AUDIO SIGNAL RECONSTRUCTION USING COMPRESSIVE SENSING THEORY

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Abstract—In this paper, we use Compressive Sensing (CS) theory for audio signal acquisition. In sampling theorem number of compression steps were used to reduce the data but by implementing Compressive Sensing (CS) theory on input signal i.e., audio signal they can be reconstructed using 1 minimization method. In this paper, we propose STFT as representation domain where signal becomes sparse. The results of another method called Wigner Distribution (WD) are also presented which is advanced method of STFT. The experimental results of STFT are illustrated on basic sine wave and audio input signal and the waveform output of basic wave using Wigner Distribution is also presented for understanding the advanced method. You will observe that, there will be reduction in time of audio signal for input and output signal after reconstruction using STFT and WD.

Keywords: Compressive Sensing Theory, Short Time Fourier Transform(STFT), Wigner Distribution(WD)

1. INTRODUCTION:

Compressive Sensing (CS) Technique requires reduced number of samples when compared to regular Sampling Theorem. The main advantage of reducing number of samples is that the reconstruction can be done using single minimization technique. Where signal sampled by using traditional sampling theorem requires more compression techniques while reconstruction.

Traditional method of signal sampling is based on Shannon-Nyquist theorem. In this the signal must be sampled following the Nyquist rate which is nothing but of the signal must be sampled at a frequency atleast 2 times the maximum signal frequency. There are signals, which require high Nyquist rate

Sampling the signal using Shannon-Nyquist Technique results into large number of samples, storing and transmitting such signal through the communication channel is risky because there are chances, where we can lose few samples while transmitting since channels have bit rate limitation.

In time-frequency representation domain, the signal is sparse which means, only few coefficients of sampled signal have large values and most of the coefficients are close to zero.

For signal acquisition Compressive Sensing (CS) have alternate way [1]-[7]. Instead of considering huge number of samples through traditional sampling theorem and then using compressive sensing technique, CS allows us to compress the data and then acquisition of signal simultaneously.

The two conditions on which this compressive sensing is based are:

- The measurements should be incoherent
- The signal should have sparse representation.

Compressive sensing theory applications:

The case where nyquist sampling is not often feasible or is very expensive. Possible application of CS is in audio signal reconstruction. In the field of medicine, MRI(Magnetic Resonance Imaging) requires high resolution in such cases where sampling theorem fails.

This paper is organized as follows: section 1 Basic concepts of Compressive Sensing Theory and Sparsity. Section 2 is literature review. Section 3 and 4 is Concepts and Theoritical representation of STFT and Wigner Distribution. Section 5 is Conclusion and Section 6 is Results.

2. Literature Survey:

The main advantage of using time-frequency representation domain for any signal i.e., Audio or Image is that it requires only fewer measurements when compared to traditional one. Compressive Samples which are also called Compressed Sensing mainly depends on sparsity. Where only few samples of interest are considered. Generally all the signals, which are naturally available are sparse. But Compressive sensing theory has to deal with both signal and noise. The CS method is mainly used to avoid Nyquist criteria. Using CS the space required for storing is also reduced as usual method requires more storage as the number of samples increases, as the sampling frequency required should be equal to or greater than twice the highest component of frequency. The Bandwidth requirement is also large for usual sampling method.

As the signal is compressed the parameter SNR also enhances. The other advantage of using CS is that the samples taken need not be in equidistance manner, They can be random and the reconstructed signal is not compressed.

The two main requirements or properties of CS are:

- Sparsity and
- Incoherence

In any given signal if the density at any particular period is more then it is considered that the signal has useful information than the other part of signal with less density so such part of signal samples are mainly concentrated. The number samples required is always not same in CS. The requirement of samples reduces as the complexity of signal is reduced. Speech signals have much more harmonics when compared to music signals so speech signals has high requirement of recovering in short frames.

3. Short-Time Fourier Transform:

The most popular general purpose tool for audio signal processing is Short-Time Fourier Transform (STFT). It defines Time-Frequency (TF) representation of input signal i.e., different frequency components at particular point of time. The spectrogram, developed at Bell Laboratories during WW2, has been used for several years to display short time spectrum of sound.

Spectrograms are analyzed using STFT, which is nothing but of a sequence of FFT's over time. Where main application of spectrogram are mostly in the field of music, speech processing and seismology.

