Journal of Theoretical and Applied Information Technology
15th March 2022. Vol.100. No 5
2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

BROADBAND SPECTRUM CHANNELS SENSING FOR CO-OPERATIVE NETWORK USING SUB SAMPLING SUBSPACE ESTIMATION APPROACH

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ABSTRACT

Focus of this article on the scheme of sensing of spectrum for co-operative communication for cognitive radio applications to face issues of sensing of spectrum at sampling rate with high values signal having broadband. Under broadband sensing of the spectrum scenario a model developed in for applying concept of a scheme based on sub sampling for reducing the need of high sampling frequency in sensing of spectrum. Noise added to transmission antenna side and the finite samples correlation evaluation performed for finding the channels occupancy in estimation of subspace of spectrum.

Keywords: *Co-Operative Network, Sensing Of Spectrum, Allocation Of Band, Cognitive Radio*

1. INTRODUCTION:

In cooperative network communication multiple antenna based system decision of the number of received signals by an antenna array is very significant for the estimations of spectrum. The process for determining the number of sources gives estimates of finding direction at high-resolution. The model order selection scheme is applied to estimate the number of sources by determining he number of covariance matrix eigen values [1]. This method is based on rank reduction algorithm incorporating the steps of elimination of the components of noise using the information of eigen values [2, 3]. For a limited amount of observed data set a method of "modified statistics" [4] and a priori on the probability density function of observation [5] is applied to detection of the number of sources. The information theory features are determined by performing[6] the minimum description length (MDL) [8–10]& Akaike information criterion (AIC) [7] schemes. Akaike information criterion is dependent on data and the minimum description length involves the free parameters number. Its results have inconsistency & issues of over-estimation while the response of MDL is under-estimated but consistent.The objective covered under this work are described as the development of a scheme that detect the status of spectrum by applying a sampling approach for wide-band signal that produce sampled data from analog signal at the information rate. After the sampling at the compressed form the estimation of spectrum performed. The spectrum density (PSD) calculated by mean squared error (MSE) and the probability of occupancy of spectrum.

2. METHODOLOGY

This approach follows an idea of visualizing the entire spectrum into multiple sub-bands. The border of each sub-band represents the variation in the spectrum occupancy. If a user utilizes a spectrum then it treated as occupied otherwise vacant. The boundary of a spectrum considered as the edges and wavelet transform applied to detect these edges of spectrum. In this research design first of all the analog signal at receiving end is passed through sampling at above the Nyquist frequency to obtain the signal in discrete format. After the sampling process, the autocorrelation is calculated by applying the averaging of the several segments of the signal. The discrete signal is made ripple free by eliminating high frequency components after applying the wavelet-based smoothing. The ripple free discrete data is smooth and less sensitive to detection errors. The smoothening is then followed by obtaining the power spectrum density using the Fast Fourier Transform. The derivative (first-order difference) of the power spectrum density used to obtain the information of the edges of the spectrum. Finally the compressive sampling is performed and edge spectrum is obtained by solving the compressive

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

sampling reconstruction problem. These information of edges are used to obtain the estimate of the wide-band spectrum.This paper considered antenna array of M receiver sensing the electromagnetic wavesof d narrow-band sources as the transmitting antenna . Suppose $\mathbf{a}(\theta)$ vector represents the values of complex gains at location θ in between source to the M receivers. $\mathbf{x}(t)$ vector of dimension $(M \times 1)$ is the sum of emitted signal $(d \times 1)$, known as s(t), and circular Gaussian complex additive noise is $\mathbf{n}(t)$ having distribution function $N(0, \sigma^2\mathbf{I})$ such that [13 to 18]:

$$\mathbf{x}(t) = \mathbf{As}(t) + \mathbf{n}(t) = \mathbf{y}(t) + \mathbf{n}(t), \qquad (1)$$

From equation (1), the covariance matrix $\mathbf{R}x$ *of* observation data set is represented as:

$$\mathbf{R}_x = E[\mathbf{x}(t)\mathbf{x}^H(t)] = \mathbf{R}_y + \mathbf{R}_n = \mathbf{AR}s\mathbf{A}^H + \sigma^2\mathbf{I}. \qquad (2)$$

Signals with the Multi-band have an additional structure in the frequency band. The sampling scheme is depending on sampling rate, set of multi-band signal and blindness (no knowledge of band locations). A sampling rate minimum value for best reconstruction of signals multi-band is termed as Landau rate [1].It is obtained by summing all the band widths[2]. For the band pass signals the minimal rate for perfect reconstruction should be more than the 2B samples per second.[19,20]

Alower bound of minimum sampling rate is determined in this work that applies for appropriate blind reconstruction. Lower bound is taken to be twice of Landau rate and lower to the Nyquist rate. spectrum-blind reconstruction (SBR) method is implemented in this work with multi-coset blind sampling scheme assumptions at the minimum sampling rate. It is shown that the results obtained at unique sparsest solution matrix from Multiple-Measurement-Vectors [8]. M as a subset is considered with maximum number of bands and the widest bandwidth is use to get the parameters of the multi-coset reconstruction of signals perfectly. The sparsest solution is found[11,12]with sub-optimal efficient [15,16,21,22,23,24].

