

STATISTICAL VS. INFORMATION-THEORETIC SIGNAL PROPERTIES OVER FFT-OFDM

ALI S. ABOSINNEE¹, ZAHIR M. HUSSAIN^{2,*}

^{1,2}Faculty of Computer Science & Mathematics, University of Kufa; Najaf; Iraq

*Professor (Adjunct), Edith Cowan University, Australia

E-mail: ¹alis.abosinnee@student.uokufa.edu.iq, ²zahir.hussain@uokufa.edu.iq,

²zmhussain@ieee.org

ABSTRACT

In this paper, properties of signals, such as speech and image are tested after transmission over OFDM system with 16-QAM under additive white Gaussian noise (AWGN). Noise could distort the signals. The statistical and information-theoretic properties of signals that are transmitted through OFDM system are analyzed by similarity measures to determine which of properties stands better against noise. For image, statistical similarity such as Structural Similarity Index Method (SSIM) and 2D correlation were used; also used are the information-theoretic measures such as entropy and joint histogram. On other hand, Pearson Correlation Coefficient (PCC), Tanimoto coefficient and Mel-frequency cepstral coefficients (MFCC) were used for speech signals. Mean Squared Error (MSE) was also used as a similarity measure for both single- and dimensional signals. The coefficients of discrete wavelet transform (DWT) and the coefficients of the discrete cosine transform (DCT) are also tested over noisy FFT-OFDM for both image and speech signals. Results found that the MFCC-correlation measure is more stable under noise than other measures. Furthermore, DWT is more robust than DCT for both speech signal and image, where it gives higher similarity with original image under very low SNR.

Keywords: *Five Keywords are Required Separated By Commas (Capitalize Each Word Italic)*

1. INTRODUCTION

Modern communications are growing and the systems demand increase in data rates. The transmission of digital data such as image or speech became important due to the increase of applications. Face recognition has been the interest of many studies due to its wide applications such as in many commercial law enforcement applications, and the airport's systems [1], [2]. It also enters into many other applications such as access control, security and video surveillance, credit card user identification, forensic analysis, entertainment, and automatic video indexing [3]. Face recognition is also useful in human-computer interaction, virtual reality, database retrieval, multimedia, computer entertainment, etc. [4]. As for speech recognition, it is used in many applications such as voice dialing, banking by telephone, telephone shopping, database access services, information service, voice mail, security control for the confidential information areas, and remote access to computers [5], [6]. Some of the previous applications need to high data rate transmission and the orthogonal frequency division

multiplexing (OFDM) appears to meet the need. OFDM is a flexible and efficient modulation technique that is widely used in wireless and wired communication systems today. In OFDM, the baseband signal cannot be transmitted without modulation [7]. Quadrature Amplitude Modulation is most commonly used, and in our case, 16-QAM modulation is used in the simulation. Inverse Fast Fourier Transform (IFFT) and Fast Fourier Transform (FFT) algorithms are used to multiplex the signal together and decode the signal at the transmitter and receiver respectively [8]. To prevent inter-symbol interference (ISI) caused by the propagation channel, OFDM systems insert a guard interval. However, noise can damage signals features [9]. In this paper, we study the robustness of signal properties over noisy FFT-OFDM system.

Section 2 presents a literature review. In section 3, a background is introduced for OFDM system, similarity measures, DWT and DCT of both speech and image, while the proposed work is presented in section 4. Experimental results are presented in section 5, with conclusions in section 6.

2. LITERATURE REVIEW

In [5] the authors presented an analysis of the error associated with speech with QAM modulation and sent through an IFFT/FFT OFDM transmission system where it used mean squared error MSE to determine the amount of error caused by transmission system for speech. Authors in [10] changed the Signal to Noise Ratio (SNR) of the channel distorted speech to compare the sensitivity of the system with clean speech with no noise or distortion present where the [4] and [5] are used Melcepstrum algorithm for feature extraction of speech signal. The authors in [11] used a two dimensional (2D) gray-scale image to evaluate the functionality and overall performance of an OFDM system under the influence of modeled AWGN channel in MATLAB simulation environment. Reference [12] proposed An image error test measure based on the normalized mean squared error (MSE), called (NMSE) and The performance of the proposed error measure has been tested over FFT-OFDM system under the effect of Gaussian noise, impulse noise, and Rayleigh noise. In [13], authors presented a novel image similarity measure, HSSIM, by using information - theoretic technique based on joint-histogram and the method was tested under Gaussian noise. Reference [2] proposed two new measures for image similarity and image recognition simultaneously ant it based on a combination of information theory and joint histogram. In [14] the power consumption was considered through a noisy channel when an image was transmitted in the OFDM system and tested the effect of IFFT on the PAPR under white Gaussian noise (AWGN).

3. BACKGROUND

3.1 OFDM

The OFDM system was first proposed by Chang in 1966 [15]. To be transmitted the data over the orthogonal carriers will be originating as a stream. This serial data after parallel transformation applied to the modulator, the step preceding the data arrive at the stage of IFFT, it is the mapping of data by QAM baseband modulator. To multiplex the data signals and transmit them simultaneously over a number of subcarriers, OFDM systems used IFFT and FFT algorithms at the transmitter and receiver respectively. The mathematical form of IFFT in the discrete time as follows [16]:

$$x_k = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} X_m e^{j \frac{2\pi km}{N}} \quad (1)$$

where, x_k is the signal represented in the discrete time domain while X_m is complex numbers

representing in the discrete frequency domain. The Cyclic prefix (CP) is inserted to reduce the chance of inter-symbol interference (ISI). It also diminishes the chances of inter-carrier interference [17]. In the channel, the incoming signal will be mixed with a noise of type AWGN and at the receiver, the cyclic prefix removed and next, the performance of FFT stage in the discrete frequency domain as follows [14]:

$$Y(m) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} y(n) e^{-j 2\pi km/N} + W(n) \quad (2)$$

where $Y(m)$ is the output of FFT, $W(n)$ is the AWGN; $y(n)$ is the received signal after passing through the AWGN channel. Figure 1 shows the basic OFDM communication system.

