International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

Wideband Spectrum Sensing in Cognitive Radio using Multicoset Sampler

Sapna Pathak
Department of Electronics & Communication
BBDNIIT, Lucknow
spsaicare@gmail.com

Dr. Manish Kumar
Department of Electronics & Communication
BBDNIIT, Lucknow
coe.bbdu@gmail.com

***Abstract*--The work will focus the area of spectrum sensing methodology used in cognitive radio. The main challenge in the spectrum sensing is the need of a very high sampling rate for sensing the wideband signal. Hence a wideband spectrum sensing model will be developed using MATLAB software based programming environment. The algorithm will utilize a sub sampling scheme that can help in reducing the requirement of very high sampling rate during wideband spectrum sensing. For this purpose a finite number of noisy samples will be generated initially and the correlation of these finite samples will be evaluated and to find out the occupied and vacant channels of the spectrum, we use subspace estimation algorithm.**

Keyword: Cognitive radio, Subspace estimation algorithm, Sampling and Wideband spectrum.

1. Introduction:

Radio frequency (RF) spectrum is a valuable but tightly regulated resource due to its unique and important role in wireless communications. With the proliferation of wireless services, the demands for the RF spectrum are constantly increasing, leading to scarce spectrum resources. Onthe other hand, it has been reported that localized temporal and geographic spectrum utilization is extremely low [1]. Currently, new spectrum policies are being developed by the Federal Communications Commission (FCC) that will allow secondary users to opportunistically access a licensed band, when the primary user (PU) is absent. Cognitive radio [2], [3] has become a promising solution to solve the spectrum scarcity problem in the next generation cellular networks by exploiting opportunities in time, frequency, and space domains. Cognitive radio is an advanced software-defined radio that automatically detects its surrounding RF stimuli and intelligently adapts its operating parameters to network infrastructure while meeting user demands. Since cognitive radios are considered as secondary users for using the licensed spectrum, a crucial requirement of cognitive radio networks is that they must efficiently exploit under-utilized spectrum (denoted as spectral opportunities) without causing harmful interference to the PUs. Furthermore, PUs have no obligation to share and change their operating parameters for sharing spectrum with cognitive radio networks. Hence, cognitive radios should be able to independently detect spectral opportunities without any assistance from PUs; this ability is called spectrum sensing, which is considered as one of the most critical components in cognitive radio networks. Many narrowband spectrum sensing algorithms have been studied in the literature [4] and references therein, including matched-filtering, energy detection [5], and cyclostationary feature detection. While present narrowband spectrum sensing algorithms have focused on exploiting spectral opportunities over narrow frequency range, cognitive radio networks will eventually be required to exploit spectral opportunities over wide frequency range from hundreds of megahertz (MHz) to several Gigahertz (GHz) for achieving higher opportunistic throughput. This is driven by the famous Shannon's formula that, under certain conditions, the maximum theoretically achievable bit rate is directly proportional to the spectral bandwidth. Hence, different from narrowband spectrum sensing, wideband spectrum sensing aims to find more spectral opportunities over wide frequency range and achieve higher opportunistic aggregate throughput in cognitive radio networks. However, conventional wideband spectrum sensing techniques based on standard analog-to-digital converter (ADC) could lead to un-affordably high sampling rate or implementation complexity; thus, revolutionary wideband spectrum sensing techniques become increasingly important.

A CR can be programmed to transmit and receive on a variety of frequencies, and use different access technologies supported by its hardware design. Through this capability, the best unutilized spectrum band is chosen by a CR. In order to provide these capabilties, CR requires novel radio frequency(RF) transceiver architectures. As shown in the fig1., in the RF front end the received signal is amplified, mixed, and analog-to digital (A/D) converted. In the baseband processing unit, the signal is modulated/demodulated. Each component can be reconfigured via a control bus to adapt to the time varying RF environment. The novel characteristics of the CR transceiver is the wideband RF front end i.e. capable of simultaneous sensing over a wide frequency range. This functionality is related mainly to the RF hardware technology, such as wide band antenna, power amplifier and adaptive filter. RF hardware for the CR should be capable of being tuned to any part of a large range of spectrum. However, because the CR transceiver receives signal from various transmitters operating at different power levels, bandwidths and locations. The RF front end should have the capability to detect weak signals in a large dynamic range, which is a major challenge in CR transceiver design.

