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Research paper

Cooperative Spectrum Sensing Based on HML and Vector Quantization for Cognitive Radio Networks

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Abstract

The proposed work illustrates a novel technique for cooperative spectrum sensing in a cognitive radio (CR) network. The work includes an approach of identifying secondary users (SUs) based on Hierarchical Maximum Likelihood (HML) technique followed by Vector Quantization. Initially, the arrangement of the SUs are been observed using HML with respect to a spatial domain and then the active SUs among them are identified using VQ. The approach will not only save the energy, but the decision of the real-time and dynamic cooperative communication network becomes more accurate as we can predict the behavior of SUs movement and spectrum sensing by each individual SU at that particular place. The results and simulations of the real-time experiment justifies with the proposed approach.

Keywords: Cognitive Radio, Spectrum Sensing, Cooperative Communication, *HML*

1. Introduction

The scarcity of electromagnetic radio spectrum for wireless communication and the under utilization of licensed radio spectrum, is one of the major concern considering the ever increasing demands of wireless devices and applications.[1]
Cognitive Radio (CR) is used to minimize the spectrum underutilization problem. The sensitivity of the CR should be higher as well computationally accurate and fast.
To address this issue, multiple CRs can be designed to collaborate in spectrum sensing. [2]
Cooperative communications and networking allows different users or nodes in a wireless network to share resources and to create collaboration through distributed transmission, in which each user's information is sent out not only by the user but also by the collaborating users .[5][6]
There are different cooperative spectrum sensing schemes, decision schemes and quantized fusion scheme. In these methods, the position of Fusion Centre (FC) is constant or it may shift according to the center of all the channels. So, it is clear that allocated power in FC will be constant. [7]
In case of Hierarchical Maximum Likelihood (HML) clustering technique, position of fusion center depends on the cluster density and it always gets updated.
Based on Vector Quantization (VQ), the power allocations of the nodes are done. Further, the FC location is updated using HML. Thus, this implementation leads to a power saving communication between the secondary receivers of CRN. This technique uses VQ and HML for power allocation to the nodes and FC. VQ uses autocorrelation error for power allocation to nodes. HML uses clustering of these nodes and analysis using maximum likelihood to get the optimized position of FC.
As the proposed method is based on Euclidean Distance (ED) technique, Power Spectral Density (PSD) of each channel which is parallel is considered as the objects. HML has been analyzed with three different PSDs. The three PSDs are real time PSD, and two more PSDs which are delayed by 1 second and 3 seconds, respectively. These objects are of the same nature with a time lag. Due to that reason only two classes have been considered for simplicity. Principal Component Analysis (PCA) has been used for PSDs to find individual dominating frequency components inside these. HML per channel PSD as tree-structured clustered process is considered. The uniqueness of this algorithm is that it focuses on the similarity, differing from other algorithms, which are based on individual node's property.

The four main steps in the basic HML used to determine the position of the FC are (i) node pairs of almost same values and same PSD are to be chosen. (ii) clusters have to be formed by merging the nodes. (iii) current cluster and nearby nodes which are similar are updated, (iv) until the last node the formation of cluster process is repeated. [3]

2. Hierarchical Maximum Likelihood (HML) for Cooperative Communication

In a hierarchical framework, HML method consists of two fundamental issues to develop the maximum likelihood estimate. The first is the criterion function and the second is the distance or similarity measurement which satisfies the selected criterion function. For this class based log-likelihood of two clusters is considered. [6]
Here take X_i and X_j as clusters. Then L_i which is the log-likelihood function for a cluster X_i is expressed as,

$$L_i = n_i \log P(\omega_i) + \sum_{x \in X_i} \log[\frac{1}{(2\pi)^{d/2} |\Delta i|^{1/2}} \exp\{-\frac{1}{2}(x-\mu_i)^T \Delta i^{-1}(x-\mu_i)\}] \quad (1)$$

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Here mean is $\mu_i = \frac{1}{n_i}\sum_{x\in X_i} x$, covariance, $\Delta i = \frac{1}{n_i}\sum_{x\in X_i}(x-\mu_i)(x-\mu_i)^T$ and $x= p(i)$. Here $p(i)$ is the power of the i^{th} cluster.

