Wavelet Transform - Artificial Neural Network Receiver with Adaptive Equalization for a Diffuse Indoor Optical Wireless OOK Link

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ABSTRACT

This paper presents an alternative approach for signal detection and equalization using the continuous wavelet transform (CWT) and the artificial neural network (ANN) in diffuse indoor optical wireless links (OWL). The wavelet analysis is used for signal pre-processing (feature extraction) and the ANN for signal detection. Traditional receiver architectures based on matched filter (MF) experience significant performance degradation in the presence of artificial light interference (ALI) and multipath induced intersymbol interference (ISI). The proposed receiver structure reduces the effect of ALI and ISI by selecting a particular scale of CWT that corresponds to the desired signal and classifying the signal into binary 1 and 0 based on an observation vector. The simulation results show that the Wavelet-ANN architecture outperforms MF receiver even with the filter matched to the ISI affected pulse shape. The Wavelet-ANN receiver is also capable of providing a bit error rate (BER) performance comparable to the equalized forms of traditional receiver structure.

KEYWORDS

Indoor optical wireless links, adaptive equalization, wavelet transform, artificial neural network.

1.   INTRODUCTIONS

Future communication systems with multiple applications require huge bandwidths per user that radio and microwave frequencies are currently unable to provide. The last mile problem is becoming more acute, therefore the need for alternative link schemes is increasing. Dropping fibre to homes is a costly solution at the present time; however this will reduce over the next decade or so. There is an alternative and complementary solution based on the OWL 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 [1-3]. Compared with the RF links, OWL offers a number of advantages, including: a huge bandwidth at a single wavelength covering a small or large areas (cellular system using the same wavelength), rapid installation, security, well defined cell pattern, dynamic data rates and user base using multiple wavelengths in a single cell and protocol transparency.

The key issues in the indoor OWLs are ocular safety, mobility, beam blocking, ambient light noise and multipath induced ISI in non-line-of-site (non-LOS) links [4, 5]. Ocular safety could be overcome by shifting to a higher wavelength of 1550 nm where the eye retina is less sensitive to optical radiation [6] 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. In diffuse (non-LOS) links beam blocking and to a certain degree mobility is overcome at the cost of reduced data rate, increased path loss and ISI [5]; 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 [4, 7, 8].

The effect of artificial ambient light (AAL) is more severe in indoor applications since the average transmitted optical power level is limited due to skin and eye-safety considerations. The amplitude of the interference is often greater than signal amplitude causing severe degradation in performance. Without electrical high-pass filtering (HPF), the optical power level required at the receiver photodetector for on-off keying (OOK) is ~16 dBm/cm^2 irrespective of the bit rate [9]. An electrical HPF is often incorporated in the receiver to cut-off the ALI before signal detection is done; however, the use of HPF in OOK systems provide insignificant improvements for data rates up to 10 Mbps [9]. Some improvement can be achieved in higher data rate systems but the HPF introduces a form of ISI known as the baseline wonder (BLW), this is more severe for baseband modulation techniques with high power spectral density at DC and low-frequencies.

In non-LOS links, matched filtering is non-optimal as the power penalty would be very high even for a moderately dispersive channel. For highly dispersive channels it is impossible to improve the performance to an acceptable level even by increasing the transmission power. The optimal solution to reduce ISI is to use maximum likelihood sequence detection (MLSD), but memory requirements, processing delay and the complexity associated with MLSD make it a difficult scheme to realise. The practical, though sub-optimal, solution is to use an equalizer. Decision feedback equalizers (DFE) are effective in mitigating ISI and their BER performance is close to that of the MLSD [10]. Even in a highly dispersive channel, no irreducible BER is observed at 100 Mbps with a DFE [10] . The problem with an equalizer in practical implementation is the requirement of the channel inversion, which is not always feasible. In addition, traditional equalizers based on the finite impulse response (FIR) filter suffer from severe performance degradation in time varying and non-linear channels [11].

In this work, we propose a receiver based on the CWT and ANN to overcome the effect of interference due to AAL and to mitigate ISI due to multipath propagation. The fact that digital signal detection can be formulated as a pattern classification problem [12, 13], offers the possibility of applying the ANN. On the other hand, the wavelet can effectively be used to denoise signal.