Table 1.Notations

X(t)	Continuous time signal with finite energy
X(f)	Fourier transform of x(t)
a[n]	Bounded energy sequence
Z*	Conjugate of complex number z
v	Vector
v(i)	ith entry of v
v(f)	Vactor that depends on a continuous parameter f
A	Matrix
A_{ik}	ikth entry of A
A^T,A^H	Transpose and conjugate transpose of A
S	Finite or countable set
S_i	ith element of S
$\lvert S \rvert$	Cardinality of a finite set S
T	Infinite non countable set
$\lambda(T)$	The lebesgue measure of $T \subseteq R$

The ℓp norm for v is expressed as:

$$\|v\|^p{}_p = \sum_i |Vi|^p, \quad p \geq 0 \qquad (3)$$

The value p is2andℓ$_2$ norm of v is represented as||v||. $A_i$is i^{th} column of A, $(A^T)_i$ represents the i^{th} row of A. For vectors and matrices the indicator sets are respectively defined as:

$$I(v) = \{k \mid v(k) \neq 0\}, \quad I(A) = \{k \mid (A^{T)})_k \neq 0\} \qquad (4)$$

I(v) : indices of non-zero values in v. I(A) : indices are non-identical zero rows in A. A_S: matrix having columns of A with indices associated with set Sand named as*(columns) restriction* of A to S.

$$(A_S)_i = (A)_{Si}, \quad 1 \leq i \leq |S| \qquad (5)$$

In same manner A to S *rows restriction* is named as A_S.

M is band limited multi-band signals with F =[0, 1/T] having N maximum number of bands having B as band widths upper limit(see in Figure 1).

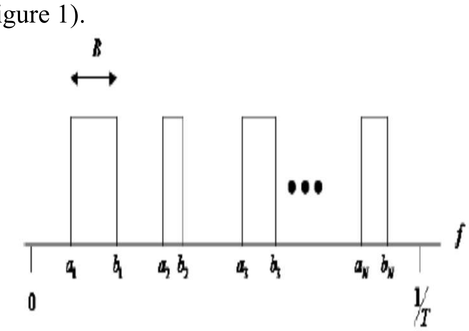

Fig.1. Band spectrum for signal of x(t) ∈M.

For signal $x(t) \in M$ the Nyquist rate is 1/T and FFT of M is union of disjoint intervals in F having limits $[a_i, b_i]$. For reconstructing x(t) perfectly two constraints are followed (1) the blindness in such a manner that band locations information cannot utilized on acquiring of the samples and also cannot applied during process of reconstruction and (2) minimal sampling rate. Landau's theorem is applied in this work for defining minimal sampling rate.
To achieve this objective bandlimited functions is applied under the restriction for support vector $T \subseteq F$:

$$B_T = \{x(t) \in L^2(R) \mid \text{suppport vector } X(f) \subseteq T\} \quad (6)$$

Sampling for x(t) follow over a known countable set at pointer location of $R = \{r_n\}$. The R is a set named *as sampling set* of B_t, such that x(t) from the discrete samples $x_R[n] = x(t = r_n)$for reconstructing perfectly . The stable process of reconstruction dependent on the limit of $\alpha > 0$ and $\beta < \infty$ and follows the condition:

$$\alpha\|x-y\|^2 \leq \|xR-yR\|^2 \leq \beta\|x-y\|^2,\ \forall x,y \in B_T \quad (7)$$

As per the Landau theorem [1] if B_T has sampling set of value R then it will consist of a density value $D(R) \geq \lambda(T)$, follows the relation:

$$D(R) = \lim_{r\to\infty} \inf_{y \in R} \frac{|R \cap [y, y+r]|}{r} \quad (8)$$

Known as lower limit of the Beurling density, and $\lambda(T)$ is known as the Lebesgue measurement of T . The numerator in equation covers the counts of the number of points in R at every interval of size r of the real axis. The obtained resultant is called as the minimum *average* sampling frequency required for the B_T , at Landau rate $\lambda(T)$.
The next part is developing of the unknown spectrum support. To accomplish it a set N is taken for band limited signals F given as:

$$\lambda(\text{supp } X(f)) \leq \frac{\Omega}{T},\ \ \forall\, x(t) \in N_\Omega \quad (9)$$

The minimal sampling frequency for N cannot be lower than T because it is the Landau rate for the known spectrum support. The blind sampling set R for N is the set of samples having a design that do not have knowledge of supp{X(f)}.
The stability concerns says that R requires $\alpha > 0$ and $\beta < \infty$ such that:

$$\alpha\|x-y\|^2 \leq \|xR-yR\|^2 \leq \beta\|x-y\|^2,\ \forall x,y \in N_\Omega \quad (10)$$

For the minimum sampling frequency for the R a blind samples set for N as D(R) is given by:

$$D(R) \geq \min\left\{\frac{2\Omega}{T}, \frac{1}{T}\right\} \quad (11)$$

The next partis the generation of the multiple co-set of sampling structures[8].x(t) at sampling on Nyquist rate is given as $x(t = n.T)$ consisting the information of x(t). Multiple co-set developed by selection ofspecific samples. For this purpose the signal is divided insegments of size L. Set C ofsize p at indices of p samples is kept in each block of segmented with rest of the elements value to be zero. C = {ci}pi=1 is the sampling pattern given by $0 \leq c_1 \leq c_2 \leq \ldots\ldots\ldots\ldots \leq c_p \leq L-1$.
i th sample sequence for $1 \leq i \leq p$ is defined by-

$$xci[n] = \begin{cases} x(t = nT),\ n = mL + ci, forsomem\epsilon Z \\ \quad\quad 0,\ otherwise \end{cases} \quad (12)$$