Similarly, log-likelihood of j^{th} cluster is given as:

$$L_j = n_j \log P(\omega_j) + \sum_{x\in X_j} \log[\frac{1}{(2\pi)^{d/2}|\Delta j|^{1/2}} \exp\{-\frac{1}{2}(x-\mu_j)^T \Delta j^{-1}(x-\mu_j)\}] \quad (2)$$

$$L_i + L_j \cong -d.\log(2\pi) - \log(|\sqrt{\Delta_i}|.|\sqrt{\Delta_i}|) \quad (3)$$

The priori probabilities are $P(\omega_i)$ and $P(\omega_j)$.

Increasing number of log-likelihood clusters, this can be expressed as:

$$L_i + L_j + \cdots + L_k \approx -k.\frac{d}{2}.\log(2\pi) - \log(|\sqrt{\Delta_i}|.|\sqrt{\Delta_i}| \ldots |\sqrt{\Delta_k}|) \quad (4)$$

The change in log-likelihood function (class based) with respect to the number of clusters that are merged is expressed by eq. 4. The function increases and approaches the exact FC position without any inconsistency.

The implementation of the above HML analysis for multichannel cooperative communication can be done using the method shown in fig. 1. Here the entire channels being sensed, are parallel and continuous.

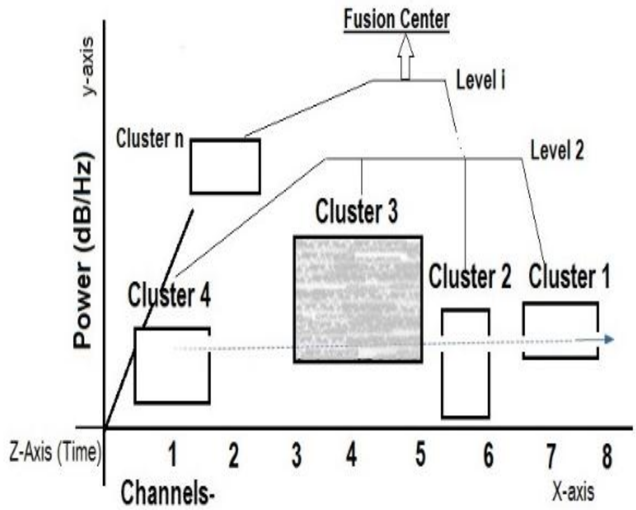

Fig. 1 Implementation of HML in Cooperative communication

In this method, a number of clusters with different PSDs are analyzed with respect to their levels. Based on power, frequency and time ,the decision is made at each level .

Using USRP, three different time instances of PSD for same channels are considered. Here 100 levels have been taken.

d is taken as sample dimension for sample objects (PSD) $X= \{x_1, x_2, x_3, \ldots, x_n\}$ for n-channels. The value of d=3 and 2 is taken as the class value.

Fig. 2 shows the variation in log-likelihood with respect to different levels also to minimize probability of error. Each level implies a fixed channel with different number of probable cluster formation based on PSD for each channel. Variation in log-likelihood implies that the positioning of FC is based on the final level after all the clustering is performed.