Hence combination of the wavelet and ANN can be used for both reducing the ALI and ISI at the receiver. The effect of interference is reduced by properly selecting the wavelet scales and ISI is mitigated by training ANN to classify the signal based on the received signal sequence. Since no channel inversion is necessary, the ANN based receiver can be effective in any channel. The BLW effect will not be in the receiver since there is no need for the HPF; hence, the proposed receiver has potential to provide improved performance in any channel even in the presence of the AAL and noise.

The paper is organised as follows: the traditional receiver for OOK in LOS and non-LOS channels is discussed in the Section 2. The proposed receiver model is given in the Section 3 with detail descriptions and algorithm of the receiver. The simulation algorithm, parameter simplification including sample window reduction, wavelet scale reduction and neural network size reduction and simulation results with analysis are presented in Section 4. Finally concluding remarks are given in Section 5.

2. OOK

The most simple and common modulation technique for intensity modulation and direct detection (IM/DD) is the well known OOK scheme, offering bandwidth efficiency and resilience to multipath induced ISI, but at the cost of high average optical power. A block diagram of the unequalized OOK system under consideration is shown in Fig. 1. At the transmitter end, the electrical signal at the output of the transmitting filter $p(t)$ is scaled to make the average transmitted power P_{avg}. The scaling factor is $2P_{avg}$ for non-return-to-zero (NRZ) scheme and $4P_{avg}$ for RZ with a duty cycle of 50%. The receiver end consists of a photodetector for optical to electrical conversion and a MF, matched to the transmitter filter $p(t)$, a sampler sampling at data rate R_b and followed by a threshold detector. This is the optimum detection technique for LOS links in which additive white Gaussian noise (AWGN) is the only source of noise.

The BER at different received power levels is often used to measure the effectiveness of digital modulation techniques. For OOK, the BER in AWGN channel is given by:

$$P_{e,bit,OOK} = \frac{1}{2} Q\left(\frac{RP_{avg}\sqrt{T_b}}{\sqrt{N_o/2}} \right) \tag{1}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_{-x}^{\infty} e^{(-y^2/2)} dy$, T_b is the bit duration, $N_o/2$ is a double-sided power spectral density of background Gaussian noise and R is the photodetector responsivity.

There are two main factors that limit the link performance of the indoor OW system: (a) ambient noise due to AAL and natural light and (b) ISI due to the multipath propagation. Background radiation is modelled as white, Gaussian and independent of the received signal; however, the interference produced by the AAL is deterministic and periodic. These periodic interfering signals have the potential to seriously impair link performance. The

interference from a fluorescent light driven by an electronic ballast is the dominant cause of performance degradation as the interfering signal contains harmonics of the switching frequency that can extend into the MHz range [14]. The probability of BER in the presence of fluorescent light is given by:

$$P_{e,bit,OOK} = \frac{1}{2M} \sum_{k=1}^{M} \left[Q\left(\frac{RP_{avg}\sqrt{T_b} + m_k}{\sqrt{N_o/2}} \right) + Q\left(\frac{RP_{avg}\sqrt{T_b} - m_k}{\sqrt{N_o/2}} \right) \right] \tag{2}$$

where M is the total number of bits over a 20 ms interval and m_k is the output of the MF due to the fluorescent light interference (FLI) signal, sampled at the end of each bit period, given as [15]:

$$m_k = m_{fl}(t) \otimes r(t) \big|_{t=kT_b} \tag{3}$$

where the symbol $\otimes$ denotes convolution, m_{fl} is the photocurrent due to the fluorescent light. m_{fl} comprise of a low frequency component and high frequency components details of which can be found in [15]. The amplitude of the photocurrent due to interference is often larger than that produced by the signal and the optical power requirements are approximately given by the inference amplitude [9].

A combination of band pass optical filter and HPF is used to reduce the effect of the AAL at the receiver. Using a HPF introduces BLW, which is more severe for modulation techniques that contain a significant amount of power located at DC and low frequencies. A HPF does not reduce the average power requirement at low bit rates; but at high data rates (> 100 Mbps), a HPF can effectively reduce the effect of the interference due to the AAL interference. However, the ISI due to multipath propagation limits the link performance at high data rates.

