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An Adaptive Compression Technique for Efficient Video Reconstruction in Future Generation Wireless Network

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Abstract: The mmwave (millimeter wave) with massive MIMO (Multiple-input and multiple-output) leverages larger antennas with spatial diversity and multiplexing gain brings about positive vibe for future generation wireless networks for provisioning bandwidth hungry multimedia applications However, the fronthaul link that links a remote radio head (RRH) and carries video frames as bitstreams to the baseband unit (BBU) can fluctuate the overall speed and capacity of massive MIMO if suitable data compression (encoding-decoding) techniques are not functional. This paper presents an error detection aware compression (EDAC) scheme which first performs encoding using low-rank approximation considering both spatial and time domain to reduce video frame size; later, the encoded video frames are compressed using Huffman codewords. Experiment outcome shows the proposed video compression model achieves much better compression efficiency with improved bit error rate (BER), symbol error rate (SER), error vector magnitude (EVM), and compression ratio when compared with the fixed code dictionary huffman video coding (FCDHVC), exiting video compression (EVC) technique and huffman video coding (HVC). The proposed EDAC model achieved compression efficiency of 30.52 whereas the FCDHVC, EVC and HVC model achieved compression efficiency of 26.50, 21.75 and 22.35 respectively.

Keywords: Compression, Error detection, Fifth generation network, Sparse feature, Spatial, Temporal, Video encoding.

1. Introduction

In recent times social networks have become an essential communication mode, where multimedia content such as audio, video, photos are major information that have been shared through Internet [1]. The multimedia content such as video frames are generally has much larger information [1] in comparison with audio and text, thus prerequisite higher bandwidth [2-3]. In meeting research challenges the fifth-generation (5G) have been emphasized, which provide higher data rate, better coverage, and low latency [4-5]. Besides, it is anticipated that 5G would pave the way for augmented and virtual reality services, connected vehicles, and smart cities [6]. The 5G and smart cities go hand in hand because of the following [7]: (1) smart surveillance requires more accurate recognition accuracy and identification as wireless technology advances, (2) artificial intelligence (AI) technologies are essential for connected vehicles to assess and respond to their surroundings, (3) 5G offers a much more accommodating environment for the internet of thing (IoT) services, which need analysis of data generated by internet-connected gadgets at the edge networks. Hence, mobile networks necessitate increased data transfer speeds and decreased network latency for customers to have a satisfying experience and good quality of experience (QoE) with video streaming applications [7-8].

In meeting the aforementioned requirement for provisioning video streaming application, the centralized radio access network (CRAN) design, which features higher frequencies and many antennas, has been stressed with positive results to fulfill the aforementioned demand for supplying video streaming applications [9]. Usually, the CRAN consists of a BBU and RRH which communicate with the fronthaul link [10-11]. The baseband unit are usually residing in the data centers, from where the computing resources can be shared which will also further help in reducing the operational-cost and resources usage. A disadvantage of using CRAN network is that it requires a high bit rate of the fronthaul, which is the connection between the RRH and BBU which allows for the transmission of the video frames in the form of data streams [12].

The functional split [13] and time-domain video frame compression [14-15], are some of the methods which have been used for reducing the fronthaul rate. Also, some of the techniques of time-domain video frame compression include high-efficiency video coding (HEVC) [16-18], using vector quantization [19], linear prediction [20] and Huffman [21, 22]. The functional split compression technique, on the other hand, divides the network processing among the RRH and BBU. The functional split compression makes it possible to reduce the bit rate of the fronthaul, but they need the RRH to carry out additional computational processing. Combining the two approaches and making use of video frame compression methods [23] in conjunction with functional splits is still an effective solution. Further, an instance of how the fronthaul compression uses the functional split has been shown in [23], where the devices make compression-decompression on the fronthaul and allocate resource blocks according to the cell usage. The model decreased the RRH computational cost but increased the fronthaul bit rate since all subcarriers of an LTE symbol are sent, regardless of whether or not they carry information that is useful to the video sequence.

