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Letter to the Editor

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Vector Quantization based Power Allocation for Non-Ergodic Cognitive Radio Systems

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Abstract

This Letter addresses the problem of dynamic power allocation based on spectrum sensing outputs for non-ergodic systems. On such type of systems, the power allocation for each corresponding nodes to be sensed by cognitive transmitter may not require all the time. The dynamic power allocation in nodes of each channel in cognitive radio (CR) network using vector quantization based on autocorrelation error is proposed.

Keywords: Vector Quantization, Euclidean Distance, Cooperative Communication, Fusion Center, Wireless Communication, Cognitive Radio Network

1. Introduction

Cognitive radio is all about dynamic spectrum sensing, which is now one of the best possible solutions for efficient spectrum utilization. Thus the sensitivity of the CR should be high as well as computationally accurate and fast. Finally the sensing output is being forwarded to the spectrum management where the power and coordinating access to the channel with a given user is performed. Many different optimization algorithms are being analyzed for power allocation [1, 2] which plays a major role for cooperative communication. Here we have considered the minimum Euclidean distance which yields the shortest possible distance between the nodes [3,4,5]. We consider a small set of PSD based autocorrelation output which acts as repeated or closed values. As there is a continuous variation on the Power Spectral Density (PSD) of a signal, autocorrelation error is calculated for performing further calculation based on the consistency of the error as shown in section 2. This provides the system an opportunity to work in any non-ergodic environment. The error is then used as a 2-D vector and Euclidean distance is calculated using the dynamic autocorrelation error which is basically the worst case as shown in section (III).

2. Analysis of Asymptotic Autocorrelation through Blind Source Separation

The analysis of asymptotic autocorrelation through Blind source separation method has been implemented. The frequency dominating components are firstly separated using blind source separation method and the autocorrelation error of multiple channel with respect to a single channel is calculated. Considering each individual signal PSD, is denoted by *a(k)* for k channels having time lag Γ . The error is denoted s the difference in time lagged transfer function based real-time signal based PSD. The autocorrelation function can be written as

$$R_{a_{l(k)}a_{l+1}(k)} = lim_{T\to\infty} \frac{1}{T}\int_{T=0}^{T} \sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_{l+1}(T)\ dt \quad (1)$$

$$Error\ ACF(T) = \sum_{i=1}^{p-1} R_{z_i z_{i+1}}(k)(\Gamma) - \sum_{l=1}^{p-1} R_{a_{l(k)}a_{l+1}(k)} \quad (2)$$

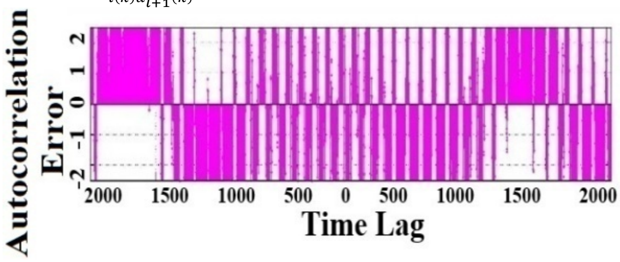

Fig1. Asymptotic ACF for two sources and error estimation

The above figure 1 shows the autocorrelation error i.e. the difference between true PSD (real-time) and a PSD with a previous time in same signal (2-3 seconds). As shown in the Eq. (10), the mathematical analysis of the error ACF gives an approximate proximity with the simulated results.

3. Simulation and Analysis

Applying the source identified with respect to the majority frequency components in above equation of continuous autocorrelation [6, 7], we get:

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$$R_{z_i z_{i+1}}(k)(\Gamma) = lim_{T\to\infty} \frac{1}{T}\int_0^T \sum_{j=1}^{p} z_j\,(k)(t+\Gamma) * \hat{z}_j(k)dt \quad (3)$$

For real functions we are considering, $z_j(k) = \hat{z}_j(k)$

$$R_{z_i z_{i+1}}(k)(\Gamma) = lim_{T\to\infty} \frac{1}{T}\int_0^T \sum_{j=1}^{p} z_j\,(k)(t+\Gamma) * \hat{z}_j(k)dt$$

$$= lim_{T\to\infty} \frac{1}{T}\sum_{T=0}^{T}\sum_{j=1}^{p} z_j\,(k)(T+\Gamma) * \hat{z}_j(k)(T) \quad (4)$$

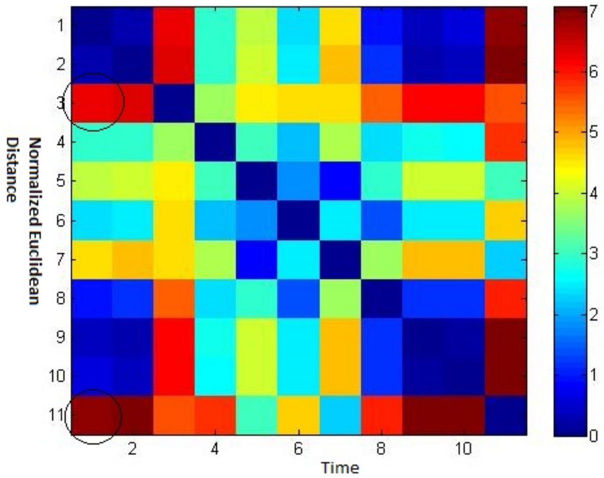

Fig 2. Variation of Euclidean distance based on for first 10 autocorrelation errors and using 1 as minimum distance