Similarity measures that will be implemented in this paper are divided into two types 2D and 1D similarity measures.

3.2 Similarity Measures for 2D Signals

Similarity measures that deal with 2D signals can be explained as follows:

3.2.1 Image Structural Similarity Index (SSIM):

In [18] Wang et al. introduced a new measure for image quality index entitled Structural Similarity index method (SSIM). This measure has been widely used in image processing and communication. They found that the SSIM has many advantages when measuring signal distortions.

SSIM between two images A and B is defined as follows:

$$SSIM(A, B) = \frac{(2\mu_A \mu_B + C_1)(2\sigma_{AB} + C_2)}{(\mu_A^2 + \mu_B^2 + C_1)(\sigma_A^2 + \sigma_B^2 + C_2)} \quad (3)$$

where μ_A and μ_B represent the local means of images A and B, respectively, σ_A and σ_B represent the standard deviations, σ_{AB} is the cross-covariance of the two images, σ_A^2 and σ_B^2 represent the variances, respectively, while the constants C_1 and C_2 are defined as $C_1 = (K_1 L)^2$ and $C_2 = (K_2 L)^2$ with $K_1=0.01, K_2=0.03$ and $L=255$.

3.2.2 2D Correlation

We can compute the correlation coefficient between two images by using by the following equation [2]:

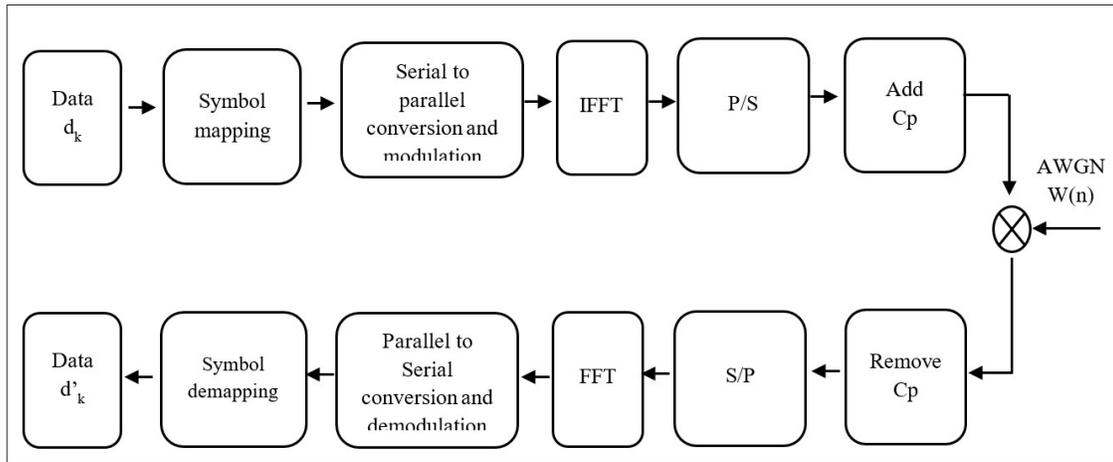


Figure 1: The Basic OFDM System

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{(\sum_m \sum_n (A_{mn} - \bar{A})^2)(\sum_m \sum_n (B_{mn} - \bar{B})^2)}} \quad (4)$$

Where \bar{A} is the mean A of and \bar{B} is the mean of B.

3.2.3 Entropy

Entropy is a measure of unpredictability or information content. Shannon’s entropy is used as a measure of uncertainty, and it can also be computed for an image, by focusing on the distribution of the grey values of the image [19]. The use of information-theoretic analysis in image processing is possible when, we assume that image is 2D random variable [2]. Shannon entropy measure $H(X)$ of a discrete random variable X can be defined as [13]:

$$H(X) = - \sum_{x \in X} p(x) \log_2 [p(x)] \quad (5)$$

3.2.4 Joint Histogram

The joint-histogram between two images can be defined as the joint occurrence of intensity levels (pixel values) in the two images [3]. The joint histogram between two images is a square matrix of size $M \times N$, where M is the number of gray levels in the first image and N is the number of gray levels in the second image [20].

3.3 Similarity Measures for 1D Signals

Now the methods that used to measure similarities when sending and receiving sound signals are different from the previous ones because

they work on signals with a single dimension as shown below:

3.3.1 Tanimoto Coefficient

Tanimoto coefficient is one of the most widely used similarity measure algorithms for speech recognition [21], [22]. Tanimoto coefficient measure of similarity for the two sets of data. It uses the ratio of the intersecting set to the union set as the measure of similarity. Represented as a mathematical equation:

$$T(a,b) = \frac{N_c}{N_a + N_b - N_c} \quad (6)$$

Where, N represents the number of attributes in each object (a, b) and c is the intersection set. The Tanimoto coefficient gives values in the range of zero (no bits in common) to unity (all bits the same); it is also known as the Jaccard coefficient [23].

