Wavelet Analysis & Artificial Intelligence For Equalisation And Detection In Diffuse Indoor Infrared Communication Systems

(With Simplified Wavelet AI Receiver)

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Contents

• Aims & objectives, motivators, timetable & progress
• Review of diffuse indoor IR and the communication channel
• Channel compensating techniques
• The wavelet transform
• Artificial intelligence
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• Wavelet AI receiver simplification
• Publications
• Further work
Aims And Objectives

• To investigate the use of **Wavelet Analysis** and **Artificial Intelligence** as an alternative to traditional equalisation techniques for the detection of signals in diffuse indoor infrared systems.

• The research will consist of system simulations and analysis as appropriate.
Why Wavelet Analysis & Artificial Intelligence?

- The indoor IR channel is quasi-static and does not fade.
  
  *Rx system will not require equaliser re-training at regular intervals.*

- Current implementations dominated by ‘borrowed’ RF techniques.
  
  *New techniques may be able to leverage channel stability into a performance advantage.*

- Much research interest in wavelet analysis and artificial intelligence.
Neural network-based receiver for wireless communications

S. Haykin, J. Nie & B. Currie

Features wavelet analysis and neural networks for detection of Minimum Shift Keying Modulation (MSK) in GSM.
BEGIN:
Initial literature search.

Construct standard communication models and verify with simulation.

Modify models to incorporate wavelet and AI techniques. Compare probability of error with standard models.

PRODUCE: M.Phil report and construct seminar material for both SHU and external conferences.

BEGIN:
Initial literature search.

CORE THEME
Study and apply optical wireless, communication, wavelet and Artificial Intelligence theory.

Study and apply optical wireless, communication, wavelet and Artificial Intelligence theory.

Construct Optical Wireless specific models and verify with simulation.

Verify analysis and simulation results as required.

Modify models to incorporate wavelet and AI techniques. Compare probability of error with standard models.

Prepare and offer papers for publication / seminars as opportunities arise.

END:
Write up results, conclude research and complete PhD thesis for submission.

Verify analysis and simulation results as required.

Modify models to incorporate wavelet and AI techniques. Compare probability of error with standard models.
Timetable

- Research Begins October 2001
- M.Phil to Ph.D Transfer Report March 2004
- Research Concludes October 2007
Progress

• Initial literature review
• Review of IR communications
• Modelling and simulation of the indoor IR channel
• Review, model and simulation of wavelet analysis
• Review, model and simulation of neural network architectures
• Review, model and simulation of traditional compensating techniques
• Model and simulation of a wavelet AI receiver
• Simplification and simulation of the wavelet AI receiver.
Indoor IR Configurations

- LOS configurations have higher data rates but are susceptible to device movement and beam blocking.
- The diffuse configuration is not susceptible to beam blocking and the receiver can be moved around the room.
Limitations Of The IR Communications And The Diffuse Configuration

Issues:

- **Multiple paths (reflections)**
  - Result in inter-symbol interference (ISI).
- **Noise from natural and artificial light sources**
  - Degrade the received signal further.
- **Limited transmission power**
  - At popular wavelengths (~850nm) due to eye safety considerations.
- **Limited bandwidth**
  - Due to large capacitance of the large area detectors.
Modulation Techniques

- Due to the difficulty of making coherent IR receivers intensity modulation with direct detection is normally used.
- The on-off nature of such a scheme lends itself to pulse modulation techniques which dominate in this area.
- Up to now our work has focussed on OOK because it is simple and widely understood.
IR Channel Model

• Due to the small dimensions of the IR wavelength in comparison to detector dimensions and modulation frequency the channel can be regarded as time invariant.

• The diffuse indoor IR channel can be modelled as a fixed linear system with additive white gaussian noise where \( x(t) \) is non-negative and the impulse response \( h(t) \) produces ISI.
The Channel Impulse Response

- Generic 2 stage mathematical model for the indoor diffuse IR channel developed by Carruthers & Kahn.
- Calculate delay spread for co-located Tx/Rx pair.
- Then apply a correction based on Tx/Rx separation and specific room dimensions

- The delay spread is given by: \( D(h(t,a)) = \frac{a}{12} \sqrt{\frac{13}{11}} \)

- Where: \( a = \frac{2H}{c} \) And ‘H’ is the height between Tx/Rx and ceiling, ‘c’ is the speed of light.

