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Signal Detection and Adaptive Equalization Using a Discrete Wavelet Transform - Artificial Neural Network for OOK Indoor Optical Wireless Links

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Abstract: *The paper presents an alternative approach for signal detection and equalization using the discrete wavelet transform (DWT) and the artificial neural network (ANN) in diffuse indoor optical wireless links. The received noisy signal is sampled at multiple rates and the DWT is used for feature extraction while the feedforward backpropagation ANN is used for the pattern classification (i.e. equalization). Different window lengths are investigated and a window of 3-bit is being used for signal classification (i.e. equalization). The simulation results show that for a highly dispersive channel the proposed receiver/equalizer outperforms the traditional equalizer by offering SNR gain of more than 6 dB at the data rate of 155 Mbps.*

Keywords: Adaptive equalization, indoor optical wireless, neural network, discrete wavelet transform.

1. Introduction

The future communication system with multiple applications requires a huge bandwidth per user that radio and microwave frequencies currently are unable to provide. The last mile problem is becoming more acute, therefore the need for alternative link schemes. Dropping fibre to homes is one solution but costly at the present time, which will reduce over the next decade or so. There is an alternative and complementary solution based on the optical wireless (OW) link that is capable of providing bandwidth in excess of 150 Mbps for both indoor and outdoor applications, and can

readily be linked to the high-speed fibre backbone [1, 2]. Compared with the RF links, OW offers a number of advantages including a huge bandwidth at a single wavelength, no need for the frequency reuse, rapid installation, security, well defined cell pattern, offering different traffic using multiple wavelengths in a single cell, and being protocol transparent.

The key issues in the indoor OW communication links are the eye safety, mobility, blocking and multipath induced inter-symbol-interference (ISI) in non-line-of-site (non-LOS) links [3, 4]. Eye safety could be overcome by shifting to a higher wavelength of 1550 nm where the eye retina is less sensitive to optical radiation [5] or by adopting more power efficient modulation techniques like pulse position modulation. Lack of mobility and blocking is an issue in LOS links, thus limiting its application to a specific environment. Whereas in diffuse (non-LOS) links, blocking, and to a certain degree mobility, is overcome at the cost of reduced data rate, increased path loss and ISI [4], thus making it more appropriate for portable indoor applications. Reduced data rate and increased ISI is compensated by employing equalization techniques at the receiving end as outlined in [3, 6, 7].

The classical approach of digital signal detection is based on the matched filter, which maximized the signal-to-noise (SNR) when the signal is corrupted

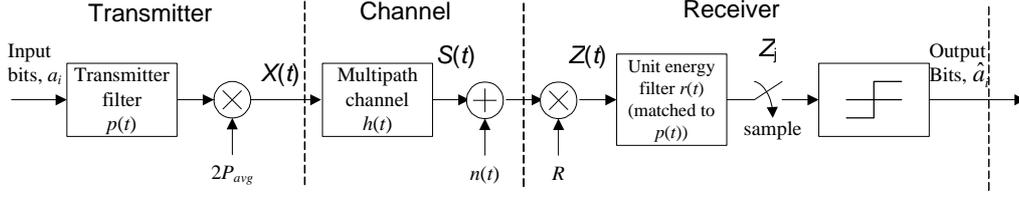


Fig.1: Block diagram of the unequalized OOK system.

by the adaptive white Gaussian noise (AWGN) [8]. However, not all physical channels and signals are Gaussian in nature [9], and the maximum SNR is susceptible to the exact position of sampling instants. Additionally, the traditional equalization based on the finite impulse response (FIR) filter suffers from severe performance degradation in time varying and non-linear channels [10, 11]. In [12] signal detection in a non-stationary environment has been formulated as one of pattern classification problem, thus offering the possibility of applying neural network based classifier at the receiver to improve the performance.

