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Robust Techniques for Signal Processing: A Comparative Study

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Abstract: In order to develop the robust technique for signal processing, the simulation signal has been developed and close frequency components associated to signal is analyzed using MATLAB. Further, same simulated signal is processed with three signal processing techniques viz. Empirical Mode Decomposition (EMD), Local Mean Decomposition (LMD) and merged Wavelet Denoising and Local Mean Decomposition (WDLMD) technique. The demodulated signals from these signal processing techniques have used for spectrum analysis. From the analysis it is inferred that the WDLMD technique is more efficient than EMD and LMD technique for frequency extraction.

Keywords: Stability analysis; LMD; EMD; WDLMD; CNC lathes

1. Introduction

The analysis of signals and its associated frequency is the most important steps to identify the nature of signals. Signals are generally four types viz. linear signal, non-linear signal, stationary signal, and non-stationary signal [1,2]. There are many applications where signals have mixed characteristics such as chatter signals acquired from machining process. The chatter signals are non-linear and non-stationary in nature [3,4]. In the manufacturing industry, due to the fact that about 15% of the downtime is endorsed to tool replacement and tool failure. Some industries have switched to automatic tool changing system for minimizing the downtime [5,6,7]. This reduces downtime and increases efficiency [8,9]. However, the problem of sudden tool failure has not been sorted by time. Later on, it has been reported by several researchers that the sudden failure of the tool is due to the regenerative chatter. This self-excited phenomenon also results in the poor surface finish and excessive cutting force [10,11]. To eliminate these problems the use of sensors came into existence to monitor the condition of tool and work piece [12,13,14]. Condition monitoring has achieved a lot of importance. To monitor the tool state, the required sensor is mounted near the tool or any nearby suitable area [15,16]. The choice of the sensor is subjected to the type of process and features to be extracted [17].

In order to extract frequency components there is a need of a technique which can detect its components without mode mixing [18,19]. Zhang Z et al. have proposed the decomposition based signal processing techniques for signal analysis [2]. Research shows that this technique is useful for non-stationary and linear signal only. Many researchers have used EMD technique for spectrum analysis [3,18,19]. The EMD technique shows the mode aliasing problem and this problem has been resolved customarily by LMD [5,20,21] and shows better decomposition effects than EMD [22,23]. However, LMD also has certain constraints which doesn't allow it to eliminate the EMD's problem completely [24,25,26]. Hence, authors have proposed WDLMD to remove ambient noise and extract information from the signal. In order to the applicability of proposed method, a simulated signal has been taken and its frequency components have been extracted using EMD, LMD and WDLMD techniques. It has been found that WDLMD signal processing technique has capability to extract frequency components clearly.

2. Methodology

The outlay proposed methodology has been represented in the form of flow chart as shown in Fig. 1.

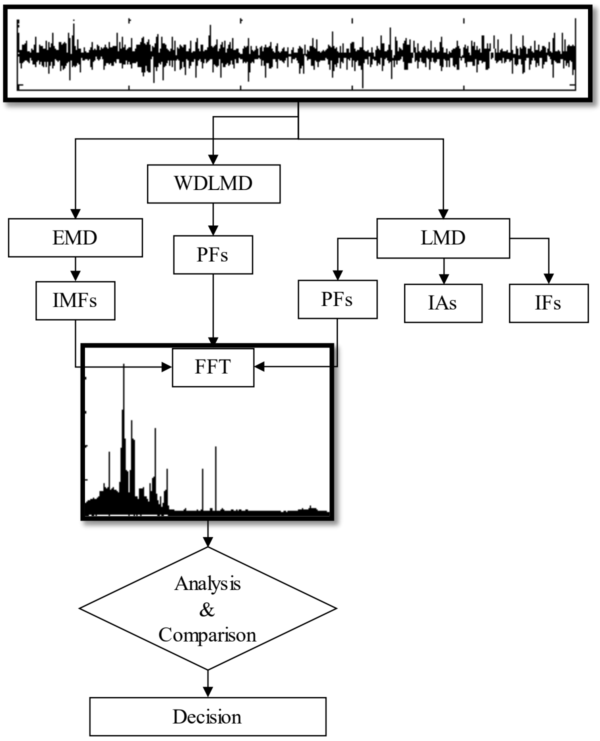


Fig. 1. Outlay of methodology

2.1. Signal Simulation

The signal is consisting three components which are shown in Fig. 2 as follows:

