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Research Article

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DOI: https://doi.org/10.21203/rs.3.rs-554306/v1

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ABSTRACT:

Visible light is considered one of the foremost exciting areas of communication science and industry, gaining prominence over data broadcast and radiance instantaneously using low-cost light-emitting diodes (LEDs). Though, the high speed characteristics of this network are restricted by the truncated bandwidth of the LED. Therefore, amazing efficient, advanced modulation and demodulation schemes are considered for establishing high data rates in VLC. Carrierless amplitude-phase (CAP) modulation is such an attractive and effective modulation that it is gaining a good position due to its high efficiency and practical implementation. But multi-path scattering factors, noise factors, vigorous jamming and low sensitivity can have a significant impact on the performance of CAP-VLC systems. To overcome this problem, this paper examines the implementation of the CAP-VLC system based on the High Speed Feed Forward Neural Network, which operates on the principle of Extreme Learning Machines. The experiment was carried out by new simulated datasets used to train cap demodulators and parameters such as accuracy, retrieval, accurate bit error ratio (BER), noise ratio (SNR). Also the proposed learning based CAP-VLC systems has shown better performance such as 92.4\% accuracy at various conditions, increase in BER by 40\% and 50\% of reduction of noise respectively.

Keywords: Visible Light Communication, Carrier Less Amplitude Modulations, High Speed Feedforward Networks, Extreme Learning Machines

DECLARATIONS:

Funding: No
Conflicts of interest/Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
Availability of data and material: Yes
Code availability: Yes
Authors' contributions: --
1. INTRODUCTION:

On rapidly emerging huge volume mobile and edge devices, leads to the shortage of bandwidth and faces the huge bottleneck in enhancing the network capacity. Visible light communication is the latest technology that can support next generation network. Visible light communication (VLC) is a compelling technology that is distinctively achievable with the new generation of cellular system in order to increase the channel capacity. [1]. On the other hand, the VLC attocell network is a type of combination of communication as well as lighting for a large area of an indoor environment. For the optical communication different types of LED transmitters and photodiodes receiver are employed. [2]. For the recent active communication system the inexpensive and most widely held LEDs are phosphorescent layered blue light LEDs. Those LEDs chips emitted alters the blue light component into yellow, which together with the blue one generates white spectrum. [3]. The very important characteristics of commercial LED is its restricted bandwidth that gives higher data rate in transmission with the modern modulation technique adaptation. In most of the VLC systems various types of modulation techniques with different rates were utilized by many researchers. Among these, CAP modulation is predominantly used by VLC system for simplicity, less complexity and more accuracy. [4][5]. Linear power amplifiers (PAs) in a VLC system requires modulated signals with low peak amplitude to power ratio (PAPR). But the PAs have more efficiency in power level during the nonlinearity part lies in saturation. The data output from the VLC channel has a significant nonlinear distortion. Considering all these it requires equalization on both at the transmitter and at the receiver end to compensate the nonlinear distortion. [6][7][8]. When the nonlinearities are higher, linear and nonlinear equalizers are employed. [9]. When the system is employed with proper complementary equalizers then it may acquire proper rate of convergence and less error rates. This helps the system to get proper illumination as well as power distribution for effective communication. With the variation in LED lamps and the characteristics of neural network shows the better performance of the VLC system. [10]

CAP-VLC systems are implemented with the algorithms such as Support vector Machines [11], K-Nearest Neighborhood (KNN) [12], Artificial Neural Networks (ANN) [13],[14] and even Deep learning algorithms [14],[15]. But still learning based CAP-VLC systems requires more brighter side of research to overcome the challenges mentioned.

In this paper, a new technique of modulation have been proposed with the intelligent data driven framework that shadowed by ELM. Also the new methodology of creating the datasets
using the simulated environment has also been discussed in the paper and various experimentations are carried by using the open & simulated datasets. The research responsibility is been shared

1. This paper propose the new data driven CAP-VLC simulated environment to collect the open data sets which are then used to study the characteristics of receiver end of CAP-VLC demodulation technique. An open dataset for CAP-VLC systems is truly taken.

2. High Speed Feed forward Neural Networks based demodulators were designed. The working principle of extreme learning machines (ELM) were deployed in proposed neural network with 15 hidden layers and 100 neurons. Then modulation features were extracted to implement the ELM based intelligent CAP demodulators.

