

Nakagami-m Fading Detection with Eigen Value Spectrum Algorithms

B Vivekanandam

Senior Lecturer, Faculty of Computer Science and Multimedia, Lincoln University College, Malaysia
E-mail: vivekanandam@lincoln.edu.my

Abstract

One of the most crucial roles of the cognitive radio (CR) is detection of spectrum ‘holes’. The ‘no a-priori knowledge required’ prospective of blind detection techniques has attracted the attention of researchers and industries, using simple Eigen values. Over the years, a number of study and research has been carried out to determine the impact of thermal noise in the performance of the detector. However, there has not been much work on the impact of man-made noise, which also hinders the performance of the detector. As a result, both man-made impulse noise and thermal Gaussian noise are examined in this proposed study to determine the performance of blind Eigen value-based spectrum sensing. Many studies have been conducted over long sample length by oversampling or increasing the duration of sensing. As a result, a research progress has been made on shorter sample lengths by using a novel algorithm. The proposed system utilizes three algorithms; they are contra-harmonic-mean minimum Eigen value, contra-harmonic mean Maximum Eigen value and maximum Eigenvalue harmonic mean. For smaller sample lengths, there is a substantial rise in the number of cooperative secondary users, as well as a low signal-to-noise ratio when employing the maximum Eigen value Harmonic mean. The experimental analysis of the proposed work with respect to impulse noise and Gaussian signal using Nakagami-m fading channel is observed and the results identified are tabulated.

Keywords: machine learning, sentiment analysis, deep learning, ensemble performance

1. Introduction

Over the years, the frequency spectrum that is used by various applications like Wi-Fi, military, industry and LANs have been found to be extremely costly and scarce. As a result, the Federal Communications Commission (FCC) has established that numerous organisations are underutilizing certain spectrums, resulting in unnecessary spectrum band wastage. A cognitive radio concept was defined by the authors in [1] where unlicensed spectrum band is detected and then allocated to be used by unlicensed spectrum users with the aid of a software-defined radio. Here, the cognitive radio (CR) is typically used to find the solution for the spectral usage efficiency. Spectrum sharing, spectrum mobility, spectrum management and spectrum sensing are some of the functions that are displayed by the CR [2]. This sensing of spectrum will lead to hole-detection in a more efficient manner at low probability of false alarm and high probability of detection. In this paper, a number of access methods on spectrum sensing are analyzed. In [3] the authors have surveyed multiple methodologies that are used for home detection. Authors in [4] have used Energy detection as a semi blind detection scheme due to its ease of implementation and low complexity. The biggest drawback of this methodology low signal to noise ratio (SNR) caused because of interruptions in power with respect to noise. In [5] it has been observed that identically distributed and independent signals are the best applications for using energy detection. However the power density is affected by correlated signals posing as a serious drawback [6]. Diversity in gain significantly improves performance of the detector when using cooperative spectrum sensing. Analysis of cooperative sensing methodologies is made in [7] along with its positive and negative aspects.

In order to address the issues faced in ED, authors in [8] have suggested the use of eigenvalues of sample covariance matrix in non-cooperative and cooperative techniques. Authors in [9] present a brief overview of the maximum eigenvalue detection methodology that utilizes ratio of maximum eigenvalue to that of noise. It has been identified that this a MED [10] serves as a better methodology when compared with ED in terms of noise uncertainty with correlated signals. In an attempt to prove this methodology by eliminating noise power estimate

a maximum eigenvalue minimum eigenvalue (MME) technique [11] has been introduced. Analysis of the same shows significant improvement in PD for correlated signals. The MME technique was further enhanced with the help of energy-to-minimum eigenvalue ratio. A positive influence is observed in the performance of correlated signal as well as noise-power uncertainty when using EME methodology. Authors in [12] have introduced arithmetic geometric mean (A-GM) and maximum eigenvalue to trace detection (MET) to determine Rayleigh fading channel. Similarly, A-GM [13], MET [14], EME [15] and MME [16] methodologies have been examined by the authors in [17] using Nakagami-m channel. They also gave a novel methodology along with analytical results that indicate better performance in comparison to previously existing scheme of MET in terms of cooperating secondary users [18] and smaller length of samples [19].

