Multi-User Spectrum Sensing based on Multi-Taper Method for Cognitive Environments

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ABSTRACT
This paper gives a brief but comprehensive review of the Multitaper spectrum estimation method that uses the data tapers or windows in digital signal processing. Instead of using a single kind of window functions, here a cluster of window functions are mentioned, which is known as Slepian tapers. This taper family minimize leakage also, and computing them requires solving eigenvalue problems that are large for long time series. However, the eigenvalue problems have a special structure that makes a fast algorithm possible.Secondly, the enabling of the algorithmic method with Cognitive Radio (CR) Technology, which is an advanced version of Software Defined Radio (SDR) Technology is discussed. SDR Technology is supposed to become a prevailing technology in the field of wireless communication. The Software Radio is an interesting area, in which the GNU Radio explores and then the Universal Software Radio Peripheral (USRP) formulates it. Here the paper also proposes the idea of constructing a block in GNU Radio Companion using the same algorithmic method in GNU Radio.

Keywords— Slepian tapers, Software Defined Radio, Cognitive Radio Networks, GNU Radio, USRP.

1. INTRODUCTION
There is a basic and primary trade-off in communication systems. Simple hardware can be used in case of transmitter- receivers for passing information. But a large portion of spectrum is needed for this, which can limit the number of users. Alternatively, same amount of information can be sent using more complex transmitters and receivers over less bandwidth.

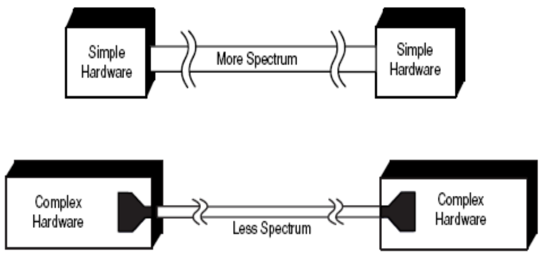

Figure. 1. The Fundamental Tradeoff in simplicity and bandwidth

So the complexity in hardware becomes more, for the transition to more and more spectrally efficient transmission techniques. But complex hardware is very difficult in case of designing, testing, and building. This trade-off exists whether communication is over air or wire, analog or digital.

Also the signal transmission in low frequency range becomes a problem when the antenna length becomes very large and there are high losses. So in such cases we have to perform the signal modulation for transmitting the signals over long distances. For effective transmission, the frequency should be large and the antenna length can be reduced by the equation, $\lambda = C / f$. Here the requirement of power is also less, when there is an increase in the frequency. According to the Shannon's theorem, $C = B \log (1 + s / n)$; where C is the channel capacity, B represents the bandwidth and s / n indicates the signal to noise ratio. In case of real time systems, multi-carrier systems can be used and here each channel will work at different carrier frequencies and they will be having different phases too for each path. This can affect the hardware and it may not be practicable to alter the hardware all the time. So we consider the case in which there is only little hardware like antenna only and the rest of the design, say the frequency, power etc. to be implemented in software without any additional cost. In such cases, Software Defined Radio is a good choice, in which simply modifying or replacing the software programs can completely change its functionality. Cognitive radio, which is the advanced version of SDR, is an immature but rapidly developing technology area that should, in time, offer great benefits to all members of the radio community from regulators to users. In terms of spectrum regulation, the key benefit of CR is more efficient use of spectrum, because CR will enable new systems to share spectrum with existing legacy devices, with managed degrees of interference. So for spectrum estimation, efficient spectrum estimation method is to be done.

In signal processing, a window function (also known as tapering function) is known as a function that is zero-valued only outside of a particular chosen interval. Windowing of a simple waveform, like cos(ωt) makes its Fourier transform in having non-zero values, which is commonly called spectral leakages, at frequencies other than ω. It tends to be highest near to ω and least at frequencies away from ω. If there are two sinusoids, with different frequencies, leakage can intervene with the ability to differentiate them spectrally. If their frequencies are unlike, then the leakage intervenes as one sinusoid is much smaller than the other in case of amplitude. That is, its spectral component cannot be revealed because of the leakage from the larger component. But when the frequencies are nearer, the leakage is enough to interfere even when the sinusoids are of equal strength; that is, then they become *irresolvable*.

