function (Monocomponent function waves arround, that is, it is symmetrical with respect to the zero mean level, without riding waves (purelly oscillatory function)) [7]. Since $\theta(t)$ is derived from $f(t)$, $f(t)$ should be monocomponent as well. However, the most of the real world signals, and especially those obtained from dynamic systems, are not monocomponent. In order to decompose a multicomponent signal into monocomponent modes, Huang [7] has proposed the Empirical Mode Decomposition (EMD) technique. Using EMD, the signal is represented as a sum of Intrinsic Mode Functions (IMF) that are counterpart to simple harmonic functions in Fourier transform. IMFs are monocomponent functions that should satisfy the following conditions: 1) the number of extrema and number of zero crossings should be equal or differ at most by one; 2) the mean value of the envelopes defined by local minima and maxima should equal zero at each point.

IMFs are obtained from the initial signal using sifting process. In this process a cubic spline is put through local minima and local maxima and lower and upper envelops are created. The envelops mean m_1 is subtracted from the signal $f(t)$ to obtain the first component h_1. Ideally, h_1 is an IMF, but in reality this rarely happens. In order to create an IMF the sifting process is successively applied to h_i k times, until IMF is obtained:

$$h_{1k}=h_{1(k-1)}-m_{1k} \tag{6}$$

The sifting process stops when standard deviation between two consecutive results is lower than 0.2-0.3. The first IMF, which carries information about the highest frequency, is defined by:

$$c_1=h_{1k} \tag{7}$$

Afterwards, c_1 is subtracted from the original signal, and the residue r_1:

$$r_1=f(t)-c_1 \tag{8}$$

that contains information about lower frequency components ($f(t)$ is multicomponent signal) is obtained. In the sequel, r_1 is treated as the starting signal and the procedure repeats – c_2 is calculated etc. n times until one of the following conditions is fulfilled: 1) c_n or r_n have small energy, or 2) r_n is monotonic function. Applying the aforementioned procedure, signal $f(t)$ is decomposed as:

$$f(t)=\sum_{i=1}^{n} c_i + r_n \tag{9}$$

Each IMF (c_i) is subject to HT using (5) to compute instantaneous frequencies. Since $f(t)$ is a multicomponent signal, it has more than one instantaneous frequency. Thus, the decomposition of $f(t)$ using HHT has the following form:

$$f(t)=\mathrm{Re}\left(\sum_{i=1}^{n} a_i(t)\exp\left(j\int \omega_i(t)dt\right)\right) \tag{10}$$

where the amplitude $a_i(t)$ and the frequency $\omega_i(t)$ are time variant. On the other hand, Fourier transform, decomposes signal $f(t)$ as:

$$f(t)=\mathrm{Re}\left(\sum_{i=1}^{\infty} a_i \exp(j\omega_i t)\right) \tag{11}$$

where amplitude a_i and frequency ω_i are constant over time. Therefore, FT decomposes the signal into predefined simple harmonic functions, while HHT decomposes it into data driven intrinsic oscillatory functions. Based on relations (9), (10) and (5), it can be inferred that HHT provides a complete, adaptive and almost orthogonal representation of the signal. The time and frequency resolution of HHT are as high as the sampling rate allows.

One of the shortcomings of EMD is that it generates undesirable (nonexistent) components at low frequencies [9,12]. To avoid this, the cross correlation of c_i with original signal $f(t)$ - μ_i is checked [9]. Only those IMFs with cross correlation μ_i higher than a predefined threshold λ are considered as real IMFs. All other IMFs are treated as pseudo-components and are added to the residual r_n. Thus modified HHT shows a significantly improved performance at low frequencies.

