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# Comparative Study based on Transform Techniques for Signal Detection

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**ABSTRACT:** Detection and classification of an unknown signal in noisy data is crucial task for signal processing. Under this situation, the extraction of features becomes difficult and high frequency spectrum overlap with the frequency of fault. This paper presents a comparative study based on transform techniques for signal detection. Realization of transforms with distinct classifiers generates different performance correspond to the desired signal. Statistical analysis shows that, Curvelet transform is a better than other transforms available for detecting the noisy data. The motive behind is ability of sparse representation that are critical for detection, estimation of signal which are noised and weak.

**KEYWORDS**: Curvelet transform; Signal Detection; SNR; PCA; Sparse Vector.

## I. INTRODUCTION

The detection and extraction of an unknown signal in noise is important issue in signal processing. When a signal is severely corrupted by strong background noise, it is usually very difficult to perform signal detection and parameter estimation in either the time domain or the frequency domain. By taking the time frequency transform, random noise tends to escalation its energy over the entire time frequency domain, while signals often concentrate their energy within limited time intervals and Frequency. Consequently by representing the signal and noise in the joint frequency domain, signal detection much easier. By applying time-varying frequency filtering, The SNR can be enhanced. If we can distinguish those coefficients that belong to the signal from the once that belong to the noise those coefficients can be utilized to remake the signal simply by taking the inverse time frequency transform.

This paper is presented as follows. In the next section, we discussed about the different transforms techniques. Section 3 describes Realization of transforms for signal detection. Results and discussions are shown in Section 4 and Section 5 concludes the paper.

## II. BACKGROUND WORK

### A. *CHIRPLET TRANSFORM*

The chirplet transform is the generalized form of fast Fourier Transform, short-time Fourier transform, and wavelet transform. It has the most supple time frequency window and successfully used in practices. It is considered as the "phase correction" of the Chirplet Wavelet Transform (CWT). The CWT W (b, a) of a function h (t) is defined by

$$W(b, a) = \int_{-\infty}^{+\infty} h(t)w(t-b, a)dt \quad \text{......(1)}$$

Where w is scaled replica of the fundamental mother wavelet and a determines the width of the wavelet w and controls the resolution.

The improved chirplet transform of a function h (t) is defined as a CWT with a specific mother wavelet

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$$W(t, f) = \sqrt{f^2 + iq} / \sqrt{2\pi} \quad e^{-t2(f2 - iq)/2}\, e^{-i(2\pi ft + qt2)} \ldots\ldots\ldots\ldots(2)$$

The improved chirp wavelet in (2) does not please the condition of zero mean for an acceptable wavelet. Therefore, it is not strictly a CWT, Written out explicitly, the improved chirplet transform is

$$IC(b, f) = \sqrt{f2 + iq} / \sqrt{2\pi} * \int_{-\infty}^{+\infty} h(t)\, e^{-t2(f2 - iq)/2}\, e^{-i(2\pi ft + qt2)}\, e^{-i(2\pi f + q(t-b)}2\, dt \ldots\ldots\ldots (3)$$

If the improved chirplet transform is indeed a representation of the local spectrum, one would anticipate a simple operation of averaging the local spectra over time to give the Fourier spectrum. It is shown as follows

$$\int_{-\infty}^{+\infty} IC(b, f)db = H(f) \ldots\ldots\ldots\ldots(4)$$

It follows that h(t) is accurately recoverable from IC (b, f) Thus

$$h(t) = \int_{-\infty}^{+\infty}\{\int_{-\infty}^{+\infty} IC(b, f)db\}\, e^{i2\pi ft} df \ldots\ldots\ldots\ldots(5)$$

### B. *HOUGH TRANSFORM*

The Hough transform is a feature eradication technique used in image analysis and computer vision. The aim of this transform is to find immature instances of objects within a certain class of shapes by a voting procedure. The Hough transform has significant features like robustness to impulsive noise and detachments of partial occlusion of patterns are suitable to use in non-image applications, e.g. parameter estimation. The Hough transform based on normal parameterization of a line

$$H(r,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x, y)\, \delta(r - x\cos\theta - y\sin\theta)\, dx\, dy \ldots\ldots\ldots\ldots(6)$$

Where f (x, y) = binary image, d = Dirac delta function.