The periodogram is the classical spectral estimator for stationary signals. Here rectangular windows are used. When it is asymptotically unbiased, it is subjected to high variance. In Thomson's Multiple-Window Method, for small, finite signals, Thomson suggested a heap of accurate bandpass filters or windows, instead of the rectangular windows as used in the periodogram method. These bandpass filters compute several periodograms of the whole signal. Then it averages the resulting periodograms in order to construct a spectral estimate. For obtaining a low bias and low variance estimate, the windows must be orthogonal. This is to minimize the variance within each window. For minimizing the bias during the selection of windows and are optimally concentrated in frequency. The optimal windows which satisfy these requirements for finite length signals are Slepian sequences or discrete prolate spheroidal sequences.

When we use Matlab to do simulation, it is believed that in order to write the code cleanly and efficiently, we need to memorize a number of Matlab built-in functions and tool boxes well and use them skillfully. The same applies to GNU Radio. About 100 frequently used blocks come with GNU Radio. For a certain number of applications, we can complete the designing using these existing blocks, programming only on the Python level, without the need to write our own blocks. So in this article, we will take a tour around the GNU Radio blocks.

2. SLEPIAN TAPERS

From the past records, Slepian functions and series are originally known as discrete prolate spheroidal wave functions or DPSWF. But discrete prolate spheroidal sequences or DPSS were known long before or around the 50's. In the 60's David Slepian and others published a number of papers which set up the discrete prolate spheroidal wave functions as the series of functions. It optimizes the energy concentration in both time and frequency at the same time, when either or both has a definite limit. This defines the dimensionality of a time–frequency region. But in fact, it was for continuous time and continuous frequency problems.

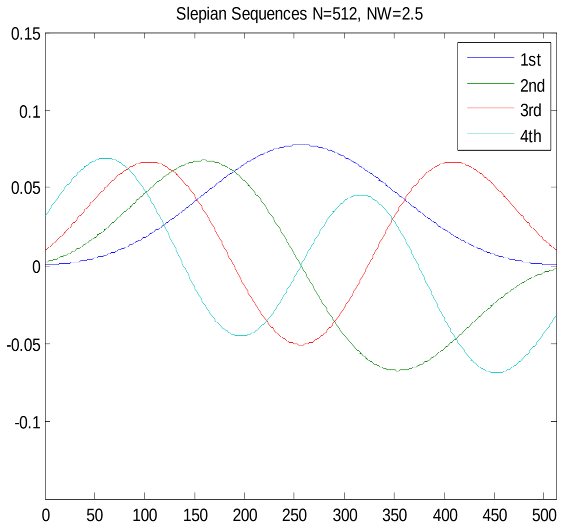

Figure 2. Slepian Sequences

Usually mathematical functions that are time or space limited cannot be simultaneously band limited (in frequency). The finite precision of the calculation and computation band limits our remarks and represents the scientific data. Often the studies and research are mainly based on which are specially bounded. In the geosciences we may be interested in spectrally modelling a time series defined only on a certain interval, or we may want to characterize a specific geographical area observed using an effectively band limited measurement device. It is clear that analysing and representing scientific data of this kind will be facilitated if a basis of functions can be found that are "spatiospectrally" concentrated, i.e. "localized" in both domains at the same time.

3. MULTI TAPER METHOD

The Multi-Taper method (MTM) [1] of spectral analysis provides a novel means for estimation of spectral components and reconstruction of the signal components of a time series. It refers to method for estimating coherence and related quantities using an orthogonal set of data tapers called Slepian Sequences. This is about to reveal a spectrum which contains both continuous and singular components. MTM comes under nonparametric spectrum estimation, in which it does not recommend a right (e.g., autoregressive) model for the process generating the time series under analysis. MTM tries to reduce the variance of spectral estimates by using a small set of tapers rather than the unique data taper or spectral window used by methods like Blackman-Tukey methods. A set of independent estimates of the power spectrum is calculated, by pre-multiplying the data with orthogonal tapers and they are constructed so as to minimize the spectral leakage due to the finite length of the set of data values. These optimal tapers are called "Eigen-tapers". They belong to a set of functions known as discrete prolate spheroidal sequences (DPSS) and are defined as the Eigen vectors of a suitable Rayleigh-Ritz minimization problem as in Fig. 2. Averaging out these small set of spectra produces a better and more stable estimation, which is of low variance than obtained using single-taper methods.

