An Improved Digital Communication System for Doubly-Spread Underwater Acoustic Channels using Evolutionary Algorithms

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***Abstract*- This paper presents an improved system for high data rate digital acoustic communication over a shallow underwater channel that is doubly spread. The method uses cancellation of interfering multipath signals rather than delay equalisation. In this improved system, an Evolutionary Algorithm is used to obtain an accurate estimate of the Doppler spread. This novel implementation of a Doppler estimator significantly improves the accuracy of the channel estimator thus enabling more effective interference cancellation. BER performance results of the improved system in a typical underwater scenario are presented.**

I. INTRODUCTION

There is a pressing requirement for high data rate digital communication over an underwater acoustic channel in the littoral environment. However, the channel characteristics are affected by multipath propagation and the Doppler effect. Multipath propagation causes severe time-delay spread, of the order of tens of milliseconds [1] and as a result, the received signal suffers from inter-symbol interference. The Doppler effect causes the signal to be time-scaled. For narrowband signals this is often viewed as a frequency shift but for broadband signals, time scaling results in a change in the signal bandwidth. In a multipath environment, it is possible that each path may have a different Doppler velocity. Consequently, the received signal suffers from differing amounts of time scaling and this results in the signal being further spread in the frequency domain. Channels with time-delay spread and Doppler spread are said to be doubly spread. These problems are aggravated by the time varying nature of the channel.

In order to improve data transmission over such a channel, these two effects must be compensated for in the receiver. This requires that the time and frequency characteristics of the channel are estimated very accurately within the channel coherence time. Errors resulting from inaccurate channel estimation can cause the bit error probability characteristics to have irreducible error floors. One of the key requirements of the channel estimator in this application is that it must have a wide dynamic range to be able to detect weak multipath components in the presence of much larger components. It must also be able to estimate the effect of different Doppler velocities on each path. This latter requirement is particularly challenging because the estimator needs to be able to handle a wide frequency spread but with high resolution.

In an earlier paper [2], the authors presented a new architecture of a coherent digital underwater acoustic communication system that operates under conditions where the channel is characterised by severe multipath delay spread and Doppler spread. The method was based on the suppression of the interference caused by the multipath signals rather than by equalization using a fractionally spaced equalizer, for example. The system did not rely on the use of directional acoustic transducers or arrays to mitigate multipath propagation. It used a Doppler estimator based on the transmission of a pilot tone to identify the Doppler spread in conjunction with a broadband pilot sequence to estimate the delay spread.

The Doppler estimator used in [2] was Fourier-based. It estimated the Doppler shift in the frequency of the pilot tone on each path of the multipath channel and this information was further used in the estimate of the time-delay spread. It was found that the resolution of the Fourier analyser ultimately set the limit on the performance of the interference cancellation circuit. The principal problem with Fourier-based methods when the pilot signal has a limited duration is the presence of frequency sidelobes due to time-windowing. This sets the limit on the frequency resolution of such an estimator, especially when the sidelobes of the main path mask the weaker multipath components, thereby also setting a limit to the dynamic range of the estimator. .

This paper presents a novel implementation of an underwater acoustic channel estimator using Evolutionary Algorithms (EAs) that outperforms Fourier-based methods both in frequency resolution and dynamic range. Whereas Fourier methods are limited by windowing, the new method exploits it and implicitly takes into account the time-scaling that occurs due to the effect of Doppler.

II. COMMUNICATION SYSTEM

Fig. 1 shows the schematic block diagram of the system architecture. The system uses a coherent phase modulated signal and, for the results shown in this paper, the transmitted signal is QPSK modulated onto the acoustic carrier. A pilot tone is transmitted in parallel with the data in order to estimate the Doppler velocity profile and a pseudo-random sequence, clocked at the data rate, replaces the data periodically in order to estimate the delay spread profile of the channel.