- The correction of ‘a’ is given by: \( a(unshadowed) = 12\sqrt{\frac{11}{13}}(2.1 - 5.0s + 20.8s^2) \times D(h_1(t)) \)

  Where ‘s’ is the ratio of the distance between the Tx and Rx, and the length of a diagonal that intersects them both and extends to the wall of the room under consideration.

- The impulse response is given by: \( h(t,a) = \frac{6a^6}{(t+a)^7} u(t) \) Where u(t) is the unit step response.
Unequalised Performance Of OOK-NRZ & OOK-RZ with ISI

- At low data rates OOK RZ has a performance advantage over OOK NRZ.
- As data rates increase OOK RZ performance diminishes dramatically.
Compensating Techniques

• **Noise Filtering:** Reduces the effect of noise by rejecting out of band frequencies. (Optical / Analogue /DSP)

• **Match Filtering:** Maximises SNR, the optimum detection method in the presence of noise. (Time reversed copy of received pulse convolved with received data stream)

• **Coding:** Block codes, convolutional codes (MLSD), turbo codes. Increase performance by adding redundant data!

• **Equalisation:** Channel distortion compensating filters:
  » Zero Forcing Equaliser (ZFE).
  » Minimum Mean Square Equaliser (MMSE).
  » Decision Feedback Equaliser (DFE).

• **Diversity:**
  Multiple receivers, multiple transmitters, fly-eye detectors, multi-beam transmission etc etc.

• **Alternatives**
  Neural Network based equalisers.
  Wavelet AI
Filtered Performance

Low Pass Filtering
- For NRZ Carruthers et al. suggest a normalised cut-off frequency of 0.6/T which our simulations confirm.
- For RZ our simulations show the cut off is 0.35/T.
- LP filtering improves performance for both RZ and NRZ.
- Most of RZ advantage at low data rates is lost.

Match Filtering: Preliminary results show performance is severely limited by ISI.
Coding

Coding is concerned with detecting errors in the data stream. Further redundant data is sent with the information. This redundant (in an information sense) data is used to correct errors.

Block codes

- Information mapped onto a fixed size block.
- An \((n/k)\) code has \(k\) data bits and \(n-k\) check bits.

Convolutional Codes

- Theoretically infinite length.
- Described as block codes but with a third figure describing constraint length.
- Some preliminary simulations on MLSD conducted.
- Not pursued as the technique can be added after detection.
• ISI minimisation is achieved by considering only those inputs that appear at the correct sample times. For convenience $x(kT) = x_k$ and $y(kT) = y_k$. For zero ISI we require:
  – $y_k = 1$ for $k = 0$
  – $y_k = 0$ elsewhere
• The output $y_k$ can be expressed in terms of the inputs and tap weights: $y_k = \sum_{n=-N}^{N} a_n x_{k-n}$
  – Therefore: $y_k = 1$ for $k = 0$ and $y_k = 0$ for $k = \pm 1, \pm 2, \ldots \pm N$
• A transversal equaliser can force the output to go to zero at $N$ points either side of the peak output and we can solve the $(2N+1)$ equations in matrix form as follows:
• Where ‘$a$’ is the filter coefficient array, ‘$X$’ is the sample point matrix and ‘$q$’ is the output array.

\[ a = X^T q \]
Performance Of The ZFE

- No pre filter.
- Irreducible BER not reached at 250Mbps.
- RZ performance degraded for low bit rates!
- ZFE would perform better preceded by a Match filter
- ZFE can enhance noise by boosting frequencies attenuated by the channel.
The output from the equaliser is given as:

\[ y(k) = \sum_{n=0}^{N-1} w_n x(k - n) = \mathbf{w}^T \mathbf{x}(k) \]

The squared error between the output and training sequence is given as:

\[ e^2(k) = (d(k) - \mathbf{w}^T \mathbf{x}(k))^2 \]

The aim being to minimise the squared error. This is accomplished through a pre defined training sequence prior to data transmission.

Does not boost noise in the same way as the ZFE.

Also works best preceded by a match filter.

Our simulations show performance of MMSE and ZFE preceded by a match filter are very similar.
Diversity Techniques

- Multi-beam Tx
- Multi element Rx
  (Many variations on the theme)
Wavelet Transform - Introduction

• Is a process of scaling and translating (shifting) the ‘Mother Wavelet’ with respect to the signal under analysis.

• The process produces a coefficient that can be thought of as the goodness of fit between a particular wavelet at a particular scale and time.

• Wavelets are:
  – best at analysing waveforms that are similar to themselves.
  – also good for detecting discontinuities within a waveform.
Wavelet – What is it?

