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NON-ORTHOGONAL SIGNAL-BASED OPTICAL COMMUNICATION SYSTEMS USING FUZZY LEARNING FOR INTERFERENCE CANCELLATION

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A B S T R A C T

Non-orthogonal signal-based systems are a type of communication system that uses signals that are not mutually perpendicular (i.e., not orthogonal) to transmit information. These types of systems can increase the spectral efficiency of communication systems by allowing for more data to be transmitted in the same bandwidth. Groups of signals with non-orthogonal waveforms can increase spectral efficiency, but they also increase the potential for interference. Spectrally efficient frequency division multiplexing (SEFDM) is a well-studied waveform that was originally proposed for use in wireless systems but has since found application in millimeter wave communications at 60 GHz, optical access network architecture, and long-distance optical fiber transmission. However, non-orthogonal signal-based systems are also more susceptible to interference from other sources, which can degrade the quality of the transmitted signal. To address this problem, this paper suggests using fuzzy learning techniques to cancel out interference and improve the signal-to-noise ratio. Fuzzy learning is a type of machine learning that uses fuzzy logic (FL) to handle uncertainty and imprecision in data. By using FL techniques to cancel out interference, the non-orthogonal signal-based optical communication (OC) system could potentially achieve better performance in noisy environments. Overall, this research topic has the potential to contribute to the development of more efficient and reliable OC systems that can operate in challenging environments.

1. INTRODUCTION

These Non-orthogonal signal-based OC systems are a type of communication system that uses signals that are not mutually perpendicular (i.e., not orthogonal) to transmit information (Xu, T. and Darwazeh, 2019). These systems have gained increasing attention in recent years due to their potential to increase the spectral efficiency of OC systems.

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In traditional orthogonal frequency division multiplexing (OFDM) systems, the subcarriers are orthogonal to each other, which allows for easy demodulation and decoding of the transmitted signal (Ragheb et al., 2022). However, this also limits the spectral efficiency of the system, as the subcarriers cannot be closely spaced without causing interference between them. Non-orthogonal signal-based systems, on the other hand, use signals that are not mutually orthogonal, which allows for more closely spaced subcarriers and higher spectral efficiency. This is achieved by using advanced modulation techniques, such as quadrature amplitude modulation (QAM) and pulse amplitude modulation (PAM) that are optimized for non-orthogonal signaling (Chen et al., 2022; Zhang et al., 2023).

As a result, interference cancellation techniques have been developed to improve the quality of the transmitted signal in non-orthogonal systems. One approach to interference cancellation in non-orthogonal signal-based systems is to use advanced signal processing techniques such as time-domain equalization (TDE) or frequency-domain equalization (FDE) to remove the interference. TDE and FDE are used to equalize the channel response and suppress interference from other sources. Another approach is to use machine learning-based techniques such as artificial neural networks (ANNs) or FL systems for interference cancellation. Machine learning techniques can learn and adapt to interference patterns in real time, which can improve the signal-to-noise ratio and enhance the quality of the transmitted signal (Bilim, M. and Kapucu, 2019; (Baradaran and Navi, 2020). The FL system can learn and adapt to changes in interference patterns, which allows for real-time interference cancellation (Peng et al., 2021, Alamu et al., 2023). However, non-orthogonal signal-based systems are also more susceptible to interference from other sources, which can degrade the quality of the transmitted signal. To address this problem, various interference cancellation techniques, we propose FL-based interference cancellation techniques can be used to model the relationship between the input signal (received signal) and the output signal (desired signal).In addition to interference cancellation, non-orthogonal signal-based OC systems can also benefit from other signal processing techniques such as channel estimation and modulation optimization.

Overall, non-orthogonal signal-based OC systems have the potential to significantly increase the spectral efficiency and data rates of OC systems. With the development of advanced interference cancellation techniques and signal processing algorithms, these systems can become even more reliable and robust in the presence of interference (Jiang & Schotten, 2023).
The further part of the portion includes such as part 2 denotes the literature survey, part 3 represents the suggested technique, part 4 represents the experimental result and part 5 denotes the concluded part.