In [18, 19] the concept has been taken further by employing the continuous wavelet transform (CWT) for the feature extraction and ANN for the pattern classification at the receiver. Wavelet based equalization has also been adopted to combat the problem of channel induced distortion, a major difficulty in diffuse OW systems [13, 14]. The ANN is an adaptive system with learning capabilities under a supervised environment. The learning process can further be enhanced (i.e. faster convergence) by removing the noise from the training signal and reducing the number of input (if possible). Furthermore feature extraction could also be improved by removing the redundant coefficients in the CWT. In this paper we propose signal detection and channel equalization based on the DWT and ANN, which offer reduced complexity compared to the CWT-ANN based receiver and improved performance compared to the equalizers based on the FIR digital filters. Furthermore in CWT with a large number of coefficients, to find the best scales extensive search is a requirement, whereas in DWT this can readily be realized using the digital filters [15].

The paper is organised as follows: the bit error analysis of OOK in diffuse channel is presented in Section 2 and DWT is discussed in Section 3. The proposed receiver based on the DWT and ANN is outlined in Section 4, followed by the BER performance results in Section 5. Finally, the conclusion is given in Section 6.

2. Unequalized On-Off Keying

The simplest and the most common modulation technique for intensity modulated and direct detection (IM/DD) is the well known on-off keying (OOK) scheme. It offers bandwidth efficiency and resilience to multipath induced ISI, but at the cost of a high optical average power. The effect of ISI is significant for bit rates above 10 Mbps [16]. A block diagram of the unequalized OOK system under consideration is shown in Fig. 1. The discrete-time impulse response of the cascaded system is given as:

$$c_k = p(t) \otimes h(t) \otimes r(t) \Big|_{t=kT_b}, \quad (1)$$

where bit duration $T_b = R_b^{-1}$, and R_b is the bit rate. The impulse response $h(t)$ of the optical channel in the ceiling bounce model can be approximated to [16]:

$$h(t) = \frac{6(0.1D_{rms})^6}{(t + 0.1D_{rms})^7} u(t), \quad (2)$$

where $u(t)$ is the unit step function and D_{rms} is the delay spread which depends on the size and design of the room.

Unless the channel is nondispersive, c_k contains a zero tap, a single precursor tap (with the largest magnitude) and possibly multiple postcursor taps. On a non-dispersive channel, the optimum sampling point, i.e. that which minimises the probability of error, occurs at the end of each bit period T_b . However, on dispersive channels, the optimum sampling point changes as the severity of ISI changes. The receiver filter output y_i corresponding to the penultimate bit, in the absence of noise, is given by:

$$y_i = 2RP_{avg} \mathbf{a}_i \otimes c_k \Big|_{k=m}, \quad (3)$$

where R is the photodetector responsivity, P_{avg} is the average transmitted optical signal power, \mathbf{a}_i is the m -bit sequence, $a_i \in \{0,1\}$ is the value of the penultimate bit in \mathbf{a}_i , m is the number of taps.

Thus, the average probability of error is given by:

$$P_{e,bit,OOK} = \frac{1}{2^m} \sum_{i=1}^{2^m} \varepsilon_i, \quad (4)$$

where the probability of error for the penultimate bit in \mathbf{a}_i is given by:

$$\varepsilon_i = \begin{cases} Q\left(\frac{y_i - \alpha_{opt}}{(0.5N_0)^{0.5}}\right) & \text{if } a_i = 1 \\ Q\left(\frac{\alpha_{opt} - y_i}{(0.5N_0)^{0.5}}\right) & \text{if } a_i = 0 \end{cases}, \quad (5)$$

where α_{opt} is the optimum threshold level, set to the midway value of $RP_{avg} \sqrt{T_b}$.

Beyond the normalized delay spread of 0.52, the error rate becomes irreducible, i.e. the target bit error rate (BER) cannot be achieved simply by increasing the transmitter power. To mitigate the ISI, the optimum solution would be to use maximum likelihood sequence detector (MLSD), but in a practical system the decision feedback equalizer (DFE), a suboptimal equalizer, has been adopted [17]. In [18] it has been reported that the power penalty in diffuse channel can be reduced by 5.7 dB when using a zero-forcing DFE (ZF-DFE) at data rate of 100 Mbps, thus making it practically feasible for implementation. Unlike the unequalized OOK, there is no simple relation to predict the power penalty and the error probability in equalized systems. However, the trend of power penalty can be approximated by [18]:

$$\text{Power penalty (ZF-DFE)} = 3(c_0^{-1} - 1), \quad (6)$$

where c_0 is the zero tap given in (1), normally due to LOS path. More recently, equalizers based on the WT-ANN have been studied [19], showing a BER performance outperforming that of the DFE.