3. DISCRETE WAVELET TRANSFORM – A BRIEF INTRODUCTION

Similarly to FT, Discrete Wavelet Transform (DWT), decomposes signals into predefined elementary building blocks (atomic functions) called wavelets. Wavelets are functions that are obtained by translation and dilatation of a predefined function called "mother wavelet". DWT can be represented as [13]:

$$T_{m,n}=\int f(t)a_0^{-m/2}\psi(a_0^{-m/2}t-nb_0)dt \tag{12}$$

where $f(t)$ is the analyzed signal, ψ is the mother wavelet, a_0^m, $m\in\boldsymbol{Z}$ is the discretization of dilation parameter (a_0 is the dilatation step such that $a_0\neq1$), while b_0 is the translation step. The presented discretization ensures that narrow wavelets with high-frequency content are translated by small, and wide wavelets with low-frequency content by larger time steps. Consequently, DWT has better time resolution for high and better frequency resolution for low frequency components.

In order to make DWT unique, it is necessary that wavelet family $\psi_{m,n}$ makes an orthonormal basis. There are a number of wavelet families that satisfy this condition. The most known are Daubechies wavelets, coiflets, biothogonal wavelets, symlets etc. The choice of wavelet to be used depends on its characteristics and desired results of the analysis.

There is a fast hierarchical algorithm for DWT computation - subband filtering scheme [14,15]. It is based on convolution of the signal with corresponding FIR filters and signal upsampling and downsampling.

DWT gives complete, *a priori* and orthogonal representation of the signal.

More detailed and nonetheless brief introduction into DWT and hierarchical algorithm for its implementation (subband filtering scheme) can be found in [18].

4. COMPARISON OF HHT AND DWT

This section presents two examples as a basis for a comparative study of HHT and DWT. The first example represents a simple synthesized signal that clearly highlights the differences between two transforms. The second example represents an experimentally obtained signal of acceleration during intermittent turning.

4.1 Numerical example

This subsection provides a comparative analysis of HHT and DWT using the synthesized signal:

$$\begin{array}{ll} 14\sin(2\pi 8t)+29\sin(2\pi 31t) & t\in[0,1] \\ 22\sin(2\pi 15t) & t\in(1,2] \end{array} \tag{13}$$

The sampling frequency was Fs=200Hz.

Figure 1a presents the signal analysis using HHT. Appling the modified EMD with the threshold λ=0.05, two IMFs are identified. IMF_1 contains the part of the signal that corresponds to the highest frequencies in the given time instants (31 and 15 Hz), while IMF_2 contains the part of the signal corresponding to the frequency of 8Hz. IMF_2 has significant energy only during the first second (Figure 1a and relation (13)).

The original EMD has given 7 IMFs. Nevertheless, the cross correlation of the remaining 5 IMFs with the original signal are lower than the threshold. The IMF_3-IMF_7 are added to r_2. Consequently, the residue r_2 is neither monotone, nor monocomponent function, and carries certain energy that corresponds to low-frequency pseudo-components.

Hilbert spectrum of the signal gives an excellent time localization of the given frequencies: around 8 and 31Hz in the 1st and around 15Hz in the 2nd second. Besides, the corresponding amplitudes (colorbar) are identified: 14 and 29 during the 1st, and 22 during the 2nd second. Time and frequency resolutions are as high as the sampling rate allows. The frequency range (0-100Hz) is discretized by 1Hz, while the time resolution is 0.005s.

DWT of the signal (13) is presented in Figure 2b. The analysis is carried out using the Daubechies wavelet of order 2 – 'db2'. The impulse response of the corresponding filter applied in the subband filtering scheme [14,15], contains 4 samples. Using subband