This article explored many strategies that work well when a lower sample size is used [20]. Contra-harmonic-mean-p (CHM-p) [19], contra-harmonic-mean (CHM) [20], harmonic-mean (HM) and geometric-mean (GM) are some of the common operations that are applied on datasets and are also used to remove impulse noise such as salt and pepper noise in images. These methodologies also serve well in filtering the impulse noise [21] and AWGN noise [22] present in the images. The advantage of using them is that they have the tendency to suppress negative and positive transient noise. Let us take a dataset of non-equal elements, it is observed that AM is always greater than GM, which is greater than HM. Similarly, it is observed that CHM-p is smaller than HM through it is greater than AM [23]. When the secondary users count increases, the GM-ME methodology proves to perform better with smaller length samples. Moreover, since GM is greater than CHM-p and HM, the latter are more sensitive to performing well with respect to impulse noise and filtering Gaussian in images because of non-linearity [24-26]. In this methodology, about 3 detection algorithms are used to improve PD for two-noise environment and smaller sample length. This uses the ratio of maximum-eigenvalue-harmonic mean, eigenvalue-to-the contra-harmonic mean uses the ratio contra-harmonic mean minimum eigenvalue and maximum eigenvalue to harmonic mean with the ratio of CHM to

minimum eigenvalue of sample covariance matrix. CH-ME, ME-HM and ME-CHM-p are analysed with Nakagami-m fading channel [27].

Simulation results and analytical methodology are presented using MET, CH-ME, ME-GM, MEHM [28] and ME-CHM-p [29] using analytical expressions with the help of EME and MME. In the proposed work, we have used the CR for a spectrum sensing device and next generation networks in order to improve the spectral efficiency with radio frequency. Hence, these schemes are not analysed with respect to particular criteria [30]. Moreover, the performance of correlated signals is determined for wireless microphone transmission. This paper is organized such that Section 2 shows the proposed Eigenvalue based sensing algorithms. Section 3 provides experimental analysis and the results are recorded in section 4. Section 5 concludes the work and proposes future work using this methodology.

2. Eigenvalue-based Sensing Algorithms

2.1 System Model

A group of population of cognitive radio provides service through a cognitive radio base station (CRBS) as shown in Fig.1. This CRBS communicates with the CRs using the control channel in order to transmit beacon signals that request information from the sensors. From the volunteer notes, suitable nodes are selected to establish a rapport with the CRBS. These nodes are used to capture samples and send them to CRBS, where a binary hypothesis test is used to diagnose the spectrum detection problem.

$$\widehat{x}_0: y_i(n) = \mu_{G_i}(n) + \mu_{I_i}(n) \quad (1)$$

$$\widehat{x}_1: y_i(n) = \mu_{G_i}(n) + \mu_{I_i}(n) + a_i x(n) \quad (2)$$

Where $n=1,2,\dots,N$, $i=1,2,3,\dots,M$. \widehat{x}_1 and \widehat{x}_0 are used to denote the signal present and absent denotation respectively. The n^{th} sample sent by the i^{th} cognitive user is represented as $y_i(n)$. Here M is the maximum the value of i denoting the number of CRs that are cooperative.

The fading coefficient is α_i and $x(n)$ is the signal component. It is assumed that, the impulse noise samples used in this work are distributed based on Laplace distribution and are independent in nature. This is primarily due to the presence of noise and its existence in nature as random bursts of high instantaneous power of short duration.