Signal (a) $4\sin(74\pi t)$, Signal (b) $5\sin(30\pi t)$, Signal (c) noise,

Signal (d) $4\sin(74\pi t)+5\sin(30\pi t)+noise$

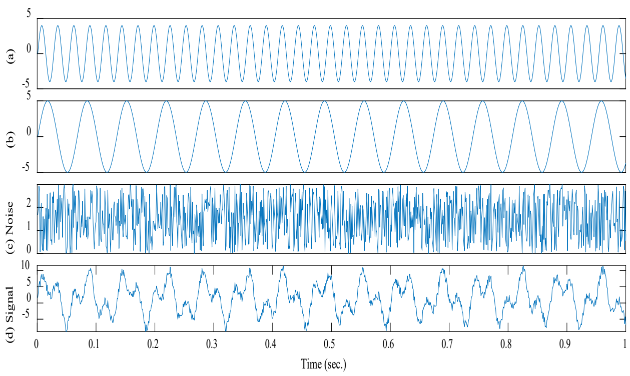
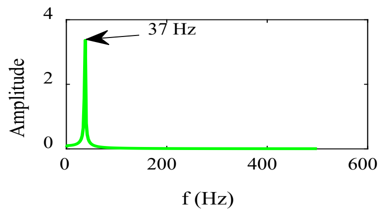
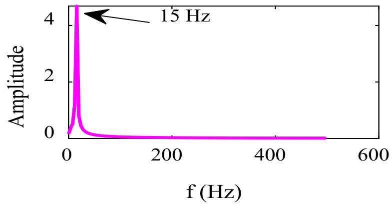


Fig. 2 The simulated signal: **(a)** $4\sin(74\pi t)$, **(b)** $5\sin(30\pi t)$, **(c)** Noise **(d)** $Signal = 4\sin(74\pi t)+5\sin(30\pi t)+noise$

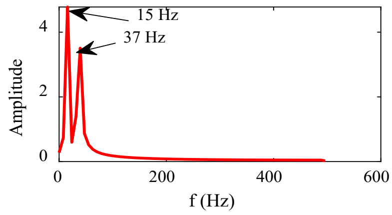
The sampling length 1008 is selected and the time domain waveforms are shown in Fig. 1. Using Fast Fourier Transform (FFT) the amplitude-frequency (spectrum) plots are drawn as shown in Fig. 3. From Fig. 3, it is clear that the frequency components appear at f1 = 37 Hz, and f2 = 15 Hz.



(a) FFT of signal a



(b) FFT of signal b



(c) FFT of signal without noise (a + b)

Fig. 3. IMFs and FFTs of attained signal

2.2. Processing of Acquired Signal Using EMD

EMD was first practiced and proposed by Huang in 1998 [13,27]. EMD extracts the intrinsic physical features hidden in a non-stationary signal. EMD decomposed the signals into number of IMFs. Steps involved in EMD are as follows [9,7,10]:

1. Identify all the extrema point 'k_i (t)' of the signal 'x(t)'.
2. Using cubic spline create the upper envelope 'k_{max}(t)' and lower envelop 'k_{min}(t)'.
3. Determine the local mean of the upper and lower envelopes, using the formula;

$$m(t)=\frac{k_{\max}(t)+k_{\min}(t)}{2}$$, where, 'm(t)' represents the mean

4. Thereafter subtract the mean from the signal to obtain the mode function, using the formula;

u(t)= x(t)-m(t),

where, 'u(t)' represents the mode function

The calculated mode function must satisfy the IMF condition 'a and b'. If it does not satisfy, consider u(t) as a new signal and iterate the above steps until it fulfills the aforementioned conditions 'a and b'. If u(t) satisfies these IMF conditions, then '$h_i(t)=u(t)$' refers to the IMF, where 'i' refers to the 'i^{th}' IMF. Moreover, the residual signal is computed by subtracting the IMF from the original signal as given by: $r(t) = x(t) – h_i(t)$