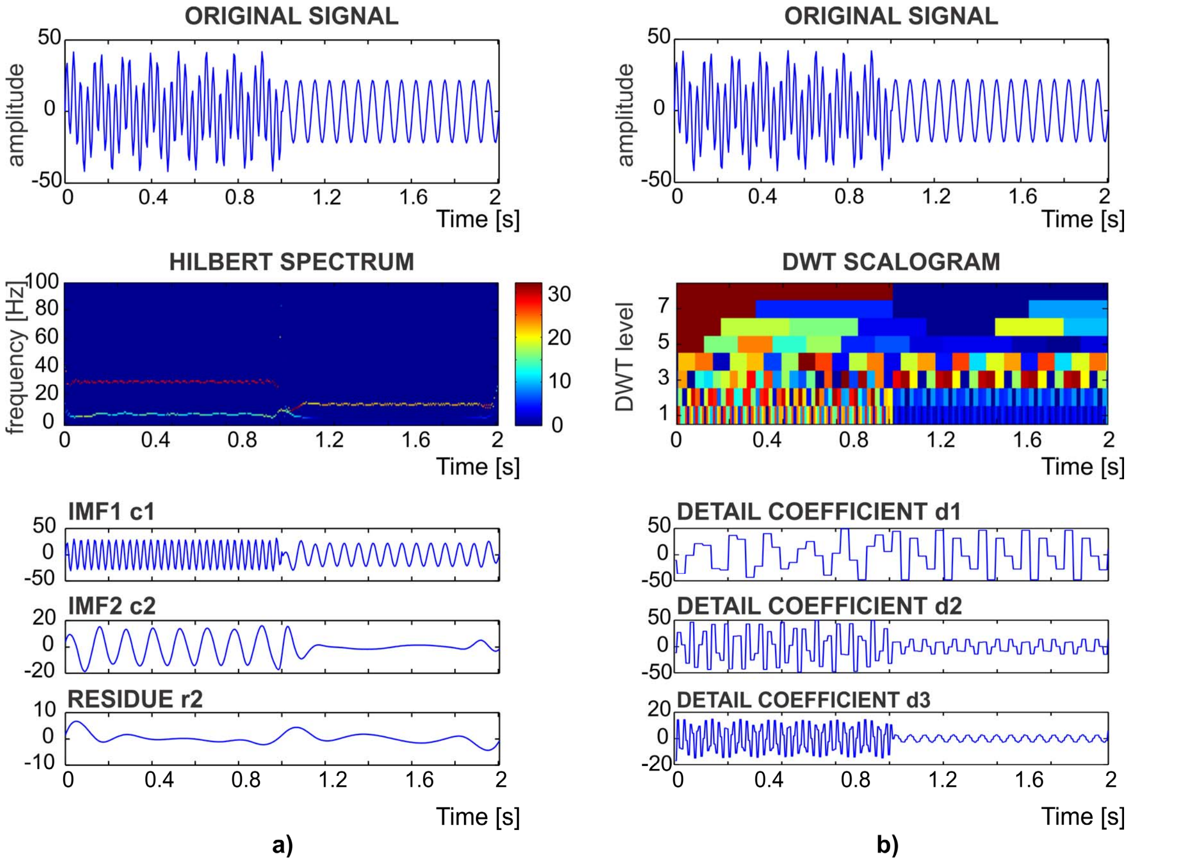


Figure 1. a) HHT decomposition of the synthesized signal (13); b) DWT decomposition of the synthesized signal (13) at 8 levels using 'db2' wavelet – the first three levels are shown independently

filtering scheme, at each level of the transformation signal is downsampled by 2. Since the original signal contains 400 samples, the maximum level of transformation is 8. Thus, the signal is decomposed into 8 levels using 'db2'.

DWT scalogram (Figure 2b) shows excellent time localization for different frequencies. Nevertheless, although DWT is able to provide sharper time localization of appearance of different frequencies than HHT, it is not capable to determine the instantaneous frequency of the signal.

4.2 Experimental example: detection of cutting process stop in intermittent turning

The second, experimental example used for comparative analysis of HHT and DWT deals with the detection of cutting process stop in intermittent turning. Experimental installation is given in Figure 2. Cylindrical workpiece is laterally grooved and has two mutually perpendicular flat surfaces of interest. Surface A provides extremely sharp stop of the cutting process (step excitation), while on surface B the tool gradually enters into the process and the cutting depth is gradually increased (ramp excitation). The groove provides extreme nonstationarity of the process that is mapped into abrupt changes in the acquired signal. This kind of intermittent turning can be used for the simulation of tool breakage [6,16].