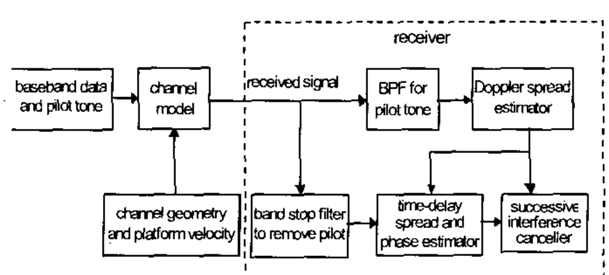

Fig. 1 Schematic block diagram of the communication system

This signal is then passed through the channel simulator described in [2]. Briefly, it consists of N paths and is based on a ray theory model of the physical channel that is used to compute the time of arrival and the angle of arrival for each of the paths[1]. Different Doppler velocities can be assigned to each of the paths. Gaussian acoustic channel noise is also added to the signal.

The received signal, $r(t)$, is represented by the sum of the signal components on each of the N paths, each with its own time-delay, τ_n:

$$r(t) = \sum_{n=1}^{N} p_n(t) * \delta(t - \tau_n) + \eta(t) \tag{1}$$

where $p_n(t)$ is the received signal component due to the n^{th} path, $\delta(t-\tau_n)$ represents the time delay on the n^{th} path and $\eta(t)$ is the additive acoustic noise. The signal component, $p_n(t)$, comprises two terms, the data signal and the received pilot signal and is given by:

$$p_n(t) = s'_n(t) + A_{p_n} \cos\left(\omega_{dp_n} t + \phi'_{p_n}\right) \tag{2}$$

where $s'_n(t)$ is the Doppler time-scaled passband data for the n^{th} path, ω_{dp_n} is the Doppler shifted pilot tone frequency, ϕ'_{p_n} is the random phase shift on the pilot tone caused by the n^{th} path and A_{p_n} is the amplitude of the received pilot tone over this path. The Doppler shifted and time-scaled data signal for m^{th} symbol on the n^{th} path is represented as:

$$s'_{n,m}(t) = A_n \cos\left(\left(\omega'_{c_n} t + \phi_n\right) + \phi_m(t)\right) \quad \text{for } 0 < t < T_{d_n} \tag{3}$$

where A_n is the amplitude of the data signal for this path, ϕ_n is the random carrier phase shift on the data signal, ω'_{c_n} is the Doppler shifted carrier frequency, $T_{d_n} = T_0\omega_c / \omega'_{c_n}$ is the time-scaled symbol duration for the n^{th} path due to Doppler, ω_c is the transmitted carrier frequency and $\phi_m(t)$ is the phase shift introduced by the QPSK phase modulator appropriate to the m^{th} symbol.

These equations highlight that the symbol duration of each path may be different due to the effect of the different Doppler velocities on each path and this must be corrected in both the demodulation circuit and the interference cancellation circuit. In the receiver, both the pilot tone and the pilot sequence are extracted [2] and used for channel estimation. The receiver resolves the Doppler spread and compensates for delay spread for each of the multipath components using purely temporal processing. The approach used is to view all multipath components, bar one, as interference and to use successive interference cancellation to remove the 'interference' of each of these unwanted components from the received signal, leaving only one wanted component. Accurate interference cancellation is achieved by time-scaling the delayed signal to compensate for the effect of Doppler prior to cancellation. This emphasises the importance of accurate channel estimation.

[1] Experimental measurements [3] have shown that a typical shallow underwater channel has three prominent paths. Thus for testing the new estimator, three paths have been considered, whilst for the assessment of the overall system performance, four paths have been used.

III. CHANNEL ESTIMATION

One approach to Doppler spread estimation is to use a narrowband signal, such as a pilot tone. In contrast, estimation of the delay-spread profile generally requires a broadband signal with good correlation properties, such as a pseudo-random pilot sequence. The approach used in this paper is to use both types of signal with the added refinement that once the Doppler velocity of each multipath component has been obtained, the receiver uses this information to compensate the time-scaled broadband pilot sequence used to obtain the delay-spread profile, thereby removing the effect of Doppler spread from the delay-spread estimates. This method permits accurate time-delay estimation of multipath components that are both smeared in time and experience different Doppler shifts. However, any error in the estimate of the Doppler velocities results in errors in the time-delay estimate, especially for the weaker multipath components. Consequently, it is vital to achieve very high accuracies for the estimate of the Doppler velocity profile.