The residue can be treated as the new signal and perform the above steps to extract the rest of the IMFs until final residual signal becomes monotonic or constant. As a result, the original signal x(t) is decomposed into number of IMFs and residue. Finally, x(t) it can be expressed as;

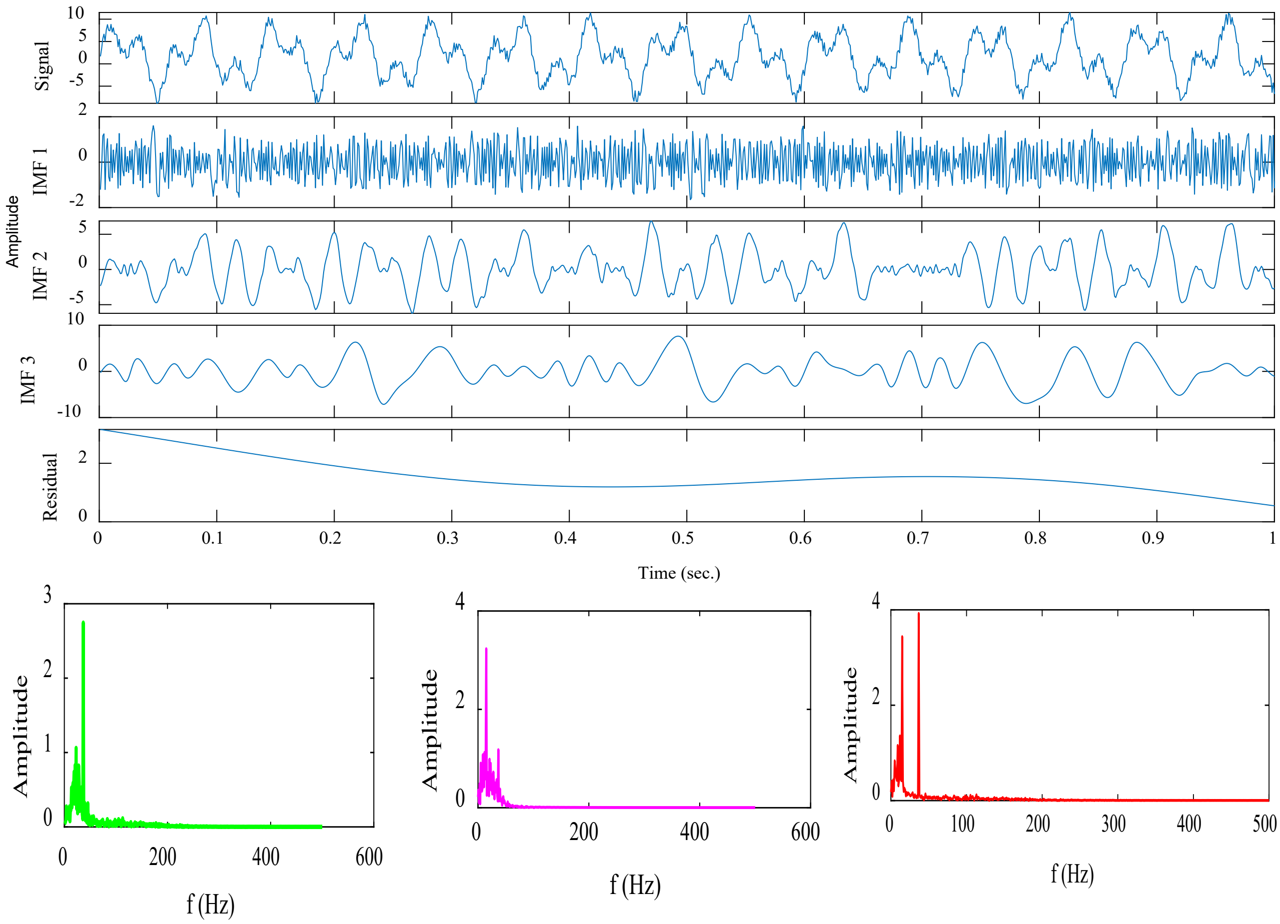
$$x(t) = \sum_{i=1}^{n-1} h_i(t) + r_n(t)$$

Adopting the above-mentioned procedure, simulated signal has been decomposed into intrinsic mode functions. These IMFs have been further processed using Fast Fourier transform (FFT). The demodulated results and FFTs are shown in Fig. 4. From Fig. 4, it is clear that when EMD is applied to decompose the signal, the severe mode aliasing problem can be seen.