3. This paper also shows the design of reconfigurable and scalable CAP-VLC software test beds for the extraction of different features which can be used for experimentation. Moreover, the main objective in designing software test beds to reduce the cost and computational complexity.

4. Based on the data collected and model designed, various machine learning machines such as Support Vector Machines (SVM), K-nearest neighborhood (KNN), Artificial Neural Networks (ANN) along with the proposed extreme learning machines were investigated at different scenario such as distance, SNR’s and modulation parameters. Experimentally proved that the accuracy of the proposed Extreme learning Machine based demodulators is higher than other ML based demodulators.

The structure of the paper is as follows : Section-II discusses about the related works. Section-III presents the CAP modulation. Proposed methodology composed in section IV. The results analysis and discussion are demonstrated in the Section-V. Finally Conclusion along with future scope were presented in Section-VI

2. RELATED WORKS :
Shuai Ma et. al [13] designed end-to-end data driven demodulation mechanism and they have collected received data with different modulation schemes of OOK, QPSK, PPM and various QAM in real physical prototype model. The system works with real modulated dataset and measured the transmission distance as 0cm to 140cm. CNN based demodulators are designed to support image classification with required number of convolutional and pooling layers. DBN and RBMs were used by them to extract the modulation features. Here a strong classifier was constructed with many week classifiers which makes the system more complex
and impractical. But it can have accuracy with various modulation schemes. It is limited to short distance or high SNR scenario. Adaboost demodulators shows best accuracy than any other demodulators and it prefers high order demodulation.

Guoqiang Li et. al [14] shows the mitigation of linear distortion using linear equalizer, Volterra model and DNN with linear equalizer. Both the linear and nonlinear distortion is occurred in this system. This experiment make us reveal that it effectively supports for linear distortion but not suitable for nonlinear distortion. However, Volterra and DNN are not much supportive for non-linear distortion.

Qing Wang et al [15] shows the performance of indoor VL communication can be estimated by correlated color temperature (CCT), but illuminance is not a proper factor for estimation. Most of the ML related researches do converting the input signal into image of one dimensional and two dimensional for showing improvement in its performance.

G. E. Hinton and R. R. Salakhutdinov [16] show the theoretical concepts of converting the image and reducing its size so that the speed of training in ML is high. The reconstruction of high dimensional input vectors are made easy. In autoencoder networks gradient descent is utilized for adjusting the weights for the improvement of framework. PCA (principal component analysis) is utilized in earlier cases to reduce the dimensionality of information, but the effect of gradient descent is more in such cases. So he presented a active strategy of setting the weights for autoencoder to learn low-dimensional codes for better execution than PCA. This works productively when the underlying weights are near to a solution.

Shengliang Peng et.al [17] detailed about some of the ML mechanism like CNN, AlexNet & GoogLeNet to show that the effect of reduced vanishing gradient and the improvement using computer vision mechanism. To show the improvement in entire ML system the author decided to use two main characteristics - sparse connectivity and parameter sharing. The computation complexity is more as the iteration is more in ML based system than DL based system. Here in this system features increases or SNR decreases makes the system slower and complex in implementation.

Sanqing Hu et.al [18] used Support vector machines (SVM) for feature identification by finding an optimal hyperplane. The feature separation can be done by SVM as line, plane and hyperplane. SVM detects the spectrum availability as the features are considered as received signal strength. This increases the detection probability. Different types of networks are considered such as TDMA, CDMA/CA, ALOHA for MAC protocol identification. But it is limited for physical layer protocol identification.
Hurmat AliShah et.al [19] to transmit the waves as a global decision combined with a local decision spectrum with the help of altered K-nearest neighbor supervised network. Verification of real time dataset is performed with profiles of PU spectrum using this network. Manipulation of spectral hole is augmented using the proposed network. Limitation of proposed network is not adaptable for huge networks, but it is suitable for small CR networks.

3. CAP MODULATION:
CAP modulation is another sort of staggered and measurement based modulation innovation, which was right off the bat proposed by Bell Lab in 1970s. Limited bandwidth spectrum to achieve high data rate and spectral efficiency with reduced system complexity may possible in utilizing CAP modulation. In CAP modulation the electrical or optical conversion is no longer required because it utilizes two symmetrical digital filters. So it doesn’t rely on carrier for transmission. At the same time Discrete Fourier transform (DFT) is also not required for CAP modulation which can moderate system complication expressively. [14]

Machine learning algorithms are mostly widely implemented for better performance of the entire VLC system which has more accuracy, distortion less transmission, responsivity, better BER and so on. With the help of these latest technology todays communication can be well established in many of the applications.