The Continuous Kernel Hough transform (CKHT) is a new modification of HT and improves its several features. Definition of Hough transform of a line with the continuous kernel

$$HT(r, \theta) = \sum_{i=1}^{L}\sum_{j=1}^{L} f(xi, yj)\, \frac{T}{T + (x\cos\theta_i + j\sin\theta - r)^2} \ldots\ldots\ldots\ldots \quad (7)$$

HT (r,θ ) is corresponding parameter space and T is a constant determining a sensitivity of CKHT.

### C. *WAVELET TRANSFORM*

Wavelet transform is one of the most popular of the time-frequency-transformations. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution and the wavelets are discretely sampled. It captures both frequency and location information.

A continuous wavelet transform (CWT) is used to divide a continuous-time function into wavelets. The continuous wavelet transform of a function x(t) at a scale (a>0) a ∈ R +*and translational value b ∈ R is expressed by the following integral

$$X^{\omega}(a, b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} x(t)\, \overline{\Psi}\left(\frac{t-b}{a}\right) dt \ldots\ldots\ldots\ldots (8)$$

Where $\Psi(t)$ mother wavelet .The main purpose of the mother wavelet is is to provide a source function to produce the daughter wavelets which are simply the translated and scaled versions of the mother wavelet. Let L2(R) denotes the space of all square integral functions on R. In signal processing parlance, it is the space of functions with finite energy. Let ψ (t) ∈ $L_2(R)$ be a preset function. The function ψ(t) is said to be a wavelet if and only if its FT ψ (ω) satisfies

$$C\psi = \int_{\infty}^{0} \frac{\Psi|\omega|2}{|\omega|} < \infty \ldots\ldots\ldots\ldots (9)$$

The relation is called the admissibility condition, which implies that the wavelet must have a zero average

$$\int_{-\infty}^{\infty} \Psi(t)dt = \Psi(0) = 0 \ldots\ldots\ldots\ldots(10)$$

And therefore it must be oscillatory. In other words, ψ must be a sort of wave. Let us now define the dilated–translated wavelets ψ a, b as the following functions

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \ldots\ldots\ldots\ldots (11)$$

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Where b∈R is a translation criterion, whereas a R+ (a ≠ 0) is a dilation or scale parameter.

D. ***Walsh Transform***

The Walsh functions may be viewed as a discrete, digital counterpart of continuous, analog system of trigonometric functions on the unit interval. The functions take the values −1 and +1 only, on sub-intervals defined by dyadic fractions. We define the sequence of Walsh functions, Wk: [0, 1] → {−1,1}, k ∈ N0 Wk: [0, 1] as follows.

For any k ∈ N0, X ∈ [0, 1] let

$$k = \sum_{j=0}^{\infty} k_j 2j,\ kj \in \{0,1\} \quad x = \sum_{j=1}^{\infty} x_j 2\text{-}j,\ xj \in \{0,1\} \ldots\ldots(12)$$

Such that there are only finitely many non-zero kj and no trailing xj all the same to 1, be the canonical binary representations of integer k and real number x, in the same way. Then, the definition

$$Wk(x) = (-1)^{\sum_{j=0}^{\infty} k_j x_{j+1}} \ldots\ldots (13)$$

W2m is precisely the Rademacher function rm. Thus, the Rademacher method is a subsystem of the Walsh system. Moreover, each Walsh function is a product of Rademacher functions:

$$Wk(x) = \prod_{j=0}^{\infty} r_j (x)kj \ldots\ldots (14)$$

E. ***CURVLET TRANSFORM***

Curvelet transform is a new multiscale transform which was designed to represent edges and other singularities onward curves much more efficiently than traditional transforms Curvelet is a higher dimensional generalization of the wavelet transform intended to represent images at different scales and different angles. Therefore, Curvelets will be superior over wavelets in following cases: 1. Optimal sparse representation in object with edges 2.Optimal image reconstruction of severely ill-posed problems 3.Optimal sparse representation in wave propagators