The multipath channel is model using the ceiling bounce model in which the channel impulse response is given by:

$$h(t, a) = \frac{6a^6}{(t+a)^7} u(t) \tag{4}$$

where $u(t)$ is the unit step response, $a = 2H/c$, H is the height between transmitter-receiver (Tx/Rx) and ceiling, and c is the speed of light. The parameter 'a' is related to RMS delay spread D_{rms} given by:

$$D_{rms}(h(t,a)) = \frac{a}{12}\sqrt{\frac{13}{11}} \tag{5}$$

And in the shadowed link,

$$a(unshadowed) = 12\sqrt{11/13}(2.1 - 5.0s + 20.8s^2) \times D_{rms}(h_1(t)) \tag{6}$$

where s is related to the ratio of the distance between the receiver transmitter and a diagonal that intersects them both and extends to the walls of the room under consideration.
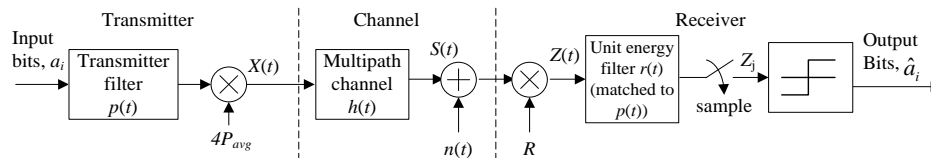

Figure 1. Block diagram of the unequalized OOK system.

The optical power penalty due to multipath propagation increase exponentially with increase in normalised delay spread D_T (D_{rms}/R_b). For higher values of delay spread ($D_T > 0.5$), there is an irreducible BER regardless of transmitted power. An equalizing filter with impulse response inverse to the channel is often incorporated at the receiver. A bit rate of 100 Mbps is achievable using a DFE even on the worst channels, though the normalized power requirements can reach 7.1 dB and 9.1 dB for shadowed diffuse and LOS channels, respectively [10]. 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 [10] :

$$\text{Power penalty (ZF-DFE)} = 3(c_0^{-1}-1) \qquad (7)$$

where c_o is LOS component at the output of MF.

3. WT-ANN BASED RECEIVER MODEL

The block diagram of the OOK Wavelet-ANN receiver is shown in Fig. 2. It can be seen from the figure that from a schematic point of view, the model is similar to the MF system. The unit energy MF in Fig. 1 is replaced with a feature extraction and pattern classification module composed of the WT and ANN units. However, the model operates in an entirely different manner. The wavelet section collects the incoming signal samples and sorts them into overlapping W-bit samples as shown in Fig. 3. It is the centre position of the window that will ultimately be detected by the receiver. The rationale behind this being that the ANN is able to extract further information from the W-bit window to help it make the correct decision. This may be particularly important under the influence of multipath dispersion where previous bits interfere with the present bit. In all simulations the incoming data is sampled at 1 ns intervals and assumes perfect timing alignment, all the samples being passed on to the ANN.

The CWT is used to obtain the wavelet coefficients from sample set where the mother wavelet used is the 'Symlet 2'. The CWT would potentially provide all wavelet coefficients up to some arbitrary maximum, producing a large number of coefficients. This would greatly increase computational burden and ultimately slow the detection process to a point of being unfeasible even for simulation proposes. The changes in the value of the coefficients between one scale to the next are potentially very small and in the majority of cases can be considered redundant, where the redundancy could span many scales. The wavelet section calculates the coefficients at some pre-determined scales that are considered to contain significant information. Unfortunately, a technique for detecting redundancy, or more importantly significance of a particular scale needs to be developed. In this work the scales are selected by visual inspection of 2 and 3 dimensional time-scale-amplitude plots. It is sometimes useful to note the difference between plots of the noise free and noisy signal, this visual technique can afford the opportunity to select scales that are less affected by interfering sources.
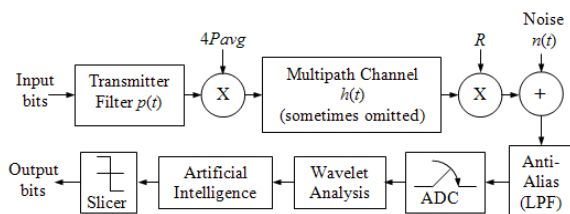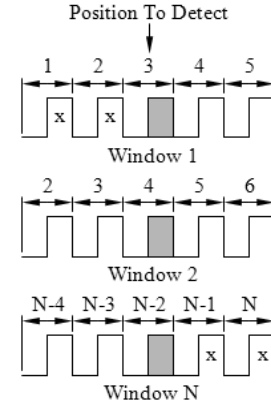

Figure 3. The 5 bit sliding window.

