Machine Learning Based Spectrum Sensing for Secure Data Transmission Using Cuckoo Search Optimization

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Abstract. This article is about machine Learning (ML) depending spectrum sensing in using cuckoo search optimization method. In Present days as the number of mobile users is increasing, scarcity of spectrum is arising due to allocation of the available spectrum to growing number of the users in cognitive radio. So there is a need to efficiently utilize the limited spectrum that is available for use. Spectrum sensing is one of the prominent method for effective utilization of the spectrum. Among the existing methods of spectrum sensing using Energy detection, Machine learning based sensing is more prominent. For efficiently optimizing the spectrum sensing cuckoo search based optimization has been used in this paper. For analyzing the channels under noise conditions Gaussian function has been considered. Average information per message based classifier is a good technique of detection for spectrum sensing. Classification has been done with the help of support vector machine and K-Nearest Neighbor algorithms. From the obtained results it has been shown that average information based SVM, KNN techniques outperforms the conventional energy detection based techniques and cuckoo search based optimization has yielded better sensing accuracy with minimum loss.

Keywords: Machine Learning (ML) · Cognitive radio · Optimization · Gaussian function · spectrum sensing

1 Introduction

The current state of the electromagnetic spectrum demonstrates a significant underutilization. Some parts of the radio spectrum have been found to be highly dense. As 5^{th} Generation networks and the IoT advance, numerous equipment may need to be wirelessly connected. Thus, bandwidth - an expensive and limited resource is in high demand. Therefore, efficient bandwidth utilization lowers costs and enhances the numeral of devices which would send data. Spectrum can be found as both in licensed band as well as in unlicensed bands. Owners or primary users of a licensed spectrum control the spectrum. Smart devices, such as cognitive radios (CR), are able of utilizing licensed spectrum if primary unit is not active in its licensed spectrum. Since a CR uses the spectrum only if the PU is inactive, in that case it can be treated as a secondary user (SU) [1].

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To get connectivity to a channel as a secondary user, primarily spectrum sensing (SS) must be conducted in cognitive radio. The SS role is critical since it assures that such CR somehow doesn't create interference towards the licensed spectrum user. SS has been assumed as a detection task wherein detector chooses between two hypotheses: null hypothesis and alternate hypothesis, where null hypothesis denotes the presence of nothing but noise while alternate hypothesis denotes its presence of both signal and noise. Noise statistics, fading due to multiple paths, shadowing, and other factors can all impede a detector's effectiveness in this scenario [2].

In the literature, various approaches for doing SS indeed been suggested. Energy detector (ED), matching filter detector (MFD), lastly cyclostationary feature detector are three prevalent approaches in conventional SS. To recognize PU behavior in a specific frequency band, the received signal energy is judged against to a threshold in ED. Because the ED is the most common and straightforward detector, it has been frequently used. For the detection of the PU presence, the MFD compares the received data to a predefined transmission message. The PU signal's second order cyclostationary qualities are used by the cyclostationary feature detector to detect PU activity. Nevertheless, those approaches have significant drawbacks, like as ED's poor efficiency at less Signal to Noise Ratio, the cyclostationary detector's complexity, and Matched Filter Detector requirement for set of assumptions on the primary user signal, as well as synchronisation between SU and PU. Such detectors' efficacy has been assessed under existing and projected noise situations. Because of its ease of calculation, Gaussian noise which will be additive in nature (AWGN) is frequently used for explain the noise. Nevertheless, in several circumstances, such as ultra-wide band communication systems, the effect of interference and noise was seen to resemble a Generalized Gaussian distribution (GGD). Furthermore, in a real-world scenario, information about the primary signal, distribution of noise, also fading characteristics of the channel is frequently restricted [3–5].

Similarly Under Advanced Spectrum Sensing Techniques, the Techniques are Wide-band Compressive method, Adaptive Compression method, covariance based methods, and Machine Learning Methods are given in literature [6].

To solve the drawbacks of the aforesaid conventional signal processing procedures, we apply supervised machine learning (ML) techniques to Spectrum Sensing. Machine Learning - based Spectrum Sensing is also now being researched The bulk of the solutions discussed in the literature, however, have two key flaws. To begin, these algorithms use the test energy measuring parameter for obtained readings for training the corresponding procedures, and it has been shown to perform badly in less SNRs as well as GGD noise. In this article, we propose using the Average information per symbol vector for signal received to be the feature vector to train and assess some of the most prominent supervised ML techniques for Spectrum Sensing using empirically collected datasets. By considering hypothesis cases also when compared to ED this method works well in the presence GGD Noise and it is good to a not known [7].