2. LITERATURE SURVEY

(Kurzo et al., 2020; Zhou et al., 2021) provides a hardware design for a non-linear self-interference (SI) canceller that makes use of a neural network and then compare it to our hardware design of a traditional polynomial-based SI canceller. After normalizing the image, thresholding occurs when many sources are in the camera's field of view. (Ahmed et al., 2021; Zhou et al., 2020) uses deep learning to remove interfering light sources and concurrent thresholding to fix data. According to the (Ploder et al., 2022) offer two innovative neural network-based designs that are adaptable to a wide range of SI effects without the requirement for specialized structures. The study (Baumgartner et al., 2022; Hama & Ochiai, 2023) presented new neural network architecture for model-based soft interference cancellation that uses frequency domain equalization for single carrier systems. Article (Shlezinger et al., 2020) offers a multi-user MIMO receiver that trains to cooperatively identify in a data-driven manner, without making any assumptions about the channel or requiring any channel state information (CSI). For this reason, they present Deep SIC, a data-driven version of the iterative soft interference cancellation (SIC) technique. The NOMA interference cancellation (SIC) de-multiplexing technique fails under such conditions. (Thai et al., 2022; Xu et al., 2018) introduced a probabilistic neural network de-multiplexing technique (PNN). (Aref and Jayaweera, 2020) presents a unique uplink multiple-input multiple-output non-orthogonal multiple-access (MIMO-NOMA) system using successive interference cancellation (SIC) based on deep learning (DL)

2.1. Problem statement

One potential research problem related to non-orthogonal signal-based OC systems is the development of interference cancellation techniques that can effectively mitigate the impact of inter-user interference. Another related research problem is the development of low-complexity interference cancellation techniques that can be implemented in real-time OC systems with limited computational resources. Overall, the development of effective interference cancellation techniques for non-orthogonal signal-based OC systems is an important research problem that has the potential to significantly improve the performance and reliability of these systems in practical applications. To overcome this limitation we use FL-based interference cancellation techniques that can significantly improve the performance of non-orthogonal signal-based OC systems, making them more robust and reliable in the presence of interference.

3. METHODS

3.1. Leave Waveform for non-orthogonal signal

All of these characteristics are typical of SEFDM, a non-orthogonal signal waveform. As compared to conventional orthogonal frequency division multiplexing (OFDM), the SEFDM signal waveform requires less bandwidth to transmit. The greater the bandwidth savings, the greater the inter-carrier interference (ICI)

$$Y[l] = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} t_n . e^{\frac{j2\pi nl\alpha}{N}} \quad (1)$$

The sub-carrier count is denoted by N.

$Y[l]$ - sample of time at index l^{th}, where $l = [0, 1, \ldots, N-1]$

n^{th} Subcarrier modulated sign is t_n.
$\frac{1}{\sqrt{N}}$is a scaling factor.

Consequently, the orthogonal feature is confirmed by associating 2 modulated signals, and the “correlation coefficients” are commonly presented as a matrix whose elements are supplied for every two random sub-carriers with indices m and n.

$$D_{m,n} = \frac{1}{N} \sum_{k=0}^{N-1} e^{\frac{j2\pi nl\alpha}{N}} e^{-\frac{j2\pi nl\alpha}{N}} = \begin{Bmatrix} 1 & m = n \\ \frac{1-e^{k2\pi\alpha(m-n)}}{N\left(1-e^{\frac{k2\pi\alpha(m-n)}{N}}\right)} & m \neq n \end{Bmatrix} \quad (2)$$

Here the non-diagonal terms $m \neq n$ in (2) represent the influence of ICI due to non-orthogonal overlapping. The interference component that has to be eliminated is mathematically demonstrated to be the second term in (2). The goal of all of our prior effort has been to get eliminate this phrase. There has been several signal detection techniques investigated. The detection technique essentially involves a trade-off between complexity and performance... The interference component that has to be eliminated is mathematically demonstrated to be the second term in (2). The goal of all of our prior efforts has been the elimination of this phrase. The detection strategy is essentially a compromise between efficiency and complexity.

3.2. Complex optical detector with channel specifications

The optical reception can be modified in response to variations in the optical channels' properties, such as air absorbance values, dispersing component radius, transparency, reflecting particle sizes, etc. In addition to an integrated approach for the evaluation of the climatic impact on the ambiance, they refer to the architectural simulation of an intelligent receiver for optically wireless communication (WC) across a turbulent air stream that accounts for the variations in distortion due to the surroundings as well as the effects of snowfall or rain on the transmitted power and reflection power Changes.

3.3. Control Scheme Based on FL

Even though controllable or paired optical filters based on fiber Bragg gratings are an adaptable and encouraging method of compensating for dispersion, they still suffer from shifts in the surroundings, the problem of fluctuating optical channel features, and the disregard for dynamic uses necessitating the redesign and redesigning an appropriate fiber a Bragg grate for every circumstance. To solve these issues, a unique approach is needed for signal identification, and one that utilizes an adaptive, intelligent optical method is suitable.