The samplesare takenat p intervalsof 1/(LT)time period. Here the address of i^{th} sample shiftsis c_iT. Themethodsof co-set sampling are based onL, p and C (pattern of sampling)parameters.
The L, p,C as parametersare mainly found at which perfect reconstruction ofX(f) occurs. In matrix form:

$$[y(f)] = [A].[x(f)] \quad (13)$$

$Xci^{(ej2\pi fT)}$: DTFT ,y(f) : vector with i^{th} value is $Xci^{(ej2\pi fT)}$; x(f): contains L unknowns for each f

$$x_i(f) = X\left(f + \frac{i}{LT}\right) \quad (14)$$

The matrix A depends on parameters L, p and Cdefined as:

$$A_{ik} = \frac{1}{LT} exp\left(j\frac{2\pi}{L}ci * k\right) \quad (15)$$

For a samples of multiple co-set set the average rate of sampling is:

$$\frac{1}{Tavg} = \frac{p}{LT} \quad (17)$$

Statistical tests appliedfor better result using the significant eigen value.If**y**(*t*) is a signal without noisespanning a subspace producedthrough

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

steering vectors.Then it is defined as the "signal subspace".Let$d < M$ (d:dimension of signal subspace)with nonzero eigenvalues of $\mathbf{R}_y$is equal to d, with $(M - d)$ zero eigenvalues. Ifeigenvalues of$\mathbf{R}x$ is arranged indecreasing order then eigenvalues of signal and noise can bediscriminated easily.The determination ofnumber of sources in presence of noise is performed by Rissanen's minimum description length (MDL) and Akaike information criterion (AIC) [7,8,10,23].Theyare usedtodiscriminate the coherent sources using correlation matrix **Rx** as different subspaces of noise and signal. MDLB applies maximum likelihood estimation (MLE). The AICmethod applies following expression [9].

$$\mathrm{AIC(m)} = -\mathrm{N(M-m)}\log\left(\frac{g(m)}{a(m)}\right) + \mathrm{m(2M-m)}, \quad (18)$$

g(m) & a(m): geometric and arithmetic means [26,27].

Finally the signal is reconstructed with the help of sparsity. A vector is K-sparse if the number of non-zero values in v is notmore than K. ℓ_0 pseudo-norm applied for expressing the sparsity [14].

If matrix A rank is givenas σ(A) then a maximumvalue q exist at which q columns of A is linearly independent. A prior on x(f) is used for recovery[8].The condition required for spectrum reconstruction is that $x(f)\, isp-sparse$.

3. RESULTS AND DISCUSSIONS:

In this paper the data sample that simulated here related to baseband having a wide frequency band from -40 to 40 MHz. It consists of ten non-overlapping channels of 8 MHz bandwidth. These channel types used for licensed system transmission signal under OFDM modulation standard followed under the Digital Video Broadcasting-Terrestrial (DVB-T). In this data the generated 8 MHz OFDM symbol consist of 8192 frequency tones with a length of cyclic prefix band is 1024 for one OFDM symbols is associated for spectrum sensing. The over-sampling factor of 16 times is applied. The occupancy ratio is 50%, it means that half of the channels occupied by licensed transmission signals and the remaining 50% channels kept vacant.In this sectionthe results are given for channel spectrum sensing usingalgorithm of subspace estimation. A signal is generated as x(t) generated by antenna and given as:

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

fi=[5.20 11.40 16.60] MegaHz; Ei =[4.0 ;4.8.0 ;3.60];ti = [12.0 26.0 38.0]; Ei =[4.0 ;4.8.0 ;3.60]
Bi=[0.90 0.90 0.90]; Sampling frequency,Fs=20Mega Hz
LL(Length of signal)= 1024; t = 0 to 51.5 sec ; (Time vector); NFFT = Number of FFT points

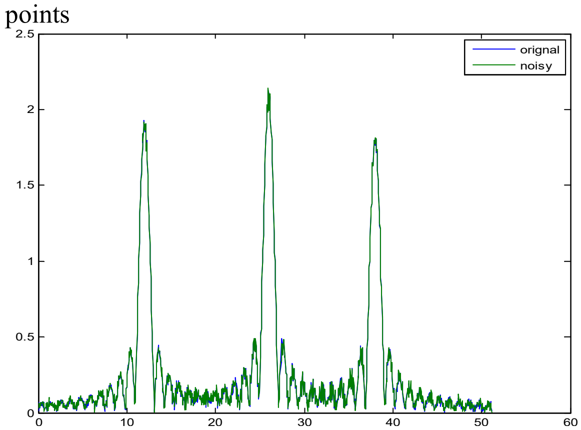

Figure 2: signal x(t) in time domain withdifferent frequencies without (blue original) and with (red noisy)noise.