Error Detection and correction coding techniques are coming under channel encoding techniques. Even though the channel encoding is an additional overhead to the overall communication system and complexity gets increased. Optimization is now a days one of the emerging field for finding the best possible solution among the existing methods. With the help of optimization method. To use optimization for spectrum sensing channel power Values under various conditions can be given, and optimization can take these values and suggests the best possible value for utilizing the channel that means, when the SU can utilize the channel. So with the help of optimization a better result can be obtained in spectrum sensing. Cuckoo search algorithm is a meta-Heurisitic algorithm which has been inspired by cuckoo birds lay their eggs in other birds nests, which enhances their existence and productivity. This cuckoo search algorithm is one of the best optimization algorithm in order to find the optimal solution with fast convergence [21, 22].

In the subsequent portion, we discuss the ML algorithms used in this paper.

2 Design Methodology

In presence of GGD noise we formulated sample static based on the average information per message. In normal cases the average information per message of primary is known, then it easy to obtain Probability of detection. From simulation results it had been shown that GGD noise has less severity on the performance when compared to ED. In case of measured value in channel Hypothesis will be considered. In this case measurement is given to detection processing and then it makes decisions as H_0 or H_1 that means false alarm will be considered if signal energy or average information per message is below threshold i.e. H_0 and decision is in favor of $H_{1.}$ And missed detection is noticed if energy or average information per message is above threshold but decision is in favor of H_0.

In this article a different detection technique used which is relied on average information per message. Average information per message is given by

$$\mathrm{K(l)} = -(-1/log2)\int_{-\infty}^{\infty} g_l(l)log(g_l(l))dl \tag{1}$$

where $g_l(.)$ is the pdf of l.

The average information centered check for finding if an available group of samples are belonging to g_l are indicated by.

$\widehat{K(l)} \underset{<}{>} T$, for given $g_{l.}$ Where T is the threshold selected aimed at certain p_f€(0, 1).

i. Detection in the presence of Generalized Gaussian Noise(GGN): Noise signal is chosen to be GGN with probability density function given as

$$\mathrm{g_N(l)} = \frac{1}{2£\Gamma\left(\frac{1}{\xi}\right)} e^{\left(\frac{-|l|^{\xi}}{£}\right)} \tag{2}$$

where the parameter ξ varies from 0 to 2. Where Γ is the Euler's gamma function. The maximum likelihood estimate H_0 of Average information per message can be approximated as [4]

$$\begin{aligned}\mathrm{R(q/H_0)} = (1/\xi) - \log(\xi) - \log\left(2\Gamma\left(\frac{1}{\xi}\right)\right)\\ + (1/\xi)\log[\left(\frac{\xi}{L}\right)\sum\nolimits_{o=1}^{L}\left|Qi - Q'\right|{}^\wedge\xi\end{aligned} \tag{3}$$

similarly, Probability of detection moreover false alarm equations can also be applied. With the inclusion of this channel encoding techniques overall secure data transmission can be attained.

2.1 Support Vector Machines

Support vector machines (SVM) can be employed to classify data into binary categories. The SVM classifies data from group of points belonging to vector space whose dimension is N in nature and in turn it gives a hyperplane dividing the 2 classes. Each subsequent data point will be classified using hyperplane formula. To increase separability, significantly greater order feature combinations are used. Considering various kernels, the hyperplane expression varies. In this paper modified Support vector machine algorithm has been used. The SVM classifier is often trained using several kernels [8].

2.2 K-Nearest Neighbors (KNN)

K-Nearest neighbor algorithm comes under supervised machine learning algorithm that categorizes the incoming information relying over Euclidean distance among data to measured or tested & neighbors which are nearest of the data to be trained. It calculates the distance among supplied data points and the training samples for a given sample of data. The number of points in the training data that are nearest towards testing data is K–that means distance weight – represents set. In this method Classification has been performed in terms of representing label and recurring in fundamental set. Though, afore acquaintance of numeral of classes has needed in KNN for getting a better output [9].

2.3 Cuckoo Search Optimization Algorithm (CSO)

In this paper in order to apply CSO the following assumptions were made. The levy flight for cuckoo birds has been calculated using the following formulas [15–20, 23–25].

$$þ = \frac{\varepsilon(1+\mu)*\sin(pi*\frac{\mu}{2})}{\left(\frac{\varepsilon(1+\mu)}{2}\right)*\mu*2^{(\mu-1)/2}} \tag{4}$$

Using power law index n levy steps can be taken using þ.

A total of 200 search agents haven been considered in this paper with maximum number of 50 iterations, and objective function has been used for finding the optimum sensing value in this cuckoo search algorithm by considering the SNR Values.