2.3. Processing of Acquired Signal Using LMD

The following steps are involved in LMD technique as shown in Fig. 5. LMD decompose signal into number of product function (PFs) [11,12].

LMD reduces mode aliasing problem of EMD because of its moderate time–frequency analysis [13]. Further, LMD is adopted to decompose the signal as shown in Fig. 6.



(i) FFT of IMF 1 (ii) FFT of IMF 2 (iii) FFT of IMF 1+ IMF 2

Fig. 4. IMFs and FFTs of simulated signal

Signal '$x(t)$'

Identify all the extrema points '$l_i(t)$' from original signal '$x(t)$'

Calculate Local mean $n_i(t) = \dfrac{l_i(t) + l_{i+1}(t)}{2}$ & Amplitude envelope $b_i(t) = \dfrac{|l_i(t) + l_{i+1}(t)|}{2}$
of two successive extrema. Where. $i = 1.2........N-1$ (*N*= number of extrema)

Calculate smooth continuous local mean function $n_{ij}(t)$ and amplitude envelope function $a_{ij}(t)$

By taking the moving averaging of $n_{ij}(t)$ and $b_i(t)$

$v_{11}(t) = x(t) - n_{11}(t)\, and\, r_{11}(t) = v_{11}(t) / b_{11}(t)$
Where $r_{11}(t)$ is a pure frequency modulated signal, fluctuates between -1 to 1.

Instantaneous phase $\theta_1(t) = \arccos(r_{1p}(t))$ & instantaneous frequency $f_1(t) = \dfrac{1}{2\pi}\dfrac{d\theta_1}{dt}$

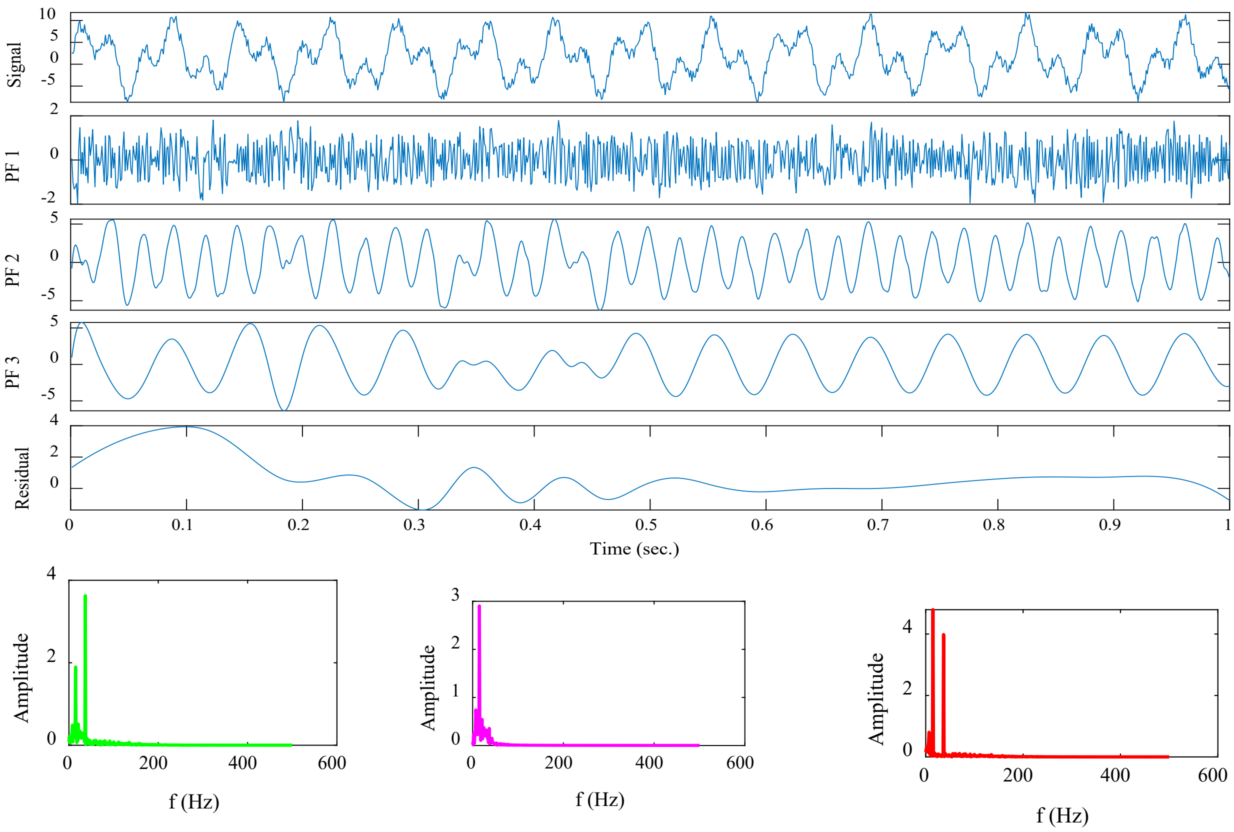
$PF_1(t) = b_1(t) r_{1p}(t)$
New signal= $x(t) - PF_1(t)$