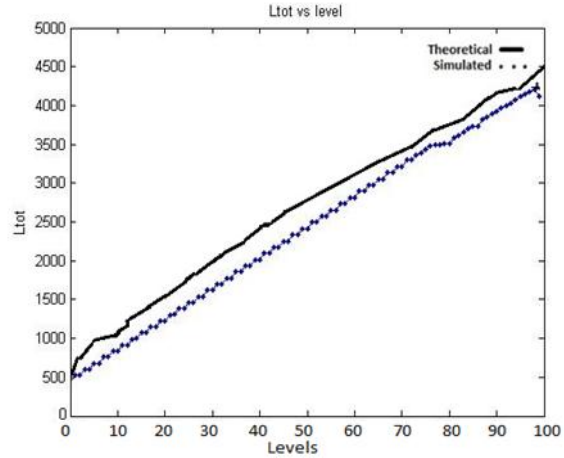

Fig. 2. Variation of Likelihood ratio based on different levels at 845 MHz

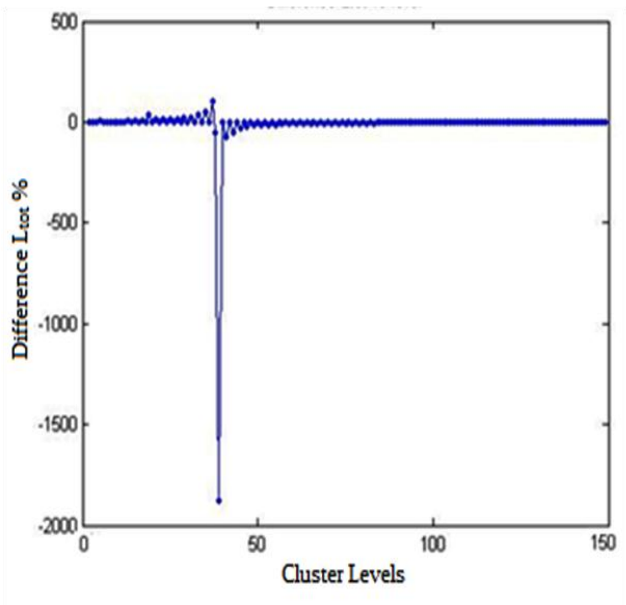

Fig . 3. Differential likelihood for FC at 845 MHz

100 clusters have been used for calculating the differential likelihood for optimal FC for 150 levels at 845 MHz shown in Fig. 3.

It is observed that at 40, the approximate change occurs. This implies that likelihood varies maximum and it therefore the ideal position of the fusion center (FC) is at level 40. The algorithm therefore is suitable for decision making of the position. In other techniques, the FC position was generally taken randomly. The proposed method reduces this ambiguity.

3. Introduction to Vector Quantization

Among many quantization methods, VQ is a classical method which is based on PDF by distributing prototype vectors which are a large set of points. These points are divided into approximately even groups. Each group consists of a centroid and the data points are represented by their closest centroid. In practice, these are used for density estimation and lossy data compression. The VQ is a type of deep learning algorithm used in self-organizing map model and sparse coding models. The training algorithm in VQ follows the below steps:

A. A random sample is taken.

B. VQ centroid is moved by the smallest distance sensitivity (minimum) towards the sample.

C. (A) and (B) are repeated.

Mainly in the proposed methodology, we have introduced VQ for Pattern Recognition (PR). The clusters are an example of unsupervised learning. Individual cluster centroids are called code-words and the set of cluster centroids represents a codebook. These are basically a type of *K-means* clustering. In case of PR, for each class, one codebook is created using the user's vector. The codebooks obtained in training phase are used for testing the quantization distortion. Thus, for identifying the user, smallest VQ is provided by the codebook. [4][13]

As VQ centroid seeks for density points of other nearby samples, these are used for prototype-based clustering method. Here every centroid is treated to be associated with one prototype. The squared quantization error is reduced. In simple words, VQ discovers the data structure by searching the data cluster pattern. These results are further used for data compression and encoding.

4. Analysis of Vector Quantization in Cooperative Communication

Applying the source identified with respect to the majority frequency components in the equation of continuous autocorrelation:

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

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

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

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

Expanding the series and by substituting:

$$= lim_{T\to\infty}\frac{1}{T} g_j{}^2 \sum_{T=0}^{T}\sum_{j=1}^{p}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_l(k)(T) \tag{3}$$

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

$$R_{a_{l(k)}a_{l+1}(k)} = lim_{T\to\infty}\frac{1}{T}\int_{T=0}^{T}\sum_{l=1}^{p} a_l(k)(T+\Gamma) * a_{l+1}(T)\ dt \tag{4}$$