3.3.2 Pearson Correlation Coefficient (PCC)

PCC has been widely used in many applications such as time-delay estimation, pattern recognition and data analysis [24]. This metric shows how correlated are two variables and it ranges from -1 to +1; where, 1 indicates that the data objects perfectly correlated but a score of -1 means that the data objects not correlated. PCC measures the strength and direction of a linear relationship between two variables X and Y and can be defined as [25]:

$$PCC(x,y) = \frac{\sum(X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum(X - \bar{X})^2 \sum(Y - \bar{Y})^2}} \quad (7)$$

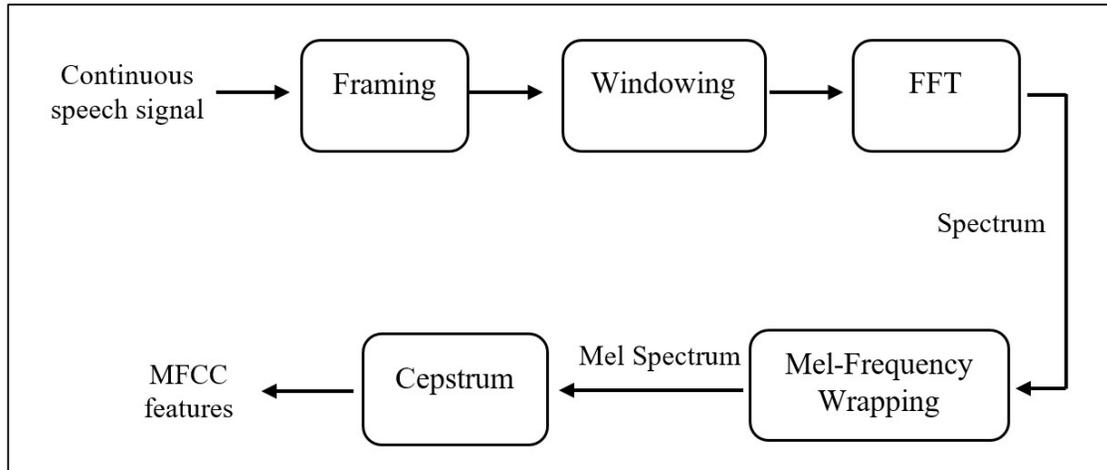


Figure 2: MFCC Processing Steps

Where \bar{X} and \bar{Y} denote the means of the two variables.

3.4 Mel-Frequency Cepstral Coefficients (MFCC)

The speaker-dependent features of human speech can be extracted and represented using the mel-frequency cepstral coefficients [5], [26]. Mel-frequency cepstral coefficients (MFCC) method is very common and one of the best method for feature extraction when talking about the 1D signals and Figure 2 represents the MFCC algorithm steps [27]: First, the speech signal is blocked into frames of N samples. Next, the Hamming window is used to minimize the signal discontinuities at the beginning and end of each frame. Then, the magnitude of the Fourier Transform is passed into twenty triangular filters. The start and end points of these filters were calculated firstly by evenly spacing the triangular filters on the Mel-Scale and then to convert these values back to the linear scale by using equation (7):

$$Mel(f) = 2595 \log_{10} \left(1 + \frac{f}{700} \right) \quad (8)$$

Finally, by equation (8) the Cepstral Coefficients were calculated from the log-energy outputs of these filters [5]:

$$MFCC(i) = \mu(i) = \sum_{k=1}^{20} X_k \cos \left[i \left(k - \frac{1}{2} \right) \frac{\pi}{20} \right] \quad (9)$$

Figure 3 shows the resulting filters in simulation.

3.5 Mean Squared Error (MSE)

Because of its simple formulation and clear interpretation, this technique has become one of the most widely used metrics in the field [28]. MSE measures the average of the squares of the errors that is, the average squared difference between the estimated values and what estimate. The mathematical form is as follows [29]:

$$MSE = \frac{1}{n} \sum_{i=1}^n (A_i - \bar{A})^2 \quad (10)$$

Notice that the MSE is used for both 1D and 2D signals as similarity measure.

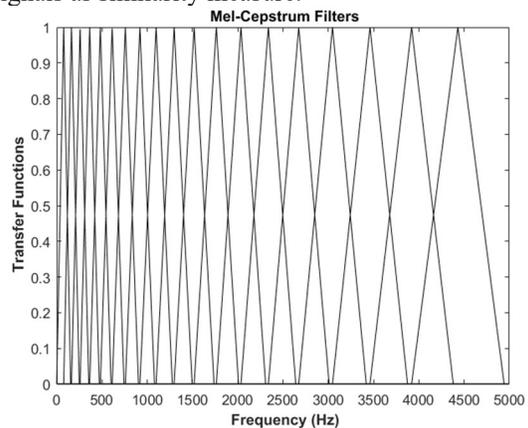


Figure 3: Triangular Mel-Scale Filter Bank.