4. PROPOSED METHODOLOGY:
The proposed methodology used in the research work is shown in figure 1. The proposed methodology consists of different phases such as System Model Design (Transmitter and Receiver), Feature extractions and finally implementation of ELM based demodulators. The working mechanism of the each and every phases are discussed in the preceding section.
4.1 MODEL OF THE SYSTEM:

A flexible end-to-end VLC system is as shown in figure 2. As suggested in figure 2 the self-generated digital signal \( v(n) \) which is considered as \( ...101010... \) is modulated using CAP modulation in the base of QAM scheme. With the filter size of 31 and tap value of 3 or 5 the system performance can be improved. The real part of the signal is fed to LED and wireless channel. Those signals before transmission will get added with bias for balancing system. But the addition of forward current and DC bias introduced non-linearity in the transmission signal. Also this addition of DC bias leads to greater device bandwidth. The digital modulation process in this paper is CAP comes out with \( X(t) \) as follows,

\[
X(t) = \text{Re}[v(t) \ast g(t)e^{2\pi f_c t}], 0 < t \leq T
\]  

---(1)
As shown in Figure 2, the transmitter and receivers design specifications employed for the CAP-VLC system are tabulated in the Table I and Table II.

**Table I**  Transmitter Specification Used in the System CAP-VLC Model

| Parameter                                      | Dimension          |
|------------------------------------------------|--------------------|
| Distance between LED                          | 170 cm             |
| Semi-half degree angle $\phi_{1/2}$           | $(7.5*\pi)/180$    |
| Power transmitted $P_t$                       | 0.1w               |
| Centre luminous intensity $I_0$               | 24                 |
| Reflectance factor of the wall                | Rho                |
| Bit period $T$                                | 0:0:01:4           |
| Gain of optical filter $T_s(\varphi)$         | $Prx_{total}$/PLED |
| No. of LEDs                                   | 4                  |
| Angle of incidence $\psi_i$                   | atand(xydist.*heightLED^-1) |
| Angle of irradiance $\phi_i$                  | $(7.5*\pi)/180$   |
| No. of LEDs                                   | 4                  |

**Table II**  Receiver Specification Used in the System CAP-VLC Model

| Parameter                                      | Dimension          |
|------------------------------------------------|--------------------|
| Photodiode responsivity $R$                    | 0.55 A             |
| Refractive index of optical concentrator $(i)$ | 1.46               |
| Detector area of PD (APD)                     | 7.8E-7 m^2         |
| Power received $P_{rx}$                       | 4.2366e-05         |
| Detector angle $(\psi_c)$                     | $(20*\pi)/180$    |
| Data rate                                     | 115200             |

At the detector point the optical signals with AWG noise is filter and down sampled. The size of filter and tap is same as in transmitted side. Then the synchronized signal is fed to pre-equalizer to mitigate linear distortion. After CAP demodulation and decoding the original signal can be received.

### 4.2 HSFNN BASED DEMODULATOR:

Deep learning neural network plays a vital role in prediction problems. SLFN (ELM) is a single layer feed forward neural network which is efficient than other neural networks such as gradient-based network, backpropagation ANN in terms of time-cost density. The intricacy of
such networks is training complexity in terms of parameters updation and concealed neurons are retrained several times which increases the time complexity at runtime. To overcome this, Huang et. al. developed a low-complexity network named as single-layer feedforward network or ELM [20]. The parameters of the proposed neural network are generated randomly and need not be tuned at runtime. Even though, the prediction exactness, planning velocity, incredible speculation are enhanced to the global optimum. To utilize these benefits, this work comes up with designed ELM for the spectrum prediction.