During experiments, the accelerations in two perpendicular directions were measured (Figure 2). A pair of accelerometers (Kistler 8002) was fixed on the

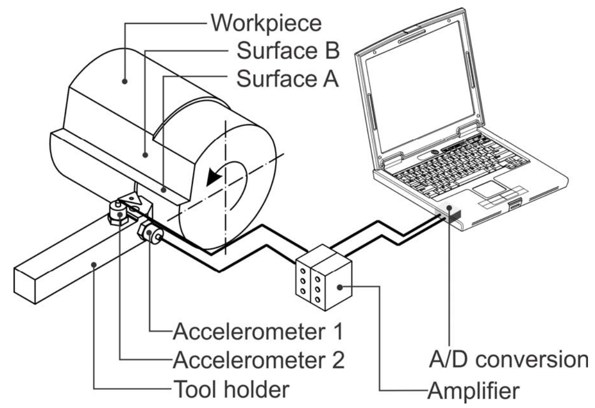


Figure 2. A scheme of the experimental setup

tool holder. Signal is acquired with sampling rate of 10KHz. Experiments were carried out on Hasse & Werde lathe. The speed (118-950 rpm) and feed (0.05-0.2 mm/r) were varied. Two types of P25 tool inserts (TNMM 220408 and TNMM 220424) were used.

The signals from different accelerometers show high correlation, so the Figure 3 shows a part of the signal form one accelerometer acquired during an experiment. In this experiment, the following parameters were used: n=950 rpm, s= 0.2mm/r, a=0.75mm, tool insert TNMM 220408.

Although it seems that the cutting process stop is easily recognizable, it is not such a simple task. During the cutting process stop high vibrations occur. They are mapped into the high energy of the signal. However, there are a lot of other phenomena that have similar signature in the signal (transients after process stop,