2. Related Work:

RamanVenkataramaniet. al. (2001) [13],studied the problem of optimal sub-Nyquist samplingfor perfect reconstruction of

ISSN: 2454-6844

multiband signals. The signalsare assumed to have a known spectral support that does not tileunder translation. Such signals admit perfect reconstruction fromperiodic nonuniform sampling at rates approaching Landau'slower bound equal to the measure of F(frequency). For signals with sparse, this rate can be much smaller than the Nyquist rate. Unfortunately,the reduced sampling rates afforded by this scheme canbe accompanied by increased error sensitivity. In a recent study, they derived bounds on the error due to missmodelling and sampleadditive noise. Adopting these bounds as performance measures,we consider the problems of optimizing the reconstruction sectionsof the system, choosing the optimal base sampling rate, and designingthe nonuniform sampling pattern. Optimizingthese parameters can improve system performance significantly.Furthermore, uniform sampling is optimal for signals withthat tiles under translation. For signals with nontiling , whichare not amenable to efficient uniform sampling, the results revealincreased error sensitivities with sub-Nyquist sampling. However,these can be controlled by optimal design, demonstrating thepotential for practical multifold reductions in sampling rate.

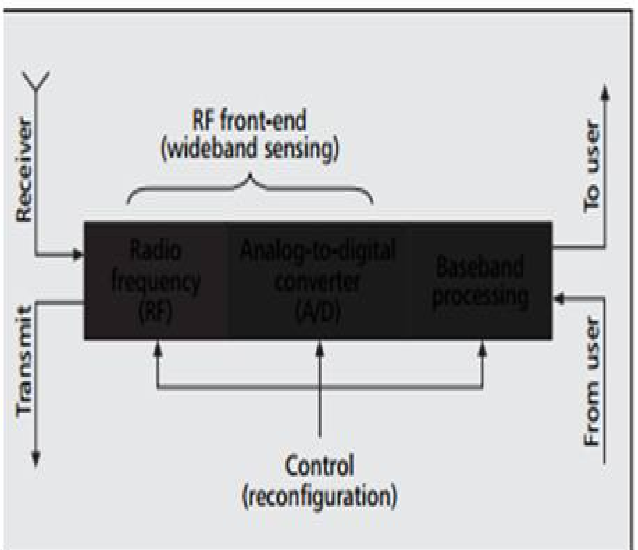

Fig. 1. Cognitive Radio Transceiver Architecture.

Moshe Mishali and Yonina C. Eldar, (2007) [14], address the problem of reconstructing a multi-band signal from its sub-Nyquist point-wise samples. All reconstruction methods proposed for this class of signals assumed knowledge of the band locations. Butthis work develop a non-linear blind perfect reconstruction scheme for multi-band signals which does not require the band locations. This approach assumes an existing blind multi-coset sampling method. The sparse structureof multi-band signals in the continuous frequency domain is used to replace the continuous reconstruction witha single finite dimensional problem without the need for discretization. The resulting problem can be formulatedwithin the framework of compressed sensing, and thus can be solved efficiently using known tractable algorithmsfrom this emerging area. This also develop a theoretical lower bound on the average sampling rate required forblind signal reconstruction, which is twice the minimal rate of known-spectrum recovery. This method ensuresperfect reconstruction for a wide class of signals sampled at the minimal rate. Numerical experiments are presenteddemonstrating blind sampling and reconstruction with minimal sampling rate.

