Performance of short-time spectral parametric methods for reducing the variance of the Doppler ultrasound mean instantaneous frequency estimation

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Abstract—*To achieve an accurate estimation of the instantaneous turbulent velocity fluctuations downstream of prosthetic heart valves* in vivo, *the variability of the spectral method used to measure the mean frequency shift of the Doppler signal (i.e. the Doppler velocity) should be minimised. This paper investigates the performance of various short-time spectral parametric methods such as the short-time Fourier transform, autoregressive modelling based on two different approaches, autoregressive moving average modelling based on the Steiglitz–McBride method, and Prony's spectral method. A simulated Doppler signal was used to evaluate the performance of the above mentioned spectral methods and Gaussian noise was added to obtain a set of signals with various signal-to-noise ratios. Two different parameters were used to evaluate the performance of each method in terms of variability and accurate matching of the theoretical Doppler mean instantaneous frequency variation within the cardiac cycle. Results show that autoregressive modelling outperforms the other investigated spectral techniques for window lengths varying between 1 and 10 ms. Among the autoregressive algorithms implemented, it is shown that the maximum entropy method based on a block data processing technique gives the best results for a signal-to-noise ratio of 20 dB. However, at 10 and 0 dB, the Levinson–Durbin algorithm surpasses the performance of the maximum entropy method. It is expected that the intrinsic variance of the spectral methods can be an important source of error for the estimation of the turbulence intensity. The range of this error varies from 0.38% to 24% depending on the parameters of the spectral method and the signal-to-noise ratio.*

Keywords—*Doppler ultrasound, Turbulence estimation, Spectral analysis techniques, Heart valve diseases, Mean velocity estimation*

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1 Introduction

TURBULENCE IS an irregular eddying motion in which velocity and pressure fluctuations occur about their mean values. These perturbations are known to be irregular or random in time and space, and may be composed of many small eddies or larger vortices (STREETER and WYLIE, 1985). Turbulent flow motions are usually decomposed into their mean and fluctuating parts. Formally, the presence of turbulence necessarily involves three-dimensional random velocities. However, in practice, the verification of the existence of random fluctuations in one plane only is sufficient to confirm the presence of turbulence (STREETER and WYLIE, 1985). The intensity of the velocity fluctuations is an important parameter used to characterise turbulence. This index is obtained by dividing the root-mean-square of the time-varying velocity fluctuations by the mean velocity averaged in time and/or space (STREETER and WYLIE, 1985; CLOUTIER *et al.*, 1996).

To achieve an accurate estimation of the turbulence downstream of prosthetic heart valves *in vivo*, a reliable method should first be established. In the past, the hot-film anemometry method was used to measure turbulence in pigs and humans (HASENKAM *et al.*, 1988; NYGAARD *et al.*, 1992). However, this approach requires high technical skills and can be performed only during open heart surgery. In addition, calibration problems due to fibrin deposition on the heated sensor is a major drawback. Other techniques, such as laser-Doppler anemometry and particle image velocimetry are limited to *in*

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vitro evaluation and translucent fluids. Recently, Doppler ultrasound has been used to quantitatively evaluate the turbulence produced downstream of native and prosthetic heart valves *in vivo* (NYGAARD *et al.*, 1994a, 1994b).

The accurate evaluation of turbulence is important, especially in the case of mechanical prosthetic heart valves as the characteristics of the flow through the valve have been associated with blood cell trauma (JONES, 1995). Downstream of obstructed mechanical prosthetic heart valves, high turbulence intensities are expected because of the perturbing influence of the leaflets on the flow dynamics, and the presence of much higher Reynolds numbers in this region of the cardiovascular system. Physiologically, the characterisation of turbulence is of relevance because of its association with red blood cell lysis and thrombus formation (SCHMID-SCHÖNBEIN *et al.*, 1981; WURZINGER and SCHMID-SCHÖNBEIN, 1987). Furthermore, turbulence is also associated with the lack of pressure recovery observed downstream of mechanical heart valves (VANDERVOORT *et al.*, 1995; NIEDERBERGER *et al.*, 1996).