In this kind of system, regardless of the data speed or spectrum, adaptive tuning parameters and the control technique are continuously updated to account for the scatter, by monitoring the pulse profile for distortion due to atmospheric turbulent effects. In Figure 1, we see a schematic representation of the suggested FL control

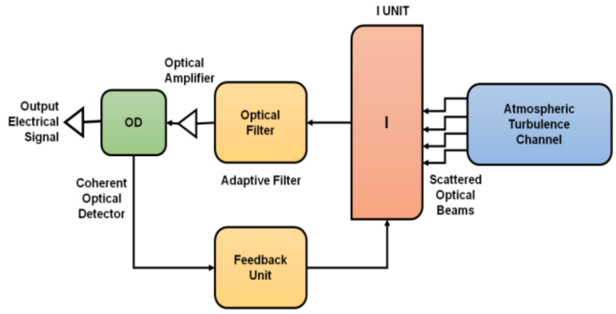

Figure 1. Schematic representation of FL control

A control system method for resolving issues called FL may be used in systems ranging from compact embedded microcontrollers to very large ones, making it a profitable instrument for the management of complicated operations. It's a straightforward technique for generating conclusions from data that is otherwise hazy, inconclusive, inconsistent, or nonexistent.

Instead of attempting to formally model a system, FL uses a simplistic, rule-based *IF X AND Y THEN Z* technique to solve control problems. In this work, FL control was chosen for the following reasons:

- A relatively simple method of implementation,
- Adaptable to various beginning circumstances,
- As the FL control model is an empirical one, it uses a knowledge base system to store all of the operational parameters and optical filter tuning optimization constraints, and it is also capable of learning and updating this information on its own.
- The flexibility to adapt to unpredictable shifts in meteorological pressure allows for a more extensive light signal-detecting procedure in the event of adverse climatic conditions. To regulate the oscillations of the optical signal, the FL controller's outputs are implemented.
- The key element that allows all of the systems adaptable is the FL control.

In contrast to a control system with feedback, In this instance, the error cooperative's goal is to promote the FL control rules' implementation to lower the signal for failure to nil. Signal identification in an optical WC system using an "intensity modulation approach" is enhanced with the help of FL equations. Conventional algebraic functions are combined with fuzzy multiplying, addition, and integration to provide a framework for a new generation of fuzzy signal detection methods. To complete the work of fuzzy detection, the concept referred to as "conventional cross-correlator detector" is being enlarged, which involves determining which of M modulating signal is represented in a waveform. To locate signals in a receiving wavelength that is normally noisy, we employ the "fuzzy Hamacher product, the fuzzy algebraic sum," also the innovative mixed fuzzy product. It is explored if the fuzzy detector may be used in an "Intensity Modulated (IM)-Coherent Perception OC" device.

The 20 Gbps coherent optical receiver was constructed to maintain the receiver's sensitivities. Hence, the adaptable filter is developed using the function.

$$G(g) = [(Z_1 - Z_0)/(A^2 + 2A + 1)H_1] * \left[\{l_1/(l_2 - k2\pi g)^2\} + \{l_3/^{(l_4 - k2\pi g)^2}\} + \{l_5/(l_6 - k2\pi g)^2\} + \cdots + \{l_{n-1}/(l_n - k2\pi g)^2 \right] \exp(-k2\pi g u_d) \quad (3)$$

where,

$G(g)$adaptable filters transfer operation,

$Z_1 \& Z_0$processes using transmitting energy and detecting parameters to produce, accordingly, 1 and 0,

$l_{1,} l_2, \dots, l_n$The visibility affects the N-gamma functional values.

g is the operating frequency, and The period that the signal is at the result of the filter is given by u d.

$A^2 = (F_0/F_1)$, where $F_0 \& F_1$ are the noise spectral density of the receivers for receiving 0 and 1 correspondingly.

The light signals arrive and are then analyzed by a smart device that uses an FL algorithm to perform non-linear noise cancellation before passing through an optical filter, being amplified by an optical amplifier, and finally being converted from an electrical signal into an electrical signal by a "coherent optical detector".

3.4. Numerical analysis

Interference cancellation using FL:

High-accuracy additive white Gaussian noise models the optical WC system's noise. The air turbulence channel scatters optical signals, which the receiver receives. To identify numerous turbulence channel signals from different directions, a specific algorithm is needed. FL detects the turbulence channel's reflected signal. A sampled optical pulse information signal (y) at $1550nm$ $(\approx 194THz)$ over $6 * 10^{-13}$ seconds is defined below.