Yvan Lamelas Polo, Ying Wang, Ashish Pandharipande, and Geert Leus, (2009) [15], presented a compressive wide-band spectrum sensing scheme for cognitive radios. The received analog signal at the cognitive radiosensing receiver is transformed in to a digital signal using ananalog-to-information converter. The autocorrelation of this compressed signal is then used to reconstruct an estimate of the signal spectrum. Then evaluate the performance of this scheme in terms ofthe mean squared error of the power spectrum density estimate and the probability of detecting signal occupancy.

It presented a compressive wide-band spectrum sensing schemewherein an AIC operates on the received analog signal. Spectrumestimation is done based on CS reconstruction using the auto correlation vector of the resulting compressed signal. The spectrumestimate was used to determine the spectrum occupancy of the licensed system. Performance evaluation using MSE and probability of detection showed that the proposed scheme performs comparably to the scheme based on **Z. Tian and G. B. Giannakis[16]**. The loss in incoherence thus does not substantially affect spectrum estimation and spectrum occupancy detection.

ZhiTian, et. al. (2012) [17],developed robust and compressive wideband spectrum sensing techniques by exploiting the unique sparsity property of the two-dimensional cyclic spectra of communications signals. For this, a new compressed sensing framework is proposed for extracting useful second-order statistics of wideband random signals from digital samples taken at sub-Nyquist rates. The time-varying cross-correlation functions of these compressive samples are formulated to reveal the cyclic spectrum, which is then used to simultaneously detect multiple signal sources over the entire wide band. Because the proposed wideband cyclic spectrumestimator utilizes all the cross-correlation terms of compressive samples to extract second-order statistics, it is also able to recover the power spectra of stationary signals as a special case, permitting lossless rate compression even for non-sparse signals. Simulation results demonstrate the robustness of the proposed spectrum sensing algorithms against both sampling rate reduction and noise uncertainty in wireless networks.

3. Methodology:

Step 1: Antenna signal modelling

We consider an array of M sensors located in the wave field generated by d narrow-band point sources. Let $\mathbf{a}(\theta)$ bethe steering vector representing the complex gains from one source at location θ to the M sensors. Then, if $\mathbf{x}(t)$ is the observation vector of size $M \times 1$, $\mathbf{s}(t)$ the emitted vector signal

ISSN: 2454-6844

of size $d \times 1$, and $\mathbf{n}(t)$ the additive noise vector of size $M \times 1$,we obtain the following conventional model:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) = \mathbf{y}(t) + \mathbf{n}(t), (1)$$

Step 2:Multi-band signals Formulation:

Multi-band signals are band limited signals that posses an additional structure in the frequency domain. The spectral support of a multi-band signal is restricted to several continuous intervals. Each of these intervals is called a band and it is assumed that no information resides outside the bands. The design of sampling and reconstruction systems for these signals involves three major considerations. One is the sampling rate. The other is the set of multi-band signals that the system can perfectly reconstruct. The last one is blindness, namely a design that does not assume knowledge of the band locations. Blindness is a desirable property as signals with different band locations are processed in the same way. Landau [27] developed a minimal sampling rate for an arbitrary sampling method that allows perfect reconstruction. For multi-band signals, the Landau rate is the sum of the band widths, which is below the corresponding Nyquist rate. Uniform sampling of a real bandp ass signal with a total width of 2B Hertz on both sides of the spectrum wasstudied in [2]. It was shown that only special cases of band pass signals can be perfectly reconstructed from their uniform samples at the minimal rate of 2B samples/sec.

Step 3: Minimal sampling rate determination:

We begin by quoting Landau's theorem for the minimal sampling rate of an arbitrary sampling method thatallows known-spectrum perfect reconstruction. It is then proved that blind perfect-reconstruction requires a minimal sampling rate that is twice the Landau rate.