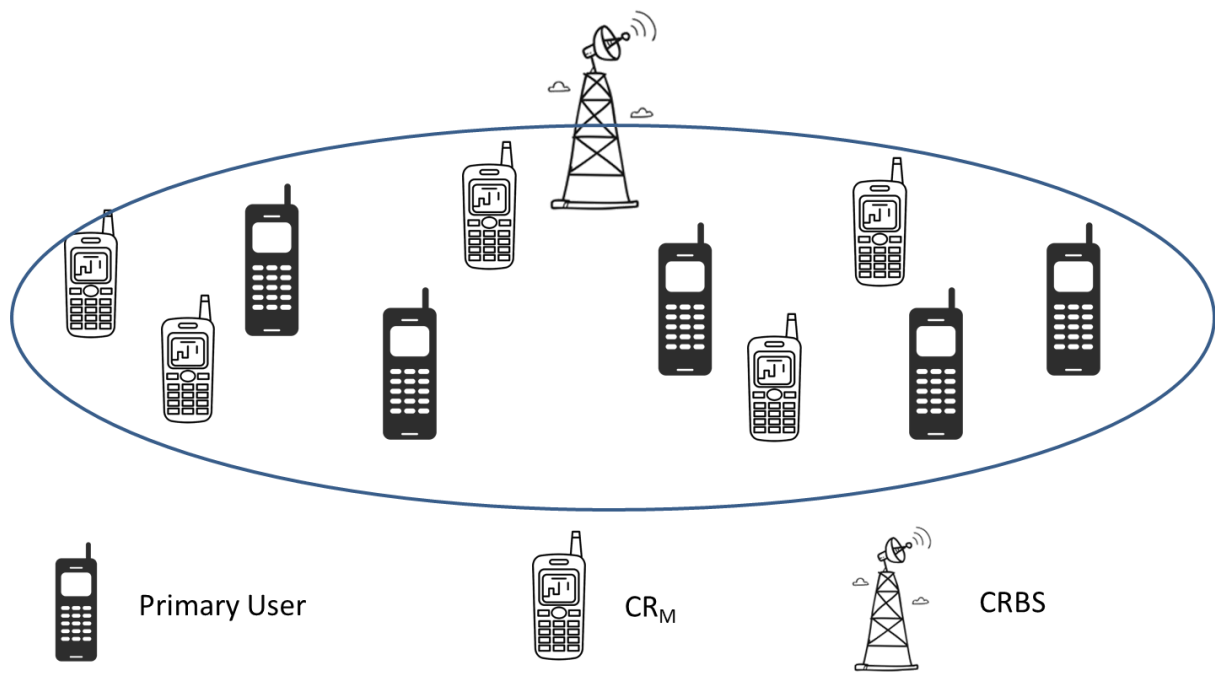


Figure 1. Scenario of Secondary and Primary Users in a Cognitive Radio Base Station

The normalized SNR on the n^{th} branch is represented by $\beta_n = \alpha_n^2 \left(\frac{E_g}{N_o} \right)$ such that N_o represents noise-power spectral density and E_g denotes the signal energy. Moreover, SNR can be represented using the expression:

$$\begin{aligned} \bar{\beta}_n &= E\{\beta_n\} \\ &= E\{\alpha_n^2\} \left(\frac{E_g}{N_o} \right) \text{ assuming that } E\{\cdot\} \text{ shows the mathematical expectation and } E\{\alpha_n^2\}=1 \end{aligned} \quad (3)$$

This work assumes that $\bar{\beta}_n = \beta$ when the channel is identical. Hence, the probability density function for Nakagami-m fading channels can be represented as

$$f_{N-m}(\beta_n) = \frac{1}{\Gamma(z)} \left(\frac{z}{\beta}\right) \beta_n^{z-1} e^{(-m\beta_n/\beta)} \quad (4)$$

Where, $\Gamma(z)$ and m are the gamma function and Nakagami-m parameters.

Considering the two-noise case, it is observed that

$$Z_x(N) \cong HZ_s(N)H^\forall + (\delta_\theta^2 + \delta_I^2)I_M \quad (5)$$

Where, \forall denotes the transpose-conjugation, H is the channel response matrix and $Z_x(N)$ and $Z_s(N)$ are the received and signal-only sample covariance matrices. Similarly, I_M represent the identity matrix of M order and $\delta_\theta^2 + \delta_I^2$ shows the addition of variances of impulse noise and AWGN. The following equation denotes the minimum Eigen value and the maximum Eigen value, respectively.

$$e_{MIN}(Z_x(N)) \cong \sigma_{MIN} + e_{MIN}((Z_{\theta_I}(N))) \quad (6)$$

$$\cong \sigma_{MIN} + \delta_\theta^2 + \delta_I^2 \quad (7)$$

$$e_{MAX}(Z_x(N)) \cong \sigma_{MAX} + e_{MAX}((\delta_\theta^2 + \delta_I^2)I_M) \quad (8)$$

$$\cong \sigma_{MIN} + e_{MAX}(Z_x(N)) \quad (9)$$

2.2 Eigenvalue based Spectrum Sensing Methodologies

There are a number of eigenvalue-based spectrum sensing methodologies that are used to analyse Nakagami-m fading. Based on the various schemes compared, a ME-GM scheme will prove to be an improvement in Power density. Similarly, for samples that are larger in size a comparison is made with the MET result for PD showing better performance overall when compared with A-GM, MED, EME and MME. In general, these almost all the algorithms

respond well to larger lengths of sample which is attained by oversampling the signal or increasing the sensing duration. To limit the occurrence of Impulse and Gaussian noise, there are two theorems to be followed:

Theorem 1: For real noise with the assumption:

$$\varphi(N) = \frac{I}{\delta_{\theta}^2 + \delta_I^2} Z_{\theta_I}(N) \text{ and } 0 < \lim_{I \rightarrow \infty} \frac{M}{I} < 1 \quad (10)$$