The discrete curvelet transform useful to represent an image with intensity values given by the function f (y1, y2), x1 = 0, 1,..., M1 - 1, x2 = 0, 1,..., M2 - 1, whose discrete Fourier transform (DFT) is

$$\hat{f}(m_1, m_2) = \sum_{y2=0}^{M2-1} \sum_{y1=0}^{M1-1} f(y_1, y_2)\, e^{-2\pi i}(m_1 y_1 / M_1 + m_2 y_2 / M_2) \ldots\ldots(15)$$

The discrete curvelet transform is now a disintegrate into the curvelet coefficients such that

$$f(m1,m2) = \sum_{j=1}^{j} \sum_{l=0}^{Lj-1} \sum_{k1=0}^{Kjl,1-1} \sum_{k2=0}^{Kjl,2-1} cjlk\ sjlk\ (y_1,y_2) \ldots\ldots(16)$$

Where k= (k1, k2), s is the curvelet on level j with orientation l and spatial shift k.

$$\sum_{jlk} |cjlk|2 = \sum_{y1,y2} + |f(y1, y2)|2 \ldots\ldots(17)$$

The discrete curvelet transform provides a disintegration of the image f into J detail levels, with Lj orientation on each level, and Kjl,1 × Kjl,2 spatial shifts for each Where k = ($k_1$, $k_2$) and s is the curvelet on level j with orientation l and spatial shift k. additionally, the curvelet transform preserves $l_2$-norms, i.e.

$$\sum_{jlk} |cjlk|2 = \sum_{y1,y2} + |f(y1,y2)|2 \ldots\ldots(18)$$

The discrete curvelet transform provides a disintegration of the image f into J detail levels, with Lj orientation on each level, and Kjl,1 × Kjl,2 spatial shifts for each directions.

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## III. REALIZATION OF TRANSFORMS

### A. *Hough-based Signal detection*

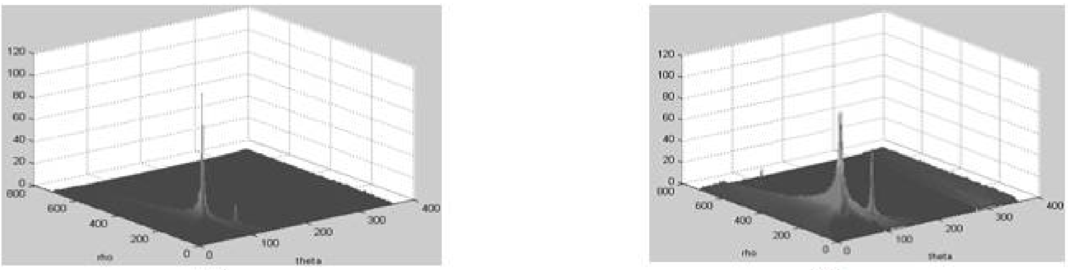
The Wigner-Ville Distribution (WVD) and Pseudo-Wigner-Ville Distribution (PWVD) are very popular and effective methods for notice Linear Frequency Modulated (LFM) signals in noisy environments. Hough transform is also widely used method for discovery and parameter assessment of chirp signals. However, when there are signals with very different strength from each other, it is complicated to simultaneously detect both of them. Two LFM signals are generated with the following parameters: amplitudes are 1 and 0.35, core frequency f0 equals 40 Hz and 100 Hz respectively and the chirp pace k of these signals is 100 Hz/s and 175 Hz/s respectively. The amount of samples is 1000. In the simulation the span of the Gaussian filter is equal to the length of the signal. The two chirps are refined with PWVD-Hough Transform and PWVD and binary integration of Hough space. White Gaussian noise is joined into the signals. The simulations are conducted for SNR equals to -3 dB, 0 dB and 3 dB. Fig. 2 (a) shows that when the SNR = -3 dB, the weak signal much cannot be seen, only the strong signal can be detected. After the signal is processed by the novel method (Fig. 2 b), the weak signal is still not noticeable. Since the SNR is too low, some of the intrusion terms produce almost the same number of curves in the Hough space, which makes them and the weak signal appear the same size in the parameter domain. The results after performing PWVD and Hough transform when SNR is 0 dB and 3 dB in figures 3 (a) and 4 (a) are that the weak signal does not raise significantly although the SNR is better.