In a recent study by our group (CLOUTIER *et al.*, 1996), blood flow turbulence at several positions downstream of a 86% area reduction stenosis was characterised using parameters extracted from the Doppler spectrum. In that study, turbulence was quantified by computing the relative temporal Doppler velocity fluctuations and the Doppler backscattered power using autoregressive modelling of 2 ms Doppler signal segments. In Cloutier's study, although the relative changes in turbulence intensity were correctly mapped, unexpected high values were measured compared to hot-film anemometry. Among the reasons explaining these high values, the variance in time associated with the estimator of the instantaneous Doppler frequency shift may have contributed significantly. The accuracy of indices extracted from the Doppler signal may be affected by the bias and variance of the estimator, the compatibility of the spectral method with the signal, the signal-to-noise ratio (SNR), and by parameters such as data window, model order or smoothing window type.

Although several studies have been carried out on the Doppler signal to investigate the performance of different spectral analysis methods (KALUZYNSKI, 1987; TALHAMI and KITNEY, 1988; VAITKUS *et al.*, 1988; SCHLINDWEIN and EVANS, 1990; AHN and PARK, 1991; DAVID *et al.*, 1991; FORSBERG, 1991; ZEIRA *et al.*, 1994; GUO *et al.*, 1994; WILLINK and EVANS, 1995; KEETON *et al.*, 1997), little effort has been made to study these methods in the context of turbulence velocity fluctuation measurements. The objective of this paper is to investigate the performance of various spectral estimation techniques in terms of their specific variance and bias when applied to the estimation of the Doppler mean instantaneous frequency, which is used to extract the flow velocity as a function of time. The impact of various parameters such as the model order, window length and SNR is investigated for the following techniques: short-time Fourier transform (STFT), autoregressive modelling (AR) based on two different approaches, autoregressive moving average modelling (ARMA) based on the Steiglitz–McBride method, and Prony's spectral method. The variance and bias of each estimator were assessed using a simulated Doppler signal representing an aortic flow waveform.

2 Spectral analysis methods

Traditionally, the time–frequency analysis of the Doppler signal is performed using the STFT, in which the signal is divided into small sequential or overlapping segments and the fast Fourier transform (FFT) applied to each segment. However, the joint time–frequency resolution of the STFT is inherently limited due to the uncertainty principle, which states that the analysis resolution in time and frequency cannot be arbitrarily small because the product of these resolutions is lower bounded (ZEIRA *et al.*, 1994).

In an attempt to alleviate the inherent limitations of the FFT approach, other alternative time–frequency estimation procedures have been proposed. These alternatives fall into three categories: (a) short-time parametric methods; (b) bilinear time–frequency methods; and (c) wavelet transforms. Within each of these categories one can implement different methods in accordance with the specific parameters of interest and the signal characteristics. This paper focuses only on short-time *parametric* methods which assume a generating model for the process. This parametric approach to spectral estimation can be divided into three steps. In step one, an appropriate parametric time-series model is selected to represent the basic characteristics of the experimental signal. In step two, an estimate of the parameters of the model is computed. In the final step, the estimated parameters are inserted into the theoretical power spectral density expression appropriate for that model. Because of their autocorrelation extension property, short-time parametric methods can use shorter windows than the STFT without unduly compromising their frequency resolution. However, short-time parametric methods are sensitive to poor model fit and non-stationarity within the short signal segments (KAY and MARPLE Jr., 1981). As all the implemented parametric methods used in this paper are well established in the literature, only a brief description of these methods is presented below.

AR and ARMA modelling: The general ARMA model, also known as pole–zero modelling, assumes that a time series $x[n]$ can be modelled as the output of a filter containing p poles and q zeros:

$$x[n] = -\sum_{i=1}^{p} a[i]x[n-i] + \sum_{i=1}^{q} b[i]w[n-i] \tag{1}$$

excited by a zero-mean, unit-variance, uncorrelated random data sequence (i.e. normalised white noise) $w[n]$ which is taken to be unobservable. In terms of system identification, the ARMA model is characterised by a rational system function of the form:

$$H(z) = \frac{B(z)}{A(z)} = \frac{\sum_{i=0}^{q} b[i]z^{-i}}{\sum_{i=0}^{p} a[i]z^{-i}} \tag{2}$$

where $A(z)$ and $B(z)$ represent the z-transform of the autoregressive (AR) and moving-average (MA) branch of the ARMA model with $a[0] = 1$. Having estimated the system parameters $a[i]$ and $b[i]$, one can then estimate the power density function as:

$$\hat{S}(f_k) = \frac{|\hat{B}(\exp(-2j\pi f_k))|^2}{|\hat{A}(\exp(-2j\pi f_k))|^2} \tag{3}$$

where the hat notation, ˆ, represents an estimator operator rather than the real value, and f_k is the frequency corresponding to the spectral index k.