The envelop signal $a_1(t) = a_{11}(t) a_{12}(t)........a_{1p}(t) = \prod_{q=1}^{p} a_{1q}(t)$
Where $\lim_{p\to\infty} a_{1p}(t) = 1$ and q is the number of iterations

Repeat all the above steps with new signal to derive $PF_2(t)$. These steps are repeated until the last signal becomes monotonic

$$x(t) = \sum_{l=1}^{n-1} PF_l(t) + v_n(t)$$

Fig.5. Steps of LMD



(i) FFT of PF 1 (ii) FFT of PF 2 (iii) FFT of PF 1+ PF 2

Fig.6. PFs and FFTs of simulated signal

2.4. Processing of Acquired Signal Using WDLMD

In WDLMD, wavelet denoising technique remove the unwanted ambient noise and LMD demodulates the signals into number of product functions, which separates the chatter frequencies. Wavelet denoising technique applied in simulated signal is shown in Fig. 7.

Further, LMD has been applied for processing the wavelet denoised signal and get the demodulated signal. LMD decomposes the signal into a number of PFs as shown in Fig. 8. LMD method extracts the hidden features of signals.

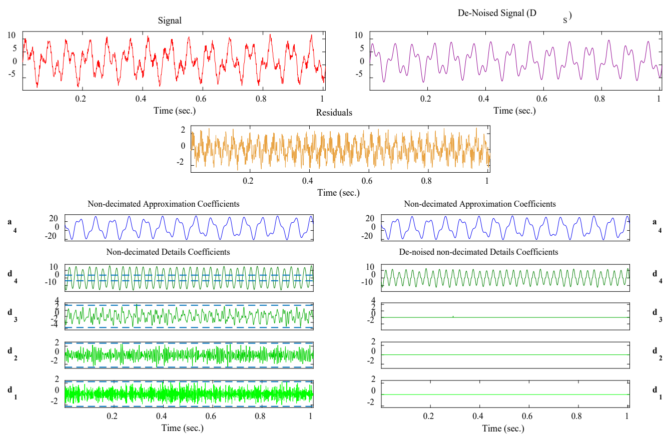


Fig. 7. Wavelet denoising

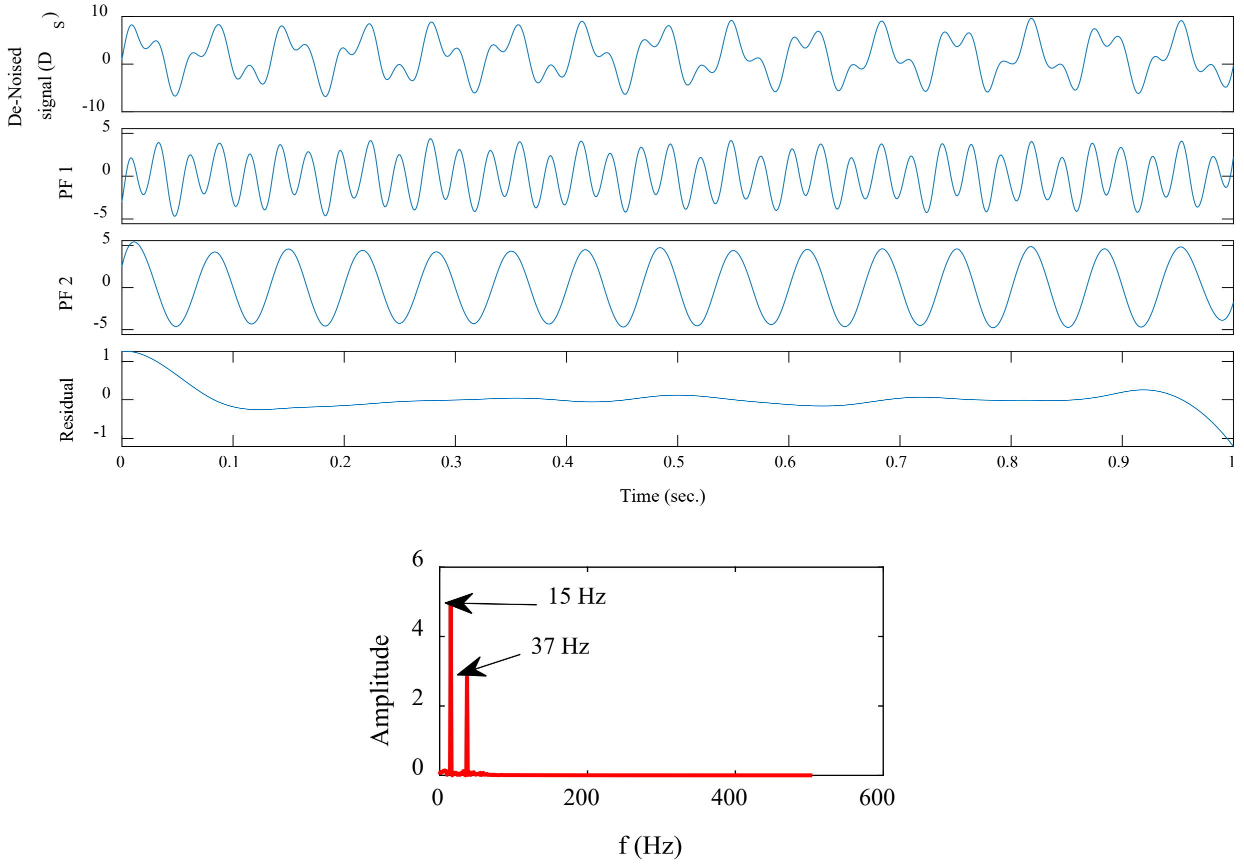


Fig.8. Signal decomposition of denoised signal

From the attain PFs the most influential PFs has been selected and signal has been reconstructed using correlation coefficient. Hence, signal reconstruction using first two PFs of high correlation coefficient is done. This can be seen that more than 90% of the energy of original signal is concentrated in reconstructed signal. Further, for amplitude-frequency analysis, Fast Fourier Transform (FFT) has been performed on simulated