Theoritical Representation of STFT:

The main advantage of STFT is that, it considers particular block of signal as the input signal is multiplied by window signal. We usually use Hamming window function which is the extension of Hann window.

Applying windowing function to signal

$$X\text{win}(K)=X(K).W(K) \tag{1}$$

$$X'(K) = \sum_{m=0}^{M-1} X(m).e^{-2\pi mi(\frac{K}{M})} \tag{2}$$

Where M= number of samples in the given input signal.

signal. Now let us look into the equation which we The above is the normal discrete time fourier transform of any given input audio consider for STFT

$$S(n,k) = \sum_{m=0}^{M-1} X(m+nHS)W(m).e^{-2\pi mi(\frac{K}{M})} \tag{3}$$

Where HS=Hope Size

n=signal present in the current frame

S(n,K)=Short Time Fourier Transform of n^{th} frame with K^{th} frequency

M = Number of samples

m+nHS = covering all samples in the frame

X(m+nHS)W(m)= windowed signal.

4. Wigner Distribution:

Wigner Distribution is also Time-Frequency domain representation where signal is considered to be sparse.

The representation of Wigner Distribution of input signal V(t)

$$W_{wigner}(t,f) = \int_{-\infty}^{\infty} V'\left(t+\frac{\tau}{2}\right) V'^{\theta}\left(t-\frac{\tau}{2}\right) e^{-2\pi i f \tau} d\tau \qquad (4)$$

$$W_{wigner}(t,f) = \int_{-\infty}^{\infty} V'\left(t+\frac{\tau}{2}\right) V'^{\theta}\left(t-\frac{\tau}{2}\right) e^{-2\pi i f \tau} d\tau \qquad (5)$$

Where V'(t) is analytical signal, whose imaginary term is proportional to Hilbert transfoem of waveform.

$$V'(t) = V(t) + i(\frac{1}{\pi}) \int_{-\infty}^{\infty} \left[\frac{S(\varepsilon)}{\varepsilon - 1}\right] d\varepsilon \qquad (6)$$

5.RESULT:

Introduction to reconstruction of non-sparse audio signals using compressive sensing technique. Compressive Sensing is a revolutionary technique with limited scopes. Considering younger generations mainly to help them understand the signal reconstruction through Compressive Sensing Technique.

Below figures shows the basic block diagram representation to show the variation between traditional sampling theorem and compressive sensing technique.

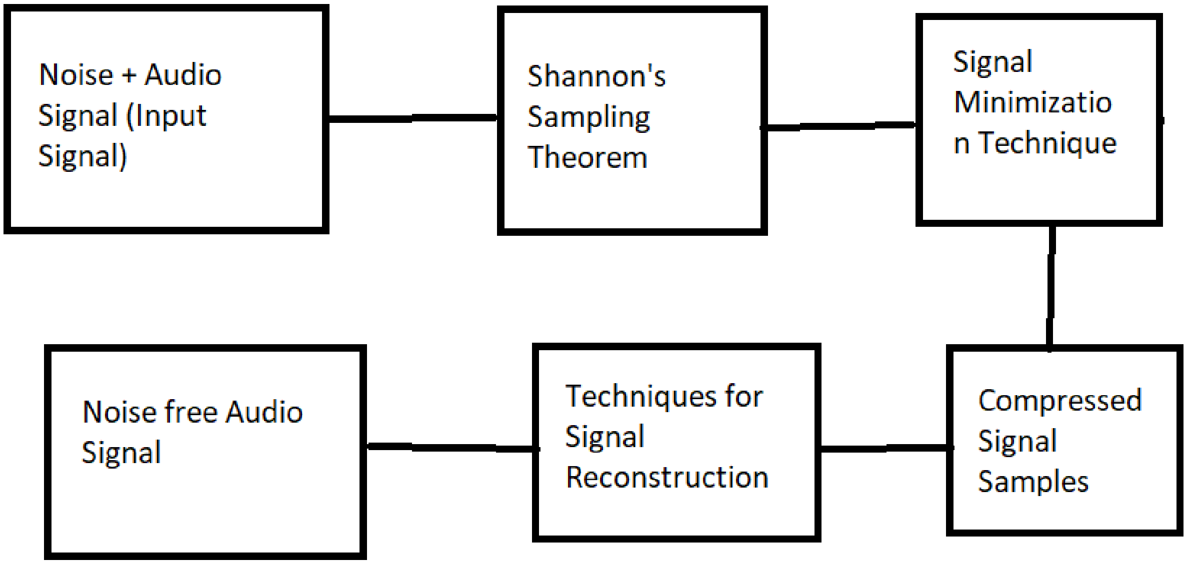

Fig 1: Block Diagram representation of signal reconstruction using sampling theorem