On contrary to existing encoding method, this paper presents an adaptive error detection aware encoding and compression scheme to reduce video frame size with higher reconstruction quality at the receiver side. First to achieve higher compression efficiency the model cooperatively extracts information from both temporally and spatially of the received video frames considering a complex massive MIMO environment. Then, using low-rank approximation the video frames are encoded to reduce its size; later, Huffman codewords is used to perform compression on encoded video to achieves lossless compression with higher compression efficiency. The significance of research work:

- The proposed adaptive encoding technique is very efficient in reducing the video frames size by exploiting both spatial and temporal frequency domain and employing Huffman compression.
- The proposed model achieves very good compression efficiency.
- Achieves higher BER, SER, and EVM efficiency with respect to different SNR levels.

Further, in the next section, section 2, literature survey has been given. After this the proposed model has been given in section 3. The results have been discussed in section 4 and finally the conclusion of the proposed work has been given in section 5.

2. Literature survey

This section present survey of various encoding method designed for future generation network. In [20], it was shown that the researchers are looking into various new frameworks and architectures for cloud radio access networks (RANs). After reviewing the various new frameworks and architectures it was assumed that the different parts of the network have different functions. Therefore, many different assumptions corresponding to different video frame distortion, and tradeoffs between data rate, computing cost, and delay underpin the study of radio data compression for the research work of the fronthaul. In this research work, they have proposed a method for long term evaluation (LTE) downlink point to point video frame compression depending on the Huffman coding and Linear prediction, which is best for reducing the cost during the encoding and decoding units. They have also focused to reduce the consumption of energy during encoding and decoding [21]. In [22], they have developed a model called as distributed-energy-efficient data-reduction, which will help in the compression of the data transmission to reduce the data compression and predict the data compression in the IoT infrastructure. This model is used for decision-making and they have used an auto-regressive prediction which will be used for the prediction of the data, i.e., to send the data to the gateway or not. During the transmission of the data, the unnecessary data are removed using fixed-code-dictionary, adaptive-piecewise-constant-approximation, and symbolic-aggregate-approximation. All these dictionary and approximation methods are dependent on Huffman Coding.

In [14], they introduced a method, channel state information-based compression method, by exploitation of the physical framework of the rician fading channels. In this method, the channel state information-based compression method decomposes the channel matrix into the non-line-of-sight and line-of-sight, and further, compresses them by utilizing a model which is based on the singular value decomposition (SVD). In this method, they have also proposed two more optimization algorithms that will help to get a stage during the formation of the line-of-sight component of the channel. These two algorithms are further then used for proposing the decomposition of the channel matrix. In [15], they have proposed a method for compression technique that will transport the downlink radio video frames in the form of packets into the fronthaul of the centralized radio access network (C-RAN). The method is adapted for frequency domain functional splits, where packets may exclude non-active LTE (or 5G new radio) resource elements. Due to this, this method provides to decrease the link data rate, only when the cell load is less. Further, the compression technique is built in two stages. In the first stage, the side information is transmitted which will indicate whether the resource element of the long-term evaluation is inactive or active. In the second stage, a non-uniform scalar quantization method has been used for the compression of the QAM symbols of the active resource elements. This technique shows that the number of links can be reduced by reducing the cost of the computation.

In [23], they have utilized the lossy-dimension reduction technique, which has been applied at every RRH, for the reduction of the fronthaul traffic. In the initial stage, this model considers the uplink and identifies where all the linear dimensional reduction filters must be applied at every RRH. Further, it has been seen that in this model, the karhunen-loeve transform method has been used for optimal dimensional reduction filters. Furthermore, every RRH is then given the ability to independently determine its dimensional reduction filter depending on the slow fading of the network coefficients and instantaneous channels.

In [20], because of very less space, they have evaluated their results only for the uplink and have not considered the downlink. Also, they have not considered the Orthogonal Frequency Division Multiplexing signals. Further, in [21], [22] and [26], they have used encoding and decoding methods but have failed to achieve a good compression rate. Also, the model [23] has not considered the issue of MIMO in their research work. Hence due to all these issues, the proposed error detection aware compression (EDAC) has been proposed.