Such that the minimum and maximum eigenvalues are represented as

$$e_{max}(Z_{\theta_I}(N)) \cong \frac{\delta_{\theta}^2 + \delta_I^2}{N} (\sqrt{M} + \sqrt{N})^2 \quad (11)$$

$$e_{min}(Z_{\theta_I}(N)) \cong \frac{\delta_{\theta}^2 + \delta_I^2}{N} (-\sqrt{M} + \sqrt{N})^2 \quad (12)$$

Theorem 2: For real noise with the assumption:

$$\varphi(N) = \frac{I}{\delta_{\theta}^2 + \delta_I^2} Z_{\theta_I}(N) \quad (13)$$

$$\text{If } 0 < \lim_{I \rightarrow \infty} \frac{M}{I} < 1, \text{ then } \frac{e_{MAX}(bi\varphi(N)) - \epsilon}{\epsilon}$$

This converges to a distribution such that

$$\epsilon = (\sqrt{N-1} + \sqrt{M})^2 \quad (14)$$

$$\epsilon = (\sqrt{N-1} + \sqrt{M}) \left(\frac{1}{\sqrt{N-1}} + \frac{1}{\sqrt{M}} \right)^{\left(\frac{1}{3}\right)} \quad (15)$$

3. Results and Discussion

In this paper, we have analysed an improvement in PD and have plotted the results based on the number of p values. It is observed in Fig.2 that these samples will result in a decrease in ME-CHM-p and ME-HM. Similarly, when the value of M differs, there is also a significant reduction in PD. In ME-CHM-p, we can choose the value as -5. Moreover, it proves

that a suppression in image noise filtering and spiked noise is improved for the immunity in impulse noise and Gaussian. Similarly, Fig.3 shows that for a variation in samples between 10 and 200, it was observed that the PD was low for MET when compared with the other methodologies.