AR modelling can be considered as a special case of the ARMA process. It is one of the most widely used approaches due to its assumption that the signal comprises a set of resonances or sinusoids, which is an appropriate model for many practical signals (KAY and MARPLE, Jr., 1981), including the Doppler ultrasound signal. Different algorithms were proposed to estimate the autoregressive process parameters.

In this paper, two of them are implemented; the maximum entropy method (MEM) in which the autoregressive parameters are found via a block solution of the Yule–Walker equations, and linear prediction coding based on the Levinson–Durbin algorithm (LAR). Both of these algorithms are described in detail by MARPLE (1987).

The ARMA Steiglitz–McBride method, which is an iterative algorithm for computing the model parameters of eqn. 3, was implemented. The full description of this method with its advantages and drawbacks can be found elsewhere (STEIGLITZ and MCBRIDE, 1965; JOO *et al.*, 1983). Due to the nature of the Doppler signal, the MA model order of the Steiglitz–McBride algorithm was set to zero (i.e. $b[0] = 1$ and $b[i] = 0$ for $i \neq 0$). This is justified by the fact that the simulated signal is a sum of sinusoidal components which show only peaks in the corresponding power spectrum.

Prony's method: This method seeks to fit an exponentially decaying sinusoid model to the data, in contrast to AR and ARMA methods that seek to fit a random model to the second-order data statistics. The model assumed in Prony's method is a set of p exponentials of arbitrary amplitude, phase, frequency, and damping factor (MARPLE, 1987). The discrete-time function is described by:

$$x[n] = \sum_{m=1}^{p} h[m]z[m]^n \qquad n = 0, 1, 2, \ldots, N-1 \tag{4}$$

where

$$h[m] = A[m]\exp(j\phi[m])$$

and

$$z[m] = \exp[(d[m] + j2\pi f[m])\Delta t]$$

In eqn. 4, $A[m]$ is the amplitude, $\phi[m]$ is the phase in radians, $d[m]$ is the damping factor, $f[m]$ is the frequency in hertz, and Δt represents the sample interval in seconds.

Although Prony's method normally terminates with the computation of the above mentioned parameters, it is possible to calculate the spectrum based on the following formula (KAY and MARPLE Jr., 1981):

$$\hat{S}[f_k] = |\hat{X}[f_k]|^2 \tag{5}$$

where

$$\hat{X}[f_k] = \sum_{m=1}^{p} A[m]\exp(j\phi[m]) \times \frac{2d[m]}{[d[m]^2 + (2\pi[f_k - f[m]])^2]}$$

3 Simulated Doppler signal

To compare the performance of the different spectral techniques, a synthesised signal is required which can be used as a reference signal. In this paper, a Doppler signal similar to one obtained downstream of an aortic heart valve is simulated. Fig. 1 shows Doppler flow waveforms recorded downstream of a St-Jude aortic heart valve installed in a flow phantom (DURAND *et al.*, 1998). The Doppler signal was synthesised using an approach similar to that described by MO and COBBOLD (1986, 1989) to match the spectral characteristics of Fig. 1. The method is briefly summarised below as it constitutes the basis for the spectral algorithm comparisons. The bidirectional Doppler signal was simulated as a sum of random phase sinusoids covering the frequency range $[0, f_{max}]$, as described by GUO *et al.* (1994).