In [2] the Doppler velocity estimate for each multipath component was estimated from the shift in the pilot tone frequency for that particular path[2]. This was achieved by extracting the frequency spread pilot tone from the data signal by filtering and then taking the power spectrum of this pilot tone using the FFT. A peak detector was used to identify the shifted tones. However, because the pilot tone is of finite duration (i.e. limited to the frame length), the resolution of the FFT-based spectral estimator is limited by windowing. Consequently, when the spread in the Doppler velocity between the various multipath components is small, the spectrally smeared received pilot tones can overlap in the frequency domain. This gave rise to inaccurate frequency estimation of low magnitude multipath signals when they were in the presence of dominant paths, placing a lower limit on the ability of the estimator to resolve the Doppler spread.

To improve the resolution of the Doppler spread estimator, the pilot tone was time-windowed at the transmitter to provide sidelobe suppression, thereby aiding the detection of the pilot tones of the weaker multipath components [2]. In this form, the Doppler estimator was able to identify signal components with a Doppler spread of ±0.6m/s. However, since this method relied on spectral peak detection to estimate the Doppler velocities, spurious peaks due to noise or windowing limited the dynamic range of the estimator.

To overcome these limitations, a novel method for Doppler spread estimation has been developed. Rather than relying on peak detection to identify the individual Doppler velocity components in the Doppler spread pilot tone, the new method matches the change in the entire spectrum of the received signal to the Doppler velocity profile in order to obtain a more accurate estimate. This method exploits the fact that the effect of the Doppler velocity is to time-scale the signal. Consequently, the multiple time-scaled pilot signals that result from multipath propagation along the channel are related to the Doppler velocity profile of the channel using the new method.

In a recent paper [4], the authors presented a method for parameterisation of linear chirps using Evolutionary Algorithms (EA). This concept has been utilized in the new Doppler spread estimator and the method has been extended to relate the multi-dimensional changes in the signal

[2] For example, if the channel has three dominant paths, each with a *different* Doppler velocity, the result is a Doppler spread received signal in which the pilot tone has three frequency components.

characteristics due to the Doppler spread brought about by the Doppler velocity profile in a multipath channel. The EA is used to find the optimal Doppler velocity profile from the spectrum of the received pilot tone signal. The method is described in the next section.

IV. EA-BASED DOPPLER SPREAD ESTIMATOR

The Doppler spread estimator extracts the Doppler-spread pilot tone from the received signal by filtering it from the transmitted data. This is facilitated by ensuring that the transmitted pilot tone is at a frequency corresponding to a spectral null in the data signal. The signal is digitised at the transducer and all filtering is performed digitally. The samples of the received pilot signal are collected for one frame period of 0.4352s. The sampled signal is then down-converted and resampled at a much lower sampling rate and the spectrum of the sampled pilot signal is obtained from this block of samples. The aim of down-conversion and resampling is to maintain a high spectral resolution without the overhead of a large FFT. Limiting the measurement of the pilot to a short frame length of 0.4352s, ensures that the estimate of the time-varying channel characteristics can be updated frequently.

The Doppler estimator is based on regenerating a signal locally in the receiver whose spectrum best matches that of the received pilot signal. It assumes that there may be an arbitrary number of multipath components. Each path is assigned a Doppler velocity and the algorithm both frequency shifts and time-scales this component of the regenerated pilot signal according to the assigned Doppler velocity. The estimator obtains the optimum values for this set of Doppler velocities, together with their phases, that minimises the mean square error between the regenerated spectrum and the received pilot tone spectrum.

Using this approach, the Doppler spread estimator problem has been redefined as an optimisation problem. However, this problem is multi-modal and, in addition, there may be little, or no, *a priori* knowledge about the order of the model. The multi-modality prevents the use of conventional gradient-based optimisation techniques and the lack of *a priori* knowledge rules out the use of super-resolution spectral estimation techniques such as MUSIC. EAs, on the other hand, do not rely on *a priori* knowledge of the order of the model and, since they examine multiple potential solutions spread over the entire search space simultaneously, the optimisation process is far less likely to converge to a local minimum.