3.6 Discrete Cosine Transform

The discrete cosine transform (DCT) is used to process one- or two-dimensional data. It is used for good data compaction, that is, it concentrates the information content in relatively few transform

coefficients [30]. The DCT uses cosine function wave among many waves as basis function and deal with real-valued signals and spectral coefficients. In the 1D case of DCT for a signal $x(i)$ of length M is defined as [31]:

$$F(m) = \sqrt{\frac{2}{M}} \sum_{i=0}^{M-1} x(i) \cdot C(m) \cos\left(\pi \frac{m(2i+1)}{2M}\right) \quad (11)$$

For $0 \leq n < M - 1$

$$C(m) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } m = 0 \\ 1 & \text{otherwise} \end{cases} \quad (12)$$

The principle of the 2D case of DCT is to transform the pixels of an image $x(i,j)$ to their DCT coefficients with the same number of the original image pixels and can be defined as [32]:

$$F(u,v) = \frac{2C(u)C(v)}{\sqrt{MN}} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} x(i,j) \cos\left(\frac{(2i+1)u\pi}{2M}\right) \cos\left(\frac{(2j+1)v\pi}{2N}\right) \quad (13)$$

Where the coefficients $C(u)$ and $C(v)$ in Eq. 13 are the same as in 1D case (Eq. 12).

3.7 Discrete Wavelet Transform

The wavelet transform (WT) provides a time-frequency representation of the signal [33]. DWT has a large number of applications such as in engineering, mathematics and computer science. It is a very popular and commonly used Transform for image processing. One dimensional DWT can be calculated by using the following formulas [34]:

$$W_\phi(j_0, k) = \frac{1}{\sqrt{M}} \sum_x f(x) \phi_{j_0, k}(x) \quad (14)$$

$$W_\psi(j, k) = \frac{1}{\sqrt{M}} \sum_x f(x) \psi_{j, k}(x) \quad (15)$$

For $x=0, 1, 2, \dots, M-1$.

For discrete wavelet transform for image $f(x, y)$ with size $M \times N$, can be calculated by the following formulas [34]:

$$W_\phi(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \phi_{j_0, m, n}(x, y) \quad (16)$$

$$W_\psi^i(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) \psi_{j, m, n}^i(x, y) \quad (17)$$

where $i = \{H, V, D\}$; H, V, and D refer to the decomposition direction of the wavelet (Horizontal, Vertical and Diagonal). Wavelets are often used to denoise 2-dimensional signals such as images.

4. PROPOSED WORK

At the transmitter, the data signals (1D for speech or 2D for image) are prepared to be transmitted using an OFDM technique. After modulation by 16QAM, data are converted from serial to parallel then converted from the frequency domain to the time domain by using IFFT. A cyclic prefix (CP) is inserted into each symbol to prevent the inter-symbol interference (ISI), and then converted from parallel to serial. The OFDM signal is ready for transmission. At the receiver, all stages of transmitter will be reversed, which include analog to digital converter, converting from serial to parallel, cyclic prefix removal, converting the data from the time domain to the frequency domain by using FFT, applying demodulation of 16QAM, and converting from parallel to serial. After these stages, the similarity measures are applied to know which properties of signals have been affected in the transmission process through noisy OFDM system. For image, the similarity measures that are based on statistical properties, such as structural similarity index method (SSIM) given by equation 3, and 2D correlation coefficient given by equation 4, are applied; as well as the information-theoretic properties as interpreted by entropy given by equation 5, and joint histogram. For 1-D speech signals, the similarity measures used are Tanimoto coefficient given by equation 6, Pearson Correlation Coefficient (PCC) given by equation 7, and correlation of the mel-frequency cepstral coefficients (MFCC's) given as follows:

$$mfcc - cor(\mu_i, \mu_{r,i}) = \frac{\sum(\mu_i - \bar{\mu})(\mu_{r,i} - \bar{\mu}_r)}{\sqrt{\sum(\mu_i - \bar{\mu})^2 \sum(\mu_{r,i} - \bar{\mu}_r)^2}} \quad (18)$$

where μ_i is given by equation 9, while $\mu_{r,i}$ is the received version of μ_i after being received over noisy FFT-OFDM. Mean squared error (MSE) is also applied as a similarity measure for both image and speech signals. In addition, we tested over noisy OFDM the coefficients of DWT by applying Daubechies wavelet family and the coefficients of DCT for both single- and two-dimensions data signals.

5. EXPERIMENTAL RESULTS

Using MATLAB, we implemented FFT-OFDM with 16 QAM modulation, where signal to noise ratio (SNR) ranges from -50 dB to 50 dB; assuming wired communication system, the signal passed on only via one path. After signals are received, the following similarity measures are applied to 2D-signals: SSIM, 2D correlation, and mean squared error (MSE). Figures 4-6 show the similarity between the transmitted and the received images over FFT-OFDM under white Gaussian noise by using the previous similarity measures with 10 realizations. Three types of images are used: a human face, a specific scene of peppers, and a landscape.

When information-theoretic similarity measures are compared with statistical similarity measures, we found that the entropy and the joint histogram outperform the statistical-based similarity SSIM especially at low values of SNR. However, both MSE and the 2D correlation perform better. Figures 7-9 show the results of implementing previous methods on different kinds of images.

For speech signals, the transmitted OFDM signal passes through the communication channel to the receiver under Gaussian noise, then the received speech is tested using 1D similarity measures which were Tanimoto coefficient, Pearson correlation coefficient and MSE with 10 realizations as shown in Figure 10.

Mel-Frequency Cepstral Coefficients (MFCC) are usually used to extract features for speech recognition. Similarity with MFCC-Corr is more robust versus all other 1-D measures like Pearson Correlation Coefficient (PCC), Tanimoto coefficient and MSE. As shown in Figure 11, it can be noticed that the MFCC is more robust against the noise even

at low values of signal SNR; this is because MFCC-Corr measure equation 18 applies different filters to extract signal properties, and these filters can combat noise.