3. Discrete Wavelet Transform

The topic of wavelets is multi-faceted and highly mathematical, and a subject that is arguably dominated by researchers with a mathematical background. It was developed to resolve the time-frequency resolution problem of Fourier transform (FT) and short-time Fourier transform (STFT)

[20]. The FT does not provide a time-frequency representation of signal while a STFT causes uncertainty in the time-frequency representation [21]. The WT is the ultimate solution in representing the time-varying signal. It has a variable window, enabling it to provide a more flexible time and frequency resolution than STFT [20, 21]. The CWT produces coefficients for every scale up to a scale where one chooses to stop. Unfortunately this can lead to a significant amount of computational effort and requires a reasonable amount of ‘computational horsepower’.

The redundant coefficients in CWT can be removed by selecting the dyadic (power of 2) scale and translation, thus leading to the DWT. The DWT process involves using successive, complementary low-pass $g[n]$ and high-pass $h[n]$ filters to split the signal under analysis into its approximation and detail coefficients. With the traditional digital filtering techniques this would leave us with two signals both having the same number of sample points as the original signal. However, the DWT process down-samples both signals by a factor of two [15]. Figure 2 represents the wavelet decomposition tree with the approximation and detail coefficients given as:

$$y_l[k] = \sum_n X[n]g[2k - n] \quad (7)$$

$$y_h[k] = \sum_n X[n]h[2k - n] \quad (8)$$

The high-pass and low-pass filters are related to each other and satisfy the condition of quadrature mirror filter, i.e. the sum of the magnitude response of high-pass filter and low-pass filter is equal to one for all frequencies. The approximation coefficients can further be decomposed into different DWT coefficient levels with a maximum level of $\log_2 L$, where L is the signal length.

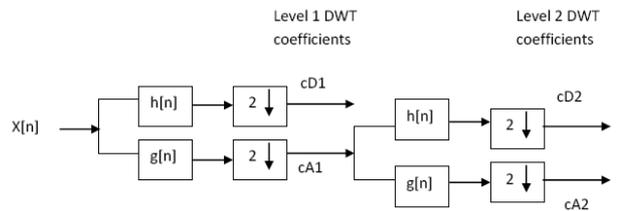


Fig. 2: The 2-level DWT decomposition of a signal.

In addition to removing the redundant coefficients in the CWT, DWT provides another dimension of flexibility compared to the CWT and that is the denoising of signal corrupted by the AWGN. Denoising is performed by hard/soft thresholding of the detail coefficients [22]. Let $\omega(X[n])$ represent the WT of the discrete signal $X[n]$. The denoised reconstruction of the signal is given by:

$$X_d[n] = \omega^{-1}(\Lambda\omega(X[n])), \quad (9)$$

where ω^{-1} is the inverse WT, and Λ is the thresholding operator defined for the hard and soft thresholdings as:

$$\Lambda(k)|_{HT} = \begin{cases} 0 & \text{if } k < \tau \\ 1 & \text{if } k \geq \tau \end{cases} \quad (10)$$

$$\Lambda(k)|_{ST} = \text{sgn}(k)(|k| - \tau) \quad (11)$$

There are a number of algorithms used to select the optimum threshold level τ . For the universal threshold scheme τ is defined as:

$$\tau = \sqrt{2 \log N \sigma}, \quad (12)$$

where σ is the variance of the wavelet coefficient in each level. Different threshold estimations are described further by Donoho [22].