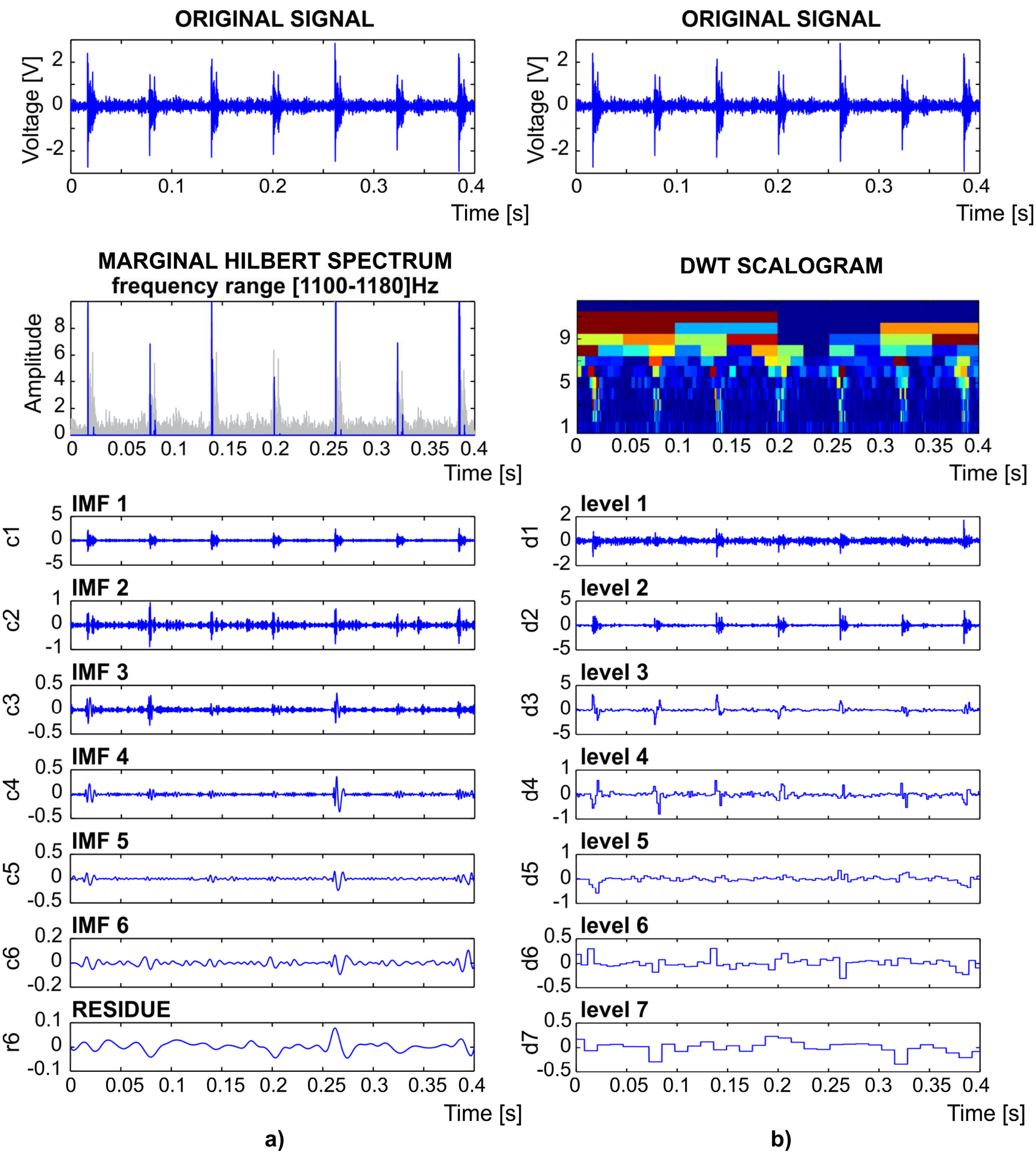


Figure 3. a) HHT decomposition of the acquired signal – in the diagram that shows marginal Hilbert spectrum the grey line shows absolute value of the original signal multiplied by 4, while blue line gives marginal Hilbert spectrum; b) DWT decomposition of the acquired signal at 12 levels using 'db2' wavelet – detail coefficients at the first 7 levels are shown independently

cutting process start, chip breakage, etc.). In order to single out cutting process stop from all these phenomena, the techniques for simultaneous time-frequency analysis have to be utilized.

HHT analysis of the acquired signal is given in Figure 3a. Modified EMD with the threshold λ=0.05 identified six IMFs. Original HHT, on the other hand, gave 12 IMFs – six of them had low cross correlation with the original signal. The analysis of the Hilbert spectrum has shown that the cutting process stop is correlated to the high energy in the spectrum at the frequencies: 1.1-1.18KHz. Marginal spectrum for this frequency band is shown in Figure 3a. In the given frequency band cutting process stop is clearly distinguished from all other phenomena with similar signature in acquired signal (transients after cutting stop, cutting start, chip breakage etc.).

DWT analysis of the same signal using 'db2' wavelet at 12 levels of transformation is presented in Figure 3b. Scalogram gives complete decomposition, while separate diagrams give the detail coefficients for the first seven levels of transform. In DWT scalogram, it can be observed that in the cutting process stop instant the energy contained in the detail coefficients at the first four levels of transform is high. This is the most expressive at the third level of transform.

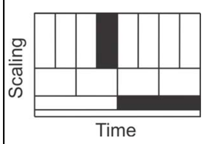
Based on previous analysis, it can be noted that both transforms are capable to adequately carry out the time localization of cutting process stop. Nevertheless, it should be emphasized that for DWT, there exists fast one-pass hierarchical algorithm that is suitable for real time operation. HHT, on the other hand, is real time applicable only by windowing the signal (in the same way as in the STFT). Windowing of the signal causes latency for the period that is predetermined by window size. DWT also has latency that is the consequence of the level of transformation at which the time localization is conducted.