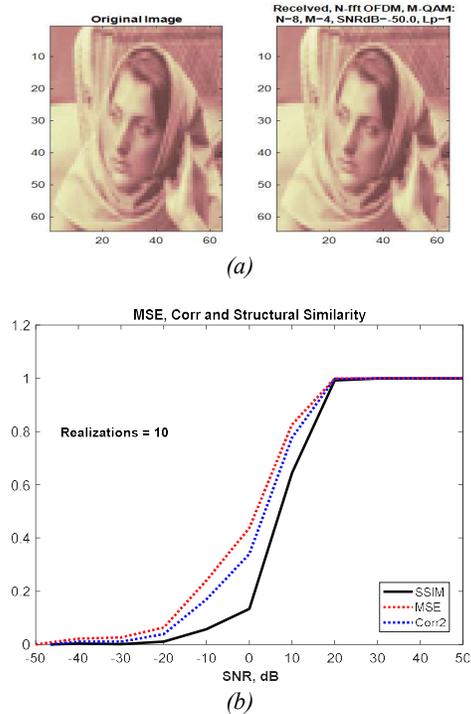


Figure 4: (a) original and received image A (b) Similarity between transmitted and received image.

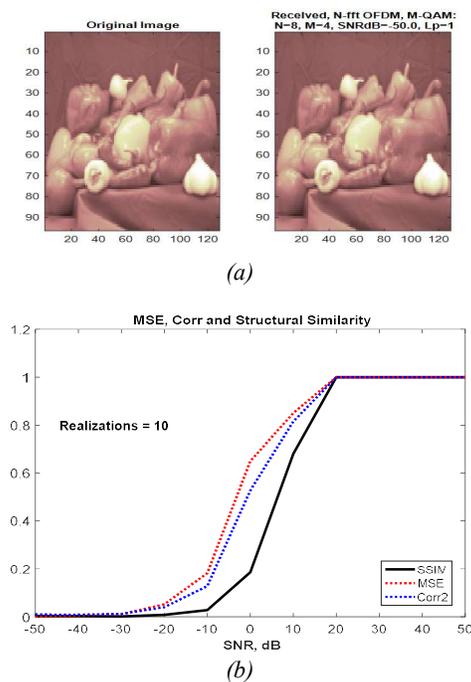


Figure 5: (a) original and received image A (b) Similarity between transmitted and received image.

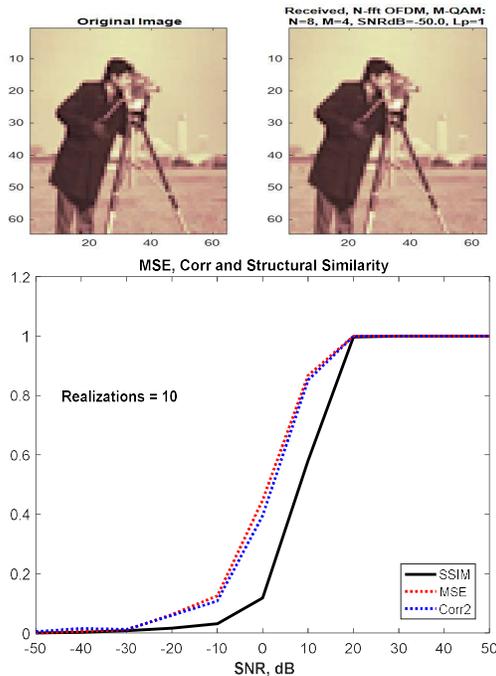


Figure 6: (a) Original and received image A (b) Similarity between transmitted and received image.

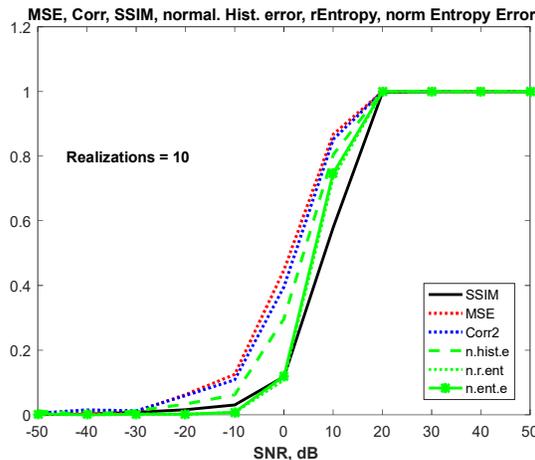


Figure 7: SSIM, 2D correlation and MSE vs. normalized histogram error, entropy and normalized entropy error between the original and received copy of image in Figure 4, with 10 realizations.

It is worth noting that different coefficients in the MFCC method are extracted by different Mel-filters and correspond to different frequency bands, hence they behave differently over noisy OFDM as shown in Figure 12. The coefficients of discrete wavelet transform (DWT) and discrete cosine transform (DCT) are fundamental in feature extraction for image and speech recognition.

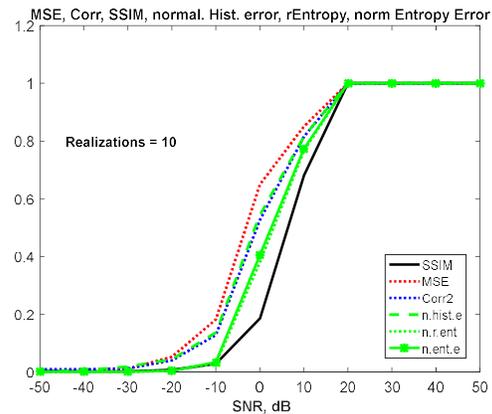


Figure 8: SSIM, 2D correlation and MSE vs. normalized histogram error, entropy and normalized entropy error between the original and received copy of image of Figure 5, with 10 realizations.