Expanding the series and by substituting:

$$= lim_{T\to\infty} \frac{1}{T}\sum_{T=0}^{T}\sum_{j=1}^{p}\sum_{l=1}^{p} g_j a_l(k)(T+\Gamma) * g_j a_l(k)(T)$$

$$= lim_{T\to\infty} \frac{1}{T} {g_j}^2 \sum_{T=0}^{T}\sum_{j=1}^{p}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) \quad (5)$$

Considering the initial received signal from USRP and their respective autocorrelation between two different instances can be given by:

$$R_{a_{l(k)}a_{l+1}(k)} = lim_{T\to\infty} \frac{1}{T}\int_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_{l+1}(T)\ dt$$

$$= lim_{T\to\infty} \frac{1}{T}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_{l+1}(T) \quad (6)$$

Finding the autocorrelation for p individual signals obtaining from the sensing band from above equations, we get:

$$Error\ ACF(T) = \sum_{i=1}^{p-1} R_{z_i z_{i+1}}(k)(\Gamma) - \sum_{l=1}^{p-1} R_{a_{l(k)}a_{l+1}(k)}$$

$$= lim_{T\to\infty} \frac{1}{T}\cdot\frac{p}{2}\sum_{j=1}^{p} {g_j}^2 \sum_{i=1}^{p-1}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) - \frac{1}{T}\sum_{l=1}^{p-1}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_{l+1}(T)$$

Applying arithmetic progression

$$= lim_{T\to\infty} \frac{1}{T}({g_j}^2.(\tfrac{p}{2}) - 1)\sum_{i=1}^{p-1}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) \quad (7)$$

$$= lim_{T\to\infty} \frac{1}{T}[\left(\frac{g_1^2}{2}+\frac{g_2^2}{2}\ldots+\frac{g_p^2}{2}\right) - 1]\sum_{i=1}^{p-1}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) \quad (8)$$

Assuming the same channel properties as considered for Rayleigh fading channel in presence of AWGN, ($g_1 = g_2 = \cdots = g_p$), we get:

$$= lim_{T\to\infty} \frac{1}{T}\left[\left(\frac{g_1^2}{2}+\frac{g_2^2}{2}\ldots+\frac{g_p^2}{2}\right) - 1\right] * \sum_{i=1}^{p-1}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) \quad (9)$$

$$= lim_{T\to\infty} \frac{1}{T}[p.\frac{g^2}{2} - 1]\sum_{i=1}^{p-1}\sum_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) \quad (10)$$

Let us denoting the coefficient of convergence of ACF error,

$$A = lim_{T\to\infty} \frac{1}{T}\left[p.\frac{g^2}{2} - 1\right] \quad (11)$$

which is a general case we can consider.

Applying the vector quantization based in Euclidean distance vector $e(D_i)$,

And

$$e(D_i) = \sqrt{\sum_{j=1}^{k} D_{i,j}^2} = \sqrt{\sum_{j=1}^{k} (I_j - C_{i,j})^2} \quad (12)$$

And thus autocorrelation error in terms of Euclidean Distance (*ED*) is represented as below. The highlighted circular parts depict the node position the node position and their importance for allocation of power to them. From the above equation we can calculate the value of Euclidean distance keeping the autocorrelation error constant for a time instant. Implementing the algorithm for a real-time continuous signal, the autocorrelation error may be updated every 1-2 seconds or less than that for getting prepared for the assignment of calculating Euclidean distance and hence allocating power to the respective cluster heads rather than all the nodes. The node allocation is based on the positions of each Euclidean distance with respect to the change in autocorrelation error as shown in figure 2.

$$A.E. = \lim_{T\to\infty} \frac{1}{T}[p.\frac{g^2}{2} - 1]\sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P} a_l(k)(T+\tau)\times a_l(k)(T)$$

$$= \lim_{T\to\infty} \frac{1}{T}[p.\frac{g^2}{2} - 1]\sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P}\{(\frac{ED^2}{2} + a_l(k)(T)\}\times a_l(k)(T)$$

$$\therefore \frac{A.E.}{\lim_{T\to\infty}\frac{1}{T}[p.\frac{g^2}{2}-1]\sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P}a_l(k)(T)} = \sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P}\{(\frac{ED^2}{2}+a_l(k)(T)\}$$
$$=\frac{ED^2}{2}\sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P}\{a_l(k)(T)\}$$

$$\therefore \frac{2A.E.}{\lim_{T\to\infty}\frac{1}{T}[p.\frac{g^2}{2}-1]\sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P}a_l(k)(T)} - \sum_{i=1}^{P-1}\sum_{T=0}^{T}\sum_{l=1}^{P}a_l(k)(T) = ED^2 \quad (13)$$

which implies the relation between autocorrelation error and Euclidean distance vector considering the continuous change in the overall PSD of the real time signal and other device properties.

4. Conclusion

Power allocation to nodes based on vector quantization is analyzed in this letter. Due to random allocation of power, based on a particular algorithm or node placements, the complexity of the system may vary and a finite and specific number of systems may get possible implementations. However, it is observed from the simulation results that the dependency of vector quantization based on autocorrelation error can save time and be used as an application independent algorithm for power allocation. As a solution, we have proposed to take the real-time signals and find their autocorrelation error based on a small time delay. This autocorrelation error which shows the cyclostationarity of the signals are taken for lowering the average distortion keeping the reconstruction levels of channels constant, using vector quantization. In these experiments, it is observed that the power allocation can be strictly controlled without compromising with the system complexity and processing time. The rate of change of the Euclidean distance depends on the updating of autocorrelation error and thus it is suggested to update the same for any random time just before starting of cognitive communication.

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