3 Results and Conclusions

In this portion we demonstrate the comparison of ML-based spectrum sensing Technique results. In the below figure, probability detection values have been taken along vertical axis and SNR values in dB were taken along x-axis. In this figure performance comparison for 4 graphs were shown they are modified KNN using Average information per message, Modified KNN using Energy detection technique, Modified SVM using Average information per message and Modified SVM methods respectively. By observing the figures, modified SVM, KNN using Average information per message Probability detection values are superior when compared to general SVM & KNN methods. Hence better detection is possible using ML – based, KNN Techniques [10–12] (Table 1).

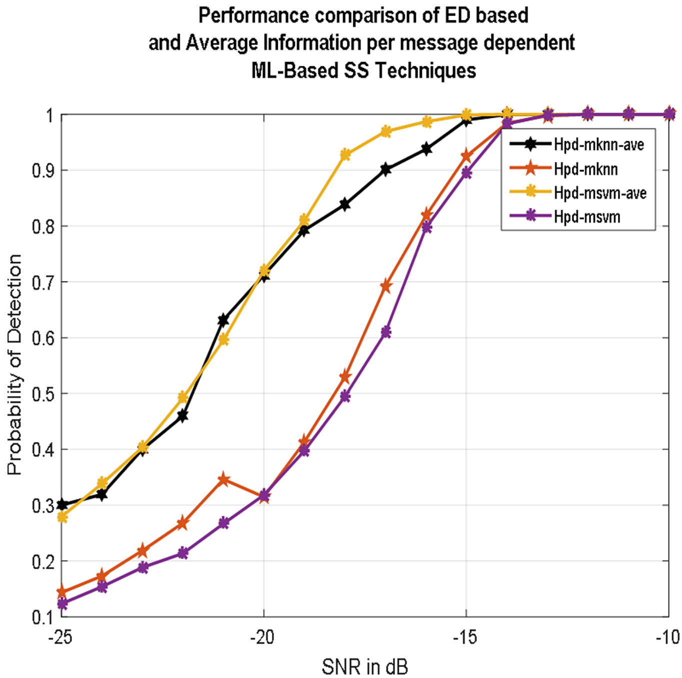
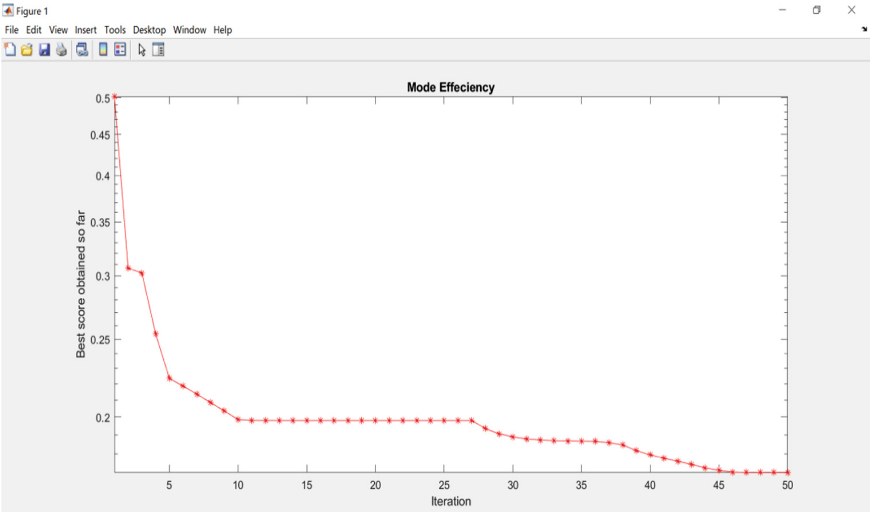


Fig. 1. Probability detection using SVM, KNN Techniques

Table 1. Comparison table for Spectrum Sensing of SVM & KNN based average information per message [4, 13, 14]

ML-Method	SNR			
	−10 dB	−15 dB	−20 dB	−25 dB
SVM-AVE	1	0.9898	0.7188	0.2954
KNN-AVE	1	1	0.7049	0.3199
SVM-ED	1	0.9159	0.3204	0.1705
KNN-ED	1	0.9139	0.3084	0.1236

The above table gives the comparison of Modified SVM & KNN methods, and it can be observed that Modified SVM based AVE method gives best results for probability detection for various SNR values.



In the above diagram using cuckoo search algorithm, the best scores obtained were shown. In lieu of a given quantity of repetitions, best score obtained using cuckoo search algorithm is 0.18302.