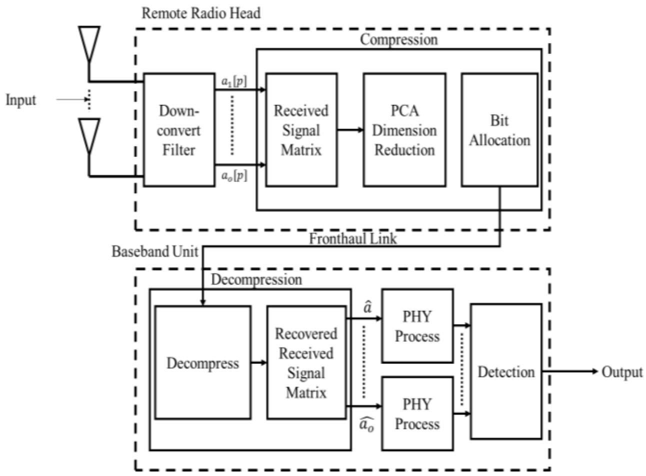

Figure. 1 Architecture of proposed adaptive error detection aware encoding scheme in massive MIMO network

3. Proposed methodology

This section presents an adaptive error detection aware encoding scheme for achieving improved compression efficiency and enhanced video reconstruction quality in massive MIMO wireless network.

3.1 System model

The proposed adaptive encoding scheme for provisioning multimedia application (i.e., video streaming/transmission) in massive MIMO wireless network is given in Fig. 1. In this work similar to [23] considers massive MIMO 5G RRH which composed of several antennas and receives video sequences (i.e., bit-streams) from users in the uplink channel. Further, the 5G network uplink channel operates using orthogonal frequency division medium access [23]; thus, provides multi-channel access and the video sequence from different users are mapped to M-QAM and video sequences information produced by different users are pre-coded with discrete fast Fourier transformation and cycle prefix coded are appended to it. The RRH obtains time domain OFDM frames with noise and interference from different users.

3.2 Adaptive encoding technique

This section presents adaptive encoding technique by efficiently detecting encoding error to improve compression efficiency with improved video sequence reconstruction quality at the receiver side. In this work the time-domain video sequence is used for performing fronthaul compression in MIMO networks composed of multiple users and RRHs. The RRHs is composed of O antennas that receives video frames from different users. The video frames as bitstreams a_o collected in o^{th} antenna is expressed as follows

$$a_o[p] = \sum_w z_w[\mathrm{p}] \times j_{o,w}[\mathrm{p}] + y_o[\mathrm{p}] \\ \mathrm{o} \in 1,2,\dots,\mathrm{O}, \mathrm{p} \in 0,1,2,\dots \tag{1}$$

where z_w defines the OFDM frames as bitstreams of w^{th} user, $j_{o,w}$ defines the channels noisy characteristic given to w^{th} user to o^{th} antenna, y_o defines the Gaussian noise of o^{th} antenna, and $(*)$ describes convolution. Using above equation, the collected video frames is represented as matrix $A \in \mathbb{E}^{P*O}$, where P defines the total video frames considered for performing compression and O defines the RRH antenna size. The matrix A is obtained using following equation

$$A = \begin{bmatrix} a_1[0] & a_2[0] & \dots & a_O[0] \\ a_1[1] & a_2[1] & \dots & a_O[1] \\ \vdots & \vdots & \ddots & \vdots \\ a_1[P-1] & a_2[O-1] & \dots & a_O[P-1] \end{bmatrix} \tag{2}$$

and the matrix A columns is defined through following equation

$$a_k = [a_k[0] \quad a_k[1] \quad \dots \quad a_k[P-1]]^U \tag{3}$$

The column $a_k, k \in \{1,2,\dots,O\}$ exhibit good correlation among them and the matrix A is approximated using low-rank computation model through following equation

