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Investigating Optical Transmission Error Correction using Wavelet Transforms

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Abstract. Reducing bit error rate and improving performance of modern coherent optical communication system is a significant issue. As the distance travelled by the information signal increases, bit error rate will degrade. Support Vector Machines are the most up to date machine learning method for error correction in optical transmission systems. Wavelet transform has been a popular method to signals processing. In this study, results show that the bit error rate can be improved by using classification based on wavelet transforms (WT) and support vector machine (SVM).

1 Introduction

Improving the bit error rate in optical transmission systems is a crucial and challenging problem. There are many different causes of the transmitted signal degradation in optical communication systems [1]. Linear Support Vector Machines (SVM) outperformed other trainable classifiers for error correction in optical data transmission; besides that it is easier to be build in the hardware in real time [2]. The wavelet transform has become widespread in analyzing and processing signals. It can be used for signal decomposition to help extract the relevant information from the signal and reduce the level of interfering noise [3]. In this paper, we investigate whether wavelets can be used on the distorted optical signals to extract the reliable information of the original signals or not. Especially, we look into whether wavelets can deal with noise in phase and/or frequency of optical signals.

2 Problem Domain

During the transmission, the optical signals are exposed to many kinds of impairments such as attenuation, dispersion broadening and nonlinear distortion [4]. These impairments generate some error information bits at the receiver of the fiber link. Increasing the distance travelled by the signal leads to a loss in the quality of the signal and further bit error rate (BER) degradation [5]. With

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the increase in speed currently achievable, the complexity of reduction in bit error rates increases. The high-speed and long distance data transmission in optical systems needs to be accompanied with as low bit error rate as possible [2]. Therefore, the reduction of bit error rate in optical data transmission is a significant issue and is difficult to be achieved. In earlier work, we investigated how a linear SVM classifier can be trained to automatically detect and correct bit errors. We took into consideration the most important neighbouring information, which can be used for training the linear SVM classifier, from each signal [5]. In this paper, we investigate using wavelet transforms to remove noise from the signals prior to classification.

3 Method

In this work, the classifying and processing of the signals was based on two methods: linear SVM and wavelet transforms (WT). Linear SVM is a soft maximum margin classifier, which has only one non-learnable/cost parameter C [6]. Wavelet transforms are a mathematical tool that can be used for the extraction of information from a variety of data forms [7]. In the field of image and signal handling, wavelet is used to compress and de-noise them [8]. In this work, we started with the simplest wavelet transform: Haar wavelet transform, which can be used for signal decomposition [9]. We have also investigated other types of wavelet; for example, Daubechies. However, the results we have obtained are very similar.

4 Description of data

Optical signal data once it has been transmitted is subjected to a distortion in its amplitude, frequency and phase. As far as we can tell wavelet transformations have not been applied to data of this type, in particular when the data is to be subsequently analysed using an SVM. In order to fully quantify how effective wavelets might be with this distorted data we started by analysing how effective wavelet transformation would be on very simple data that had simulated noise added to its amplitude, frequency or to its phase. After that we then applied the wavelet transformation to our optical data.

4.1 Simple data with frequency noise

Four classes A, B, C and D of Sinusoidal signals were generated with simulated noise added to its frequency. This frequency noise was added via a Gaussian distribution based on a different mean frequency, which is 10 (A), 15 (B), 20 (C) and 12 (D) respectively. Each class of data consists of 500 signals, and each signal consists of a vector of 640 y coordinates (samples). Each vector (wave) has a corresponding class label. Gaussian amplitude 'noise' was added at each y coordinate of each generating signal.

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4.2 Simple data with phase noise

Two classes of Sinusoidal signals were initialized with simulated phase noise via a Gaussian distribution based on a different mean values of phase; that is 0 radians (first class), and $\frac{\pi}{2}$ radians (second class). Again each class of data consists of 500 signals. Each signals has a corresponding class label, and is represented as a 640 vector (samples). Gaussian amplitude noise was again added at each y coordinate of each generating signal.

4.3 Optical signals (simulated data)

The data was generated using a simulating optical fiber link. It consists of 32,768 signals per one WDM channel encoded by the quadrature phase shift keying (QPSK) modulation scheme. The signal was detected at distance 8,000 km. Each pulse was decoded into one of four symbols according to its phase [5]. Each signal has a corresponding two-bit label. Each pulse is represented by 64 equally spaced phase samples. Furthermore, neighbouring information was used as input to the linear SVM classifier as well. The neighbouring information is using different numbers of samples from the symbol (signal) that will being decoded and different symbols either side.

5 Experimental set-up and results

The aim of these experiments is to observe whether using wavelets can extract the original information from the distorted signals, and remove the noise that corrupts them. A linear SVM classifier was used to help decode the received signals with or without using wavelets.

5.1 Experiments and results using simple data

5.1.1 Simple data with frequency noise

In these experiments, we investigate whether using wavelet transforms can enable the SVM to better distinguish between the two sets of noisy data than without using the transforms. The linear SVM was implemented using the whole samples of the signal as input vector. The data sets that were used in these experiments consist of a combination of two classes of data; they are AC, AB and AD. Each pair of classes have different distances between their means and so represent a different level of difficulty when attempting to classify the noisy data. The 1,000 data points (500 from each class) was randomly selected to give 700 data points (signals) that were used to train the model, and the rest of the data (300 data points) were used as a test set. The wavelet transforms used were Haar at level 2, although others have been tried giving similar results. Table 1 shows the linear SVM results for three different data sets with and without using wavelet transforms. As expected we can see from the final column that as the difference between the mean values of the frequency decreases so does the accuracy rate. However, the use of wavelets did improve the accuracy for the classes with a closer mean. For instance with classes A and B the wavelet transformed waves improved accuracy from 84.33% to 90%. This is the best result obtained.