The schematic of information flow is shown in Fig. 4, where the incoming data stream is decimated into 5 bit windows as previously described. Each window is processed by the CWT to produce wavelet coefficients, which are then sorted into a two dimensional matrix or array where each column contains the coefficients that relate to a single 'window'. For example a data rate of 2.5 Mbps and sample interval of 1 ns would produce 400 coefficients for each scale used. Each column is passed to the ANN section for subsequent classification.

The ANN consists of a small 2 layer feedforward, back-propagation ANN. Back-propagation is applied to multi-layer networks with non-linear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by the user. Each neuron has an associated activation function that is constant for a particular layer. In this case a two layer network, where the first layer employs a sigmoid activation function and the second layer a linear function can be trained to approximate any function (with a finite number of discontinuities) arbitrarily well [16]. There are as many inputs to each neuron in the first layer as there are scales in each column. The ANN processes its inputs in a manner that enables it to classify them into particular types. In this case ANN output is close to zero to signify OOK RZ binary '0' or 'space', and close to one to signify binary '1' or 'mark'. The actual output from the final layer varies between something less than zero to something more than one, and in a pure digital sense the information is of little use. A threshold device or 'slicer' is therefore employed to force the output to a binary state.

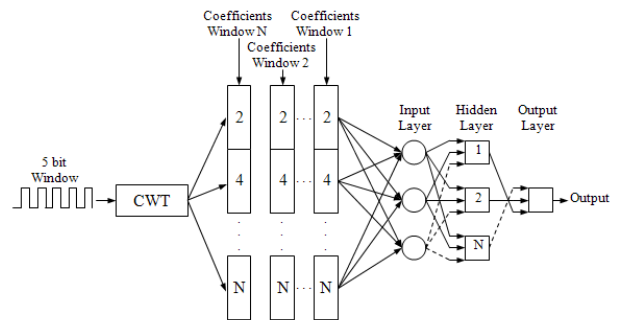**Figure 2. OOK RZ Wavelet-ANN receiver schematic.**

Figure 4. Schematic of wavelet and ANN section information flow.

For ANN to produce meaningful outputs they must be trained. Although various training algorithms are available the underlying principles for their implementation is similar. Each input to the network produces an output that is compared to the corresponding value of the target set. The training algorithm then modifies the weights associated with the neuron inputs in an effort to minimise the difference between the input and target vectors. This process may continue many times until a desired error value is attained. An interesting but undesirable property of ANN is that they can be over-trained, here the network effectively 'tunes' itself to the training inputs and loses its ability to generalise. In such a case the network would yield minimal errors between its training and target vectors, however, a new set of input and target vectors would produce significant errors. It is therefore important to adopt a training scheme that minimises the effect of over training. In this work interest in ANNs is primarily confined to its pattern recognition capability that is used to detect a pattern from imperfect data, corrupted by noise and dispersion.

There are two types of training: supervised and unsupervised. This work focuses on supervised training where the ANN is presented with a particular input vector of data to be classified and a target vector corresponding to the correct output. Together these two vectors are referred to as the training pair and are used in conjunction with a training algorithm to modify the behaviour of the ANN in such a manner that it is able to classify an input it has never seen before.

Training consists of the transmission of a pre-determined signal stream sampled by the ADC to give:

$$x = \sum_{k=1}^{k=N} x_k \qquad (8)$$

where $k = kT_b$.

Another major consideration when using a feedforward back-propagation network is the selection of training algorithm. A number of well-established algorithms exist and are available in the Matlab™ simulation package, see Table 1. A number of these algorithms were tried, however, the most successful was the conjugate gradient with Powell/Beale Restarts [17] and this was used throughout the work contained in this paper.