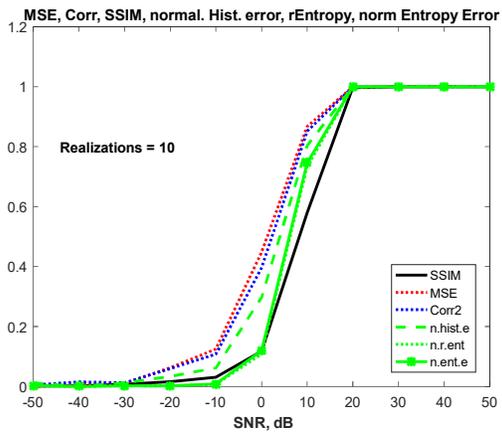


Figure 9: SSIM, 2D correlation and MSE vs. normalized histogram error, entropy and normalized entropy error between the original and received copy of image of Figure 6, with 10 realizations.

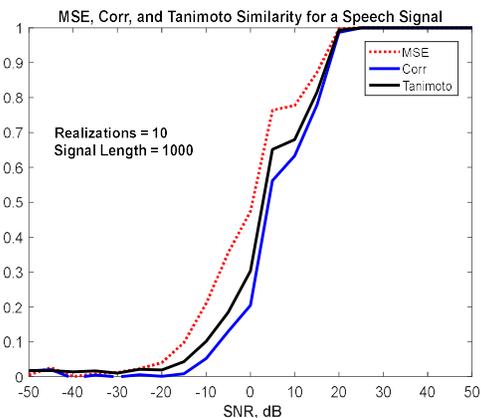


Figure 10: MSE, PCC and Tanimoto coefficient for speech signal over OFDM with 10 realizations.

We tested these coefficients over noisy FFT-OFDM. Simulation shows that 1D-DWT coefficients clearly

more robust than DCT coefficients for most of the SNR range as shown in Figure 13. The same performance is exhibited by 2D DWT for image signals as shown in Figure 14.

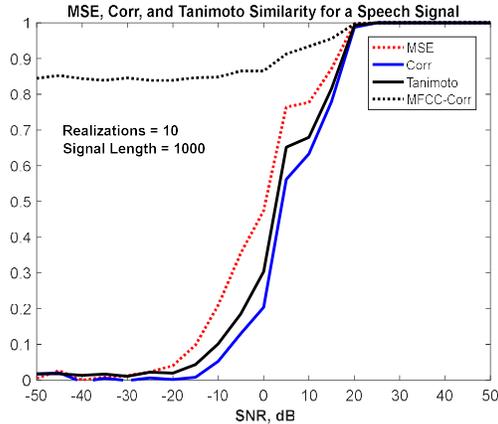


Figure 11: MFCC-Correlation, MSE, PCC and Tanimoto coefficient over OFDM for speech signal.

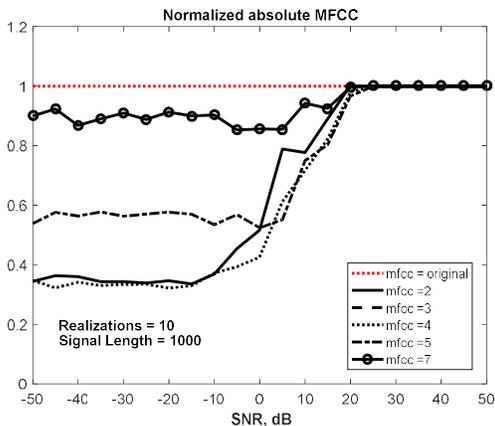


Figure 12: Different coefficients of MFCC over OFDM versus SNR.

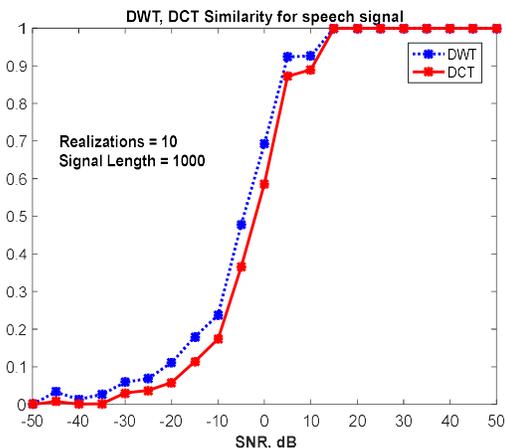


Figure 13: DWT vs. DCT coefficients over OFDM for a speech signal.

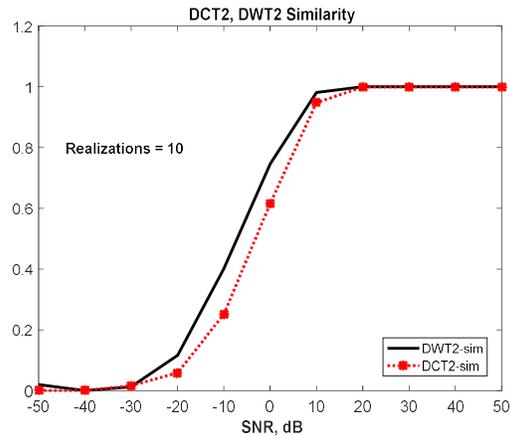


Figure 14: DWT vs. DCT coefficients over OFDM for an image.