Data set	Type of WT	Level of WT	Accuracy rate %
AC (10)	-	-	98.67 %
	Haar wavelet	2	98.67 %
AB (5)	**-**	**-**	**84.33** %
	Haar wavelet	**2**	**90** %
AD (2)	-	-	65.33 %
	Haar wavelet	2	67.67%

Note: The number in the brackets is the difference between the means of the frequency. The data (noisy signals) has both Frequency and Amplitude noise. (-) denotes corresponding results are obtained without applying wavelets.

Table 1: Linear SVM results on 3 different data sets of noisy signals.

5.1.2 Simple data with phase noise

In these experiments, we investigate whether using wavelet transforms can improve the signals that have phase noise or not. The data set used herein consists of 1,000 data points/signals. Half of the data set has the phase value of zero, and the other half has phase value of 90 degrees. 600 data points (signals) were used to train the model as a training set, and the rest of the data (400 data points) were used as a test set. Here we also normalized the extracted signals to values between [-1,1] in order to help in improving the classification process. In this section, Haar wavelet transform at level 2 is reported although others were used with similar results. The classification process was done using two types of input: the whole samples (i.e the vector of all 640 points), and the central sample (the middle point of the wave) of the extracted signals. Table 2 presents the accuracy rate of prediction using linear SVM classifier on the noisy and the normalized extracted signals. As we can see, the linear SVM results using the whole samples did not show any improvement. But, the wavelet transformations using the central sample did have an effect. interestingly the best result obtained was 93.5% (from 91.75%) which was better than that obtained using the whole samples.

Samples No.	Type of (WT)	Level of (WT)	Accuracy rate %
Whole samples	-	-	92.5 %
	Haar wavelet	2	92.5 %
Central sample	**-**	**-**	**91.75** %
	Haar wavelet	**2**	**93.5** %

Note: The data (noisy signals) has both Phase and Amplitude noise. (-) denotes corresponding results are obtained without applying wavelets.

Table 2: A comparison between linear SVM results using noisy signals and the extracted normalized signals.

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5.2 Experiments and results using optical signals (complex data)

The moderate success found using wavelets on the simple data meant it was worth experimenting on the full optical data. In this experiment, a linear SVM was implemented using lots of different input vectors. A selection of different transformations were tried, from none at all (original signal) to Haar levels (1 and 2), and other wavelets. Again for space reasons we only give the results for Haar 2, although the other results are very similar or worse. Regarding using the neighbouring information, we focused on using 7 central samples from 7 adjacent symbols (from the target symbol and three symbols either sides). We have found that using 7 central samples from 7 neighbouring symbols gave the best linear SVM results when we have used neighbouring information previously. In this experiment, $\frac{2}{3}$ of the symbols/signals were used to train the linear SVM model, and the rest of the data (a third of the symbols) was used as a test set.

Method	No. of samples	Signal types	SAR %	BER %
Threshold	Central sample	Original signal	96.3±0.15	1.87±0.08
Linear SVM	Central sample	Original signal	96.29±0.16	1.87±0.08
		Haar (level 2)	96.41±0.16	1.82±0.09
	Whole samples	Original signal	96.44±0.14	1.8±0.07
		Haar (level 2)	96.45±0.13	1.79±0.07
	Neighbouring Info.	Original signal	96.6±0.1	1.72±0.05
		Haar (level 2)	**96.67±0.11**	**1.68±0.06**

Note: Neighbouring information means that using 7 central samples from 7 adjacent symbols.

Table 3: The linear SVM results using optical signals before and after using wavelet transforms at the distance 8,000 km, compared with the threshold method result.

Table 3 shows the linear SVM results using the optical signals at a distance of 8,000 km, with and without using wavelet transform. These results were compared with the results obtained by measuring the phase of the mid-point of the signal (threshold method) which is the current hardware implemented method. The Table presents the symbol accuracy rate (SAR%) and bit error rate (BER%), which are an average over ten data sets. As we can see from Table 3, the results using samples from 7 consecutive symbols (using 3 either side of the target symbol) were best, even though they only used the central value of each of the 7 waves. The best result we have got so far is the linear SVM result using 7 central samples from 7 neighbouring extracted signals, obtained from Haar wavelet transform, level 2, which is a 1.68 BER.

6 Discussion and conclusion

In this work, we have demonstrated that the bit error rate can be improved by using classification based on wavelet transforms (WT) and support vector machine (SVM). From the results obtained using the simple data with frequency

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noise in Table 1, we can see that the best result was when we used the data set (AB) after using Haar wavelet transform at level 2. Regarding the results obtained using the simple data with phase noise in Table 2, the best result was when we used the central sample of the extracted normalized signals, which was 93.5%. Wavelets were more beneficial with the frequency distorted data than with the phase distorted data. However, overall the use of wavelet transforms was a bit disappointing. The second part of the results were obtained using wavelets on the optical signals at a distance of 8,000 km. The best result was using a linear SVM trained on the extracted data (using Haar wavelet level 2) from the target symbol and three symbols either side. So wavelet transforms did have a small effect on the accuracy, and in this work small effects can be worth a lot. In particular using the combination of neighbourhood information and wavelets gave much better results than using the threshold method, see Table 3. This is crucial since Bit Error Rates less than 2 are required for optical data and the further we can drive this rate down the better. Furthermore, this work shows that wavelet transforms can help a little with the noise on both frequency and phase since optical data has both.

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