In figure 1 originals signal (blue line)and plots of noisy signal (red line) is shown. Figure 2represents thefrequency domain spectrum X(f) . In the x-axis frequency varies from 0 to 20MHz with the peak is representing the three frequencies present in the x(t).
The representationof the frequency spectrum (figure 2) at frequencies {5.20MHz ,11.40 MHz,16.60MHz }.
The channel bandwidthis 0.90 MHz and total channels width is 20Mhz thus the number of channels are 22 allocated within these frequency band ranging from 0 to 20 MHz at0.9 MHz bandwidth. It is assumed that on average active channels areN=3 then maximum occupancy of channel isΩ_{max}=N_{max}/L=0.135 and maximum possible active channels is L=Fs/B=22 and the maximum active cells of channels are p=7 for α sub Nyquist factor =p/L and α> $\Omega_{max.[]}$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

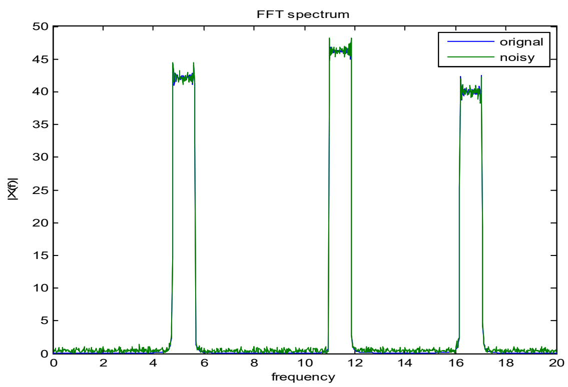

Figure 3: Instantaneous frequency value of x(t) shown in frequencydomain.

The active channels are to be determined for the multiple co-set sampling [25,26,27.28,29]. Thesignal is sampled at frequency above the Nyquist rate. In multiple co-set sample approach certain samples are selected. Signal is divided in the blocks of consecutive samples. A set C consist the address of p samples which are taken out from transmitted data and knownas the sample pattern. If S support vector is taken as [5 6 12 13 17 18] with the parameter L=22 and the value of p=7 for equation:

y(f) =A . x(f)

matrix A is described as:

$$A_{ik} = \frac{1}{LT}\exp(j\frac{2\pi}{L}c_i k)$$

$A_S$consisting thecolumns of A havingaddress that are associated toS. The matrix A_S is columns restriction of A to S.

Sample sequence Pattern by Multicoset Sampling Approach:

(a) **For m=1 and h=1 to 21 the condition index are:**

m= 1 h= 1 C = 0 1
condition index= 1.2791
m= 1 h= 2 C = 0 2
condition index= 1.2791 1.5018
m= 1 h= 3 C = 0 3
condition index= 1.2791 1.5018 1.7446
m= 1 h= 4 C = 0 4
condition index= 1.2791 1.5018 1.7446 2.1388
m= 1 h= 5 C = 0 5
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017
m= 1 h= 6 C = 0 6
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982
m= 1 h= 7 C = 0 7
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982 1.3349
m= 1 h= 8 C = 0 8
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982 1.3349 1.1139 1.3107 1.0625 1 1.0625 1.3107 1.1139 1.3349 1.4982 1.5017
-
-
-
-
m= 1 h= 18 C = 0 18
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982 1.3349 1.1139 1.3107 1.0625 1 1.0625 1.3107 1.1139 1.3349 1.4982 1.5017 2.1388
m= 1 h= 19 C = 0 19
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982 1.3349 1.1139 1.3107 1.0625 1 1.0625 1.3107 1.1139 1.3349 1.4982 1.5017 2.1388 1.7446
m= 1 h= 20 C = 0 20
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982 1.3349 1.1139 1.3107 1.0625 1 1.0625 1.3107 1.1139 1.3349 1.4982 1.5017 2.1388 1.7446 1.5018
m= 1 h= 21 C = 0 21
condition index= 1.2791 1.5018 1.7446 2.1388 1.5017 1.4982 1.3349 1.1139 1.3107 1.0625 1 **1.0625** 1.3107 1.1139 1.3349 1.4982 1.5017 2.1388 1.7446 1.5018 1.2791

Minimum condition index and sample pattern value:
C_ls = 0 11 (condition indices) and
ka1 = 1(sample pattern value)

(b) **Then m is incremented to 2 and h is re incremented from 1 to 20 the condition index are:**

m= 2 h= 1 C = 0 1 11
condition index= 1.2893
m= 2 h= 2 C = 0 2 11
condition index= 1.2893 1.6599
m= 2 h= 3 C = 0 3 11
condition index= 1.2893 1.6599 1.7715
m= 2 h= 4 C = 0 4 11
condition index= 1.2893 1.6599 1.7715 2.381
m= 2 h= 5 C = 0 5 11

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condition index= 1.2893 1.6599 1.7715 2.381 1.8398
m= 2 h= 6 C = 0 6 11
condition index= 1.2893 1.6599 1.7715 2.381 1.8398 1.8398
m= 2 h= 7 C = 0 7 11
condition index= 1.2893 1.6599 1.7715 2.381 1.8398 1.8398 2.381
m= 2 h= 8 C = 0 8 11
condition index= 1.2893 1.6599 1.7715 2.381 1.8398 1.8398 2.381 1.7715
m= 2 h= 9 C = 0 9 11
condition index= 1.2893 1.6599 1.7715 2.381 1.8398 1.8398 2.381 1.7715 1.6599
-
-
-
-
m= 2 h= 20 C =
0 11 21
condition index= 1.2893 1.6599 1.7715 2.381 1.8398 1.8398 2.381 1.7715 1.6599 **1.2893** **1.2893** 1.6599 1.7715 2.381 1.8398 1.8398 2.381 1.7715 1.6599 1.2893
Minimum condition index and smple pattern value:
C_ls = 0 11 12
ka1 = 1 1.2893