A. Evolutionary Algorithms

EAs are optimisation procedures that operate over a number of cycles (generations) and are designed to mimic the natural selection process through evolution and survival of the fittest [5]. The algorithm maintains a *population* of P independent individuals, each individual representing a potential solution to the problem. Each individual is described by a single *chromosome* of k *genes*. Each gene represents a single parameter in the problem. For this problem, the Doppler shift along each path is estimated by two parameters. These are: (a) the Doppler velocity and (b) the phase of the Doppler shifted signal. If we assume, arbitrarily, that the number of significant multipaths is six, then $k = 12$ genes define each chromosome. The three simple operations found in nature: natural selection, mating and mutation are used to generate new chromosomes and thus new potential solutions.

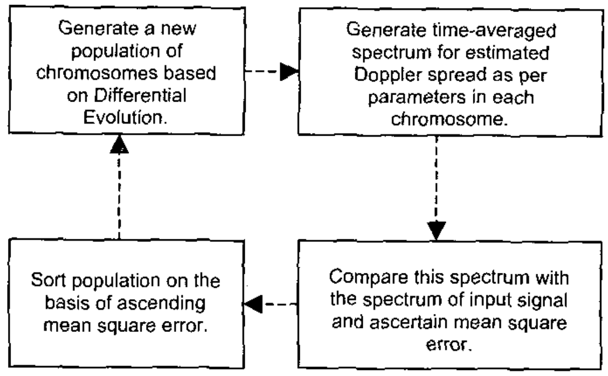

Fig. 2. Schematic block diagram for Doppler spread estimation using Differential Evolution.

Each chromosome is tested at every generation using an *objective function* that is able to distinguish good solutions from bad ones and score their performance. Based on this test, a new population of chromosomes is generated in which the highest scoring chromosomes of the previous generation are retained and new ones created using mutation, selection and crossover. To maintain the population size, the lowest scoring chromosomes are discarded to make room for the new improved offspring.

B. Differential Evolution

Although there are a number of EAs that can be used to optimise the parameters according to the chosen objective function, we have found that Differential Evolution (DE) [6] is most suitable for this type of application. Fig. 2 shows the schematic representation of the algorithm used for estimation of the Doppler spread using Differential Evolution.

The DE algorithm begins by generating an initial population of chromosomes at random. New chromosomes are then generated by adding the weighted difference between two chromosomes to a third chromosome. At each generation, for each member of the parent population, a new chromosome is generated based on the spatial spread of the current population. Elements of this new chromosome are then crossed with the parent chromosome to generate the child chromosome. The child chromosome is evaluated and if it has a better objective value than the parent, it replaces the parent. In this way, no separate probability distribution has to be used to generate new chromosomes. This makes the scheme self-organizing.

A feature of this algorithm is that the populations of the chromosomes form clusters around the possible solutions so that a number of possible solutions are investigated simultaneously in a bid to ascertain the global optimum solution. Thereafter, the algorithm is run to convergence. For each new generation, the new set of estimated parameters contained within the chromosome is generated with a scaling factor, F, and crossover factor, C. The factor F is a measure of how much the spatial spread of the estimated parameters is reduced with each successive generation. A small F means that the spatial spread of the population reduces by a large proportion for each generation, leading to faster convergence. However, this is at the expense of a less thorough search of the parameter space. On the other hand, having a larger F means that the search is more thorough at the expense of a slower convergence time. The factor C is a measure of the proportion of the old chromosome that is replaced with the new. A large value for C means that each new chromosome has a lesser proportion of the old chromosome and this controls the amount of allowable genetic change that can occur between generations. In this paper, $C = F = 0.9$ was found to be very effective.

After generating the initial population, the DE evaluates each chromosome, for each generation, to find those that provide the best fit of the regenerated Doppler spread signal with the received Doppler spread signal on the basis of a least mean squares error objective function.