Step 4: Unknown Spectrum Support Development

Consider the set N of signals bandlimited to F with bandwidth occupation no more than 0 << 1, so that

$$\lambda(\mathbf{supp}\,\mathbf{X}(\mathbf{f})) \le \frac{\Omega}{T}, \quad \forall\, \mathbf{x}(\mathbf{t}) \in \mathbf{N}_{\Omega}$$

The Nyquist rate for N is 1/T. Note that N is not a subspace so that the Landau theorem is not valid here.Nevertheless, it is intuitive to argue that the minimal sampling rate for N cannot be below T as this value isthe Landau rate had the spectrum support been known.A blind sampling set R for N is a sampling set whose design does not assume knowledge of suppX(f).

Step 5: Multi-coset sampling Structures Generation

This section reviews multi-coset sampling which is used in our development. We also briefly explain thefundamentals of known-spectrum reconstruction as derived in [8].

Uniform sampling of x(t) at the Nyquist rate results in samples x(t = nT) that contain all the informationabout x(t). Multi-coset sampling is a selection of certain samples from this grid. The uniform grid is divided intoblocks of L consecutive samples. A constant set C of length p describes the indices of p samples that are kept ineach block while the rest are zeroed out. The set C = {ci}pi=1 is referred to as the sampling pattern where

$$0 \le c_1 \le c_2 \le \ldots\ldots\ldots\ldots \le c_p \le L\text{-}1$$

Step6: Running Statistical tests for significant Eigen-value determination:

According to (1), the noiseless observations $\mathbf{y}(t)$ are a linearcombination of $\mathbf{a}(\theta 1), \ldots, \mathbf{a}(\theta d)$. Assuming independent source amplitudes $\mathbf{s}(t)$, the random vector $\mathbf{y}(t)$ spans thewhole subspace generated by the steering vectors. This is the"signal subspace." Assuming $d < M$ and no antenna ambiguity,the signal subspace dimension is d, and consequentlythe number of nonzero Eigenvalues of $\mathbf{R}y$is equal to d, with$(M - d)$ Eigenvalues being zero.Now, in the presence of white noise, according to (2), $\mathbf{R}x$ has the same eigenvectors as $\mathbf{R}y$, with Eigenvalues $\lambda x = \lambda y + \sigma^2$and the smallest $(M-d)$ Eigen values equal to σ^2. Then, fromthe spectrum of $\mathbf{R}x$ with Eigenvalues in decreasing order, it becomes easy to discriminate between signal and noise Eigenvaluesand order determination would be an easy task.In practice, $\mathbf{R}x$ is unknown and an estimate is made using $\mathbf{R}x = (1/N)Nt{=}1\ \mathbf{x}(t)\mathbf{x}(t)H$, where N is the number ofsnapshots available. As$\mathbf{R}x$ involves averaging over the number of snapshots available $\mathbf{R}x \rightarrow \mathbf{R}x$, as $N \rightarrow \infty$, resulting inall the noise Eigenvalues being equal to $\sigma 2$. However, when taken over a finite number of snapshots, the sample matrix$\mathbf{R}x$ $!= \mathbf{R}x$. In the spectrum of ordered Eigenvalues, the "signalEigenvalues" are still identified as the d largest ones. But, thenoise Eigenvalues are no longer equal to each other, and theseparation between the signal and noise Eigenvalues is notclear (except in the case of high SNR, when a gap can beobserved between signal and noise Eigenvalues), making discriminationbetween signal and noise Eigenvalues a difficulttask.