(c) Then **m is incremented to 3 and h is re incremented from 1 to 19 the condition index are:**
C = 0 11 12 21
condition index= 1.303 1.7303 2.0181 2.4308 2.2919 2.1181 3.4546 2.725 2.8943 1.8035 1.9106 2.5689 3.0393 3.5956 2.1427 3.1252 1.9907 1.7049 1.5141
Minimum condition index and smple pattern value:
C_ls = 0 11 12 1
ka1 = 1 1.2893 1.303

(d)**Then m is incremented to 4 and h is re incremented from 1 to 18 the condition index are:**
C = 0 1 11 12 21
condition index= 1.9539 2.9459 3.0872 5.4304 2.4384 5.4304 3.0872 2.9459 1.9539 1.9539 2.9459 3.0872 5.4304 2.4384 5.4304 3.0872 2.9459 1.9539
Minimum condition index and smple pattern value:
C_ls = 0 11 12 1 2
ka1 = 1 1.2893 1.303 1.9539

(e) **Then m is incremented to 5 and h is re incremented from 1 to 17 the condition index are:**
C = 0 1 2 11 12 21
condition index= 15.1102 4.67867 7.35175 4.69548 8.04797 4.71268 3.25345 2.36776 2.20901 3.20234 4.28406 9.07348 4.35777 8.14942 4.49705 32.2288 19.1998
Minimum condition index and smple pattern value:
C_ls = 0 11 12 1 2 13
ka1 = 1 1.2893 1.303 1.9539 2.209

(f) **m= 6 h= 1 to 16**
C = 0 1 2 3 11 12 13
condition index= 2.1253 2.1331 2.2561 2.5446 2.5446 2.2561 2.1331 2.1253 2.1253 2.1331 2.2561 2.5446 2.5446 2.2561 2.1331 2.1253
Minimum condition index and sample pattern value:
C_ls = 0 11 12 1 2 13 10
ka1 = 1 1.2893 1.303 1.9539 2.209 2.1253

Since NFFT=1024 and L=22 total no. of channels hence NFFT/L =45(approx.) samples are selected at given sequence numbers of C array which gives highet order of resemblance to matrix A. Thus p=7 data vectors known as cosets are generated at addresses C(1 to p) values to 1024 samples at a sample gap of L=22.Thus the sample addresses at which samples are collected are:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: Sample Pattern Sequence Generated as per condition index for restriction matrix.

Sample No.	Sample add. of coset 1	Sample add. of coset 2	Sample add. of coset 3	Sample add. of coset 4	Sample add. of coset 5	Sample add. of coset 6	Sample add. of coset 7
1.	1	2	3	11	12	13	14
2.	23	24	25	33	34	35	36
3.	45	46	47	55	56	57	58
4.	67	68	69	77	78	79	80
5.	89	90	91	99	100	101	102
6.	111	112	113	121	122	123	124
7.	133	134	135	143	144	145	146
8.	155	156	157	165	166	167	168
9.	177	178	179	187	188	189	190
10.	199	200	201	209	210	211	212
11.	221	222	223	231	232	233	234
12.	243	244	245	253	254	255	256
13.	265	266	267	275	276	277	278
14.	287	288	289	297	298	299	300
15.	309	310	311	319	320	321	322
16.	331	332	333	341	342	343	344
17.	353	354	355	363	364	365	366
18.	375	376	377	385	386	387	388
19.	397	398	399	407	408	409	410
20.	419	420	421	429	430	431	432
21.	441	442	443	451	452	453	454
22.	463	464	465	473	474	475	476
23.	485	486	487	495	496	497	498
24.	507	508	509	517	518	519	520
25.	529	530	531	539	540	541	542
26.	551	552	553	561	562	563	564
27.	573	574	575	583	584	585	586
28.	595	596	597	605	606	607	608
29.	617	618	619	627	628	629	630
30.	639	640	641	649	650	651	652
31.	661	662	663	671	672	673	674
32.	683	684	685	693	694	695	696
33.	705	706	707	715	716	717	718
34.	727	728	729	737	738	739	740
35.	749	750	751	759	760	761	762
36.	771	772	773	781	782	783	784
37.	793	794	795	803	804	805	806
38.	815	816	817	825	826	827	828
39.	837	838	839	847	848	849	850
40.	859	860	861	869	870	871	872
41.	881	882	883	891	892	893	894
42.	903	904	905	913	914	915	916
43.	925	926	927	935	936	937	938
44.	947	948	949	957	958	959	960
45.	969	970	971	979	980	981	982

The downsampled signals are assembled in a matrix having p rows and 45 columns consist of x (at lower sampling rate).

Journal of Theoretical and Applied Information Technology
15th March 2022. Vol.100. No 5
2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2: Downsampled signal sets obtained after applying multi coset sampling (initial 50 samples out of 1024 samples.)