4. WT-ANN Based Receiver Model

The unit energy filter in Fig. 1 is replaced with a feature extraction and pattern classification module composed of the DWT and ANN units, see Fig. 3. The received signal is decimated into discrete W -bit sample lengths, where the sample information content is changed by one bit. Figure 3(b) shows an example for $W = 3$, which can be thought of as a 3-bit sliding window that can slide by one bit at a time. Each window containing a total of 24 discrete samples (8 samples/bit and a 3-bit sliding window) is applied to the DWT to extract the wavelet coefficients. These coefficients can either be directly applied to the ANN for signal classification or they can be further processed to reduce the noise content of the signal prior to signal classification. The ANN is trained with 400 known samples prior to classification of the unknown data, and is set to detect the central bit of a 3-bit window as the binary '1' or '0'.

As for denoising, here we have adopted the following two schemes:

1. *Thresholding*: A threshold level for each decomposition stage is calculated using (12) before applying them to (10) and (11) to

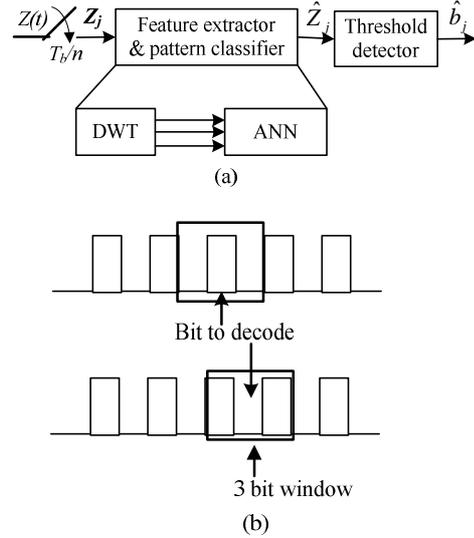


Fig. 3: (a) The block diagram of receiver and equalizer based on the feature extraction and pattern classification: with feature extractor (DWT) and pattern classifier (ANN), and (b) 3-bit sliding window.

determine the thresholding operator for the soft and hard thresholding respectively.

2. *Discarding coefficients*: With multiple samples taken per bit, discarding the entire detail coefficients will not result in the loss of information. Therefore, we only use the approximation coefficients of high-pass filter for training and classification.

5. Results and Discussion

The proposed receiver shown in Fig. 3 is simulated using Matlab. The simulation parameters are shown in Table 1.

Figure 4 shows the BER performance against the SNR for the DWT-ANN based receiver at data rates of 155 Mbps and 200 Mbps for a channel with D_{rms} of 10 ns and for different values of W . Also shown are the BER performance of unequalized (155 Mbps only) and the linearly equalized OOK, the former showing the worst performance. The results illustrate that equalization and denoising based on the DWT-ANN show a marked improvement in the BER performance compared with the linearly equalized and unequalized cases. Increasing W from 3 to 5 bits does not offer any improvement in the BER performance while decreasing it to 1 bit leads to degradation in the error performance.

Table 1: Simulation parameters

Parameters	Value
Data rate R_b	155 Mbps
Channel RMS delay spread D_{rms}	10 ns
No. of samples per bit	8
Mother wavelet	Discrete Meyer
ANN type	Feedforward back propagation
No. of neural layers	2
No. of neurons in 1 st layer	4
No. of neurons in 2 nd layer	1
ANN activation function	log-sigmoid, tan-sigmoid
ANN training algorithm	Scaled conjugate gradient algorithm
ANN training sequence	400 bits
Minimum error	1^{-30}
Minimum gradient	1^{-30}
DWT levels	3

Compared with the traditional equalizer, the new approach shows a significant improvement in performance with the SNR gains of ~6 dB and ~5.8dB at BER of 10^{-5} , W of 3 and 5 and D_{rms} of 10 ns for data rates of 155 and 200 Mbps, respectively, showing a close match to the earlier

results [23]. However, compared to [23], an identical performance is achieved by reducing the number of neurons (4 neurons is utilised in first layer in comparison to 100 neurons in [23]). This reduces the system complexity and computational time.