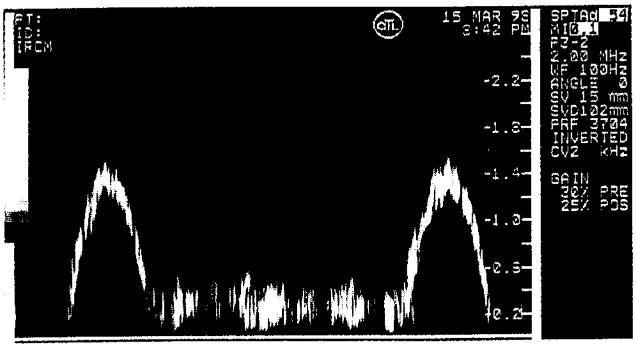

Fig. 1 *Experimental short-time Fourier frequency distribution of Doppler signals recorded downstream (four diameters) of a St-Jude mechanical aortic heart valve. The 23 mm valve was installed in a flow phantom described in* DURAND et al. *(1998), and measurements were performed at a mean flow rate of 4.5 l/min*

$$s(t) = \sum_{m=1}^{M} a_m \exp[j(2\pi f_m t + \phi_m)] \tag{6a}$$

where

$$M = 2f_{\max}T$$
$$a_m = \sqrt{2S(t, f_m)\Delta f y_m}$$

and

$$f_m = (m - 0.5)\Delta f$$

$S(t, f_m)$ is the time-varying theoretical power spectral density function defined over the range $[0, f_{\max}]$, $\Delta f = f_{\max}/M$ is an incremental frequency domain step, y_m is a χ-squared random variable with two degrees of freedom, and ϕ_m is a random phase uniformly distributed over $[0, 2\pi]$. The sinusoidal amplitudes a_m are Rayleigh distributed, and the number of sinusoids M is determined by the signal duration T.

In this study, a Doppler signal of 1 s was simulated containing positive frequencies during the systole and null values during the diastole. The maximum frequency was set at 4.5 kHz and the sampling frequency at 20 kHz. The maximum frequency waveform of the simulated signal was defined as:

$$f_{\max} = \begin{cases} 3.5\sin(2\pi f_1 t) + 1 & 0 \leqslant t \leqslant 0.3 \text{ s} \\ 0 & 0.3 \text{ s} < t \leqslant 1 \text{ s} \end{cases} \tag{6b}$$

where $f_1 = 1.67$ Hz and f_{max} is in kilohertz. In the above equation, all frequencies below 500 Hz are removed to simulate the highpass wall filter used during clinical exams.

Although both in-phase and quadrature components of the Doppler signals were generated, only a portion of the in-phase cardiac cycle signal was used in this study to investigate the performance of the different spectral estimation techniques. This choice is justified by the fact that the statistical characteristics of the in-phase and quadrature signals are the same. In addition, by analysing the signal only within a predefined time interval, the computation time of the overall process is substantially reduced. As the maximum turbulence occurs around the maximum systolic pressure (SHEN, 1961; GERRARD, 1971), this part of the flow signal was selected. Fig. 2 shows the normalised theoretical time–frequency distribution of the simulated Doppler signal. This bias and variance of the spectral methods to estimate the mean instantaneous frequency were evaluated within the time window included between 120 and 180 ms.

To investigate the performance of each method, SNR of 20 dB, 10 dB and 0 dB were used. The noise levels were not selected to mimic different turbulence intensities but to test the stability of the spectral techniques to estimate the instantaneous mean frequency. Laminar flow is considered in these simulations. If a spectral method cannot provide a low variance of the mean frequency when no turbulence is present, it is very likely that this method will perform poorly in situations where frequency fluctuations (turbulence) exist. For each of the specified SNR, 20 different realisations were generated to evaluate the variance of the estimate for each method. The desired SNR were obtained by adding white Gaussian noise to the simulated Doppler signal (ZEIRA *et al.*, 1994).

4 Assessment of the performance of spectral estimators

The performance of each technique relies on the accuracy of the assessment of the mean frequency parameter. The instantaneous mean frequency waveform was estimated according to the following equation:

$$\hat{f}_{mean}[n] = \frac{\sum_{k=0}^{N-1} f_k \hat{S}[n,k]}{\sum_{k=0}^{N-1} \hat{S}[n,k]} \tag{7}$$

where n and k correspond to the discrete time and frequency variables, respectively. The parameter $\hat{S}$ represents the power of the signal computed from the different algorithms, and f_k is the frequency corresponding to the spectral index k. The $\hat{f}_{mean}$ was estimated for each of the 20 realisations and for each SNR. Then, the mean and standard deviation of this parameter were evaluated. In order to quantify the variability of each estimate, a variance coefficient (i.e. *Var-Coef*) defined as:

$$Var-Coef = \frac{1}{N}\sum_{n=1}^{N} \frac{std(\hat{f}_{mean}[n])}{\mu[\hat{f}_{mean}[n]]} \tag{8}$$

was calculated for each method. In eqn. 8, $std(\hat{f}_{mean}[n])$ represents the standard deviation of a specific method towards estimation of the instantaneous mean frequency at each data sample position n, $\mu[\hat{f}_{mean}[n]]$ is the mean value of the estimated instantaneous mean frequency of that method obtained by averaging the corresponding 20 mean frequency values of the Doppler signal, and N is the number of spectral lines in the time window centred around the peak systole. Although expressed differently, the *Var-Coef* is equivalent to the relative turbulent velocity fluctuation index defined in CLOUTIER *et al.* (1996).

In addition, the normalised mean-square-error (*NMSE*) between the estimated and theoretical mean frequency was measured.

$$NMSE = \frac{1}{N}\sum_{n=1}^{N} \frac{(\mu[\hat{f}_{mean}[n]] - f_{mean}[n])^2}{f_{mean}^2[n]} \tag{9}$$

Of course, the theoretical mean frequency waveform can be estimated from the theoretical power spectrum density of the simulated signal using eqn. 7. However, bearing in mind that the theoretical power spectral density function underlying the Doppler signal is given by (MO and COBBOLD, 1989):

$$S(t,f) = A(f_{\max} - f)^2 \exp[-B(f_{\max} - f)^2] \tag{10}$$

one can estimate the theoretical instantaneous mean frequency waveform analytically by using,

$$f_{mean} = \begin{cases} f_{\max} - \dfrac{2}{\sqrt{\pi B}} & f_{\max} \geqslant 0 \\ f_{\max} + \dfrac{2}{\sqrt{\pi B}} & f_{\max} < 0 \end{cases}$$

where f_{max}, A, and B are time-varying parameters representing, respectively, the maximum frequency of the Doppler spectrum, the power scaling factor, and the bandwidth factor. In this study, A and B had values obtained by the procedures described in GUO *et al.* (1994).

5 Results and discussion

Fig. 3 depicts the analytical f_{mean} values for the portion of the cardiac cycle investigated in this paper (between 120 and 180 ms). In all the above mentioned parametric methods, the model order (m) investigated was varied from 8 to 40. Lower model orders were not used as the time-varying number of sinusoids (i.e. M) used to generate the Doppler signal at each moment in time for the selected part of the cardiac cycle is between six and nine, as determined by eqns. 6a and 6b. On the other hand, higher model orders are not recommended for the application in hand (SCHLINDWEIN and EVANS, 1990; FISH *et al.*, 1997) due to the nature of the mean frequency parameter. A Hanning window was used for each window length as it has been shown that this type of window is more suitable when the instantaneous mean frequency is the parameter under investigation (WANG and FISH, 1996). The window length was ranged from 1–10 ms as short windows are required to improve the

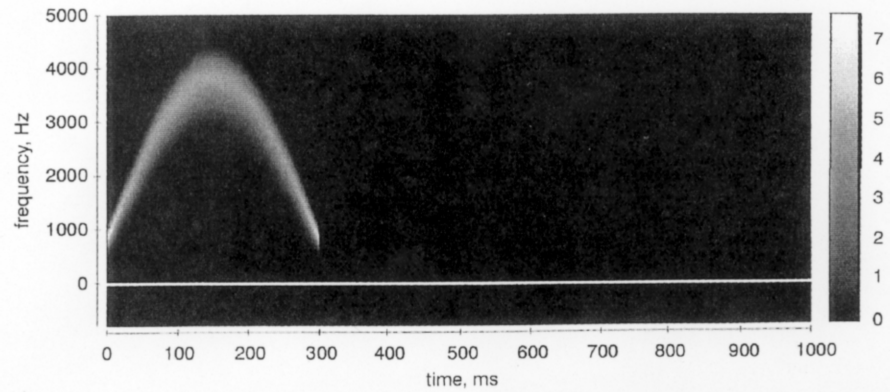

Fig. 2 *Theoretical time-frequency distribution of the simulated Doppler signal. The segment on which the spectral techniques were tested is between 120 and 180 ms*