Sample No.	1st Sampled Sequence	2nd Sampled Sequence	3rd Sampled Sequence	4th Sampled Sequence	5th Sampled Sequence	6th Sampled Sequence	7th Sampled Sequence	Original signal x(t)
1.	0.015	0	0	0	0	0	0	0.0153
2.	0	0.057	0	0	0	0	0	0.0574
3.	0	0	0.042	0	0	0	0	0.0418
4.	0	0	0	0	0	0	0	0.0365
5.	0	0	0	0	0	0	0	0.0672
6.	0	0	0	0	0	0	0	0.0732
7.	0	0	0	0	0	0	0	0.0309
8.	0	0	0	0	0	0	0	0.0637
9.	0	0	0	0	0	0	0	0.0329
10.	0	0	0	0	0	0	0	0.0671
11.	0	0	0	0.05802	0	0	0	0.058
12.	0	0	0	0	0.034	0	0	0.0343
13.	0	0	0	0	0	0.05624	0	0.0562
14.	0	0	0	0	0	0	0.05	0.046
15.	0	0	0	0	0	0	0	0.0258
16.	0	0	0	0	0	0	0	0.0377
17.	0	0	0	0	0	0	0	0.019
18.	0	0	0	0	0	0	0	0.021
19.	0	0	0	0	0	0	0	0.0391
20.	0	0	0	0	0	0	0	0.0332
21.	0	0	0	0	0	0	0	0.0252
22.	0	0	0	0	0	0	0	0.0693
23.	0.029	0	0	0	0	0	0	0.0289
24.	0	0.023	0	0	0	0	0	0.023
25.	0	0	0.069	0	0	0	0	0.0688
26.	0	0	0	0	0	0	0	0.0483
27.	0	0	0	0	0	0	0	0.0461
28.	0	0	0	0	0	0	0	0.0781
29.	0	0	0	0	0	0	0	0.0718
30.	0	0	0	0	0	0	0	0.0632
31.	0	0	0	0	0	0	0	0.0821
32.	0	0	0	0	0	0	0	0.074
33.	0	0	0	0.06325	0	0	0	0.0633
34.	0	0	0	0	0.063	0	0	0.063
35.	0	0	0	0	0	0.06007	0	0.0601
36.	0	0	0	0	0	0	0.03	0.0255
37.	0	0	0	0	0	0	0	0.0694
38.	0	0	0	0	0	0	0	0.0065
39.	0	0	0	0	0	0	0	0.0476
40.	0	0	0	0	0	0	0	0.0151
41.	0	0	0	0	0	0	0	0.0236
42.	0	0	0	0	0	0	0	0.026
43.	0	0	0	0	0	0	0	0.0049
44.	0	0	0	0	0	0	0	0.0359
45.	0.07	0	0	0	0	0	0	0.0703
46.	0	0.017	0	0	0	0	0	0.0166
47.	0	0	0.055	0	0	0	0	0.0547
48.	0	0	0	0	0	0	0	0.0704
49.	0	0	0	0	0	0	0	0.0493
50.	0	0	0	0	0	0	0	0.0642

Table 2 showing thesmall portion of downsampled signal. It shows seven co-set of the sequences which are in 2nd to 7th column at the samplingindexat C =[0 1 2 10 11 12 13] .The sample at these index capable of providingmaximumreconstruction resemblance alongfrequency and time domain. Figure 5is showing the noisy signal of x(t) after the downsampling.

Journal of Theoretical and Applied Information Technology
15th March 2022. Vol.100. No 5
2022 Little Lion Scientific

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

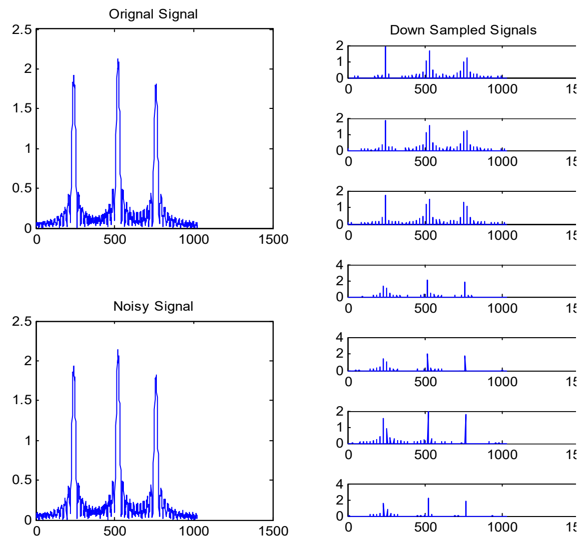

Figure 4: Original signal(top left side) noisy signal (down left side) , downsampled sequences 1 to 7 (right).

The downsampled signal are passed through the low passé FIR filter for acquiring the interpolated sequence.
The down sampled signals multi coset are convolved to the filterimpulse response to obtain reconstructed signals.

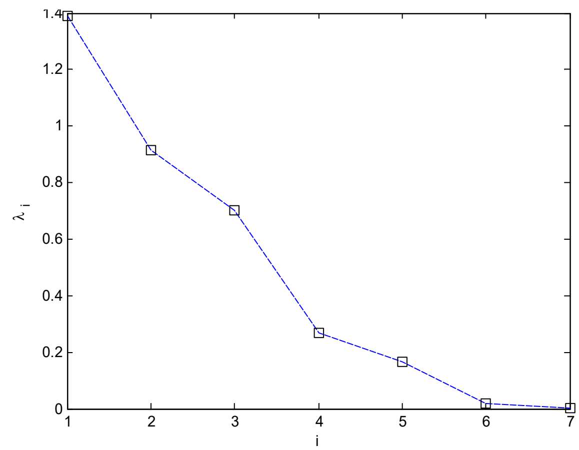

Figure 5: Auto correlation matrix of the co-sets eigen values (λ_i) arranged indecreasing order. Multiple cosetes matrix After auto correlation matrix is calculated (R_{xx}) for obtaining the eigen values in set of descending order (figure 7).