The tapers are the discrete family of Eigen functions which answer the variational problem of minimizing leakage outside of a frequency band of half bandwidth pf_n where $f_n = 1/N\delta t$ is the Rayleigh frequency, and p is an integer. For case, p=1, it reduces to the trivial Blakman-Tukey case of a single tapered Discrete Fourier Transform (DFT). Because the windowing functions or Eigen tapers are the specific solution to an appropriate variational problem, this method is less heuristic than traditional nonparametric. The choice of the bandwidth $2pf_n$ and number of tapers K thus represents the classical trade-off between spectral resolution and the stability or "variance" properties of the spectral estimate.

Multitapering [5] is a part of single taper approaches which consists of classifying the data into overlapping elements. These elements are each individually tapered, then Fourier transform is performed. The individual spectral coefficients of each subset elements are averaged in order to reduce the variance. The classification of the data is done by a set of tapers indexed by $l = 1....L$, the estimated spectral density at frequency bin f is then given by the equation (1), where $S_l(f)$ is the estimated density of spectrum using taper l and λ_l are the weights of each tapered spectral density calculation.

$$S(f)=\frac{\sum_{l=0}^{L-1} \lambda l\, Sl(f)}{\sum_{l=0}^{L-1} \lambda l} \qquad (1)$$

In the single-window approaches the spectral density is smoothed, by not losing any information at the time series end. Likewise, here multiple windows are used, which provides efficient smoothening of the spectral density. The windows are chosen as they are orthogonal to each other and reduce leakage as much as possible. Under these conditions the apt choice is this Discrete Prolate Spheroidal Sequences or Slepian sequences. The Slepian sequence treated is determined by the length of the time series N, and by a limit W which corresponds to the half-bandwidth (i.e. $w = 2\pi W$ is the half-bandwidth in radians). While using the Slepian sequences for obtaining $S_l(f)$, the weights λ_l used in equation (1) could be unity or something complex. As with the single taper approaches the limit W is chosen to balance the desired reduction in variance with minimizing the distortion of the spectral estimate.

During the processing of data, the introduction of the window function is unavoidable. When we increase the frequency spectrum's resolving power and decrease its frequency spectrum leakage, the spectrum estimation's variance must increase and the stability becomes worse at the same time. Usually single kinds of window functions are chosen. But here in MTM based algorithm [1], an analysis method for spectrum estimation is used with low variance and high resolving power. In this algorithm, a cluster of window functions are used. By getting time sequence, first the time-bandwidth product, Co is to be chosen, where Co = NW in which N is the length of the window calculated in terms of time samples and W is the normalized bandwidth. The choice of this Co is a trade-off between spectral resolution and variance. Usually the values lies in between 3 and 6. For performing the spectral estimation we use K = (2Co-1).

The time sequences are constituted of each data window and they undergo Discrete Fourier Transform and thereby obtain its eigenspectrum function. Then weighted average to the eigen spectrum function is made and spectrum estimation is obtained. So it will be a smooth spectrum which has low variance. The idea of taking an average is to reduce the variance in the spectral estimate. The mean spectrum is not an ideal estimate and we prefer a weighted average instead, one that minimizes some measure of discrepancy. While the spectral leakage properties of the $Sˆ0$ eigenspectrum are very good, since the eigenvalues are close to unity when $K < (2NW – 1)$, the leakage characteristics of the successive estimates degrade. It is clear that by using $Sˆ$ = $|Y0|2$, the least amount of spectral leakage is achieved. Nevertheless, including the other eigen components (Y 1, Y 2, . . . , Y K), while increasing spectral leakage, reduces the variance of the spectral estimate and is thus preferred.

Also, this type of algorithm makes use of the Slepian sequences as data window cluster. The noticeable feature of Slepian sequences is that its Fast Fourier Transform has maximal energy concentration in the bandwidth, if the FFT is made in the requirement that there are finite numbers of sampling points. In this method, each Slepian sequence is used in all sample data. For wide band signal, Multitaper spectrum estimation almost reaches to nonparametric spectrum estimation's Cramer-Rao bound (CRB). So this method is recognized as the best by several people.

Here Fig. 3. explains the Multitaper spectrum estimation algorithm, where $x(t)$ is a time series, W^k_t , (k = 1,2,….K) is an orthonormal sequence of K Slepian sequences, the associated eigenspectrum defined by the Fourier transforms.