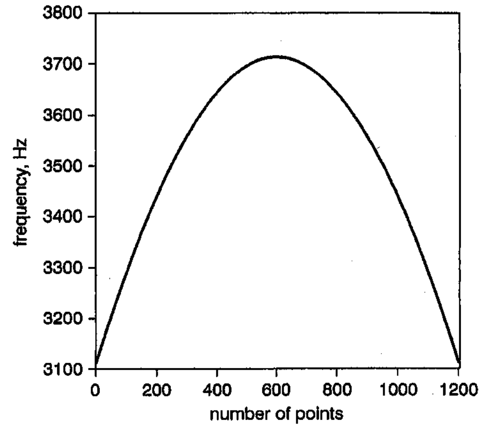

Fig. 3 *Theoretical time-varying mean frequency for the selected part of the simulated signal*

time resolution of turbulence estimators, and longer windows improve the frequency resolution but emphasise the change in non-stationary signal characteristics (CARDOSO *et al.*, 1996). A $W-1$ point overlapping window was applied from one segment to the next, where W is the number of sample points in each window length.

Fig. 4 shows the performance of the parametric methods investigated in this paper for the case corresponding to SNR= 0 dB. The characteristics of the corresponding graphs for other SNR ratios are very similar to those shown in Fig. 4, apart from the fact that the performance of each method is better when the SNR is high. From Fig. 4, it is clear that the window length is the parameter that has the strongest effect on the performance of the time–frequency distribution of all methods. With the exception of the ARMA method, the model order seems to have a minor impact on the *Var-Coef* and *NMSE*. This is due to the fact that, for the purpose of this study, we were interested only in the estimation of the instantaneous mean frequency and not in the spectral resolution or accurate estimation of frequency components within the corresponding spectrum. In this sense, results presented in this paper agree with previous works which have suggested that the model order is not such a crucial parameter when estimating the instantaneous mean frequency of the Doppler signal (SCHLINDWEIN and EVANS, 1990). It seems that a model order in the range 8–12 would give the best results. By increasing the window length the performance improves substantially for each method in terms of the *Var-Coef* and *NMSE*.

Fig. 5 depicts the performance of each method for a model order of 10 and that of the STFT using different window lengths and SNRs. Only the results of the *Var-Coef* are presented since it is this index that has to be minimised to obtain a reliable estimator of the mean frequency. However, it must be mentioned that the behaviour of the *NMSE* is very similar to that of the *Var-Coef*.

Results presented in this figure show that algorithms based on the AR model outperform all the others, and the ARMA method gives the worst results. This can be attributed to the fact that true AR algorithms reflect more closely the nature of the simulated signal than the other methods. For the iterative Steiglitz–McBride ARMA method, although it was modified to an AR model, it does not seem to be well adapted for the Doppler signal. Among the two AR algorithms, the MEM seems to perform better than the LAR method at 20 dB SNRs. However, for lower SNRs (SNR= 10 and 0 dB) the performance of LAR is superior. These results can be explained by the fact that AR modelling performs better under a Gaussian