$$A = A_0 + G \tag{4}$$

where $A_0 \in \mathbb{E}^{P*O}$ defines a matrix with no noise after performing low-rank approximation. The approximated matrix is composed information about the input video sequence represented as bitstreams a and channel behavior k, and $G \in \mathbb{E}^{P*O}$ defines realistic noise matrix through Gaussian representation. Using the above equation, the video frames are compressed and transmitted to the baseband unit through the available fronthaul channel. Later, the video frames are decompressed to obtain A and decoded in reverse manner at the baseband unit. The focus of this work is to reduce the size of matrix A using low-rank approximate computation model; thereby assuring only lesser number of video frames at bitstreams to be transmitted in MIMO network. The parameter A_0 in above equation defines low-rank matrix with size $P * O$ and for ease of understanding $P \gg O > N$, A is represented through following equation

$$A'' = \underset{\mathcal{R}ank(\hat{A})=N}{\operatorname{argmin}} \left\|A - \hat{A}\right\|H \tag{5}$$

In above equation using Frobenius distance normalization $\|.\|H$ the realistic matrix $\widehat{A}$ is obtained through following equation

$$A'' = W_N \beta_N X_N^J \\ W_N = [w_1 \quad w_2 \quad \dots \quad w_N] \\ X_N = [x_1 \quad x_2 \quad \dots \quad x_N] \\ \beta_N = \mathcal{D}iag[\alpha_1 \quad \alpha_2 \quad \dots \quad \alpha_N] \tag{6}$$

where A'' defines SVD [14] which is used to represent the parameter A'' into $(.)^J$ conjugate transpose, $x_j \in \mathbb{E}^P$ are right eigenvector, $w_k \in \mathbb{E}^P$ are left eigenvector, and α_N describes singular values diagonally. Using realistic noise matrix presented in [23] the rank N can be established. Then, using SVD, the model first collects N principal components X_N similar to N eigen vectors; later, it is multiplied to X_N for transforming the matrix A. Finally, the collected video frame vector a_k with respect to original space of O representation with respect to new space of N that has strong uncorrelation with respect to considered video sequence. The matrix $R_N \in \mathbb{E}^{P*N}$ is an optimized matrix described through following equation

$$R_N = AX_N = W_N \beta_N \tag{7}$$

where R_k, $k \in \{1,2,\dots,N\}$ defines k^{th} column of R_N, and is a video frame vector that in decorrelated. Finally, the matrix R_N are further compressed using lossless Huffman codewords [22] and are communicated over baseband unit using available fronthaul channel and anticipated low-rank matrix A'' is collected at the BBU is defined through following equation

$$A'' = R_N X_N^J = W_N \beta_N X_N^J. \tag{8}$$

The total size of video frames communicated through fronthaul MIMO network is defined through following equation

$$\mathrm{T} = ON + PN \tag{9}$$

and the compression efficiency of total video frames as a bitstreams transmitted using error detection aware compression technique is estimated through following equation

$$\mathcal{CR}_{\mathcal{P}} = \frac{O \times P}{N[O+P]}. \quad (10)$$

The rank matrix A_0 is composed of original video frame encompassed of noise; thus removing $(O - N)$ will aid in eliminating noise; the noise removal performance can be measured by rewriting video sequence matrix A'' defined in Eq. (4) as follows

$$A'' = A_0 + \delta \quad (11)$$

where δ error detected represented a matrix form after performing low-rank approximation. The parameter δ is composed of error identified from both video sequence information loss and residual noise due to performing low-rank approximation. The noise removal matrix A'' SNR efficiency is measured as a ratio of total power of noise prior and after applying low-rank approximation using below equation

$$SNR_I = \frac{\|G\|H}{\|\delta\|H} \quad (12)$$

The SNR efficiency is measured through following equation

$$SNR_I = \sqrt{\frac{\sum_{K=1}^{O} \gamma_k(G)}{\sum_{K=1}^{N} \gamma_k(G)}} \quad (13)$$

Where $\gamma_k(G)$ defines the k^{th} eigenvalue of G. The SNR efficiency is $20\log_{10} I$ in dB; thus, considering the parameter are γ_k are identical, thus the error detection and removal efficiency becomes $\sqrt{\frac{O}{N}}$, and the SNR efficiency in dB is measured as follows

$$I_{dB} = 10\log_{10}\frac{O}{N} \quad (14)$$

The compressed video frames are obtained at the baseband unit and later decompression operation is performed for reconstruction of video sequence are reconstructed. The EDAC technique is expected to achieve very good performance by reducing frame error with higher frame reconstruction and compression efficiency.