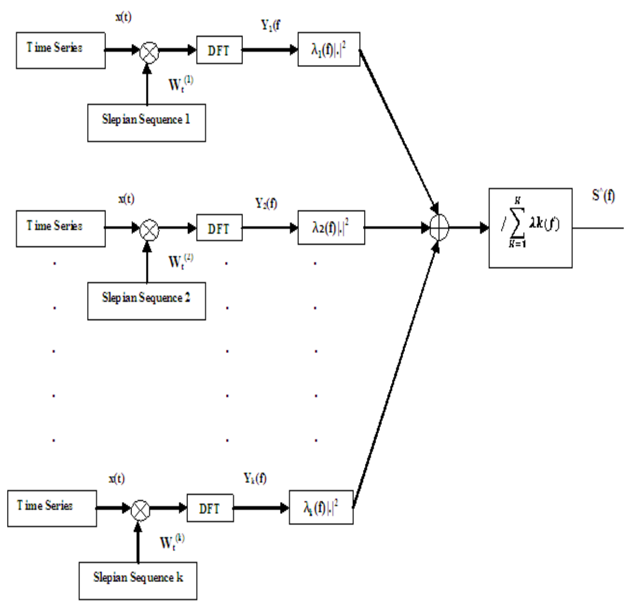

Figure 3. Multitaper spectrum estimation

$$Y_k(f) = \sum_{t=1}^{N} W_t^{(k)} x(t) e^{-j2\pi f} \qquad k = 1, 2 \cdots K \tag{2}$$

$$\hat{S}(f) = \frac{\sum_{k=1}^{K} \lambda_k(f) |Y_k(f)|^2}{\sum_{k=1}^{K} \lambda_k(f)} \tag{3}$$

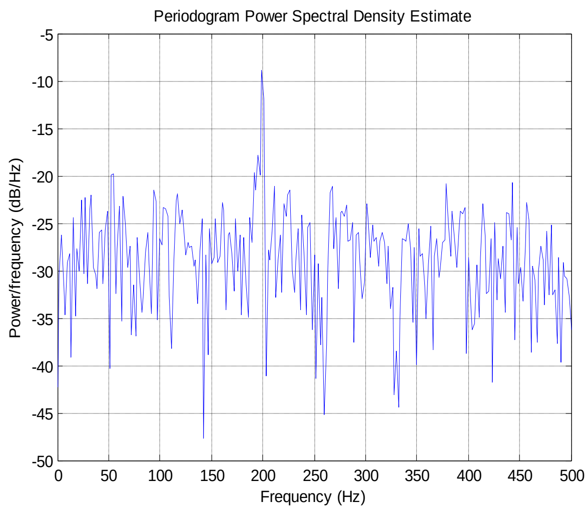

Figure 4. PSD Estimate of the received signal

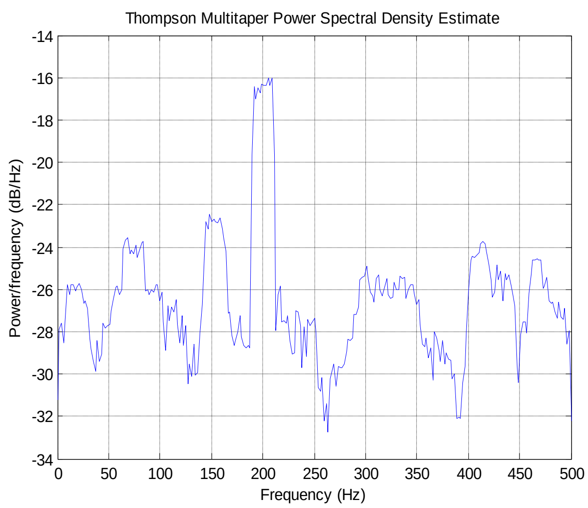

Figure 5. MTM PSD estimate

The received signal from a Cognitive enabled sensor will consists of a variety of signals with different modulation transmit over the same time or frequency, signals of different sensors are diverse in SNR and fading.