In these simulations a training length of 1000 or 1500 OOK-RZ symbols (bits). In a practical system this would not be a huge burden since the transmission of 1000 bits at 2.5 Mbps would theoretically only take 400 μs. Obviously the training process may take longer depending on the architecture and performance of the receiver processor. However, the indoor diffuse IR channel is slow moving and does not suffer from fade; therefore the number of training (redundant) bits to sustain a given BER may well turn out to be very low compared to the number of potential information bits. For this model training is confined to signals with particular SNR figures, rather than a training signal for every SNR subsequently simulated. The network was therefore trained with SNRs of 11 dB, 12 dB and 13 dB. These values were empirically selected to be near the noise value corresponding to a BER of approximately 10^{-6}.

Table 1: Training algorithms.

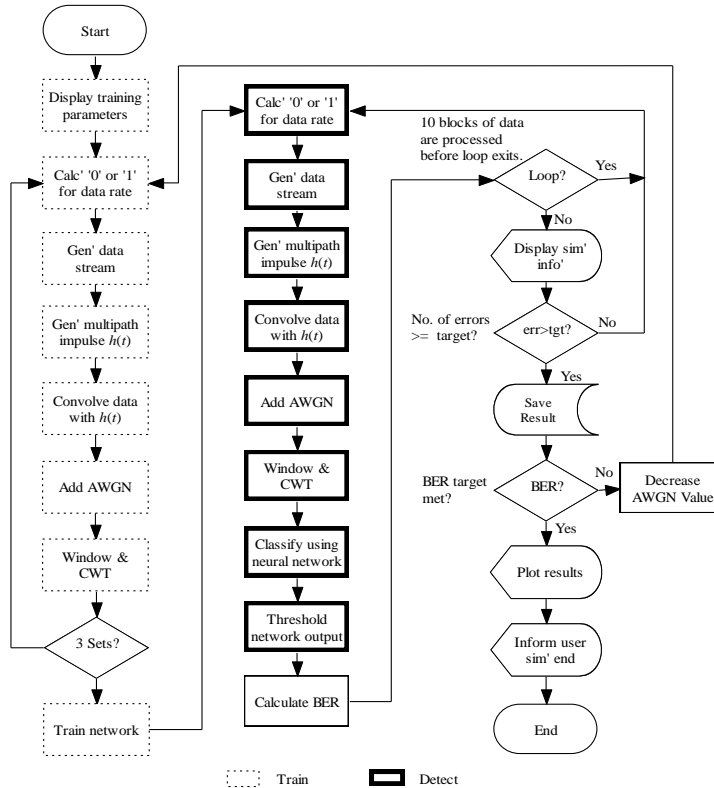|	Algorithm
1	Levenberg-Marquardt
2	BFGS Quasi-Newton
3	Resilient Backpropagation
4	Scaled Conjugate Gradient
5	Conjugate Gradient with Powell/Beale Restarts
6	Fletcher-Powell Conjugate Gradient
7	Polak-Ribiére Conjugate Gradient
8	One-Step Secant
9	Variable Learning Rate Backpropagation

Figure 5. Flowchart for simulation model shown in Fig. 2.

4. RESULTS AND DISCUSSION

The proposed receiver based on the Wavelet-ANN for OOK RZ scheme with a duty cycle 'γ' of 0.5 is simulated in Matlab using the flowchart given in Fig. 5. The effect of the FLI and ISI due to multipath propagation is dealt separately. In all simulation, it is assumed that background interference with an average photocurrent I_B of 200 μA is present. The channel impulse response is normalized to 1 so that total energy of the system is conserved. The first task in the design is to optimise the system parameters in order to reduce complexity and maximised the performance. Since no definitive method exists to optimum structure of ANN or the window size for equalization, the parameters are using the simulations and results are present as follows.