Simple description:

• A finite duration waveform
• Has an average value of zero
• Is a basis function, just like a sine and cosine in Fourier analysis.
The Wavelet - Applications

- De-noising
- Image Compression
- Earthquake
- Electrical Fault Detection
- Mechanical Plant Fault Prediction
- Apple Ripeness
- Communications
Wavelet Analysis - Difficulties

- Mathematically complex
- Computationally complex
- Choice of scales and levels of decomposition
- Choice of wavelet
- Choice of wavelet transform
The Fourier Transform
The Continuous Wavelet Transform
The Discrete Wavelet Transform (DWT)

- **CWT** produces every scale in range leading to large amounts of similar information.

- **DWT** produces scales and positions based on powers of 2 (dyadic scales and positions)

- **DWT** process uses successive complementary low-pass and high-pass filters with characteristics based on wavelet shape.

Each set of results (approximations and details) are down sampled by a factor of 2.

**Synthesis is accomplished by upsampling**
DWT Tree

• ‘S’ - Signal of interest
• cA1 - First approximations (low pass filter)
• cD1 - First details (high pass filter)
• Approximations are always the source for the next set of filters.
Wavelet Packet Analysis

Wavelet packet analysis is a generalisation of wavelet decomposition.
Both approximations and details can be decimated further.
Need to consider effective contributions from further decomposition.
Artificial Intelligence (Neural Network)

- Artificial Neurons loosely based on biological neurons are generally configured as parallel processors with numerous elements and layers.
- Each neuron has one to many inputs weighted by a scalar ‘w’; a summing junction and an activation function ‘F’.
- A network can be trained to accomplish many tasks including pattern recognition, by use of a training algorithm.
Some Neural Network Architectures

- **Feed Forward Back Propagation**
  Probably the most widely used

- **Radial Basis Function**

- **Recurrent Networks**
  - Elman architecture
  - Hopfield architecture
## Backpropagation Training Algorithms

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<th>Algorithm</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>Levenberg-Marquardt</td>
</tr>
<tr>
<td>2</td>
<td>BFGS Quasi-Newton</td>
</tr>
<tr>
<td>3</td>
<td>Resilient Backpropagation</td>
</tr>
<tr>
<td>4</td>
<td>Scaled Conjugate Gradient</td>
</tr>
<tr>
<td>5</td>
<td><strong>Conjugate Gradient with Powell/Beale Restarts</strong></td>
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<tr>
<td>6</td>
<td>Fletcher-Powell Conjugate Gradient</td>
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<tr>
<td>7</td>
<td>Polak-Ribiére Conjugate Gradient</td>
</tr>
<tr>
<td>8</td>
<td>One-Step Secant</td>
</tr>
<tr>
<td>9</td>
<td>Variable Learning Rate Backpropagation</td>
</tr>
</tbody>
</table>
Problems With Backpropagation Networks

- Network architecture
- Number of layers
- Number of neurons per layer
- Choice of transfer functions
- No rigorous way of defining optimum parameters.
Direct Detection Using Neural Networks
(Neural Network & Slicer)

• Back propagation network.

• Neural network detector followed by slicer.

• 100 neurons in layer 1, 1 neuron in layer 2.
Direct Detection Using Neural Networks
(Rx Filter Neural Network & Slicer)

- Model incorporates 0.35/T LP Rx filter.
Direct Detection Using Neural Networks
(Rx Filter Downsampler Neural Network & Slicer)

- Model includes down-sample to reduce network inputs (computational complexity)
- Large variations in results.
Wavelet Neural Networks (Wavenets or WNN’s)
The match filter and the equaliser of the MMSE model are replaced by the CWT and neural network section.
Wavelet-AI Receiver Operation

- Signal is detected by opto-electronic front end and buffered.

- Signal decimated into 5 bit sliding windows.

- Each window is transformed into wavelet coefficients by the CWT process.