(a) (b)

Figure 2: (a) PWVD and Hough transform and the PWVD and binary integration of Hough space (b) (SNR = -3 dB).

(a) (b)

Figure 3: The (a) PWVD and Hough transform and the PWVD and binary integration of Hough space (b) (SNR = 0 dB).



(a) (b)

Figure 4: The (a) PWVD and the Hough transform and the PWVD and binary integration of Hough space (b) (SNR = 3 dB)

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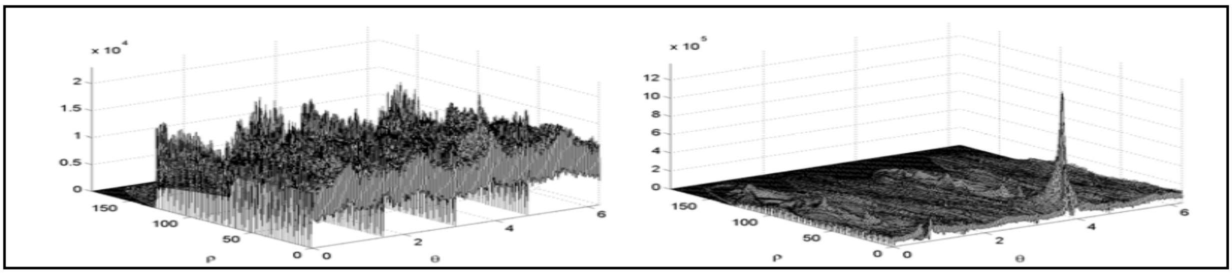
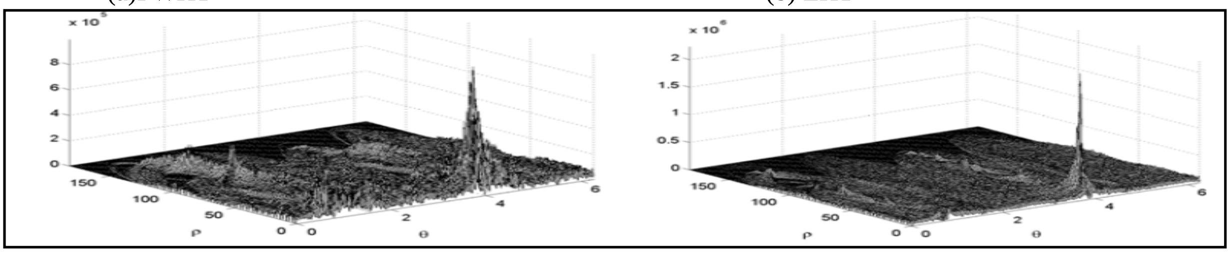
### B. *CHIRPLET-BASED SIGNAL DETECTION*

The Reassigned Local Polynomial Periodogram forth the Frequency direction (RfLPP) is shown to be able to perfectly localize the chirp signal. Due to this property, the RfLPP is collective with the Hough transform for chirp signal detection in the parameter domain. The performance of the RfLPP-Hough transform is tested for chirp signal detection in white Gaussian noise and impulsive noise, with comparisons to the PWHT, LHT, and RLPPHough transform. The comparisons verify the benefit of the RfLPP-Hough transform for chirp signal detection.