4.1. Window Sizes

Window size and the number of scales employed directly affect the computational burden imposed by the CWT process. The effects of window size on Wavelet-ANN receiver performance is explored using simulations. The CWT with 'Sym2' wavelet with scales from 2 to 74 in steps of 2 is used for feature extraction. The model employs a ANN trained with 1500 symbols with varying noise values added, providing SNRs as follows: 12 dB in the first 3000 symbols, 6 dB in the second 3000 symbols and 15 dB in the third 3000 symbols, 9 dB in the forth 3000 symbols and 18 dB in the last 3000 symbols. This strategy is aimed at reducing the training burden of the simulations by finding a near optimum BER for a given SNR using only one training set. However, as all the simulations adopt the same strategy, a like for like comparison of results is still valid. The network is trained with 1500 samples before classification of unknown data begins. The multipath distortion induced normalised delay spread D_T of 0.819 is adopted in the simulations.

The simulation result for the BER against the SNR for a range of window size is depicted in Fig. 6. It is immediately apparent from observation that a single bit window is significantly inferior to multiple windows requiring additional 4.5 dB of SNR at a BER of 10^{-3}. This may indicate that the ANN is indeed extracting information from previous and following bits to make a decision. However, employing multiple bit windows shows little significant variation in performance. Given these results, all later simulations for OOK RZ will be based on a 3-bit window with centre bit detection to reduce computational effort.
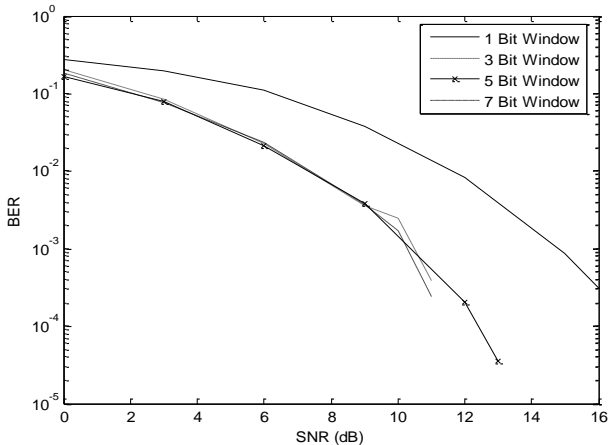

Figure 6. BER against the SNR for Wavelet-ANN detection of 100Mb/s OOK RZ with different window sizes and single training session.
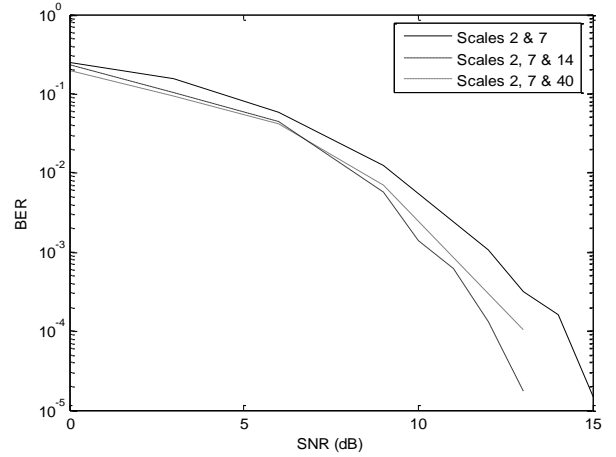

Figure 7. BER against SNR for Wavelet-ANN detection of 100Mb/s OOK RZ with 3 bit window, reduced scale inputs sizes and single training session.

4.2. Wavelt-ANN Scale Reduction

It is a relatively simple process to visually select the scales that cover as many signal features as possible; under the correct conditions this would allow perfect synthesis of the original signal. Such a brute force method would give confidence that the ANN section was passed near optimum time-scale information for classification purposes. However, such methods impose two costs, that of CWT complexity and the subsequent level of numerical calculations required to be undertaken by the ANN. We briefly investigtes the effect of reducing scales to those which visually encompass the major features of the signal as seen on a time-scale plot. These are scales 2 and 7, scales 2, 7 and 14 and scales 2, 7 and 40. Using Figs. 2 and 5 the BER against SNR for 100Mb/s OOK RZ with 3 bit window is illustarted in Fig. 7. When compared with Fig. 6, the simulation results indicate that considerable reduction in the number of scales can be made without significant reduction in system performance.

Selection of scale in presence of the FLI should be made in such a way that the effect of the FLI is minimal while making the decision using the ANN. The scales are selected manually by visualizing the CWT in 3-D and the selection scales for different data rate is given in Table 2.

Table 2. Wavelet scales for different data rates.