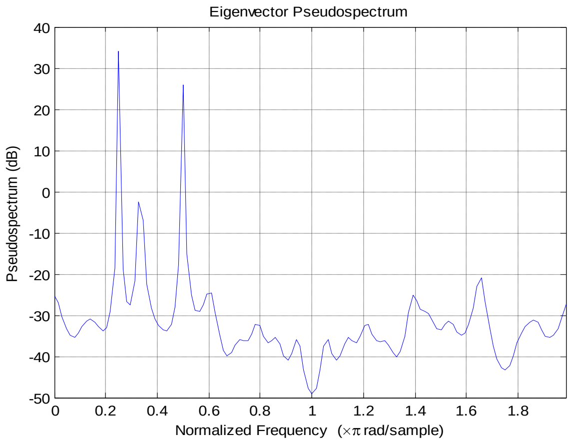

Figure 6. Eigenvector Pseudospectrum

Figure 4 is the power spectral density of that sensor signal, but it shows that estimating the "frequency spectrum hole" accurately and effectively is very difficult. Figure 5 is the eigenspectrum $Y(f)$. Multitaper spectrum estimation algorithm has the maximal energy concentration. The bandwidth which has signals has great peak value, but the smoothness is poor, this is not conducive for setting interference-temperature limit. Figure 6 is the estimation obtaining from a decomposition algorithm. It has good smoothness and stability and estimates the existence of "frequency spectrum hole" easily by the limit.

In many spectral analyses, it is advantageous to minimize out-of-band bias. To attain a further reduction of out-of-band bias, the average in equation (3) can be replaced with a weighted average with the weights taken to be either the Eigen values of the discrete prolate spheroidal sequences (the Eigen values are equal to the fractional in-band energy concentration of the discrete prolate spheroidal sequences), or adaptive weights can be found. The data taper of length N possessing the least fractional energy outside the frequency interval (−W,W), is the zeroth-order, discrete-prolate spheroidal sequence with dimensionless time-bandwidth parameter NW. That is, to obtain the direct-spectral estimate corresponding to the spectral estimator possessing the least spectral leakage bias, one first choses W. This choice sets the resolution of the estimate. For this example, let W be specified in units of Hz. Then, NW is obtained by,

$$NW = (N\Delta t)W \qquad (4)$$

where Δt is the sample period for the regularly sampled time-series. Perhaps a better nomenclature for the dimensionless time-bandwidth product would be, TW, where T is the duration of the time-series. Regardless, for historical reasons, W is specified in physical units, and NW is the dimensionless quantity.

A consequence of the data tapering is an increased estimator variance. Heuristically, this is a manifestation of the fact that data tapers with desirable in-band, fractional energy concentration tend to zero with the data at the beginning and ends of the time-series. This effective loss of data increases the variance of the estimator; as one would expect of estimators computed from a reduced quantity of data. In the multitaper method of spectrum estimation, this variance increase is controlled by averaging many approximately independent direct spectrum estimators. These estimators are constructed using the zeroth-order discrete prolate spheroidal sequence, which is used to obtain the leakage optimal direct spectrum estimator, and then the higher-order discrete prolate spheroidal sequences are used to compute the spectrum estimators which are included in the average to obtain the multitaper spectrum estimator. The higher-order discrete prolate spheroidal sequences are the sequences, possessing maximal in-band fractional energy-concentration, which are mutually orthogonal and orthogonal to the zeroth-order discrete prolate spheroidal sequence.

4. MTM TECHNIQUE ENABLING WITH COGNITIVE RADIO TECHNOLOGY

4.1 Software Defined Radio Concept

A Software Defined Radio (SDR) [4] can be defined as a radio system which can be adjusted to any band of frequencies. It enables the reception and transmission of any signal across the wide electromagnetic spectrum. Instead of doing the whole implementation in hardware, here it is done using the software on a computing device like Personal Computer (PC). Here in the SDR, the replacement or modification of programs can simply change its function. This property makes it more flexible than compared to other traditional radio communication.

4.2 SDR-Basic System Structure

By taking up of simple software, this design as in Fig.7. is supposed to behave like a radio [4], which has the ability to transmit and receive the signals. So for that, here instead of going for special purpose hardware, some amount of the processing data will be given to the General Purpose Processor. The typical receiver scheme as in Fig. 8. for the SDR has to be connected to an Analog to Digital Converter (ADC). Here the processor reads the ADC, and then our program will change the converter output to some other form in which we need.

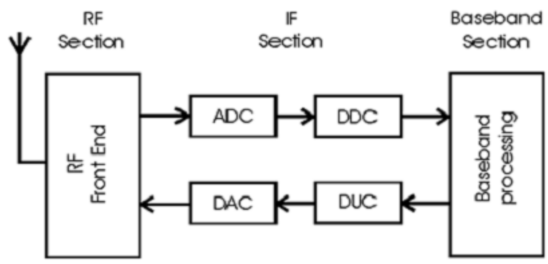

Figure.7. SDR - Basic System Structure

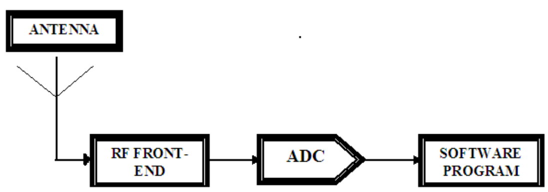

Figure. 8. Receive Path for SDR

The typical transmitter scheme is as shown in Fig.9. produces a sequence of numbers and are sent to the Digital to Analog Converter.