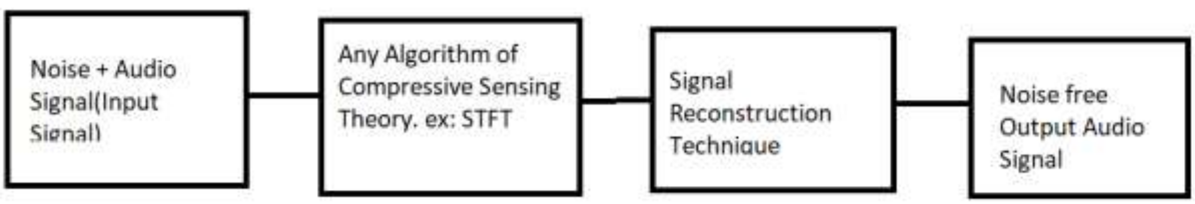

Fig 2: Block Diagram representation using Compressive Sensing Technique

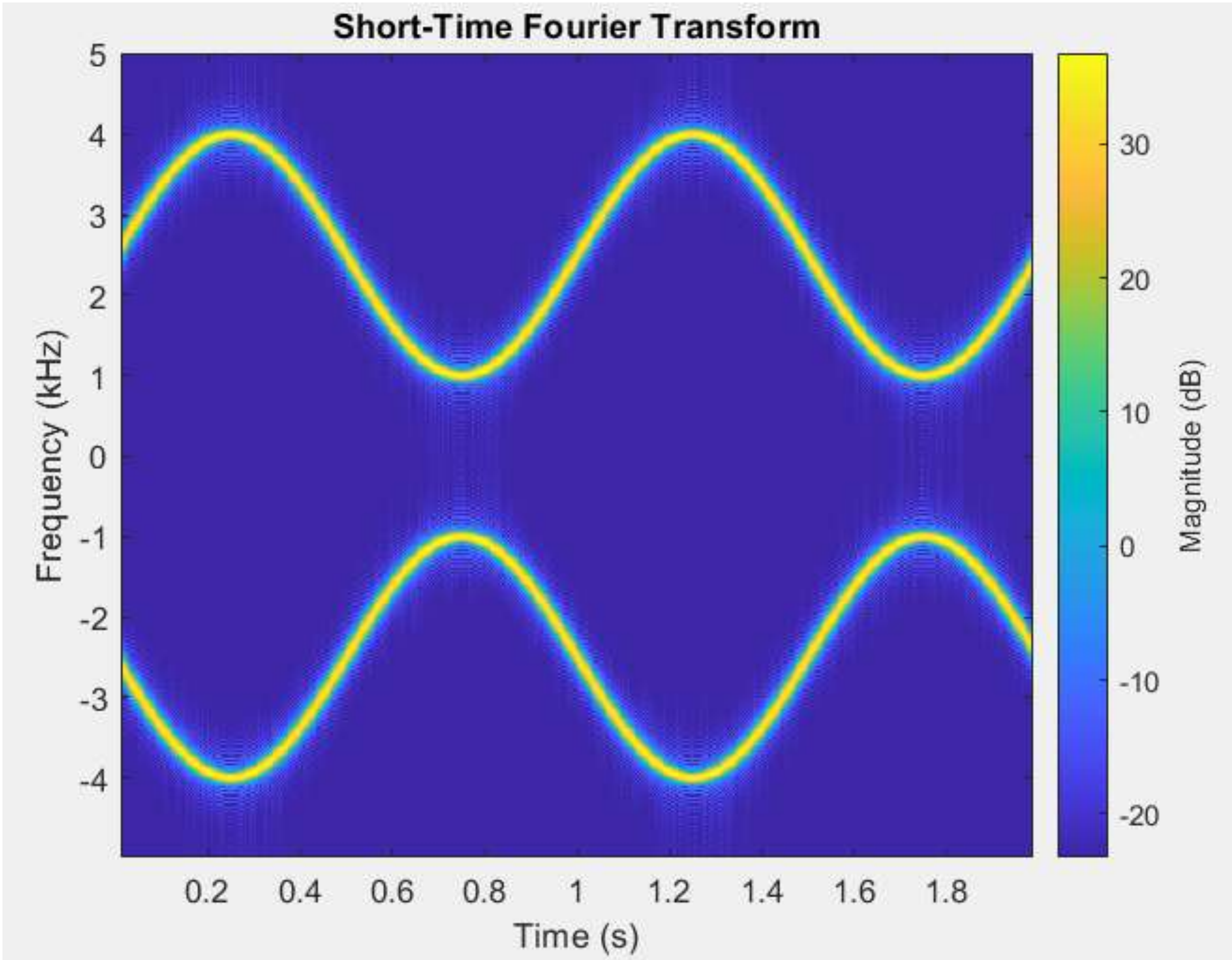