However, to assess the information signal (y), an interference signal (n_2) must first be produced, which is created from another noise source (n_1) by an unidentified nonlinear process. By using an unidentified nonlinear equation, the opposing signal (n_2) which is seen in the signal that was recorded (m) is produced

$$n_2(l) = 4 * \sin\left(n_1(l)\right) * n_1(l-1)/(1 + n_1(l-1)^2 \quad (4)$$

It should be noted that n_2 and n_1 are associated with utilizing a very nonlinear method, making it challenging to determine whether some correlation between these two indications... The actual data signal (y) and the interference (n_2) are added to create the measured signal (m), but n_2 is unknown. Recovery of the initial signals from the target is the goal. receiver's only signals, which are the measured signal (m) and the noise signal (n_1).

To determine the nonlinear connection between $n_1$and n_2, the function ANFIS is employed. Take m as an "infected" version of n_2 for training even if n_2 is not directly available. Hence, in this type of nonlinear fitting, y is considered "noise." Considering the nonlinear channel's phase to be 2 in this instance, a 2-input ANFIS is the best option for training. Because each input receives two membership functions, the total number of fuzzy rules that can be trained is four. In addition, simply amend the step size to 0.2.

The training parameters' stated step size increase or decline rate is multiplied by the Stepsize array of step sizes to increase or reduce them. When the set practice error aim is met or the epoch number is reached, the training procedure ends. When the testing error starts to rise while the training time is still declining, overfitting has occurred. Following training, the command Evalfis is used to determine the estimatedn_2. To assess the membership functions throughout the input or output range, run fuzzy inference computations that duplicate the "Fuzzy Inference System" for the input data, create the output data, and give the number of sample points.

The total values obtained along the power range at N points for each outcome. The membership functions are used to assess the input and output values to acquire the results. The ANFIS results are produced, containing the actual and estimatedn_2. The ratio between the received signals (m) and the anticipated interference is equivalent to the anticipated information signal (y). Plotting illustrates the actual data signal (y) and also the ANFIS-estimated data signal (y). For each result, the cumulative values were obtained at N points along the power range.

By the use of the membership functions, the input and output values are evaluated to provide the results. Both the original and approximated n_2 (an ANFIS output) are produced. The estimated information signal (y) is equal to the ratio of the estimated interference to the measured signal (m) (i.e., ANFIS output). Plots are shown for the initial information signal (x) and the estimated data signal (y) via ANFIS.

4. RESULTSAND DISCUSSIONS

The information signal, denoted by$y$, is to be derived from the one that is being measured (m). Thus, the FL method is put to use in this situation to derive the information signal (y) from the measured signal (m). The interference (n_2) is computed using the noise (n_1) and channel model and, as seen in Figure 2.

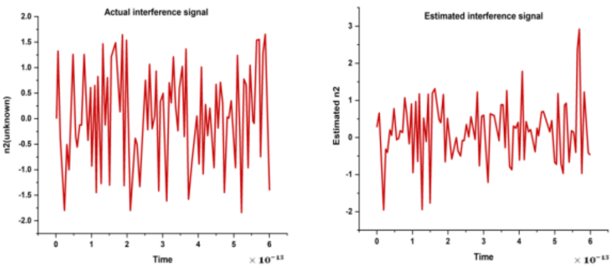

Figure 2. Interference estimated using the FL method

Figure 3(a) depicts the signal that was initially transmitted for the information. Figure 3(b) depicts the signal that was retrieved from the information at the receiver. After the estimate of the interference (n_2) and the noise that was originally recognized (n_1), the data signal (y) is then retrieved from the calculated signal (m).

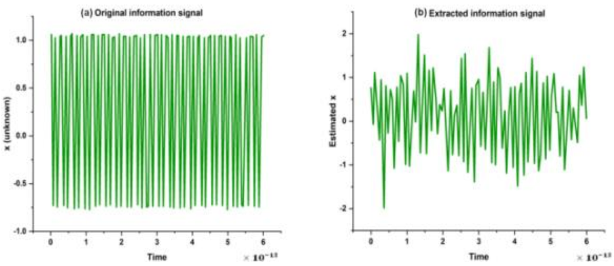

Figure 3. Original and extracted signal

The signal-to-noise ratio (SNR) quantifies the signal's intensity in relation to the noisy environment. Figure 4 depicts the SNR results. If the signal-to-noise ratio (SNR) is high, then the signal is very powerful, whereas if it's low, then the signal is relatively indistinct. Our proposed model achieves the highest possible signal-to-noise ratio, which corresponds to the point on the graph where the signal is strongest relative to the noise.