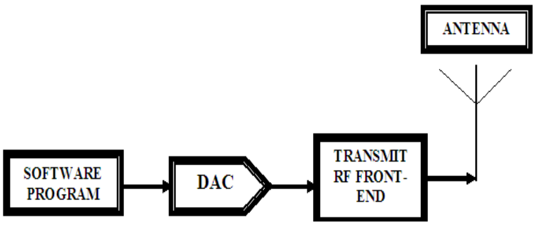

Figure. 9. Transmit Path for SDR

Here we can either use a dipole or a monopole antenna for the reception of the Radio Frequency signals. Then at the reception part, this receive RF Front End alters the frequency of the incoming signals in order to make it compatible with the ADC input. RF front end is a special term for everything in a receiver which exists in the middle of the antenna and the intermediate frequency (IF) stage. When the digital signal reaches the system or PC, the software program execution starts by making use of the library of signal processing blocks provided by GNU Radio software toolkit. These blocks are made of C++ and we can make graphs which can be made and run on Python language. An interface known as Simplified Wrapper Interface Generator is used for connecting both of these languages.

4.3 GNU Radio Toolkit

GNU Radio is a free software toolkit for the development of SDR which runs on a Linux platform. The software environment is created so as to represent the data flow in this system. The data flow here is being represented by Signal Processing Graph. In the graph, the data flow is indicated by the edges and the processing blocks will be the vertices of that graph. Based on the input-output rates on the block, the system ensures scheduling and dynamic buffer allocation and this will enable to perform any modifications in the flow graph, during the execution also. As the system control is with the Python, it can extract the information from the corresponding blocks. Being a hybrid system, all the crucial processing block sections are implemented in CPP and the other non-critical sections are implemented in Python language. This enables the programmers to make use of the user friendly, Python language for the construction of application. Then these application based Python language access the CPP blocks by means of interface provided by Simplified Wrapper Interface Generator.

4.4 Universal Software Radio Peripheral

Even though the Software Radio is independent of hardware, it can use the hardware front ends with the aid of signal processing blocks in it. So the front end design used here is the Universal Software Radio Peripheral (USRP) [3]. Fig. 10. shows the USRP kit, which mainly consists of one motherboard and four daughter boards. In that two daughter boards [3] are for transmission purpose and other two are for reception purpose. These daughter boards have the facility to directly interface to the motherboard and this enables the motherboard to do all functions such as analog or digital conversion, interfacing, decimation, interpolation etc.

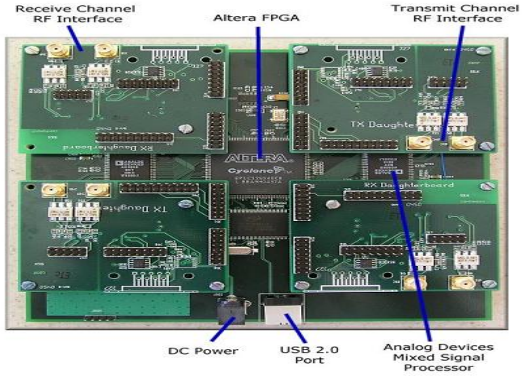

Figure. 10. USRP- Motherboard

The motherboard and PC communicate through a USB 2.0 interface. This interface will permit only an 8MHz sample, which is coming from the motherboard that is having a sampling rate of 64MHz. For the construction of typical designs, there are specific signal processing hardware associated with the convertors.

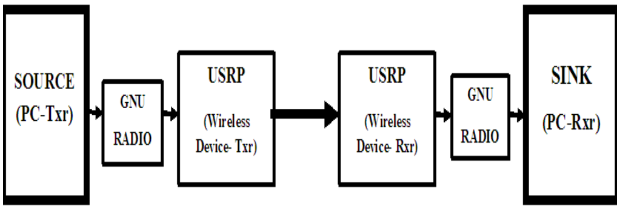

Figure.11. Block diagram of SDR

It can be sometimes a Field Programmable Gate Array (FPGA) or a Digital Signal Processor (DSP) for doing the waveform specific processing applications in USRP.