Hence, from the obtained results it can be shown that SVM & KNN Based Spectrum sensing performs better under noise over conventional technique of detection. Performance comparison of graphs as shown in Fig. 1 gives better results for Average information based SS using supervised learning procedures.

References

1. Saravanan, P., et al.: A supervised learning approach for differential entropy feature-based spectrum sensing. In: 2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET). IEEE (2021)
2. Yucek, T., Arslan, H.: A survey of spectrum sensing algorithms for cognitive radio applications. IEEE Commun. Surv. Tutorials **11**(1), 116–130 (2009)
3. Gurugopinath, S., Muralishankar, R.: Geometric power detector for spectrum sensing under symmetric alpha stable noise. Electron. Lett. **54**(22), 1284–1286 (2018)
4. Gurugopinath, S., Muralishankar, R., Shankar, H.N.: Differential entropy-driven spectrum sensing under generalized Gaussian noise. IEEE Commun. Lett. **20**(7), 1321–1324 (2016)
5. Qi, H., Zhang, X., Gao, Y.: Channel energy statistics learning in compressive spectrum sensing. IEEE Trans. Wireless Commun. **17**(12), 7910–7921 (2018)
6. Zahabi, S.J., Tadaion, A.A.: Local spectrum sensing in non-Gaussian noise. In: 2010 17th International Conference on Telecommunications. IEEE (2010)
7. Jakkula, V.: Tutorial on support vector machine (SVM). School of EECS, Washington State University 37.2.5, p. 3 (2006)
8. Auria, L., Moro, R.A.: Support vector machines (SVM) as a technique for solvency analysis (2008)
9. Zhang, M.-L., Zhou, Z.-H.: ML-KNN: a lazy learning approach to multi-label learning. Pattern Recogn. **40**(7), 2038–2048 (2007)

10. Guo, G., Wang, H., Bell, D., Bi, Y., Greer, K.: KNN model-based approach in classification. In: Meersman, R., Tari, Z., Schmidt, D.C. (eds.) OTM 2003. LNCS, vol. 2888, pp. 986–996. Springer, Heidelberg (2003). https://doi.org/10.1007/978-3-540-39964-3_62
11. Zhu, X.J.: Semi-supervised learning literature survey (2005)
12. Caruana, R., Niculescu-Mizil, A.: An empirical comparison of supervised learning algorithms. In: Proceedings of the 23rd International Conference on Machine Learning (2006)
13. Machta, J.: Entropy, information, and computation. Am. J. Phys. **67**(12), 1074–1077 (1999)
14. Knuth, D.E.: Dynamic Huffman coding. J. Algorithms **6**(2), 163–180 (1985)
15. Wang, H., et al.: Spectrum sensing in cognitive radio using goodness of fit testing. IEEE Trans. Wirel. Commun. **8**(11), 5427–5430 (2009)
16. Gandomi, A.H., Yang, X.-S., Alavi, A.H.: Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems. Eng. Comput. **29**(1), 17–35 (2013)
17. Joshi, A.S., et al.: Cuckoo search optimization-a review. Mater. Today Proc. **4**(8), 7262–7269 (2017)
18. Yang, X.-S., Deb, S.: Cuckoo search: recent advances and applications. Neural Comput. Appl. **24**(1), 169–174 (2013). https://doi.org/10.1007/s00521-013-1367-1
19. Yang, X.-S., Deb, S.: Multiobjective cuckoo search for design optimization. Comput. Oper. Res. **40**(6), 1616–1624 (2013)
20. Chong, E.K.P., Zak, S.H.: An Introduction to Optimization. Wiley (2004)
21. Gill, P.E., Murray, W., Wright, M.H.: Practical optimization. Soc. Ind. Appl. Math. (2019)
22. Liu, X., Tan, X.: Optimization algorithm of periodical cooperative spectrum sensing in cognitive radio. Int. J. Commun Syst **27**(5), 705–720 (2014)
23. Zhang, R., Jiang, X., Li, R.: Improved decomposition-based multi-objective cuckoo search algorithm for spectrum allocation in cognitive vehicular network. Phys. Commun. **34**, 301–309 (2019)
24. Yuan, W., et al.: Improved cuckoo search algorithm for spectrum sensing in sparse satellite cognitive systems. In: 2016 IEEE 84th Vehicular Technology Conference (VTC-Fall). IEEE (2016)
25. Xin, Z., Zhang, D., Chen, Z.: Spectrum allocation of cognitive radio network based on improved cuckoo search algorithm. In: Proceedings of the 2nd International Conference on Computer Science and Software Engineering (2019)