C. Objective Function

At the outset, it is assumed that the receiver has limited knowledge about the number of expected multipath returns so an upper limit, *M*, is set, represented by *M pairs* of genes. In the receiver, a Doppler spread pilot tone waveform is regenerated for each path using the Doppler velocity and starting phase parameters stored in the chromosome. The normalised regenerated pilot tone for the i^{th} path is represented as a sequence of samples, $s_i[n]$. This is carried out for all *M* gene pairs. The weighted spectra of the regenerated waveforms for each pair of genes are then summed to form the spectrum of the estimated Doppler spread pilot tone:

$$S[k] = \sum_{i=1}^{M} W_i S_i[k] \tag{4}$$

where $S_i[k]$ is the discrete complex spectrum of the sample sequence $s_i[n]$, $S[k]$ is the discrete complex spectrum of the composite regenerated signal, W_i is the weight for the i^{th} component which is obtained using a constrained least squares amplitude fit.

The objective function, given in (5), is the mean-square error, *E*, between the amplitude scaled spectrum, $S[k]$ and the discrete spectrum of the received Doppler spread signal, $R[k]$. Note that this objective function matches not only the spectral peaks but ALL spectral components thus providing an accurate estimate of the Doppler-induced spread.

$$E = \frac{\sum_{k=1}^{N} (R[k] - S[k])^2}{N} \tag{5}$$

where *N* is the number of discrete frequency components in the spectrum. The chromosome giving the least mean-square error is selected as the best fit and the others are arranged on the basis of ascending mean-square error. Since the algorithm uses a least squares fit for the amplitude estimate for each Doppler shift, it can be tasked to find a larger number of Doppler-spread pilot tones than are actually present and the algorithm will null out non-existent Doppler-spread pilot tones. Thus, this method does not rely on prior knowledge of the correct order of the model.

D. Performance of Doppler Spread Estimator

Table I lists the pilot tone parameters used to assess the performance of this method. The received signal is first sampled at 40kHz, filtered to isolate the pilot tones and down-converted using a local oscillator of frequency 14.750kHz. The filtered and down-converted signal is then resampled at 1kHz before the Doppler shifts in the tone frequency are estimated using the new method.

TABLE I

PARAMETERS OF THE PILOT TONE

Pilot Tone frequency, f_c	15kHz
Duration of pilot tone (frame period)	0.4352s
Number of multipaths	3
Frequency of Local Oscillator	14.750kHz
Sampling frequency after down conversion	1kHz
Doppler velocity of the three paths	-0.1039, 0.4226 and 0.9668 m/s
Normalised amplitudes of the three paths	0.18, 1, 0.18
Range of expected Doppler velocities	±20m/s

Due to multipath and the different Doppler velocities of each path, the received signal is likely to be Doppler spread and therefore consist of a number of tones with different Doppler shifts. The results shown here have been used to highlight the performance of this method under conditions when the weaker signals are masked by the spectrum of the dominant signals.

In an underwater channel, the sidelobe interactions can cause the generation of spurious peaks which can result in errors in the Doppler spread estimate. Fig. 3 shows such a case where in a three-path channel the received amplitude of the paths are 1.0, 0.18 and 0.18, and their Doppler velocities are 0.4226m/s, -0.1039m/s and 0.9668m/s, respectively.

In this case, although the Doppler-induced shift in frequency is clearly visible for the strongest path, there are spurious peaks in the vicinity of the weaker paths due to the sidelobes that are generated due to time-windowing of the data. Under such circumstances, it is difficult for conventional FFT-based methods to correctly identify all three spectral peaks and the peak broadening as a result of the finite duration of the signal puts a limit on the accuracy with which the shift in frequency can be estimated. In this case, in the presence of noise, there is a high probability that the peak detector would indicate the presence of either one path, or at least 5 paths, depending upon the peak detector threshold setting. Fig. 4 shows the estimated Doppler shift in frequencies (shown as thick solid arrows superimposed on Fig. 3) using the new EA method. The algorithm assumes that the number of paths is $M = 6$.