- The coefficients are passed to the neural network for classification.
Signal Sample ‘The Window’

- Signal decimated into 5 bit sections; say bits 1 to 5 for detection of bit 3.
- Window indexed by 1; bits 2 to 6 and detection of bit 4.
- Each Window is processed into wavelet coefficients by the continuous wavelet transform (CWT).
Parameters And Parameter Selection

- Window Size
- Optimum Training SNR
- Length Of Training Sequence
- Number Of Scales
- Wavelet Type
- Network Size
- Network Type (Transfer Functions, Layers, Algorithms)
- Sampling Speed
### System Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Window Size</td>
<td>5</td>
</tr>
<tr>
<td>Optimum Training SNR:</td>
<td>12 dB (for 100 Mbps)</td>
</tr>
<tr>
<td>Length Of Training Sequence:</td>
<td>1500</td>
</tr>
<tr>
<td>Number Of Scales:</td>
<td>35 (2, 4, 6…)</td>
</tr>
<tr>
<td>Wavelet Type:</td>
<td>Sym 2</td>
</tr>
<tr>
<td>Network Size:</td>
<td>100 / 1</td>
</tr>
<tr>
<td>Network Type:</td>
<td>Backpropagation</td>
</tr>
<tr>
<td>Layers:</td>
<td>2</td>
</tr>
<tr>
<td>Transfer functions:</td>
<td>Logsig/linear</td>
</tr>
<tr>
<td>Algorithm:</td>
<td>Conjugate Gradient with Powell/Beale Restarts.</td>
</tr>
<tr>
<td>Sampling Speed:</td>
<td>1 nS.</td>
</tr>
</tbody>
</table>
Wavelet-AI Receiver - Results

SNR Vs. the RMS delay spread/bit duration
Wavelet-AI Receiver - Advantages and Disadvantages

- **Complexity**
  - Many parameters & computations.

- **High sampling rates**
  - Technology limited.

- **Speed**
  - Long simulation times on average machines.
  - Similar performance to other equalisation techniques.

- **Data rate independent**
  - Data rate changes do not affect structure (just re-train).
  - Relatively easy to implement with other pulse modulation techniques.
BER Vs. SNR for Different Window Sizes

- Smaller ‘Window’ reduces the number of computations for all other parameters.
• Training the neural net with a range of SNR values obviates the need to find an ‘optimum’ figure.
• MMSE is trained at every SNR value.
Spectrum Of Source Signal

FFT 100Mbps OOK-RZ Source Signal

Magnitude

Frequency
Spectrum Of Noise Free Multipath Signal

FFT 100Mbps OOK-RZ Multipath Distorted
Scale Frequency Relationship

- Broad sense scale frequency relationship. (Pseudo-Frequency)

- Associate the wavelet with a purely periodic signal $F_c$. (The frequency maximising the FFT of the wavelet modulus)

$$ F_a = \frac{F_c}{a \cdot \Delta} $$

- $F_a = \text{pseudo-frequency}$, $F_c = \text{Wavelet centre frequency}$.
- $a = \text{Scale}$, and $\Delta = \text{the sampling period}$
$F_c$ of the Some Wavelets

- **db2**
  - Wavelet db2 (blue) and Center frequency based approximation
  - Period: 1.5; Cent. Freq: 0.86667

- **db7**
  - Wavelet db7 (blue) and Center frequency based approximation
  - Period: 1.4444; Cent. Freq: 0.69231

- **coif1**
  - Wavelet coif1 (blue) and Center frequency based approximation
  - Period: 1.25; Cent. Freq: 0.8

- **gaus4**
  - Wavelet gaus4 (blue) and Center frequency based approximation
  - Period: 2; Cent. Freq: 0.5

© Mathworks
OOK-RZ with Scale Reduction - Results

100Mbps OOK-RZ Reduced Scales & MMSE

BER vs SNR plot with different scale combinations for BER performance comparison.
Scales & Scale Reduction

- Multi-Scale detection allows the receiver to detect any data-rate within its scale range.

- Multi-Scale process is automatic; we don’t have to know about the spectral properties of the received signal.

- Limiting the CWT scales greatly improves implementation speed (reduced computations)
• No rigorous methods exist to determine optimum network.
• Size determined by empirical methods such as ‘pruning’
Comparisons

- Reduced complexity performance almost identical to original curve and close to MMSE.
- 6 Neuron Net (5 in layer 1) is almost as good as Wavelet AI, Sometimes!
Summary Of Simplifications

- Window size reduced from 5 to 3.
- Receiver trained only once with a variety of noise values.
- Scales reduced from 35 to 3.
- Neural network reduced from 100/1 to 5/1.
- Simulation times reduced from days to hours.
Further Simplification Work

- Reduction in sample rate.
- Reduction in training samples.
- Validation across data-rate range.
- Multiple symbol detection (multiple bits from 1 window)
- Use a more efficient wavelet transform?
Published Works


Possible Future Work

• **Further Simplification.**

• **Assess Performance On Other Modulation Schemes.**

• **Embedded Block Codes.**

• **Hardware Realisation.**
Thank You For Listening.