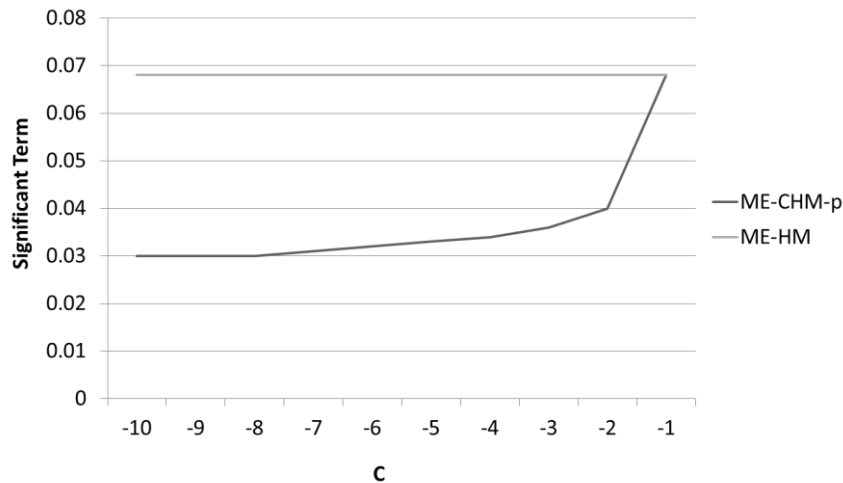


Figure 2. Analytical effect of variation values of p for ME-HM, ME-CHM-p

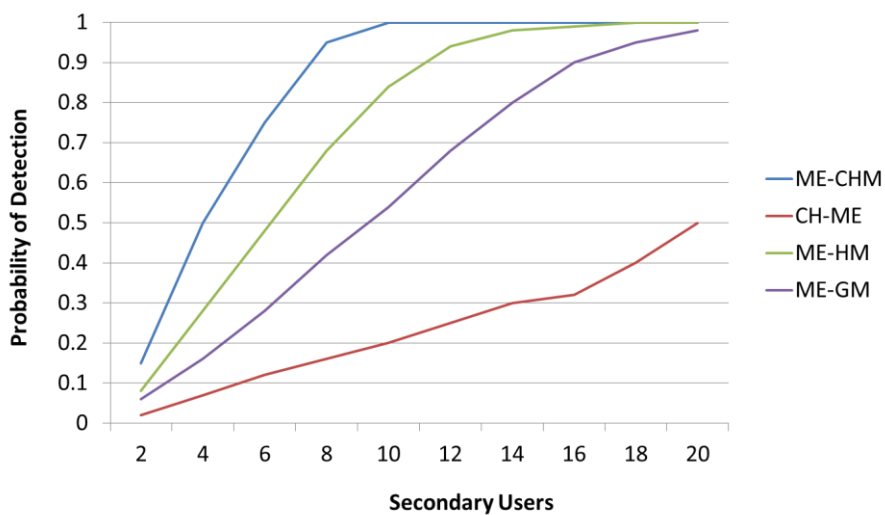


Figure 3. Variation of M for Nakagami-M fading for different Methodologies

4. Conclusion

This paper has used CH-ME, ME-CHE-p and ME-HM algorithms that are three new blind spectrum-sensing algorithms and further it is analysed based on impulse noise and thermal noise using Nakagami-m fading statistics. The performance of ED is superseded by the proposed methodology along with a significant improvement in correlated signals and noise uncertainty. As far as small sample lengths are concerned, the CH-ME performs better than MET. Moreover, the ME-MH algorithm performs better than all the other methodologies. The requirement for oversampling is totally eliminated, despite the fact that complexity is increased, and as a result, computational complexity, correlation caused by oversampling, and sensing length are greatly reduced.

References

- [1] Haoxiang, Wang, and S. Smys. "Big Data Analysis and Perturbation using Data Mining Algorithm." *Journal of Soft Computing Paradigm (JSCP)* 3, no. 01 (2021): 19-28.
- [2] Al-Mistarihi, M. F., Mohaisen, R., & Darabkh, K. A. (2019). Closed-form expression for BER in relay-based DF cooperative diversity systems over Nakagami-m fading channels with non-identical interferers. In *Internet of Things, Smart Spaces, and Next Generation Networks and Systems* (pp. 700-709). Springer, Cham.
- [3] Adam, Edriss Eisa Babikir. "Survey on Medical Imaging of Electrical Impedance Tomography (EIT) by Variable Current Pattern Methods." *Journal of ISMAC* 3, no. 02 (2021): 82-95.
- [4] Zhong, S., Huang, H., & Li, R. (2018). Outage probability of power splitting SWIPT two-way relay networks in Nakagami-m fading. *EURASIP Journal on Wireless Communications and Networking*, 2018(1), 1-8.
- [5] Jacob, I. Jeena, and P. Ebby Darney. "Artificial Bee Colony Optimization Algorithm for Enhancing Routing in Wireless Networks." *Journal of Artificial Intelligence* 3, no. 01 (2021): 62-71.

- [6] Ilhan, H. (2015). Performance analysis of cooperative vehicular systems with co-channel interference over cascaded Nakagami-m fading channels. *Wireless Personal Communications*, 83(1), 203-214.
- [7] Raj, Jennifer S. "Security Enhanced Blockchain based Unmanned Aerial Vehicle Health Monitoring System." *Journal of ISMAC* 3, no. 02 (2021): 121-131.
- [8] Shirley, D. R. A., Sundari, V. K., Sheeba, T. B., & Rani, S. S. Analysis of IoT-Enabled Intelligent Detection and Prevention System for Drunken and Juvenile Drive Classification. *Automotive Embedded Systems: Key Technologies, Innovations, and Applications*, 183.
- [9] Suma, V. "Community Based Network Reconstruction for an Evolutionary Algorithm Framework." *Journal of Artificial Intelligence* 3, no. 01 (2021): 53-61.
- [10] Meraji, S. R. (2007). Performance analysis of transmit antenna selection in Nakagami-m fading channels. *Wireless Personal Communications*, 43(2), 327-333.
- [11] Shakya, Subarna, and Lalitpur Nepal Pulchowk. "Sensor Assisted Incident Alarm System for Smart City Applications." *Journal: Journal of Trends in Computer Science and Smart Technology* March 2020, no. 1 (2020): 37-45.
- [12] Tan, N. T., Hoang, T. M., & Nguyen, B. C. (2018, December). Outage analysis of downlink NOMA full-duplex relay networks with RF energy harvesting over Nakagami-m fading channel. In *International Conference on Engineering Research and Applications* (pp. 477-487). Springer, Cham.
- [13] Adam, Edriss Eisa Babikir. "Deep Learning based NLP Techniques In Text to Speech Synthesis for Communication Recognition." *Journal of Soft Computing Paradigm (JSCP)* 2, no. 04 (2020): 209-215.
- [14] Ho-Van, K. (2013). Performance evaluation of underlay cognitive multi-hop networks over Nakagami-m fading channels. *Wireless personal communications*, 70(1), 227-238.
- [15] Sungheetha, Akey, and Rajesh Sharma. "3D Image Processing using Machine Learning based Input Processing for Man-Machine Interaction." *Journal of Innovative Image Processing (JIIP)* 3, no. 01 (2021): 1-6.