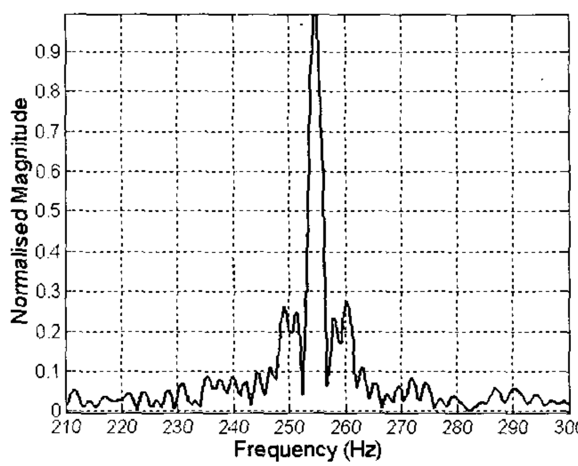

Fig. 3. Spectrum showing the three Doppler shifted/spread paths with spurious peaks at an SNR=12dB.

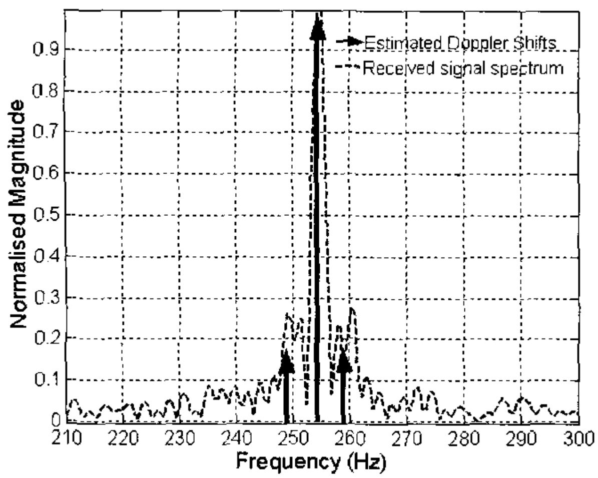

Fig. 4. Estimated Doppler shifts superimposed on the received spectrum

Based on an initial population of 350 individuals, the estimated Doppler velocities for the three paths are: 0.4237m/s, -0.1136m/s and 0.9587m/s. The mean of the errors in the Doppler velocity estimates of the three paths is less than 0.01m/s. The estimated amplitudes of the three paths are: 1.0000, 0.1614 and 0.1605 respectively.

It is clear from the figure that, despite the presence of severe sidelobe interaction, this new method is able to detect the presence of all three Doppler shifted tones with limited *a priori* knowledge about the number of paths present in the receive signal.

V. SYSTEM RESULTS

To verify the performance gains of the proposed system, a computer simulation was carried out using the system parameters given in Table II. The channel comprised four paths, each affected by Doppler. Two paths were allowed to have the same Doppler, f_{D1} but had different path delays, τ_1 and τ_2 whilst the other two paths had different Doppler offsets f_{D2} and f_{D3}, and different delays, τ_3 and τ_4.

TABLE II

PRINCIPAL PARAMETERS OF THE UNDERWATER ACOUSTIC SYSTEM

Acoustic carrier frequency	10 kHz
Modulation type	QPSK
Symbol rate	5kbaud
Frame length	2500 symbols
Coding	No FEC applied
Pilot data preamble	400 symbols
Pilot tone frequency	15kHz
Multipath time delays: $\tau_1, \tau_2, \tau_3, \tau_4$	0.00, 6.24, 12.21, 18.05 ms
Doppler velocities on the 4 paths	-0.156, 0.634, 1.450, 0.634 m/s

For the multipath propagation model used for these results, the gain of the dominant path was normalized to 0.9, whilst the weaker paths were assumed to have a normalized path gain of 0.2. However, as the algorithm is able to estimate the amplitude of the resolvable multipath components over a dynamic range better than 13dB, these path gain values can be considered to be purely illustrative. Table II provides the values that have been used for τ_1 - τ_4, as well as the Doppler velocities used on the four paths. Note that the algorithm can accommodate positive or negative Doppler velocities on any of the paths. The following simulations were carried out to illustrate the effectiveness of the new algorithm under different channel conditions.