The mono-component chirp signal is of 256 point length, the initial normalized frequency is 0, and final normalized frequency is 0.45. The multi-component chirp signal is of 256 point length, for one component, the initial normalized frequency is 0 and the final normalized frequency is 0.25; for the other component, the initial normalized frequency is 0.5 and the final normalized frequency is 0.25. In order to provide an illustrative result, the multi-component signals are assumed to be depraved by higher SNR noise level than the mono-component signals, that is SNR=10 for mono-component signal and SNR=5dB for the multi-component signal. For a mono-component chirp signal in the white Gaussian noise with the SNR = 10dB. It can be look that for the chirp signal under the heavy noise, the PWVD cannot give a correct representation, and the RLPP cannot provide the proper concentration due to the noise effect.



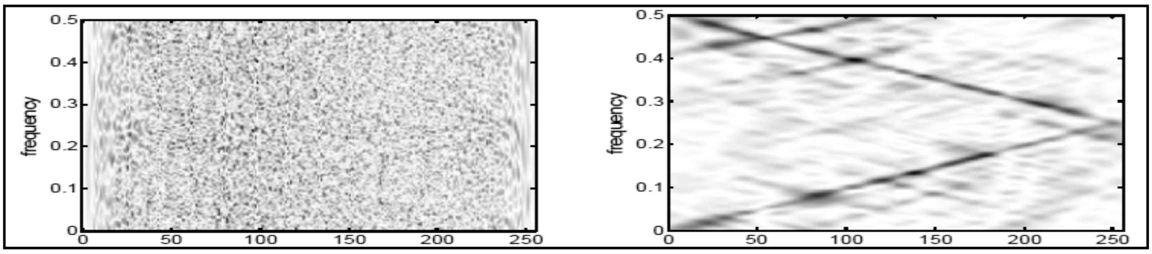
(a)PWHT (b) LHT



(a)RLPP- Hough transforms (b)RfLPP-Hough Transform

Figure 2: The PWHT, LHT, RLPP-Hough transform, and RfLPP-Hough transform for mono-component chirp signal in white Gaussian noise with SNR=10dB.

Hough transform for correctly detecting the chirp component, where ρ and θ are the distance and angle of the normal vector to the line from the origin, respectively. Moreover the RfLPP-Hough transform can provide more concentrated peak in the parameter space, which makes it much easier for chirp detection and estimation. Similar conclusion can be obtained for multiple component chirp signals, as shown in Figs. 3 and 4.



Time Time

(a)PWVD (b) LPP

Figure3: The PWVD, LPP, RLPP, and RfLPP for multi-component chirp signal in white Gaussian Noise with SNR=5dB.

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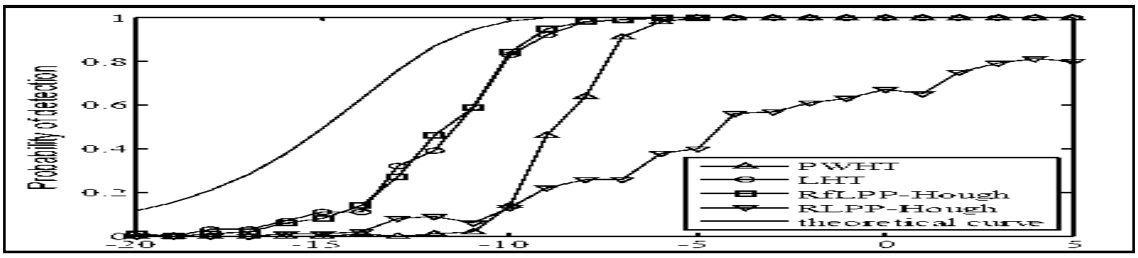


Figure5: Probability of detection performance comparisons under probability of false alarm 1%.

For better evaluating the performances of the above methods, we provide quantitative analysis of the results for mono-component chirp detection in white Gaussian noise with different SNRs. We define a grid containing 2 point by 2 point as the expected location of the peak. Detection is successful when the peak that is above the threshold is within this grid. With the probability of false alarm as 1%, the relationships between the probability of detection to the SNR are provided with the averages of 100 simulations, and also compared with the theoretical curve, as shown in Fig. 5. It shows that the RLPP-Hough transform is more sensitive to the noise and cannot detect the chirp signal with high probability of detection even in high SNR=5dB, this occurs because the RLPP cannot correctly localize the chirp signal due to the noise, and the peak in the parameter domain may off the defined grid. For signal with a low SNR, such as SNR=10dB, the probability of detection using the RfLPP-Hough transform or the LHT is much higher than that of the PWHT. The discloser performance of the RfLPP-Hough transform is comparable to that of the LHT. However, using the RfLPP-Hough transform for chirp detection, the computational complexity is reduced.