ELM network comprises of only three layers in terms of input, output and concealed layers. The mathematical formulation of the proposed ELM predictor is given below.

\[
\mu(t) = \sum_{i=1}^{\alpha} u_i \rho_i(t) = \rho(t)u
\]  

\(\text{(2)}\)

\[
u = [u_1, u_2, \ldots, \ldots, u_\alpha]^T
\]  

\(\text{(3)}\)

In this network, \(\alpha\) denotes the total number of neurons in the concealed layer, \(t\) represents the input vector layer and \(u = [u_1, u_2, \ldots, \ldots, u_\alpha]^T\) represents the vector between concealed neurons to output weights, The concealed layer output vector is denoted as \(\rho(t) = [\rho_1(t), \rho_2(t), \ldots, \ldots, \rho_k(t)]\) were \(k\) denotes the total values in output vector in equation 1.

\[
\theta = \begin{bmatrix}
\theta(t_1) \\
\theta(t_2) \\
\vdots \\
\theta(t_0)
\end{bmatrix}
\]  

\(\text{(4)}\)

The parameters such as weights and bias values between input and concealed layer is randomly generated and the output synapses are obtained through Moore-Penrose pseudoinverse method (Least-square method).

\[
u' = \theta^*\beta = \theta^T(\theta\theta^T)^{-1}\beta
\]  

\(\text{(5)}\)

\(\theta^* \rightarrow \text{inverse of known } \theta \text{ as Moore–Penrose generalized inverse.}

\[
u' = \theta^T\left(\frac{1}{C}\theta\theta^T\right)^{-1}\beta
\]  

\(\text{(6)}\)

\[
u(t) = \theta(t)u = \theta(t)\theta^T\left(\frac{1}{C}\theta\theta^T\right)^{-1}\beta
\]  

\(\text{(7)}\)

Algorithm1: ELM Prediction steps

Input: Trained dataset with random number of weights and bias values
Output: Predicted Score in terms of Exactness and loss values

Network are initialized with input neurons ‘O’

Set of concealed neurons are generated as single layer

Softwmax function is defined as an activation function

Synapses parameters are spawned through gaussian random method

After each iteration concealed matrix are updated

The output matrix values are calculated

Final prediction scores are observed for entire system

ELM utilizes the part capacity to yield great exactness for the better execution. The significant focal points of the ELM are negligible preparing blunder and better guess. Since ELM utilizes the auto-tuning of the weight predispositions and non-zero initiation capacities, ELM discovers its applications in arrangement and expectation esteems. The itemized portrayal of ELM ‘s conditions can be found in [20]. The information vectors which are determined in the collector side were taken to the system and yield from the demodulator side is planned to $f_L(x)$ for additional computation of execution.

5. RESULT & DISCUSSION:

The above system model has been used for extracting the features from the received signals which are then used to train the proposed ELM architecture. For an effective data collection and feature extraction, we have designed the simulation environment which can be adaptive to the different environment.

The software was developed using MATLAB R2018 versions which runs on Intel i7 CPU with 8GB RAM, 1TB HDD and it is used for the collecting different features at various scenario of distance and changes in modulation schemes. The software developed can be reconfigured for any modulation schemes and be scalable for getting the input vectors. The features which are extracted for training the proposed ELM based demodulator.

Nearly 2430 features were extracted and to assess the presentation of the proposed algorithm we have taken the datasets in the proportion of 80% as training and 20% as testing. The presentation assessment of the proposed algorithm can be determined by the scientific articulations which are given as follows
Accuracy = \frac{D.R}{T} \times 100 \quad \text{...(8)}

Precision = \frac{TP}{TP+TN} \times 100 \quad \text{...(9)}

Recall = \frac{TN}{TP+TN} \times 100 \quad \text{...(10)}

Where TP and TN represents true positive and true negative values and D.R & T represents number of detected results and total number of iterations. To prove the strength of the algorithm, it has also validated with the open source data sets [22] and compared with the other machine learning algorithms.

**Table III Comparative Analysis of Different ML based Demodulator along with the Proposed Methodology.**

| Dataset Details                  | Algorithms Used | Performance Metrics Measured |
|---------------------------------|-----------------|-------------------------------|
|                                 | Algorithms Used | Accuracy(%) | Precision(%) | Recall(%) |
| Datasets Created in Software Developed | SVM[13]          | 86.4%        | 85.2%        | 82.3%     |
|                                 | KNN[21]          | 87.2%        | 86.4%        | 81.5%     |
|                                 | ANN[22]          | 84.5%        | 80.4%        | 82.4%     |
|                                 | Proposed         | -      92.7% | 93.4%        | 92.8%     |
|                                 | HSFNN            |              |              |           |
| Open Data Sets collected        | SVM              | 83.5%        | 80.0%        | 83.3%     |
|                                 | KNN              | 86.2%        | 85.4%        | 84.5%     |
|                                 | ANN              | 80.5%        | 78.2%        | 80.5%     |
|                                 | Proposed         | -      92.5% | 93.4%        | 92.8%     |
|                                 | HSFNN            |              |              |           |