4. Results and discussions

The model is implemented using Python and MATLAB framework. Experiments is carried on Window 10 platform running on Intel i-7 quad-core processor with 16 GB RAM. The frame error rate (FER) also known as SER, BER, EVM, and compression ratio. A similar experiment configuration setup provided in [23] have been considered in this work. The parameter used for validating the models is given in Table 1. The Foreman video sequence dataset have been considered for validating the proposed video compression technique [24]. A sample sequence of Foreman is given in Fig. 2. The proposed model has been compared with the fixed code dictionary huffman video coding (FCDHVC) [22], exiting video compression (EVC) technique [23] and Huffman video coding (HVC) [25].

Table 1. Simulation parameter

Parameters	Values
Coverage area	200 m × 200 m
Transmission BW	10 MHz
Number of resource	50
Radio antennas height	6 m
User antennas height	1 m
Sub-carrier spacing	3.5 Ghz
FFT Size	1024
CP Lengths	72
No. of OFDM symbols	7
Modulation	QPSK, 16-QAM, 64-
Channel	AWGN
Number of RRH	16 & 64

Figure. 2 Sample frames of standard Foreman video sequence dataset [24]

4.1 BER vs SNR

The BER metrics is used for measuring total number of video frames as bitstreams correctly recovered with respect to total frames as bitstreams transmitted in wireless network. The lesser value indicates better performance. The signal-to-noise-ratio is varied between -4 to +4 considering RRH antenna size of 16 experiments is conducted and BER outcome of proposed EDAC over fixed code dictionary Huffman video coding (FCDHVC) [22], exiting video compression (EVC) [23] technique and Huffman Video Coding (HVC) [25] is graphically shown in Fig. 3. The BER performance experienced

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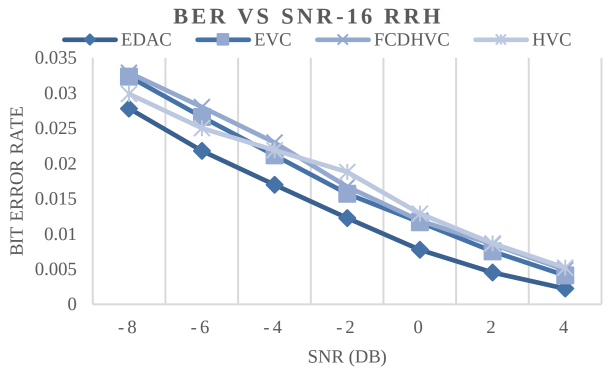

Figure. 3 BER vs SNR for 16 RRH

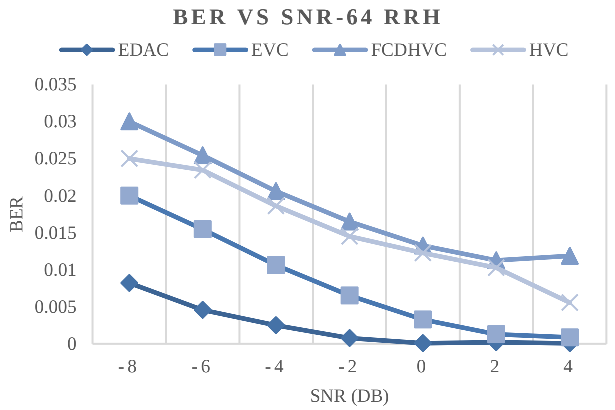

Figure. 4 BER vs SNR for 64 RRH

using EDAC is improved by 37.85%, 32.25% and 35.79% over FCDHVC, EVC and HVC technique respectively when RRH antenna size is 16.