Related Works & Future directions:

To the best of our knowledge, there has been no detailed work in the literature that handled this comprehensive research on the effects of OFDM on 1D and 2D signal similarity, apart from the work using SSI for face recognition over OFDM [35].

As future work, the system would be tested under attenuation types, e.g. Rayleigh fading [36]. The system can also be tested under the conditions of other channels models such as Nakagami or geometrical models as in [36]–[39], in addition to testing under the method of power saving [40] and testing under the integration of chaos with OFDM and space-time coding [41]. Testing the properties for compressed data would also be handled [42]. Similar to the work in [35], this work could be extended to apply these results to speech recognition over FFT-OFDM.

6. CONCLUSIONS

In this paper, we tested the properties of 1D and 2D signals after being transmitted over noisy FFT-OFDM system with 16 QAM. Similarity measures are used to test robustness against AWGN in OFDM. A comparison has been made between statistical signal properties (as displayed by statistical-based similarity measures) and information-theoretic signal properties (as revealed by information-theoretic similarity measures). For image, the statistical similarity measures such as SSIM, 2D correlation and MSE similarity are used; versus the informational-theoretic measures based on entropy and joint histogram. We found that the entropy and the joint histogram outperform the statistical similarity measures. However, MSE and the 2D correlation perform the best. For speech signals, different similarity measures are used based on Pearson correlation coefficient (PCC), Tanimoto

coefficient, MSE similarity and Mel-Frequency Cepstral Coefficients (MFCC). We found that MFCC-correlation measure is more stable under noise than other methods; the reason is that MFCC uses different filters to extract signal properties. Also tested is the performance of DWT and DCT coefficients under noisy FFT-OFDM, where it is found that DWT is more robust than DCT for both speech signal and image.

ACKNOWLEDGEMENT: The Authors would like to thank the reviewers for their constructive comments.

REFERENCES:

- [1] L. Best-Rowden and A. K. Jain, "Longitudinal Study of Automatic Face Recognition", *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 1, 2018, pp. 148–162.
- [2] M. A. Aljanabi, Z. M. Hussain, and S. F. Lu, "An Entropy-Histogram Approach for Image Similarity and Face Recognition", *Mathematical Problems in Engineering*, vol. 2018, 2018.
- [3] A. F. Hassan, Zahir M. Hussain, and D. Cai-lin, "An Information-Theoretic Measure for Face Recognition: Comparison with Structural Similarity", *International Journal of Advanced Research in Artificial Intelligence*, vol. 3, 2014, pp. 7–13.
- [4] A. C. Bovik (Ed.), *The Essential Guide to Image Processing*. Academic Press, 2009.
- [5] K. Neville, F. Al-Qahtani, Z. M. Hussain, and M. Lech, "Recognition of modulated speech over OFDMA", *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, vol. 00, 2007, pp. 1–3..
- [6] C. Ittichaichareon, S. Suksri, and T. Yingthawornsuk, "Speech Recognition using MFCC", *International Conference on Computer Graphics, Simulation and Modeling*, 2012, pp. 135–138.
- [7] E. Dahlman, S. Parkvall, and J. Sköld, "4G LTE/LTE-Advanced for Mobile Broadband", *Academic Press*, 2011.
- [8] L. M. Correia, "Mobile Broadband Multimedia Networks: Techniques, Models and Tools for 4G", *Elsevier*, 2006.
- [9] P. Kumar and A. Kumari, "BER Analysis Of BPSK, QPSK , 16-QAM & 64-QAM Based OFDM System Over Rayleigh Fading Channel", *IOSR J Electron Commun Eng (IOSR-JECE)*, vol. 11, no. 4, 2016, pp. 66–74.
- [10] K. Neville, Jusak, Z. M. Hussain, and M. Lech, "Performance of a text-independent remote speaker recognition algorithm over communication channels with blind equalisation", *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, vol. 2007, 2007, pp. 1–4.
- [11] D. Krishna and M. S. Anuradha, "Image Transmission through OFDM System under the Influence of AWGN Channel", *IOP Conference Series: Materials Science and Engineering*, vol. 225, no. 1, 2017.
- [12] R. A. Dihin and Z. M. Hussain, "Face recognition over FFT-OFDM computer networks", *International Journal of Applied Engineering Research*, vol. 12, no. 24, 2017, pp. 14764–14773.
- [13] A. F. Hassan, D. Cailin, and Zahir M. Hussain, "An information-theoretic image quality measure: Comparison with statistical similarity", *Journal of Computer Science*, vol. 10, 2014, pp. 2269–2283.
- [14] G. M. Hassan, K. Azmi, A. B. U. Bakar, and M. R. Mokhtar, "Sending Image In Noisy Channel Using Orthogonal Frequency Division Multiplexing", *Journal of Theoretical & Applied Information Technology*, vol. 96, no. 12, 2018.
- [15] T. Hwang, C. Yang, S. Member, G. Wu, S. Li, and G. Y. Li, "OFDM and Its Wireless Applications : A Survey", *IEEE transactions on Vehicular Technology*, vol. 58, no. 4, 2008, pp. 1673–1694.
- [16] K. Abdullah, and Z. M. Hussain, "Simulation of Models and BER Performances of DWT-OFDM versus FFT-OFDM", *Discrete Wavelet Transforms-Algorithms and Applications*, InTech Publishers, 2011.
- [17] K. Abdullah, and Z. M. Hussain. "Studies on dwt-ofdm and fft-ofdm systems.", *IEEE International Conference on Communication, Computer and Power (ICCCP)*, 2009, pp. 15-18.
- [18] Z. Wang, A. C. Bovik, H. R. Sheikh, S. Member, E. P. Simoncelli, and S. Member, "Image quality assessment: from error visibility to structural similarity", *IEEE Transactions on Image Processing*, vol. 13, no. 4, 2004, pp. 1–14.
- [19] D. Mistry, A. Banerjee, and A. Tatu. "Image similarity based on joint entropy (joint histogram).", *Proc. International Conference on advances in Engineering and Technology*, June 2013.
- [20] F. Dufaux, P. Le Callet, R. K. Mantiuk, and M. Mrak (Ed.), "High Dynamic Range Video: From Acquisition to Display and Applications", *Academic Press*, 2016.