Table III presents the comparative analysis between the various machine learning and deep learning algorithms for the different category of input datasets. From the table, it is clear that the new algorithm has accuracy of 92.7% from software test beds and 92.5 % from the hardware test beds which clearly proven that performance of the new algorithm is maintained with RMSE less than 0.03 which outperforms the performance of the other machine learning algorithms. Moreover, from the table it clearly shows that the developed software can also be used as the test beds in equivalent to hardware test beds which can readily reduce the cost and computational complexity.
After evaluating the performance of the proposed learning algorithms, network characteristics of the ELM-demodulator based CAP-VLC systems were analyzed at the different distances.

(a)

(b)
Figure 3 Comparative Analysis of BER vs SNR performance of different ML based Demodulators using 16- CAP-VLC systems .(a) Distance =50 cm  (b) Distance =100 cm  (c) Distance =125 cm  (d) Distance =150 cm
The comparative analysis of figure 3 (a), (b), (c) and (d) shows bit error rate (BER) for different ML based demodulators with the changes in distance d. In the comparative analysis, the result have been evaluated the performance of the ML demodulators for 16-CAP-VLC systems. When index is 16, BER performance of the proposed ELM based demodulator is maintained constant even the distance and SNR increases but the other machine learning such as SVM, ANN, KNN based demodulators has degraded performance at high SNR and long distance.
Figure 4 Comparative Analysis of BER vs SNR performance of different ML based Demodulators using 32- CAP-VLC systems .(a) Distance =50 cm  (b) Distance =100 cm  (c) Distance =125 cm  (d) Distance =150 cm

When index is 32 , BER performance from the figure 4 (a) (b) (c) & (d) shows the proposed ELM based demodulator is moderate on the event of distance and SNR increases but the other machine learning such as SVM , ANN, KNN based demodulators has shown very low performance at high SNR and long distance.
Figure 5 Comparative Analysis of BER vs SNR performance of different ML based Demodulators using 64- CAP-VLC systems . (a) Distance =50 cm  (b) Distance =100 cm  (c) Distance =125 cm  (d) Distance =150 cm

When index is 64, BER performance of the proposed ELM based demodulator is performed better when the distance and SNR increases than any other machine learning algorithms such as SVM, ANN, KNN based demodulators. The best performed output is from the system which explodes with less bit error rate is shown in figure 5 (a) (b) (c) & (d). When compared to other CAP modulation index which are experimented along with this shows bit error rate of 75% increase. Figure 4 & 6 (a,b,c,d) shows the same response in its bit error rate under the constraints of high SNR and increased distance.
Figure 6 Comparative Analysis of BER vs SNR performance of different ML based Demodulators using 256- CAP-VLC systems .(a) Distance =50 cm  (b) Distance =100 cm  
(c) Distance =125 cm  (d) Distance =150 cm

From all above figures , it is inparticular that the new ELM has outpaced the other machine learning algorithms  even when order of modulation scheme increases with the high SNR and distance respectively.

6. CONCLUSION :

In this paper, High Speed Extreme Learning Network built demodulators is intended in the physical layer of CAP-VLC systems. A Scalable and reconfigurable Software test bed is designed and experimented for data set collection and feature extraction. By using the proposed software test beds, nearly 2430 data is created which consist of the different orders (16, 32, 64 & 256) of CAP modulated signals. Comparatively index value of 64 CAP modulation shows better BER between 10e-5 and 10e-6 than other three modulation like 16, 32 and 256. Based on the datasets created, we compared and analyzed the proposed ELM demodulator with the other existing machine learning systems. The experimental results shows that ELM based demodulator has outperformed than other ML based systems in terms of accuracy, precision and recall of 92.7%, 93.4% and 92.8% respectively. Even the proposed ELM based CAP-VLC system has maintained better BERs of 92.4% than all other ML based demodulators at higher SNR of 10dB and varied distances (50cm, 100cm, 125cm and 150cm). Also it clearly shows that the proposed ELM based demodulator can find as better suitability of n-CAP-VLC systems. The performance accuracy can still be improvised by the usage of self-adaptive deep learning algorithms for higher order CAP-VLC systems.
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