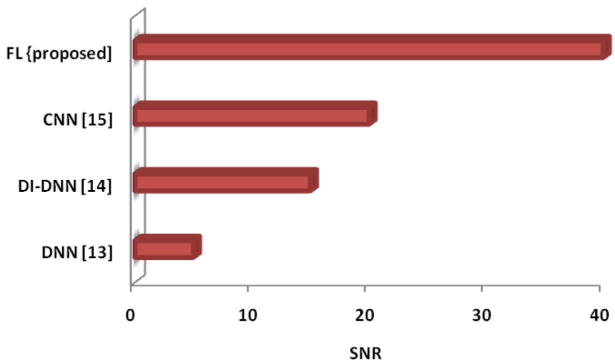

Figure 4. SNR outcome

The bit error rate is defined as the percentage of properly transmitted bits that were incorrectly received. The measured signal, denoted by$m$, is overlaid on the initial information signal, denoted by$y$, before the implementation of the FL algorithm, for comparison and BER computation. For this particular period, the BER is computed to be $\frac{28}{80} =$ 32.6%. The BER calculation signal is shown in Figure 5 superimposed with the observed signal.

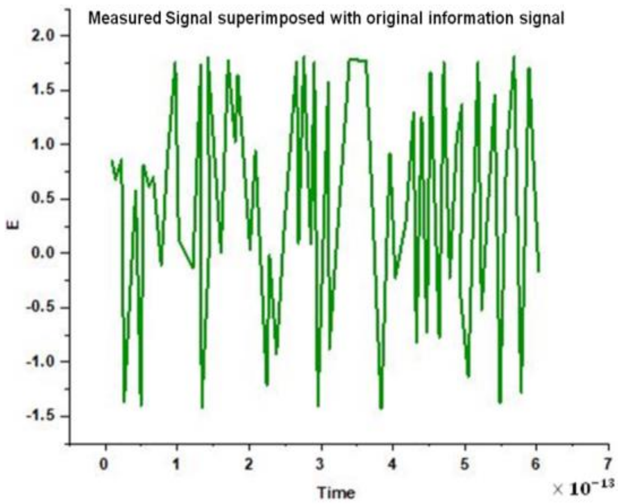

Figure 5. Information signal overlaid with measured signal for BER calculation

Following the implementation of the FL method, Figure 6 depicts the extracted signal (y) superimpose with the actual information signal (y). The BER for this period is computed to be$\frac{17}{80} = 18.76\,\%$. 15/80, This outcome demonstrates that the extracted information signal resembles the sent signal in its original form. Regarding these factors, this BER is approximately 10^{-1} more realistic.

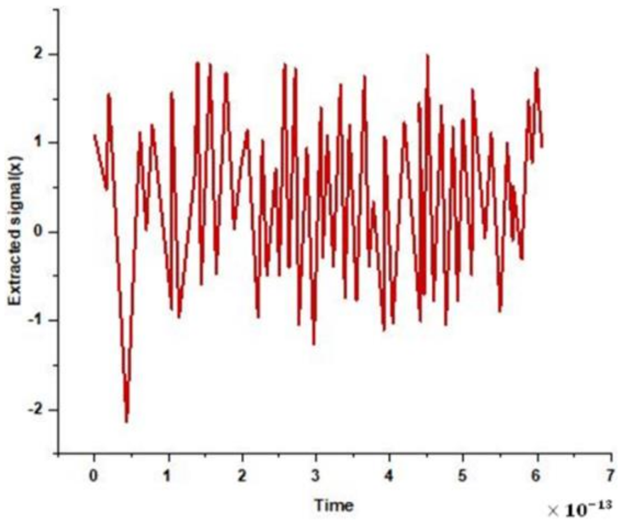

Figure 6. Original data signal overlaid with extracted signal for BER calculation

5. CONCLUSION

Severe attenuation and dispersion of optical signals are caused in the atmospheric turbulence channel. Because of this, the efficiency of optical wireless transmission is reduced. Thus, we recommend the use of fuzzy learning (FL) methods to reduce noise and boost signal strength. FL is a machine learning technique for dealing with vague or incomplete information. The performance of an OC system based on non-orthogonal signals may be improved in noisy environments by employing FL methods to cancel out interference. The limitation of FL in interference cancellation is its reliance on expert knowledge and subjective input. To create an FL model, it is necessary to define the rules and membership functions that describe the relationship between the inputs and outputs. This process requires expert knowledge and can be subjective, leading to potential errors in the model. Hybrid interference cancellation systems that combine multiple techniques, such as machine learning and adaptive filtering, can be used to improve the performance of interference cancellation systems.

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