- [21] P. Willett, J. M. Barnard, and G. M. Downs, "Chemical similarity searching", *Journal of Chemical Information and Computer Sciences*, vol. 38, no. 6, 1998, pp. 983–996.
- [22] W. Khan, P. Jiang, and P. Chan, "Word recognition in continuous speech with background noise based on posterior probability measure", *IEEE International Conference on Electro Information Technology*, 2012, p. 1-7.
- [23] P. Willett, "Similarity-based virtual screening using 2D fingerprints", *Drug Discovery Today*, vol. 11, no. 23–24, 2006, pp. 1046–1053.
- [24] J. Benesty, J. Chen, and Y. Huang, "On the importance of the pearson correlation coefficient in noise reduction", *IEEE Transactions on Audio, Speech and Language Processing*, vol. 16, no. 4, 2008, pp. 757–765.
- [25] J. L. Rodgers and W. A. Nicewander, "Thirteen Ways to Look at the Correlation Coefficient", *The American Statistician*, vol. 42, no. 1, 2006, p. 59.
- [26] T. F. Quatieri, *Discrete-Time Speech Signal Processing: Principles and Practice*, Prentice Hall, 2001.
- [27] S. Gupta, J. Jaafar, and A. Bansal, "Feature Extraction Using MFCC", *Signal & Image Processing: An International Journal (SIPIJ)*, vol. 4, no. 4, 2013, pp. 101–108.
- [28] R. Dosselmann and X. Dong, "A comprehensive assessment of the structural similarity index", *Signal, Image and Video Processing*, Vol. 5, no 1, 2011, pp. 81–91.
- [29] Z. Wang and A. C. Bovik, "Mean squared error: Lot it or leave it? A new look at signal fidelity measures", *IEEE Signal Processing Magazine*, vol. 26, no. 1, 2009, pp. 98–117.
- [30] R. G. Moreno-Alvarado and M. Martinez-Garcia, "DCT-Compressive sampling applied to speech signals", *CONIELECOMP 2011 - 21st International Conference on Electronics Communications and Computers, Proceedings*, 2011, pp. 55–59.
- [31] Wilhelm Burger and Mark J. Burge, "Digital Image Processing: An Algorithmic Introduction Using Java", 2nd ed. Springer Nature, 2016.
- [32] L. Tan and J. Jiang, *Digital Signal Processing Fundamentals and Applications*, 3rd ed. Katey Birtcher, 2019.
- [33] A. Vyas, J. Paik, and S. Yu, "Multiscale Transforms with Application to Image Processing.", Springer Nature, 2018.
- [34] R. C. Gonzalez and R. E. Woods, "Digital Image Processing", 2nd ed. Prentice Hall, 2002.
- [35] S. M. Lajevardi, K. Neville, and Z. M. Hussain, "Facial Expression Recognition Over FFT-OFDM", *IEEE International Conference on Advanced Technologies for Communications (ATC'09), Hai Phong, Vietnam*, 12-14 Oct. 2009.
- [36] Gurung, Arun K., et al., "Performance analysis of amplify-forward relay in mixed Nakagami-m and Rician fading channels.", *The 2010 International Conference on Advanced Technologies for Communications. IEEE*, 2010, pp. 321-326.
- [37] S. S. Mahmoud, F. S. Al-Qahtani, Z. M. Hussain, and A. Gopalakrishnan, "Spatial and temporal statistics for the geometrical-based hyperbolic macrocell channel model", *Digital Signal Processing: A Review Journal*, vol. 18, no. 2, 2008, pp. 151-167.
- [38] S. S. Mahmoud, Z. M. Hussain, and P. O'Shea, "A geometrical-based microcell mobile radio channel model", *Wireless Networks*, vol. 12, no. 5, 2006, pp. 653–664..
- [39] A. K. Gurung, F. S. Al-Qahtani, K. A. Qaraqe, H. Alnuweiri, and Z. M. Hussain, "General order antenna selection in MIMO cooperative relay network", *4th International Conference on Signal Processing and Communication Systems, ICSPCS'2010 - Proceedings*, 2010, pp. 1-6.
- [40] Gurung, Arun K., et al. "Power savings analysis of clipping and filtering method in OFDM systems.", *2008 Australasian Telecommunication Networks and Applications Conference. IEEE*, 2008, pp. 204-208.
- [41] Y.-S. Lau, K. H. Lin, and Z. M. Hussain. "Space-time encoded secure chaos communications with transmit beamforming.", *TENCON 2005-2005 IEEE Region 10 Conference. IEEE*, 2005, pp. 1-5.
- [42] N. Al-Hinai, A. Z. Sadik, and Z. M. Hussain, "Transmission of compressed image over PLC channel: A comparative study", *2009 5th IEEE GCC Conference and Exhibition*, 2009, pp. 2–5.