The BER metrics is used for measuring total number of video frames as bitstreams correctly recovered with respect to total frames as bitstreams transmitted in wireless network. The lesser value indicates better performance. The signal-to-noise-ratio is varied between -4 to +4 considering RRH antenna size of 16 experiments is conducted and BER outcome of proposed EDAC over Fixed Code Dictionary Huffman Video Coding (FCDHVC) [22], Exiting Video Compression (EVC) technique [23] and Huffman Video Coding (HVC) [25] is graphically shown in Figure 4. The BER performance experienced using EDAC is improved by 96.103%, 88.08% and 95.58% over FCDHVC, EVC and HVC technique respectively when RRH antenna size is 64.

4.2 SER VS SNR

The symbol error rate metric is used to study performance of total number of total numbers of video frames wrongly recovered at the receiver side. The lesser value indicates better performance. The

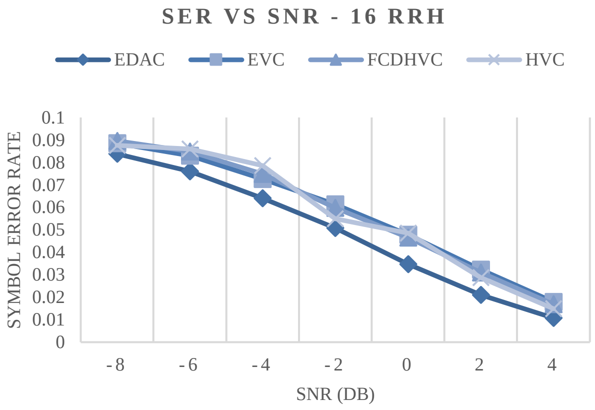

Figure. 5 SER vs SNR for 16 RRH

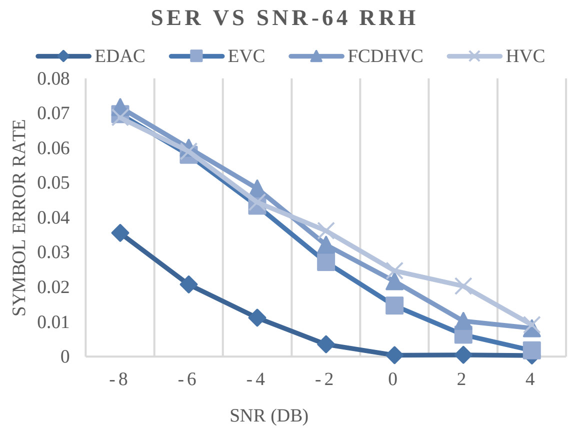

Figure. 6 SER vs SNR for 64 RRH

signal-to-noise-ratio is varied between -4 to +4 considering RRH antenna size of 16 experiments is conducted and SER outcome of proposed EDAC fixed code dictionary Huffman video coding (FCDHVC) [22], exiting video compression (EVC) technique [23] and Huffman video coding (HVC) [25] is graphically shown in Fig. 5. The SER performance experienced using EDAC is improved by 24.64% 26.22% and 21.79% over FCDHVC, EVC and HVC technique respectively when RRH antenna size is 16.

The symbol error rate metric is used to study performance of total number of total numbers of video frames wrongly recovered at the receiver side. The lesser value indicates better performance. The signal-to-noise-ratio is varied between -4 to +4 considering RRH antenna size of 64 experiments is conducted and SER outcome of proposed EDAC over fixed code dictionary Huffman video coding (FCDHVC) [22], exiting video compression (EVC) technique [23] and Huffman video coding (HVC) [25] is graphically shown in Fig. 6. The SER performance experienced using EDAC is improved