Step 7: Known-spectrum reconstruction

The presentation of the reconstruction is simplified using CS sparsity notation. A vector v is called K-sparse ifthe number of non-zero values in v is no greater than K. Using the ℓ0 pseudo-norm the sparsity of v is expressedas kvk0 ≤ K. We use the following definition of the Kruskal-rank of a matrix

4. Result and Discussion:

The results that are obtained by our channel spectrum sensing by subspace estimation algorithm. The fig 2 shows that a signal is generated as x(t) having summation of three sinc functions at different time delay 'ti' and instantaneous frequency fi with following parameters:

x(t) = ∑Ei(n)1/2*Bi(n)) * sinc(Bi(n)*(t-ti(n))).* exp(2j*pi*fi(n)*t);

fi=[5.2 11.4 16.6] Mega hertz; ti = [12 26 38]; Ei = [4 4.8 3.6 5.2]
Bi=0.9 ;Fs=20; (Sampling frequency)
T=0.05 sec; (Sample time);LL = 1024; (Length of signal)

ISSN: 2454-6844

t = 0 to 51.5sec ; (Time vector representing);NFFT = Next power of 2 from length of x

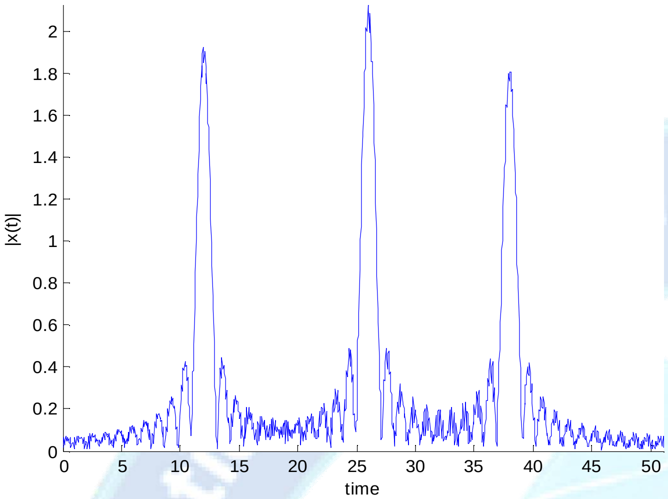

Fig 2. Time domain plot of signal x(t) having multiple frequencies.

Fig. 3 shows the original noisy signal and the reconstructed signal using column restriction matrix. In this figure the MSE value is also shown having value of 3.8% approx. We can observe that original signal is in blue color with noise and reconstructed signal is in red both are complete superimposing thus it represents perfect signal reconstruction and the detected active channels are 5th,6th,12th,13th,17th and 18th and uncertainty ratio of 0.19027**.**

Justification of the values of Fs=20MHz and BW=20MHz chosen for result analysis:

The channel bandwidth is considered to be 0.9 MHz hence there are approx 20/0.9MHz channels i.e. 22 channels are allocated in the frequency range of 0 to 20 MHz at the bandwidth of 0.9MHz. Thus the instantaneous frequencies are since {5.2 11.4 16.6} MHz so the bandwidth associated with these channels are Bi= 4.75 to 5.65, 10.95 to 11.85 and 16.15 and 17.05 Mhz. The total no. of active channels are N=3 thus the maximum channel occupancy are $\Omega_{max}=N_{max}/L=0.135$ and maximum number of active channels are L=Fs/B=22.The maximum number of active channel cells are p=7 for α sub Nyquist factor =p/L and $\alpha>\Omega_{max}$..

Sampling Frequency Vs Uncertainty Ratio:

In this proposed thesis, the value of sampling frequency that we have taken is Fs=20MHz. We took different observation of simulations below the value of Fs=20. The graph showed in fig. 4, reflects the continuous increase in uncertainty ratio. As well as, the value of sampling frequency above Fs=20 MHz also gave the regular increase in the value of uncertainty ratio. Therefore, the relevant result of simulation that we observed was in the range of Fs between 15 to 20MHz. So in this proposed thesis of wideband spectrum sensing using multi-coset sampler in cognitive radio, we have chosen the value of Fs=20MHz for getting the relevant result of detection of active channels with at least value of uncertainty ratio.