Data Rate (Mb/s)	Scales
2.5	250, 750, 1000, 1250, 1500
5	45, 160, 320, 550
10	100, 230, 380, 780
25	70, 150, 250, 300, 550
50	16, 32, 48, 64

4.3 Reduced Neurons

A further contributor to computational complexity is the size of the ANN. Given that all scales from the CWT section are passed to all neurons in the input layer further reduction in computational burden can be made by reducing the size of the network. No definitive method exists to determine the optimum size of a feed-forward back-propagation ANN and 'network pruning' is sometimes employed. In this section a simulation model derived from the previous two simplifications is used. The model utilises a 3-bit window where the CWT section processes
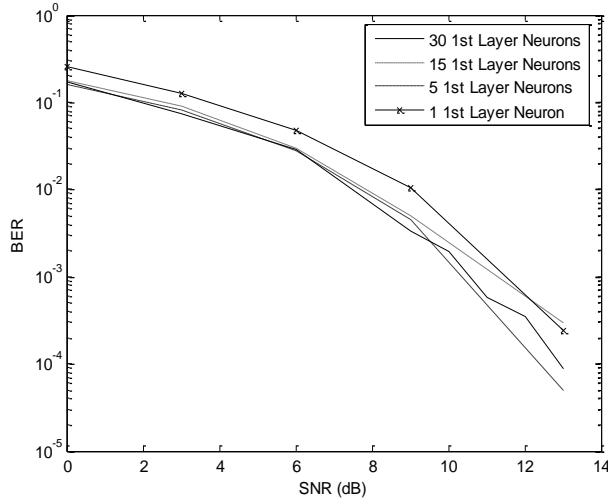
Figure 8. BER against SNR for Wavelet-AI detection of 100Mb/s OOK RZ with 3 bit window, scales of 2, 7 & 14, reduced neurons and single training session

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scales of 2, 7 and 14. Four simulations were executed with the only variation being the size of the first processing layer, or 'hidden layer' in the neural network. Simulation runs for a first processing layer of 30, 15, 5 and 1 neurons were made.

The results, shown in Fig. 8, indicate little variation between 30 first layer neurons and 5 first layer neurons. However, the results from 1 first layer neuron model show a consistently worse BER performance than other models, whilst the 15 neuron model shows some behaviour anomalies from a BER of approximately 10^{-3}. Whilst not exhaustive the results indicate that a substantial reduction in network complexity can be made without excessively compromising receiver performance providing a further minimisation of computational effort.

4.4 Performance in LOS links in presence of FLI

With the optimised parameters (window size of 3, number of neurons 5 and reduced scale), the performance of the Wavelet-ANN receiver is simulated for different data rates in the presence of the FLI. The normalised optical power penalty for the
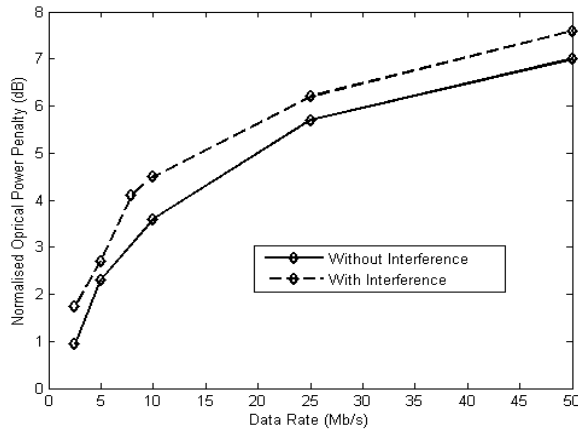

Figure 9. **Normalised optical power penalty versus data rate for OOK RZ with and without FLI for a Wavelet - ANN receiver at a BER of 10^{-5}.**

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Wavelet-ANN receiver, for both the perfect channel and that subjected to FLI is depicted in Fig. 9. The optical power penalty due to the FLI without any HPF is very high in the case of MF detection with a value of ∼ 18 dB irrespective of data rate [9, 18]. Compared to the MF receiver, the Wavelet-ANN receiver is far less susceptible to performance degradation due to the influence of FLI. There is less than 1 dB optical power penalty over the non-interfering channel using the Wavelet-ANN receiver, which is a significant performance improvement compared to the MF architecture. The improve performance can be explained by exploring roughly the inversion relation between the frequency and scale. In frequency (scale) terms, the FLI lies far away from the actual signal. Selecting a scale of wavelet transform is equivalent to choosing a particular band of frequency that relates to the signals data content thus removing the scales that corresponds to interference and is analogous to filtering out the interference. Hence, by selecting the appropriate wavelet scales the effect of the FLI can be reduced in the receiver.