Fig 3: Stft Representation of sinusoidal input waveform

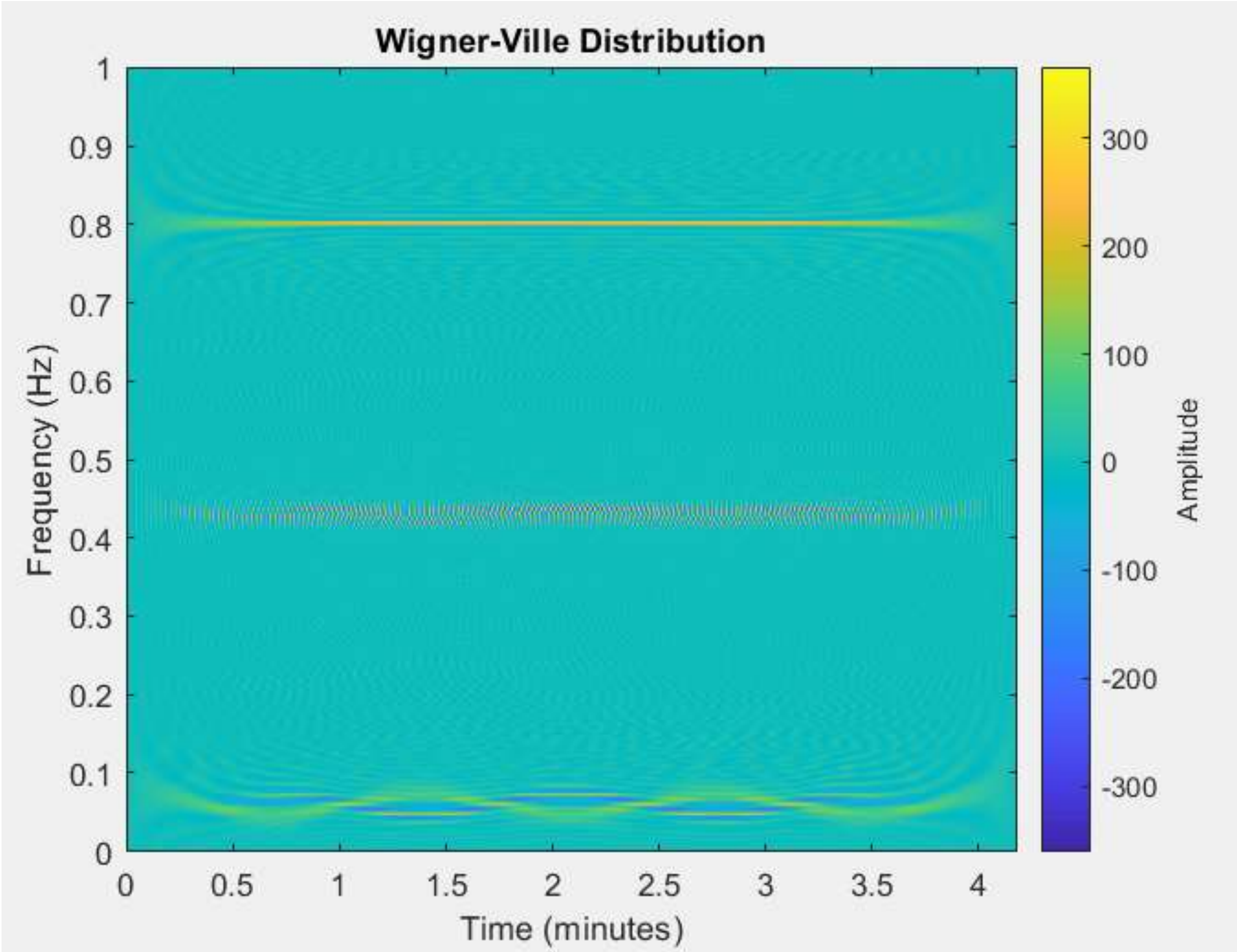

Fig 4: Wigner Distribution representation