Bandwidth Vs Uncertainty Ratio:

In this proposed thesis, the value of bandwidth that we have taken is B=0.9MHz for detecting the active channels. On varying the value of bandwidth, the value of uncertainty ratio also varied continuously as shown in fig. 5. Here the variation of bandwidth that we took was of step length 0.2 to 2. We took the values of uncertainty ratio at the various values of bandwidth below 0.9 and observed that the uncertainty ratio varied a lot. On the other hand, uncertainty ratio above 0.9 was relevant and useful in an opportunistic manner.

So, we took the value of bandwidth 0.9MHz for the detection of active channels at least value of uncertainty ratio.

5. Conclusion:

We suggested a method to reconstruct a multi-band signal from its samples when the band locations are unknown. The development enables a fully spectrum-blind system where both the sampling and the reconstruction stages do not require this knowledge. The main contribution is in proving that the reconstruction problem can be formulated as a finite dimensional problem within the framework of sensing at lower sampling rate. Conditions for uniqueness of the solution and algorithms to find it were developed based on known theoretical results and algorithms and literatures. In addition, we proved a lower bound on the sampling rate that improves on the Landau rate for the case of spectrum-blind reconstruction. One of the algorithms we proposed indeed approaches this minimal rate for a wide class of multi-band signals characterized by the number of bands and their widths. Numerical experiments demonstrated the trade-off between the average sampling rate and the empirical success rate of the reconstruction. The work composed of a compressive wide-band spectrum sensing method operates on the received analog signal. Spectrum estimation is done based on multicoset approach based reconstruction by the use of autocorrelation function of the resulting compressed signal. The estimated spectrum is applied for detecting the spectrum occupancy of the system. Performance evaluation is performed by MSE and probability of detection proves that the proposed scheme performs comparably to the other past scheme. It proves that loss in incoherence due to lower sampling rate does not significantly distort the spectrum estimation and spectrum occupancy measurements.

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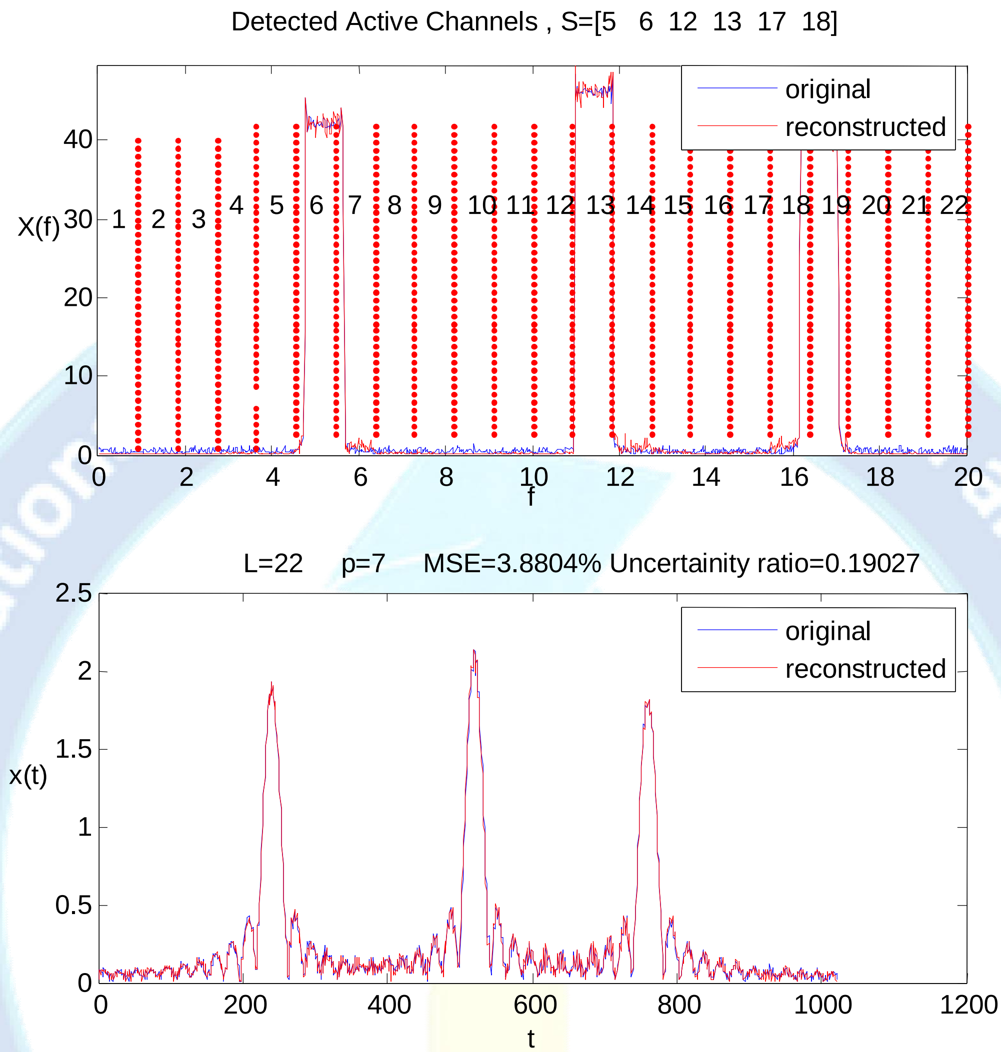