- [16] Shirley, D. R. A., Sundari, V. K., Sheeba, T. B., & Rani, S. S. Analysis of IoT-Enabled Intelligent Detection and Prevention System for Drunken and Juvenile Drive Classification. *Automotive Embedded Systems: Key Technologies, Innovations, and Applications*, 183.
- [17] Ranganathan, G. "Real time anomaly detection techniques using pyspark framework." *Journal of Artificial Intelligence* 2, no. 01 (2020): 20-30.
- [18] Shirley, D. R. A., Sundari, V. K., Sheeba, T. B., & Rani, S. S. Analysis of IoT-Enabled Intelligent Detection and Prevention System for Drunken and Juvenile Drive Classification. *Automotive Embedded Systems: Key Technologies, Innovations, and Applications*, 183.
- [19] Adithya, M., P. G. Scholar, and B. Shanthini. "Security Analysis and Preserving Block-Level Data DE-duplication in Cloud Storage Services." *Journal of trends in Computer Science and Smart technology (TCSST)* 2, no. 02 (2020): 120-126.
- [20] Belmekki, B. E. Y., Hamza, A., & Escrig, B. (2019). Cooperative vehicular communications at intersections over nakagami-m fading channels. *Vehicular Communications*, 19, 100165.
- [21] Suresh, PP Jashma, U. Dinesh Acharya, and NV Subba Reddy. "Study of Effective Mining Algorithms for Frequent Itemsets." *Intelligent Data Communication Technologies and Internet of Things: Proceedings of ICICI 2020* 57 (2021): 499.
- [22] Nguyen, B. C., Hoang, T. M., & Tran, P. T. (2019). Performance analysis of full-duplex decode-and-forward relay system with energy harvesting over Nakagami-m fading channels. *AEU-International Journal of Electronics and Communications*, 98, 114-122.
- [23] Karthikeyan, M. M., and G. Dalin. "Dynamic Congestion Control Routing Algorithm for Energy Harvesting in MANET." In *Inventive Computation and Information Technologies*, pp. 15-25. Springer, Singapore, 2021.
- [24] Rajeswaran, N., Madhu, T., & Joy, B. (2015). Ultra low voltage and low power Static Random Access Memory design using average 6.5 T technique. *Leonardo Electronic Journal of Practices & Technologies*, 14(27), 138-154.

- [25] Samantaray, Sahil, Rushikesh Deotale, and Chiranji Lal Chowdhary. "Lane Detection Using Sliding Window for Intelligent Ground Vehicle Challenge." In *Innovative Data Communication Technologies and Application*, pp. 871-881. Springer, Singapore, 2021.
- [26] Stefanović, D. M., Panić, S. R., & Spalević, P. Č. (2011). Second-order statistics of SC macrodiversity system operating over Gamma shadowed Nakagami-m fading channels. *AEU-International Journal of Electronics and Communications*, 65(5), 413-418.
- [27] Patidar, Sanjay, and Inderpreet Singh Bains. "Intrusion Detection Using Deep Learning." In *Inventive Computation and Information Technologies*, pp. 113-125. Springer, Singapore, 2021.
- [28] Reig, J. (2009). Multivariate Nakagami-m distribution with constant correlation model. *AEU-International Journal of Electronics and Communications*, 63(1), 46-51.
- [29] Rao, M. Pushyami, R. Sunitha, and Dhanesh G. Kurup. "FastICA Algorithm Applied to Scattered Electromagnetic Signals." In *International Conference on Communication, Computing and Electronics Systems*, pp. 27-34. Springer, Singapore, 2020.
- [30] Michalopoulos, D. S., Karagiannidis, G. K., & Tombras, G. S. (2008). Symbol error probability of decode and forward cooperative diversity in Nakagami-m fading channels. *Journal of the Franklin Institute*, 345(7), 723-728.

Author's Biography

B Vivekanadam is a senior lecturer in the Department of Computer Science and Multimedia at Lincoln University College, in Malaysia. His major area of research are machine learning, neural network algorithms, image processing, video and signal processing, cloud computing, deep learning, artificial intelligence, object recognition, complex feature extraction and vision graphics.