signal and on reconstructed signal. The frequency components appear at f1 = 37 Hz, f2 = 15 Hz as shown in Fig. 3 (e) but the noise is also recognized in Fig. 6 (a). From Fig. 6 (b) it is displayed that the change trend of amplitude-frequency characteristic and reconstructed signals is the same. It is proven from the FFT of signal and FFT of reconstructed signal that the proposed methodology is valid to extract the chatter features because it gives same frequency at almost same amplitude.

3. Conclusions

In order to process the raw signal to extract information, it is important step to choose signal processing technique carefully as signal develops close frequency components.

The key findings of the present work are as follows:

1. From the analysis on simulated signal the Inferences is drawn that EMD, LMD and WDLMD techniques are capable of preprocessing the acquired raw chatter signals efficiently.
2. LMD has an added advantage over EMD, because it can predict the onset of signal's features by not overlooking the incipient amplitude variations in the signal but still there are mode aliasing.
3. Fast Fourier Transform (FFT) has been performed on simulated signal and on reconstructed simulated signal. The frequency components appear at f1 = 37 Hz, f2 = 15 Hz are displayed that the change trend of amplitude-frequency characteristic and reconstructed signals is the same.
4. The proposed WDLMD technique is capable of removing the unwanted contaminations from the signal and can extract the frequency information.

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