of sinusoidal input waveform

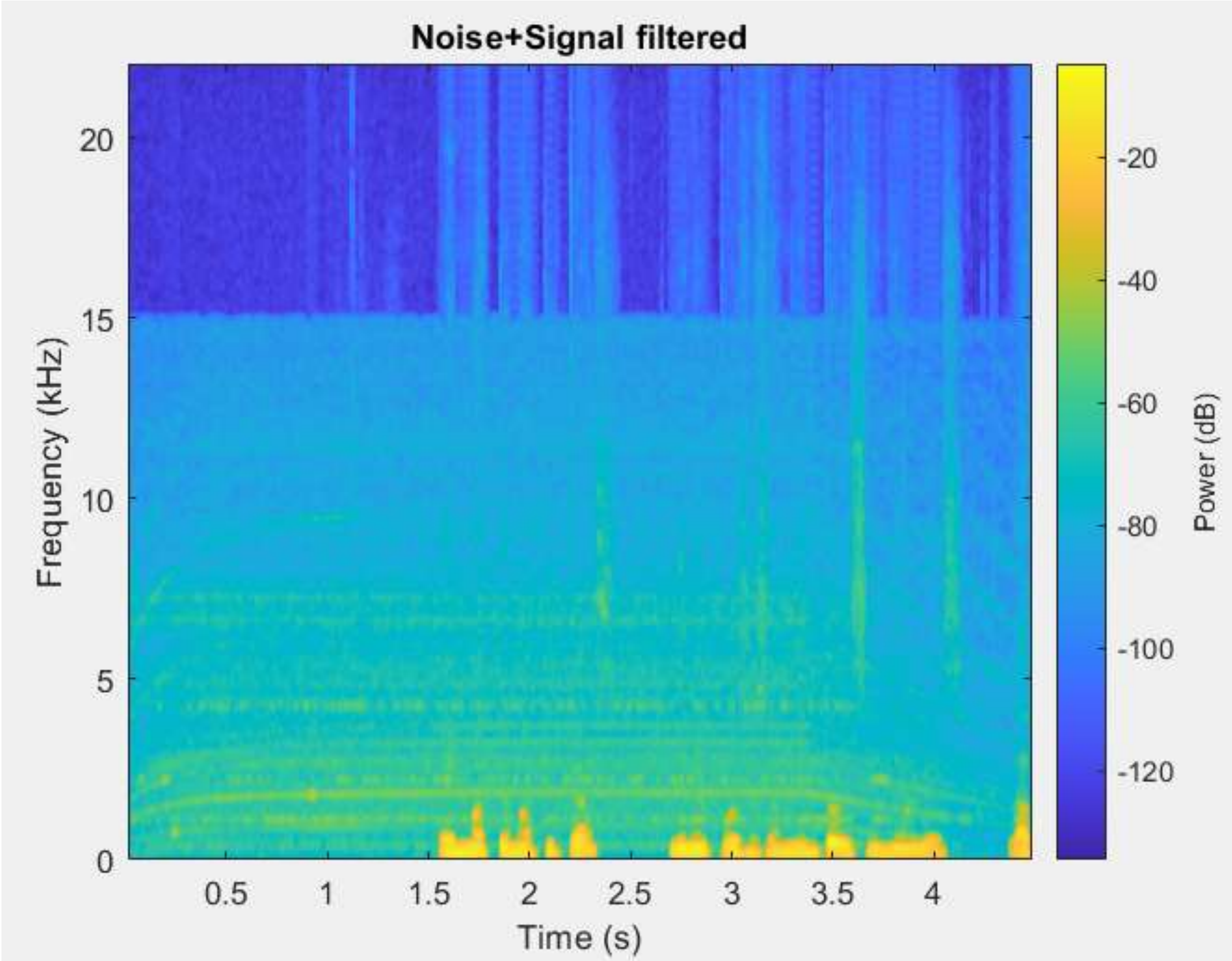

Fig 5: Time-Frequency representation of filtered noise + audio signal.