6. Conclusion

A receiver/equalizer based on the DWT-ANN is proposed and the BER performance of the proposed system is simulated in Matlab. The received noisy signal is sampled at multiple rates and the DWT is used for feature extraction (i.e. denoising) while the feedforward backpropagation ANN is used for the pattern classification (i.e. equalization) based on the DWT coefficients. Different sliding windows are studied and a window size of 3-bit is shown to be adequate for feature extraction. The simulation results show that the proposed DWT-ANN system outperforms the traditional equalizer offering a SNR gain of more than 6 dB at a data rate of 155 Mbps in a dispersive channel with D_{rms} of 10 ns. The system shows a reduced neural complexity compared to already proposed system based on the WT-ANN.

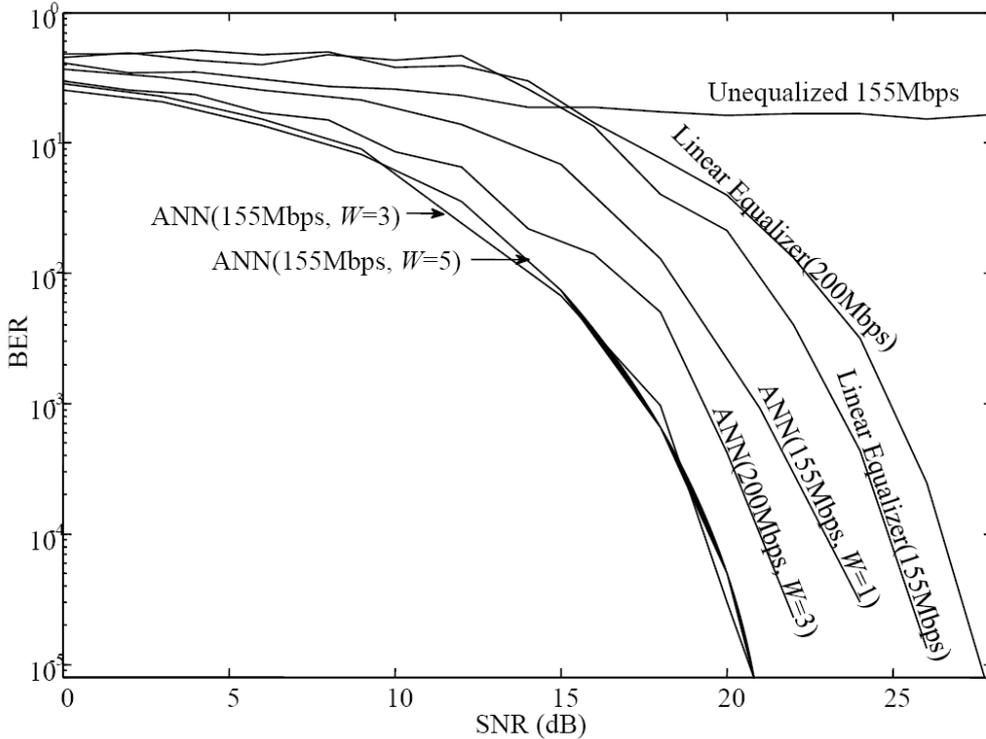


Fig. 4: The BER performance against the SNR of a linear equalizer and a DWT-ANN based receiver (for different window length) at data rate of 155 Mbps and 200 Mbps in a diffuse link with D_{rms} of 10 ns.