Fig. 5 shows the QPSK constellation of the received signal at a signal to acoustic noise power ratio (SNR) of +10dB for a partially compensated system where only the effect of Doppler time-scaling on the dominant path signal component is compensated. The figure represents the transmission of 5000 data bits. Recall, that the channel model is typical of low to moderate multipath 'interference' because the multipath gains are 0.2. This would be typical of a system that relies on coherent spatial processing to compensate for multipath in cases where the angular spread of the multipaths are small, resulting in residual multipath entering the main beam. In this figure, the effect of Doppler on the other multipath components has not been cancelled. Neither is delay spread compensated for. For this situation the average bit error probability is 1.5×10^{-2}.

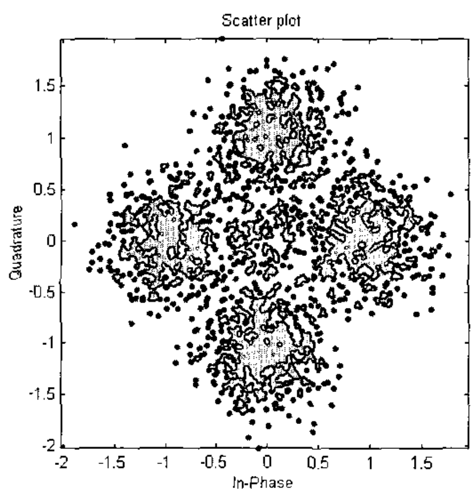

Fig. 5 Constellation of the received QPSK modulated signal after correction for only the Doppler on the dominant path

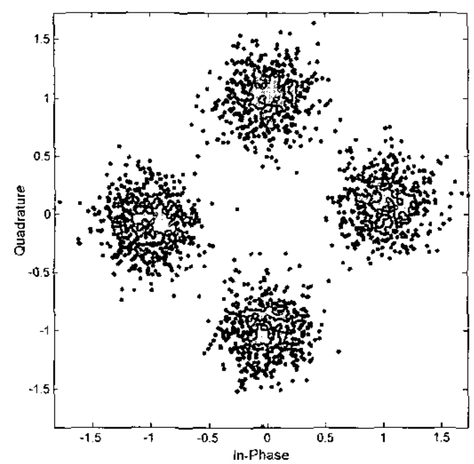

Fig. 6 Constellation of the received QPSK modulated signal after compensation for Doppler spread and time-delay spread for all paths

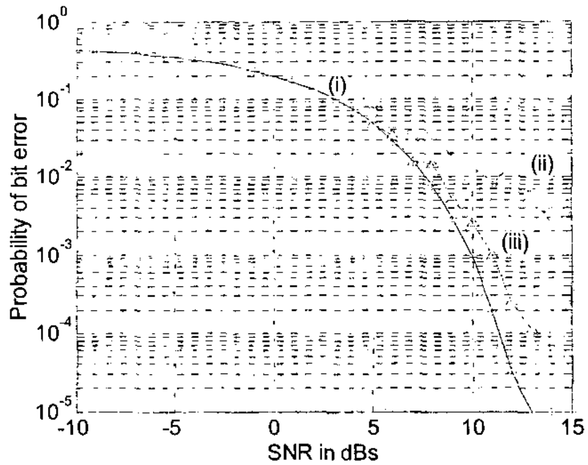

Fig. 7 Effect of the SNR on the bit error probability of the underwater acoustic communications system for channel model of Table II using the original channel estimator: (i) AWGN, (ii) compensation for the Doppler on the dominant path only, (iii) compensation for Doppler spread and time-delay spread.