Fig. 3. Reconstructed signal obtained using the interpolation in frequency domain (top) and time domain (bottom).

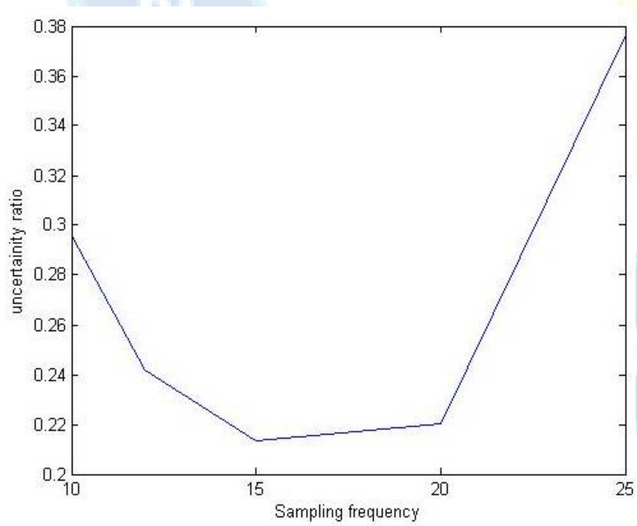

Fig. 4. Graph of variation of Uncertainty Ratio on changing the Sampling Frequency

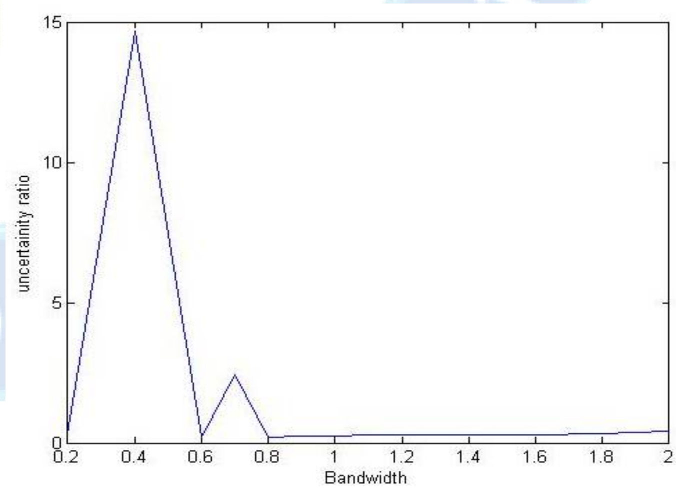

Fig. 5. The graph of variation of uncertainty ratio vs bandwidth

ISSN: 2454-6844

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