The Software Radio is an interesting area, in which the GNU Radio explores and then the USRP formulates it as shown in Fig. 11.

4.5 Cognitive Radio Networks

Cognitive Radio (CR) [2] has been investigated after Software Defined Radio. A Cognitive Radio is a Software Defined Radio with adaptive intelligence. This enables it to adapt its transmission and reception parameters with the wireless environment in which it operates. Thus a Cognitive Radio can automatically be chosen as the fine and inexpensive service for a radio transmission. Instead of any costly and fixed tools, the usage of Software Defined Radio provides more flexibility. It is very interesting to see that we are able to use the same portable design as radio, television and even for the determination of location using GPS.

CR is the key technology for the upcoming wireless era. Many CRs can form CR networks using the features of radio connectivity with the networking layers and other layers. Also they are having the advantage of Spectrum Sensing. A CR can sense, adapt and learn from its own environment. It consists of various systems of communication and networking. The CR architecture is such that it can improve the whole network efficiency.

There are two potential routes to band sharing. Either, the legacy spectrum holder (i.e. the primary user and original license holder) makes an agreement directly with a third party organization (the secondary user or band sharer). The terms on which the spectrum would be shared would be outlined and agreed between them and there would be no regulatory involvement in either setting safety criteria, monitoring that safety criteria were being complied with, or imposing penalties if they were not kept. Alternatively, band sharing in certain spectrum bands could be mandated by the regulator. In this case, it would be the regulator's responsibility to outline safety criteria, ensure that the primary user did not suffer from interference as a result of the secondary user, monitor interference levels and impose penalties if they were exceeded. In this case, the regulator would need to be convinced that the benefits of Cognitive Radio in terms of spectral efficiency, would out-weigh the dis-benefits – in terms of interference and market disruption. Whether the further development of CR is enabled by the allocation of test bands, or through the use of licence-exempt spectrum, or through band sharing of public or private spectrum allocations, the regulator's role will be to ensure that both legacy licensees and spectrum sharers are able to operate effectively without compromising the rights and integrity of each others' systems. The creation of the appropriate spectrum environment for CR will involve the development of spectrum databases, of spectrum monitoring facilities and of software spectrum policies.

4.6 Implementation of GNU Radio Block

From the Python's point of view, GNU Radio provides a data flow abstraction. The fundamental concepts are signal processing blocks and the connections between them. From the high level point-of-view, infinite streams of data flow through the ports. A block is actually a class implemented in C++ . At the C++ level, streams are dealt with in convenient sized pieces, represented as contiguous arrays of the underlying type. When we write the block, we need to construct them as shared libraries that may be dynamically loaded into Python using the `import' mechanism. SWIG, the Simplified Wrapper and Interface Generator, is used to generate the glue that allows our code to be used from Python. Writing a new signal processing block involves creating 3 files: The .h and .cc files that define the new block class and the .i file that tells SWIG how to generate the glue that binds the class into Python. The C++ class gr_block is the base of all signal processing blocks in GNU Radio. The new block class we try to create must derive from gr_block or one of it's subclasses. This new block can be used to compute spectral estimation more efficiently.

5. CONCLUSION

This paper gives an attention to the Multitaper Spectrum Estimation Method in Cognitive environments. Windows are the weighting functions applied to the data in order to reduce the spectral leakage associated with finite observation intervals. From one viewpoint, the windows are applied to data as a multiplicative weighting to reduce the order of the discontinuity at the periodic extension boundary. In this, instead of a single type of window function, a series or a cluster of windows like Slepian tapers are mentioned. As the Software Defined Radio is designed into Cognitive Radio, and by using these sorts of Slepian sequences, we can improve the spectral estimation efficiency. The Multi-taper Spectrum estimation algorithm is discussed and an encroachment towards the Cognitive Radio Technology is introduced as they are having the advantage of Spectrum Sensing. A CR can sense, adapt and learn from its own environment which makes the spectrum estimation possible in an easy way. In our paper, we first introduce the concept of software-defined radio and the capacity of GNU radio. Afterward, we describe the related hardware support and development environment respectively. The paper also proposes the idea of making a GNU radio Companion Block on the same method as a graphical interface of GNU Radio.

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