4.5 Performance in diffuse links

The performance of different receiver architectures in a diffuse channel with normalised delay spread of 0 - 0.7 is shown in Fig. 10. The results indicate that for ISI channels the inclusion of the minimum mean square error (MMSE) equalizer with a MF and Wavelet-ANN receiver significantly improves the receiver performance. In contrast with the results of the traditional system (using MF filter only) the performance curves do not diverge as rapidly and offer broadly similar performances for both the ISI and non ISI case up to a D_T of approximately 0.25. For higher values of D_T the curves diverge more noticeably. Irreducible BERs were not reached over the range of normalised delay spread D_T simulated; however, a power penalty that increases with D_T is observable. The Wavelet-ANN architecture does not incorporate any equaliser algorithm; instead it relies on the feature extraction of the CWT section and the classification of the ANN. It can be seen that the Wavelet-ANN receiver shows compatible to marginally better performance over the traditional-MMSE case. For D_T of 0.2 the equalised and Wavelet-ANN systems provide a power advantage over the unequalized ISI case of a little less than 3 dB. At a D_T of 0.25 the power penalty incurred by the unequalized ISI case has risen to just over 3 dB; however, the curves are diverging and further simulations for the unequalized ISI case reveal irreducible BERs for D_T figures a little in excess of 0.25. At high levels of D_T there is an approximately 2 dB penalty for the equalised ISI case over the non ISI case.
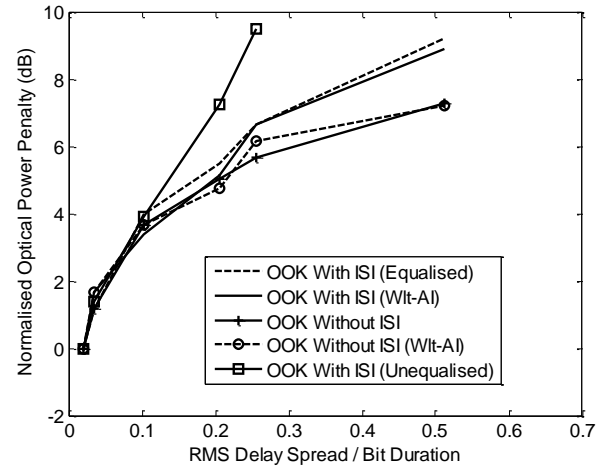

Figure 10. **Normalized optical power penalty against the normalized RMS delay spread for OOK EZ with/without equalization at a BER of 10^{-6}.**

5.   CONCLUSIONS

The paper presented a new receiver architecture based on the CWT and ANN for reducing the effect of artificial light influence and ISI at the receiver for indoor optical system. The Wavelet-ANN architecture does not incorporate any equaliser algorithms and HPF; instead it relies on the feature extraction of the CWT and the classification of the ANN. By selecting a particular scale that corresponds to the signal, the effect of AAL interference is reduced. We showed that there is little variation between 30 first layer neurons and 5 first layer neurons, with one layer ANN model showing a consistently worse BER performance than other models, whilst the 15 neuron model showed some behaviour anomalies from a BER of approximately 10^{-3}. Whilst not exhaustive the results indicate that a substantial reduction in network complexity can be made without excessively compromising receiver performance providing a further minimisation of computational effort. The concept of signal classification is implemented using ANN to effectively compensate for the multipath induced ISI. The new architecture showed a < 1 dB variation between the ideal and ISI cases at a delay spread of 0.3 and < 2 dB at a delay spread of 0.5. We showed that there hardly any improvement in the BER performance for the Wavelet-AI detection when employing a window size larger than 3-bit. Simulation results showed that the performance using CWT-ANN is comparable to the equalized forms of the traditional receiver structure employing MF.

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