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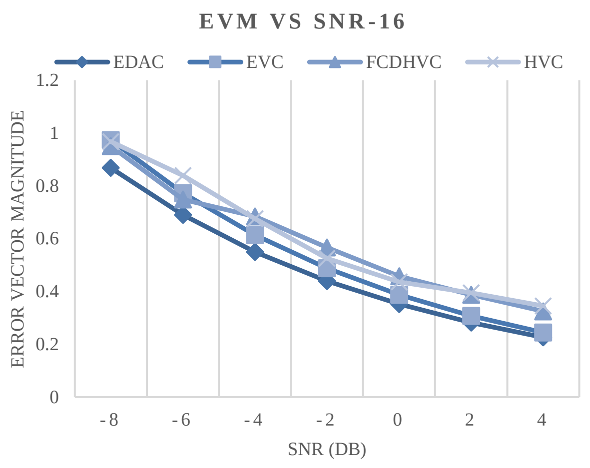

Figure. 7 EVM vs SNR for 16 RRH

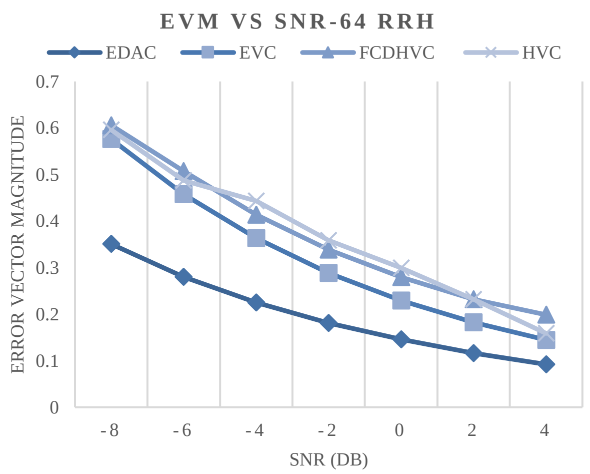

Figure. 8 EVM vs SNR for 64 RRH

by 91.13% 86.72% and 91.56% over FCDHVC, EVC and HVC technique respectively when RRH antenna size is 64.

4.3 EVM vs SNR

The error vector magnitude metrics is used for study the error detection performance of compression algorithm. The lesser value indicates better performance. The signal-to-noise-ratio is varied between -4 to +4 considering RRH antenna size of 16 experiments is conducted and EVM outcome of proposed EDAC fixed code dictionary Huffman video coding (FCDHVC) [22], exiting video compression (EVC) technique [23] and Huffman video coding (HVC) [25] is graphically shown in Fig. 7. The EVM performance experienced using EDAC is improved by 24.56% 9.047% and 23.47% over FCDHVC, EVC and HVC technique respectively when RRH antenna size is 16.

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4.4 Compression efficiency

This section evaluates the compression efficiency performance attained by the proposed video compression model over the existing video compression model. The compression efficiency of model is evaluated using Eq. (10), the EVC, FCDHVC and HVC model achieves compression efficiency of 21.75, 26.50 and 22.35 respectively whereas proposed video compression EDAC model achieves compression efficiency of 30.52. From result we can see the proposed model not only reduces size of video frames but also maintain very good reconstruction quality and assures users experience through improved BER, SER, and EVM performance.

5. Conclusion

This paper an efficient video compression technique namely EDAC for massive MIMO network; the EDAC technique is encompasses effective encoding mechanism that detect encoding error efficiently through low-rank approximation method. Further, the encoded signal is compressed using lossless Huffman codewords; the adoption of such mechanism significantly reduces the total number of frames as bitstream required to be transmitted over fronthaul link in massive MIMO network. Experiment is conducted using standard Foreman video sequence dataset under massive MIMO network. The results show the EDAC improves BER, SER, and EVM over EVC, FCDHVC and HVC technique. Similarly, the EDAC improves compression efficiency by 8.77 over EVC technique, 4.02 over the FCDHVC technique and 8.17 over the HVC technique. The future work will consider studying the perceptual video dynamic considering different environment conditions.

Conflicts of interest

The authors declare no conflict of interest

Author contributions

Aruna Kumar B T design the model and computational framework and analyzed the data, Aruna Kumar B T and Guide Dr. Manajanaik N both are carried out the implementation and performed the calculations possible results are getting and write the manuscript.

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