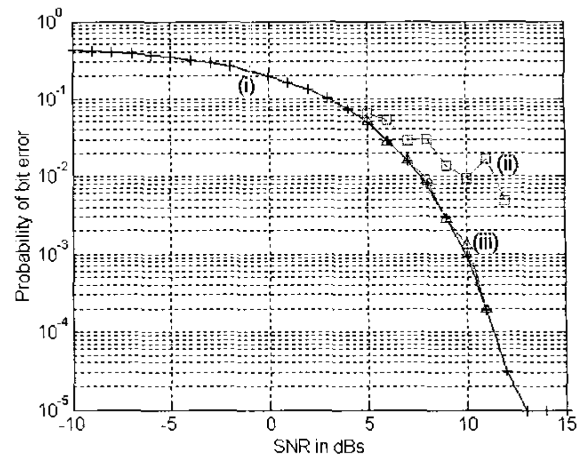

Fig. 8. Effect of the SNR on the bit error probability of the underwater acoustic communications system for channel model of Table II using the new channel estimator: (i) AWGN, (ii) compensation for the Doppler on the dominant path only, (iii) compensation for Doppler spread and time-delay spread.

In contrast, Fig. 6 shows the QPSK constellation of the received signal for 5000 data bits for the same channel conditions as the previous case, but for the new system when the 'interference' from all the multipath components bar the main path are cancelled. In this case, both Doppler spread and delay-spread have been compensated using the method detailed in [2], but using the Doppler spread estimator described in this paper. It is clear that the new interference cancellation circuit results in a significant improvement in the constellation diagram. The resulting average bit error probability is reduced to 1×10^{-3}.

The bit error probability performance for the original channel estimator [2] is reproduced in Fig. 7 for the channel model of Table II. In this figure, curve (i) is the AWGN case, curve (ii) is for the case where the receiver only compensates for Doppler on the main path, whereas curve (iii) compensates for the delay spread of all four paths as well as Doppler spread for all paths.

However, for the results in this figure, the Doppler spread estimator used the FFT method and peak detection. It is clear that the original compensation algorithm provides an overall system performance that is only approximately 1dB worse than the AWGN channel. However, when the new channel estimator is used, the bit error probability performance is further improved, as shown in Fig. 8 as a function of the SNR. The conditions under which each curve is obtained are identical to that of Fig 7. Not surprisingly, when only the effect of the Doppler on the main path is compensated, the performance is very similar to the previous channel estimator. However, when the delay spread of all four paths as well as Doppler spread for all paths is fully compensated, the performance of the system with the new channel estimator is significantly better than the previous method. Indeed, the bit error probability curve now virtually lies on the AWGN curve signifying almost complete interference cancellation under these channel conditions.

VI. CONCLUSIONS

The paper has introduced a new method that is able to provide an accurate Doppler spread estimate for doubly spread channels. The results have shown that the resolution of the new method is not limited by the effect of time-windowing due to the finite duration of the pulses. In addition, the paper has demonstrated the impact of accurate Doppler spread estimation in improving the performance of the communication system.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the Indian Navy for allowing the secondment of JS Dhanoa to Cranfield University

REFERENCES

[1] M. Stojanovic, "Recent advances in high-speed underwater acoustic communications", IEEE Journal of Oceanic Engineering, vol. 21, pp. 125-136, April 1996.

[2] J. S. Dhanoa and R. F. Ormondroyd, "Combined Differential Doppler and Time Delay Compensation for an Underwater Acoustic Communication System", OCEANS'02 MTS/IEEE, vol. 1, *pp. 581-587, Oct 2002.*

[3] C.Bjerrum-Niese, L. Bjorno, M.A. Pinto, and B. Quellec, "A simulation tool for high data-rate acoustic communication in a shallow-water, time-varying channel", *IEEE Journal of Oceanic Engineering*, vol. 21, pp. 143-149, April 1996.

[4] J. S. Dhanoa, E. J. Hughes and R. F. Ormondroyd, "Simultaneous detection and parameter estimation of multiple linear chirps", IEEE International Conference on Acoustics, Speech, and Signal Processing, vol. 6, pp. 129-132, April 2003.

[5] K. Deb, *Multi-objective Optimisation using Evolutionary Algorithms*, John Wiley and Sons, 2001.

[6] R. Storn, "On the usage of differential evolution for function optimisation", Biennial Conference of the North American Fuzzy Information Processing Society, pp. 519-523, June 1996.