Table 3: Multi coset data used to get autocorelation matrix for finding low sampling rate

S.No	**a**	**b**	**c**	**d**	**e**	**f**	**g**
i	0.480	-0.12+ 0.010j	-0.080-.030j	-0.150- 0.20j	0.160 + 0.010j	-0.160 + 0.180j	0.20 + 0.020j
ii	-0.120- 0.0170j	0.490	-0.11 + 0.030j	0.20 - 0.030j	-0.150- 0.210j	0.160 + 0.0040j	-0.150 + 0.220j
iii	-0.080 + 0.030j	-0.110 - 0.030j	0.490	-0.160 - 0.040j	0.20 - 0.020j	-0.15- 0.210j	0.170 - 0.0120j
jv	-0.150 + 0.20j	0.20 + 0.030j	-0.160 + .0470j	0.50	-0.130 + 0.020j	-0.0990 - 0.030j	-0.280 + 0.240j
v	0.160 - 0.010j	-0.150 + 0.210j	0.20 + 0.020j	-0.130 - 0.020j	0.480	-0.10 + 0.020j	-0.0930- 0.040j
vi	-0.160 - 0.180j	0.160	-0.150 + 0.210j	-0.090 + 0.030j	-0.10 - 0.020j	0.480	-0.120 + 0.030j
vii	0.20 - 0.020j	-0.150 - 0.220j	0.170 + 0.010j	-0.280 - 0.240j	-0.090 + 0.040j	-0.120 - 0.0340j	0.50

Table 4: Auto correlation matrix Eigen vectors

						* Eigen Vector :EV	
S. No	**EV1**	**EV 2**	**EV3**	**EV4**	**EV5**	**EV6**	**EV7**
1	-0.030 - 0.10j	-0.520 + 0.03j	-0.020 - 0.20j	-0.120 - 0.50j	-0.150	0.130 + 0.460j	0.310 - 0.130j
2	0.060+ 0.140j	0.07- 0.030j	0.050 - .770j	0.030+ 0.10j	.190 + 0.270j	0.140+ 0.160j	-.350 + 0.250j
3	0.070j	-0.570 - .020j	- 0.04j	-0.020 + 0.40j	0.140 + 0.48j	-0.250 - 0.30j	0.280 - 0.05j
4	0.420 - 0.380j	-0.210 + 0.10 j	-0.020 + 0.09j	-0.410 + 0.17j	-0.110 - 0.13j	-0.320 + 0.180j	-0.30+ 0.340j

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5	0.40 - 0.06j	0.35 + 0.08j	-0.30- 0.11j	0.18 - 0.05j	-0.47 + 0.43j	-0.22 + 0.06j	0.15 - 0.24j
6	0.32 - 0.21j	-0.32+ 0.13j	0.16+ 0.15j	0.51 - 0.07j	-0.16 + 0.07j	0.49- 0.23j	-0.25+ 0.07j
7	0.55	0.23	0.40	-0.21	0.35	0.24	0.48

λ_i: Eigen values of R_{xx} = [0.0006240; 0.0180; 0.16650; 0.2670; 0.7030; 0.9140; 1.3890].

The AIC method applied to determine the order of a model using information theory. This criterion does not exactlypredict the actual number of sources. The MDL approach selects the model order which requires minimum code length needed for describing the data.

AIC =[1768.60 639.240 330.500 113.410 87.0380 72.2460]

The Number of AIC with significant values representing the non-zero sources are 6. Since total number of eigen vectors is seven and the signal vectors related to noise are represented by eigen vectors out off significant vectors given as neglecting significant 6 eigen vectors:

$$\text{Un}=\begin{bmatrix} -0.0383 - 0.101\square \\ 0.0638 + 0.142\square \\ -0.00311 + 0.0723\square \\ 0.427 - 0.381\square \\ 0.404 - 0.0672\square \\ 0.323 - 0.212\square \\ 0.558 \end{bmatrix}$$

Thus the signals representing only the noise component is obtained by matrix multiplication of A with Un shown as:

A.Un= [1.650 1.660 1.650 1.0470 0.9430 0.0120 0.0230 0.8840 0.6380 1.1240 0.5840 0.69300.01110 0.0230 0.5630 0.3150 0.6170 0.01030 0.01870 0.7850 0.95499 1.5230].

Thus the channels that representonly the signal are:

1./nUnA= [0.6020 0.6010 0.6040 0.9530 1.0580 92.070 44.850 1.1270 1.5650 0.889 1.708 1.439 90.68 43.09 1.773 3.158 1.614 95.930 53.001 1.272 1.048 0.655] .

The channel representation mentioned above are shown in the figure 7.

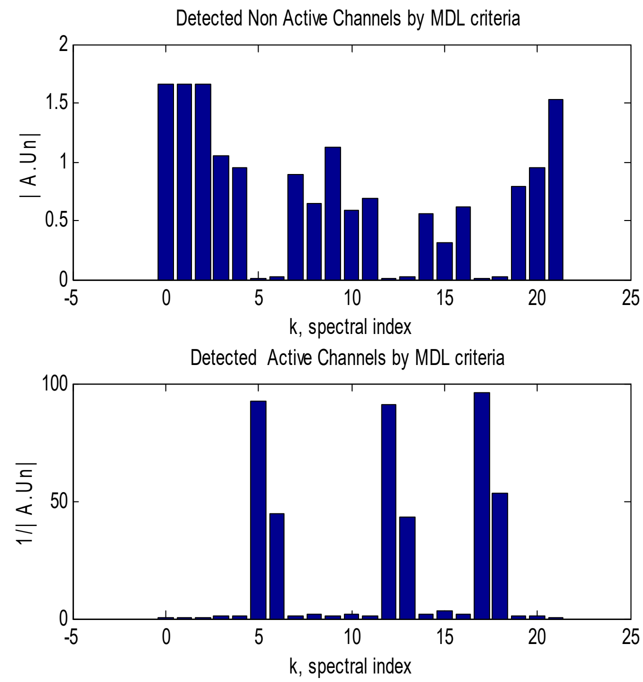

Figure 6: Representation of Noise channels (Top) and signal channel (bottom).