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

$$Error\ ACF(T) = \sum_{i=1}^{p-1} R_{z_i z_{i+1}}(k)(\Gamma) - \sum_{l=1}^{p-1} R_{a_{l(k)}a_{l+1}(k)} \tag{5}$$

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

Assuming the channel properties are same as we are taking the same Rayleigh fading channel with AWGN noise ($g_1 = g_2 = \cdots = g_p$), we get:

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

Let's denoting the coefficient of convergence of the Autocorrelation Function (ACF) error,

$$A = lim_{T\to\infty}\frac{1}{T}[p.\frac{g^2}{2} - 1] \tag{8}$$

which is a general case we can consider. Applying the VQ based on the Euclidean distance vector $e(D_i)$,

As,

$$e(D_i) = \sqrt{\sum_{j=1}^{k} D_{i,j}^2} = \sqrt{\sum_{j=1}^{k}(I_j - C_{i,j})^2} \tag{9}$$

$$m(D_i) = \sum_{j=1}^{k}\left|D_{i,j}\right| = \sum_{j=1}^{k}\left|I_j - C_{i,j}\right| \tag{10}$$

From the above equation, the value of Euclidean distance is calculated by keeping the ACE constant for a time instant. Implementing the algorithm for a real-time continuous signal, the ACE may be updated every 1 to 2 seconds or less than that for getting prepared for the assignment of calculating the Euclidean distance and hence allocating power to the respective cluster head rather than all the nodes.

5. Simulation Results and Discussions

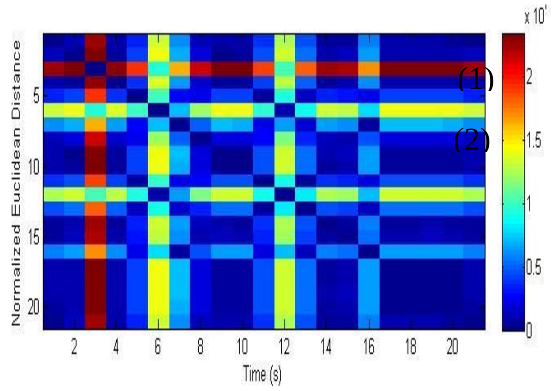

Fig .4. Vector Quantization based cooperative sensing nodes at 103.5 MHz

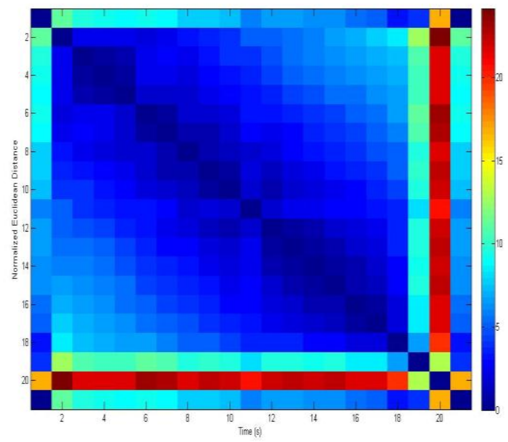

Fig 5. Vector Quantization based cooperative sensing nodes at 108.5 MHz

As shown in Fig 4 and Fig 5, 100 and 150 channels have been considered and divided in terms of 10 clusters and the normalized distance is calculated using Euclidean Vector among each cluster. The red marks show the dominating frequency components among each of the clusters. These clusters are first made with respect to the ACE output. As we have taken real-time signals and the threshold as fixed for all the continuous multiple channels, the results may vary from time to time as well frequency usage. The graph shows the output of 103.5 MHz and 108.5 MHz as center frequency and corresponding 100 and 150 channels respectively.

6. Conclusion

Power allocation to nodes based on VQ is analyzed. It is observed in the simulation results that a dependency of VQ based on ACE can save time and can be used as an application independent algorithm for power allocation.

It is observed that the power allocation can be strictly controlled without compromising with the system complexity and time of processing. The rate of change of the Euclidean distance depends on the updating of ACE and thus it is suggested to update the same for any random time just before starting of cognitive radio communication.

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