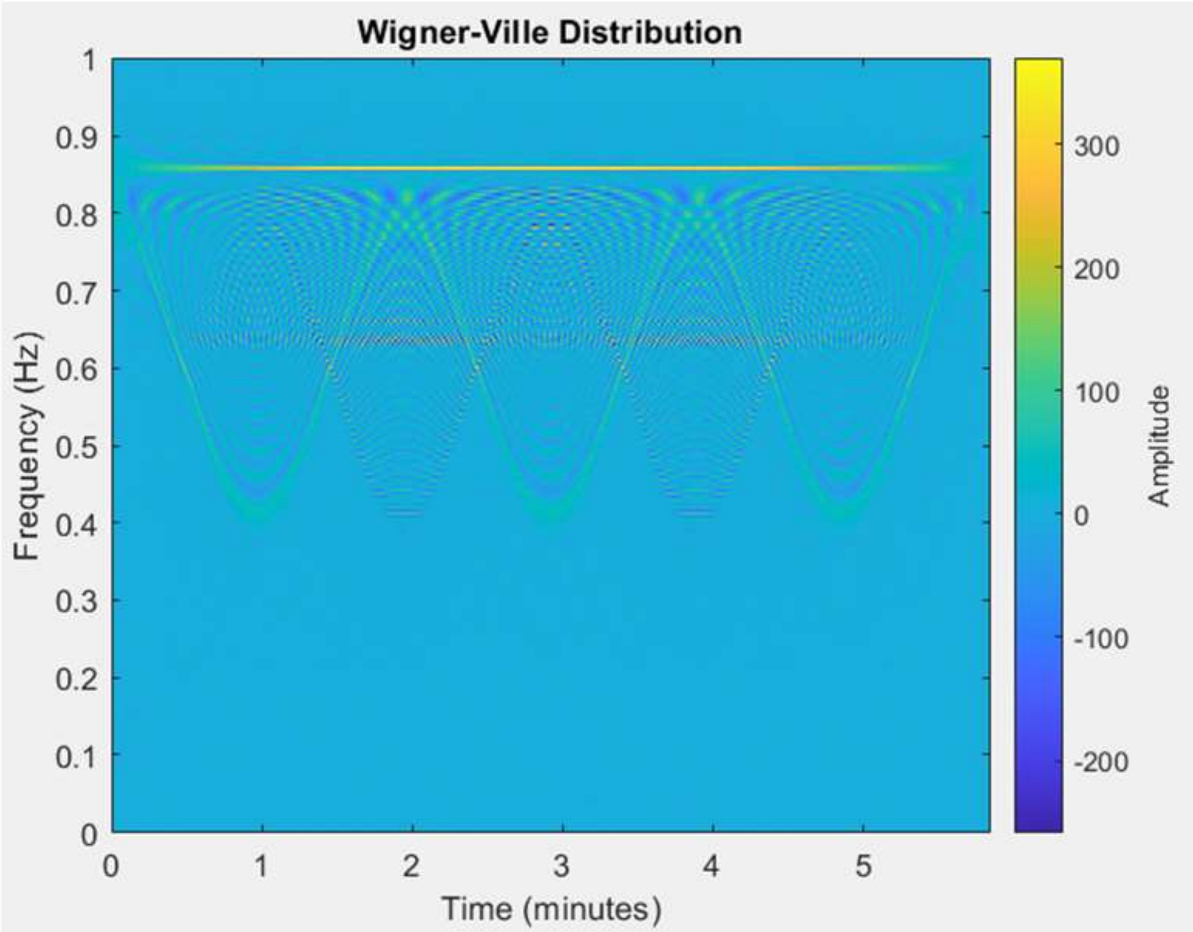

Fig 6. Wigner Distribution Representation of filtered Noise+Audio-Signal

6. CONCLUSION:

The compressive sensing theory is illustrated on basic sinusoidal signal and audio signal for basic and practical understanding. The basic sinusoidal signal is considered and it is included in MATLAB software and waveforms are obtained using two methods i.e., STFT and WD. The waveforms are shown below. The waveforms of audio input signal in time-frequency representation is also presented where practically you can observe reduction in time of output signal delivery

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