References

- [1] D. A. Rockwell and G. S. Mecherle, "Optical wireless: low-cost, broadband, optical access," SONA Communications Corporation, 2007.
- [2] A. G. Al-Ghamdi and J. M. H. Elmirghani, "Multiple spot diffusing geometries for indoor optical wireless communication systems," *International Journal of Communication Systems*, Vol. 16, No. 10, pp. 909-922, 2006.
- [3] J. M. Kahn and J. R. Barry, "Wireless infrared communications," *Proceedings of IEEE*, Vol. 85, No. 2, pp. 265-298, 1997.
- [4] N. Hayasaka and T. Ito, "Channel modeling of nondirected wireless infrared indoor diffuse link," *Electronics and Communications in Japan*, Vol. 90, No.6, pp. 9-19, 2007.
- [5] D. A. Rockwell and G. S. Mecherle, "Wavelength selection for optical wireless communications systems," *Proc. SPIE*, Vol. 4530, pp. 27-35, 2001.
- [6] G. W. Marsh and J. M. Kahn, "50-Mb/s diffuse infrared free-space link using on-off keying with decision-feedback equalization," *IEEE Photonics Technology Letters*, Vol. 6, No.10, pp. 1268 - 1270, 1994.
- [7] D. C. Lee and J. M. Kahn, "Coding and equalization for PPM on wireless infrared channels," *IEEE Transaction on Communication*, Vol. 47, No. 2, pp. 255-260, 1999.
- [8] J. G. Proakis, *Digital communications*, Fourth ed., McGraw-Hill, Inc., 2001.
- [9] S. Haykin, "Neural networks expand SP's horizons," *IEEE Signal Processing Magazine*, Vol.13, No. 2, pp. 24-49, 1996.
- [10] A. Hussain, J. J. Soraghan, and T. S. Durrani, "A new adaptive functional-link neural-network-based DFE for overcoming co-channel interference," *IEEE Transactions on Communications*, Vol. 45, No. 11, pp. 1358-1362, 1997.
- [11] C. Ching-Haur, S. Sammy, and W. Che-Ho, "A polynomial-perceptron based decision feedback equalizer with a robust learning algorithm," *Signal Processing*, Vol. 47, No. 2, pp. 145 - 158 1995.
- [12] S. Haykin and D. J. Thomson, "Signal detection in a nonstationary environment reformulated as an adaptive pattern classification problem." *Proceedings of the IEEE*, Vol. 86, No. 11, pp. 2325-2344, 1998.
- [13] D. Cariolaro and L. Favalli, "Recovery of ISI channels using multiresolution wavelet equalization," *IEEE International Conference on Communications*, New York, NY, USA, pp. 74-78, 2000.
- [14] F. Liu, X. Cheng, J. Xu, and X. Wang, "Wavelet based adaptive equalization algorithm," *Global Telecommunications Conference 1997*, Phoenix, AZ, USA, pp. 1230-1234, 1997.
- [15] G. Strang and T. Nguyen, *Wavelets and Filter Banks*. Wellesley College, 1996.
- [16] J. B. Carruthers and J. M. Kahn, "Modeling of nondirected wireless Infrared channels," *IEEE Transaction on Communication*, Vol. 45, No. 10, pp. 1260-1268, 1997.
- [17] G. W. Marsh and J. M. Kahn, "Performance evaluation of experimental 50-Mb/s diffuse infrared wireless link using on-off keying with decision-feedback equalization," *IEEE Transactions on Communications*, Vol. 44, No. 11, pp. 1496-1504, 1996.
- [18] J. M. Kahn, W. J. Krause, and J. B. Carruthers, "Experimental characterization of non-directed indoor infrared channels," *IEEE Transactions on Communications*, Vol. 43, No. 234, pp. 1613-1623, 1995.
- [19] R. J. Dickenson and Z. Ghassemlooy, "Wavelet-AI equalization and detection for indoor diffuse infrared wireless systems," *International Journal of Communications Systems*, Vol. 18, No. 3, pp. 247-266, 2005.
- [20] I. Daubechies, *Ten Lectures on Wavelets* SIAM: Society for Industrial and Applied Mathematics, 1992.
- [21] C. S. Burrus, R. A. Gopinath, and H. Guo, *Introduction to Wavelets and Wavelet transforms: A primer*. Prentice Hall, 1998.
- [22] D. L. Donoho, "De-noising by soft-thresholding," *IEEE transactions on information theory*, Vol. 41, No. 3, pp. 613-627, 1995.
- [23] R. J. Dickenson and Z. Ghassemlooy, "BER performance of 166 Mbit/s OOK diffuse indoor IR link employing wavelets and neural networks," *Electronics Letters*, Vol. 40, No. 12, pp. 753 - 755, 2004.