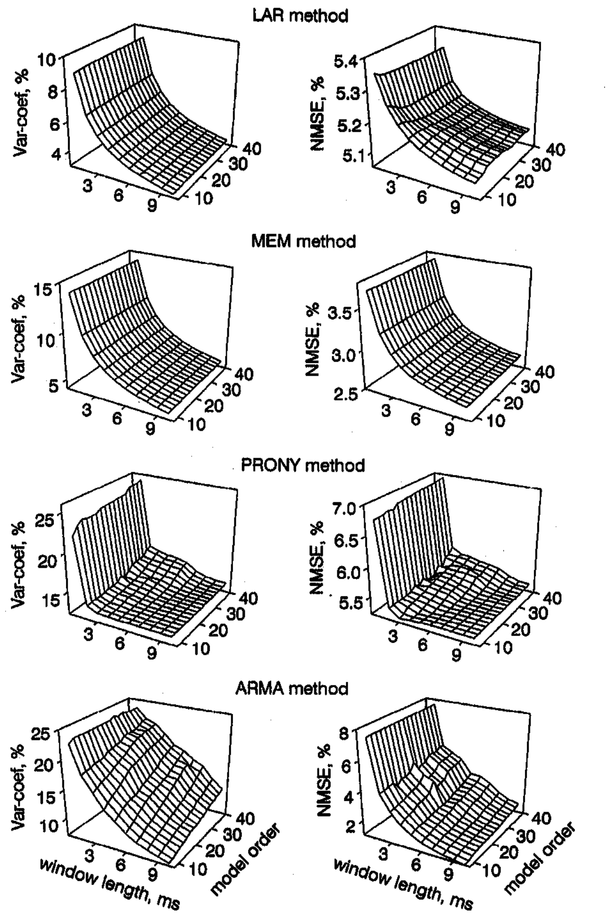

Fig. 4 *Performance of various short-time spectral parametric methods for SNR= 0 dB and varying window length and model order*

random process which is almost always the case for the Doppler signal (FONTAINE *et al.*, 1997). It can be observed from the results of Fig. 5 that the performance of all the methods improves or reaches a plateau as the window length increases. This suggests that a window length of at least 10 ms must be used when the estimation of large-scale turbulence is the primary concern under investigation. However, there might be other cases when a shorter window is needed to track down faster fluctuations of the Doppler signal attributed to small-scale turbulent motions (TRITTON, 1988). In these circumstances, our work suggests that use of the LAR is the best option among the short-time spectral parametric methods tested when the signal is corrupted with noise.

6 Conclusions

Simulated Doppler signals have been used to compare the performance of a number of parametric spectral analysis methods regarding the variance of the instantaneous mean frequency estimation in terms of the window length, model order and signal-to-noise ratio. Results show that overall, autoregressive modelling based on the LAR method gives better performance than the other methods for signal-to-noise ratios between 0 and 10 dB. However, for a higher SNR of 20 dB, the performance of MEM and LAR methods is comparable, with the MEM having the upper hand. Results also showed that the length of the window is the most important factor in terms of accurate estimation of the mean frequency of the Doppler signal. It is suggested that a duration of at least

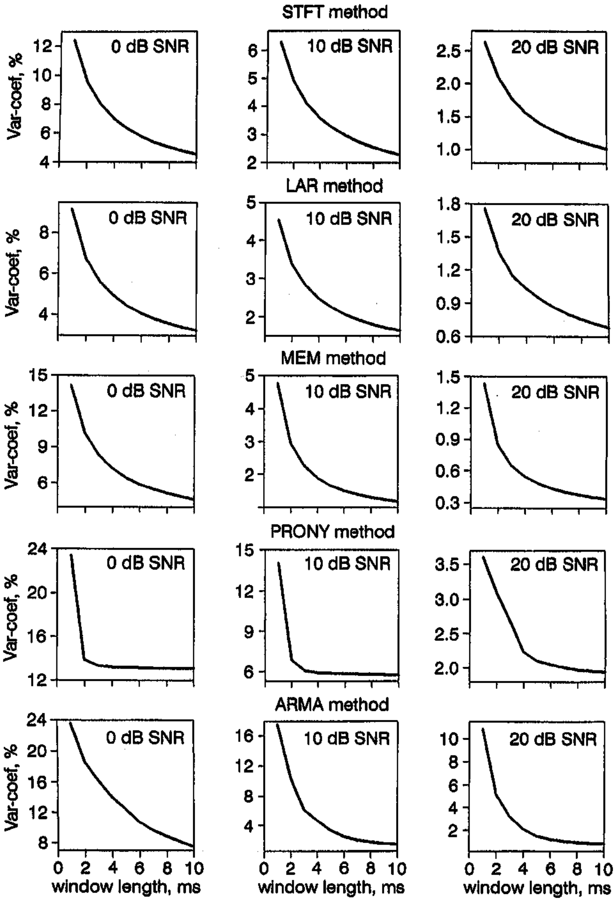

Fig. 5 *Performance of the STFT and various spectral parametric methods for different SNRs and window lengths. For parametric methods, a model order of 10 was selected*

10 ms is required to significantly reduce the variance of the spectral estimator on the overall results. However, since it is important to have good time resolution to track rapid turbulent motions, it could be of interest to investigate also the performance of joint time–frequency distribution methods or wavelet transforms. As for the order of the model, it has been shown that it does not play a significant role in the variance of the estimator or the *NMSE* parameter.

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