In this particular case, for the analysis at three levels using ‘db2’, the latency is 16 samples, regardless the sampling rate. The necessary latency in the case of HHT was less than 20 samples. Nevertheless, the latency in HHT application is dependant on the sampling rate and on the frequency at which the time localization is carried out.

5. CONCLUSION

This paper considered the application of DWT and HHT in time localization of the nonstationarities in a signal, from their comparative analysis point of view. The comparison of the two transforms can be summarized as shown in Table 1.

Table 1. Comparison of HHT and DWT

Feature	HHT	DWT
Elementary building block	IMF – intrinsic mode function Data driven - adaptive	Wavelet family A priori given
Superposition	Linear	Linear
Completeness	+	+
Orthogonality	- (almost)	+
Time/frequency space discretization	Uniform Complete	
Algoritam for fast application Real-time applicability	-	+
Decision making latency	+	+
Inverse transform	-	+

HHT provides a complete, adaptive (IMFs are data driven) and almost orthogonal (there is a residue) signal representation. DWT representation of the signal is complete, *a priori* (wavelet is chosen in advance) and orthogonal (signal is decomposed into atomic functions). HHT is capable of determining the instantaneous frequency with high precision. On the other hand, DWT can not reveal the instantaneous frequency, but it can be used to detect the relative change in the signal’s frequency content. There is a fast, hierarchical one-pass algorithm for DWT computation which can be used in real-time applications. HHT implementation, and especially the implementation of HHT with modified EMD, is computationally very expensive. Sifting process implies finding local maxima and minima and generating the cubic splines trough them for envelops generation, iteratively for each IMF, which makes it a very time consuming task. Maybe this fact, along with the fact that HHT is for a decade younger technique than DWT, is the reason that the use of HHT in cutting process monitoring has drawn a significantly less attention within the research community.

Based on the previous analysis, a set of guidelines for the choice of the transform for application at hand can be derived. When the speed of the transform implementation is crucial, and the exact value of the instantaneous frequency is not as important as its relative change, DWT is the technique of choice. On the other hand, if it is necessary to determine the exact value of the instantaneous frequency, HHT has the best performance of all the available techniques for the analysis of nonstationary signals. Furthemore, when the process does not require real time control, HHT is the technique of choice. On the other hand, DWT, due to the orthogonality, e.g. of the Daubechies wavelets to polynomial functions is capable to detect in real time the signals with high cross correlation to polynomials. The main limitation of HHT when compared with DWT in the area of frequency analysis is its computational complexity.

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УПОРЕДНА АНАЛИЗА ХИЛБЕРТ ХУАНГОВЕ И ДИСКРЕТНЕ ВЕЈВЛЕТ ТРАНСФОРМАЦИЈЕ У АНАЛИЗИ СИГНАЛА ПРИКУПЉЕНИХ ИЗ ПРОЦЕСА РЕЗАЊА: ПРИМЕР ПРЕКИДНОГ СТРУГАЊА

Живана Јаковљевић

Обрада нестационарних сигнала представља један од изазова у проучавању и управљању динамичких процеса. Најчешће коришћена краткотрајна Фуријеова трансформација и скалограм имају значајне недостатке у обради сигнала прикупљених из динамичких система. Две, релативно нове технике које имају значајно погоднија својства у обради нестационарних сигнала су Хилберт Хуангова трансформација (Hilbert Huang Transform - HHT) и дискретна вејвлет трансформација (Discrete Wavelet Transform - DWT). Процес резања представља изразито динамичан процес на који утичу многе појаве као што су процес формирања струготине и динамички одзиви и стање свих елемената обрадног система. У овом раду се врши компаративна анализа HHT и DWT са намером да се указивањем на њихова својства дају смернице за одлуку која од ове две технике представља технику избора за конкретну апликацију у складу са жељеним резултатима анализе сигнала. Поред кратких математичких основа разматраних трансформација, у раду се дају два примера: први је нумерички, а други, експериментални, се односи на детекцију прекида процеса резања током прекидног стругања.