### C. *WALSH -BASED SIGNAL DETECTION*

Spectrum sensing is a technology to improve spectrum efficiency. A novel signal detection method based on Walsh transform is used for spectrum sensing. The main idea behind is that the received signal is transformed into another domain by Walsh transform and the verify statistic is achieved by exploiting the feature of the useful signal in the new domain. The novel method can perform well at low signal-to-noise rate (SNR). The performance of the wash-based signal detector is compared with the spectral feature detector through simulation. The baseband signal used in the simulation is BPSK signal with rectangle envelope. The symbol rate is 2MB and the sample frequency is 32MHz. A couple of numerical experiments are passed out and a block of received data with 10240 samples is generated to calculate a decision result for every experiment. Figure 3: shows the variation of probability of detection with probability of false alarm for BPSK when SNR is -18dB.Figure 4: The following graphical representation illustrates the effect of SNR on the probability of detection for BPSK when the probability of false alarm is 0.01.

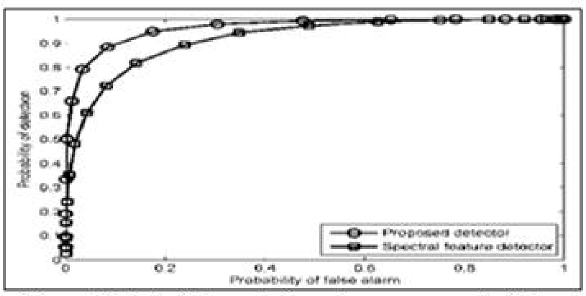


Figure 3: Probability of detection versus probability of false alarm for BPSK when SNR is -18 dB.

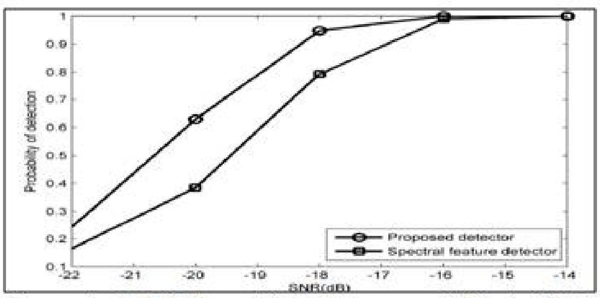


Figure 4: Probability of detection versus SNR for BPSK when the probability of false alarm is 0.01.

### D. *WAVELET -BASED SIGNAL DETECTION*

In the singular alteration signal detection, due to its signal features are very unequal, we must complete and consider all the characteristics to choose a appropriate wavelet function, then it can achieve enhanced recognition results. To sum up, according to the above scrutiny, we should select the wavelet function by considering the wave's regularity, compact support set and number of fading moments. In order to verify the effectiveness of diverse wavelet

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bases, we have constructed an experimental signal, shown in Fig.1.We can see clearly five alteration points among 0:800: two between 200:30, one between 300:400, one between 400:500 and one between 500: 600. Further using the wavelet of db2, db3, db4, db5 decompose the unique signal into 4 layer, we can get four layers information signal and the fourth floor estimated signal, as shown in Fig.2, and Fig.5.