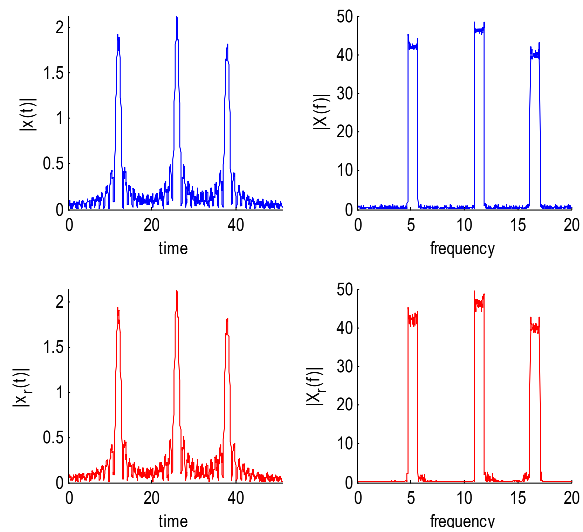

Figure 7: Original Signal with respect to time (top left) and frequency (top right) and the signal on reconstruction with respect to time (bottom left) and frequency (bottom right).

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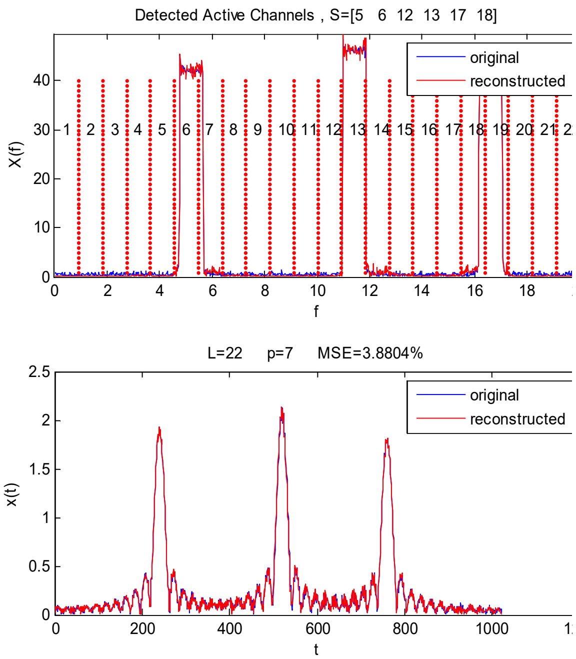

Figure 8: Signal after reconstruction obtained by the interpolating in (top) frequency domain &(bottom) time domain.

Figure 8 is showing the noisy data and the signal on reconstruction. It may be observed in this figure thatmean square error (MSE) isobtained to be 3.8% approx.Thus the error in between orginal and reconstructed signal is very small.Original signal is shown in the blue color plots with noist and reconstructed one is in red .These signals are perfectly superimposing on each other and the active channels which are detected has location index of 5^{th},6^{th},12^{th},13^{th},17^{th} and 18^{th}. The work was focused mainly for minimizing the error (MSE) in determining the status of channel occupancy but proposed scheme also helpful in improving the probability of false detection. Results are added for this probability along with the MSE.

Table 5	OMP Algorithm (2020) [30]	BPDN (2006) [31]	PKM (2021) [32]	Proposed Algorithm
MSE	1.4 to 1.1	1.1 to 0.6	0.8 to 0.2	0.3 to 0.01
P_{fa}			0.035	0.01
P_{de}			0.987	0.991
Probability of false alarm :P_{fa} Probability of detection: P_{de} Basis Pursuit De Noising Algorithm:BPDN Prior Knowledge Mining :PKM				

The results are comparing to the conventional methods of CS based on the autocorrelation of the discrete-time signal obtained by Nyquist-rate sampling. In proposed scheme, the CS directly performed on the wide-band analog signal. The results of simulation shows that compared to the OMP, BPDN and PKM algorithm the proposed scheme has the lowest value of MSE and the spectrum sensing performance evaluated as the probability of false alarm and the probability of correct detection best compared to other three schemes.

4. CONCLUSION:

This work is useful for applications related to the compressive wide-band sensing of spectrum operating on the DVB-T signal. Spectrum estimation performed using the multiple co-set schemes related to reconstruction using autocorrelation function of the resulting down sampled signal data. The spectrum estimation used for detection the occupancy of the spectrum in cooperative network system. Performance is evaluated in terms of MSE and detection probability for the proposed scheme comparable to the schemes used in past. Low value of estimation error describes that has the incoherence loss does not significantly disturbs the estimation process of the spectrum due to involvement of low value of rate of sampling. In future, we may hybrid the optimization techniques like genetic algorithm or particle swarm optimization for finding the multi-cosets with minimum estimation error for providing fast searching of sets.

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