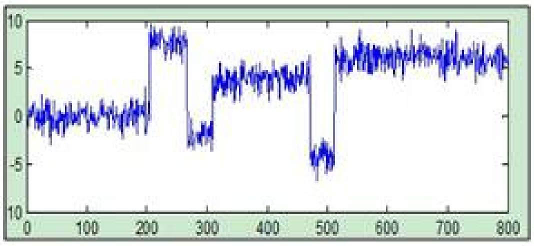


Figure: 1 an experimental signal

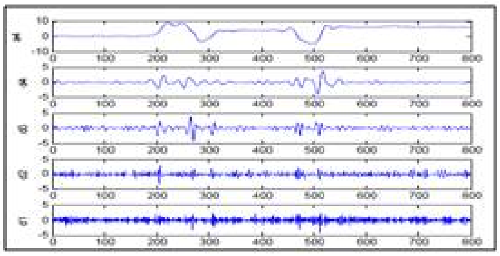

Figure.5. Signal decomposition with db5 wavelet

E. ***CURVELET-BASED SIGNAL DETECTION***

Signal detection based on Curve let transform (SDCT) approach for spectrum sensing is presented, which accomplishes the feature of the signal after applying Curvelet transformation. In order to make the revelation process fast and to resolve an optimal feature set Principal Component of Analysis (PCA) is used. The hypothetical false-alarm probability has been derived, that is helpful us to analytically and accurately calculation of the SDCT approach in practical spectrum sensing. There are many approaches for threshold selection however; statistical procedures are dependent of the noise deviation, SNR and the recording interval. The Simulation results shows that, proposed method significantly enhance the performance in terms of efficiency and accuracy as well as detect weak signals at very low signal-to-noise rate (SNR) and then animatedly adjust the radio operating parameters accordingly.

## IV. RESULTS AND DISCUSSIONS

In this paper, we have reviewed newly developed signal detection methods have been investigated. 1. Walsh transform is exploits the feature of the signal after Walsh transformation to decide the presence of the useful signal. This method is low in complexity, which makes it typically suitable for real time signal detection system. 2. Wavelet transform gives location interface precise. It offers a basic change and levels for the analysis of the accuracy of interfaces. The deliberate signal processing methods for non-destructive testing of material, are feasible and can accurately and efficiently characterize any material and determine the location and the size of its defects and they also provide application assessment for engineering practice. 3. When the SNR is low, it is crucial that the length of the filter used for PWVD adequately suppresses the cross terms but simultaneously, does not filter out the weak signal. Simulations done show that by using PWVD and binary integration in Hough space, the small target is much more noticeable in the parameter field. This means that the weak and the strong signals can be detected simultaneously. 4.The RfLPP has been proven to perfectly localize the chirp signal. The performance of the RfLPP-Hough transform is tested for chirp signal recognition in white Gaussian noise and impulsive noise, with comparisons to the PWHT, LHT, and RLPP- Hough transform. 5.Curvelet transform approach for signal detection is studied, which accomplishes the feature of the signal after applying Curvelet transform. In order to make the revelation process fast and to resolve an optimal feature set Principal Component of Analysis (PCA) is used. The hypothetical false-alarm probability has been derived, that is helpful us to analytically and accurately calculation of the Curvelet transform approach in practical signal detection. The Simulation results shows that, Curvelet transform significantly enhance the performance in terms of efficiency and accuracy as well as detect weak signals at very low signal-to-noise rate (SNR). The following table shows comparison of different transforms techniques for signal detection.

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| S.No | Application | Method | Efficiency | Result |
|---|---|---|---|---|
| 1 | Signal Detection | Wavelet Transform | Moderate | 85% |
| 2 | Signal Detection | Hough Transform | High | 92% |
| 3 | Signal Detection | Walsh Transform | High | 93% |
| 4 | Signal Detection | Chirplet Transform | High | 92% |
| 5 | Signal Detection | Curvelet Transform | Very High | 96% |

Table 1: Comparison of Different transforms techniques for signal detection

## V. CONCLUSION

In signal processing, detection of an unknown signal in noisy data is crucial task. The extraction of features becomes difficult and high frequency spectrum overlap with the frequency of fault if the noise is present in the received signal. This paper presents a comparative study based on transform techniques for signal detection. Realization of transforms and corresponding accurate results are presented to the desired signal. Statistical analysis shows that, Curvelet transform is a better than reaming transforms for detecting the noisy data. The motive behind is ability of sparse representation that are critical for detection and estimation of signal which are noisy and weak signals.

## VI. ACKNOWLEDGEMENT

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