

MATLAB for Teaching Doppler Ultrasound Blood Flow Signal Analysis to Biomedical Engineering Students*

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Biomedical signal processing and analysis is a field of great importance in current medical practice. MATLAB is the most commonly used software tool for biomedical signal processing, visualization, editing, etc. This paper presents an initiative to teach Doppler ultrasound blood flow signal analysis to biomedical engineering students. The approach was based on illustrative applications that highlight the performance characteristics of the signal processing methods (classical, model-based, eigenvector and time-frequency methods). Following a brief description of the signal processing methods, applications of the methods to the Doppler signals obtained from the internal carotid artery and ophthalmic artery were done by means of a series of MATLAB functions. The functions involved in signal processing and wavelet toolboxes of MATLAB can be used to analyse the signal under study. The author suggests that the use of MATLAB exercises will assist students in gaining a better understanding of the various signal processing methods in blood flow investigations.

Keywords: Doppler ultrasound blood flow signal; signal processing methods; MATLAB toolboxes

INTRODUCTION

BIOMEDICAL ENGINEERS, in recent years, have developed many algorithms and processing techniques in order to help doctors in the examination of many different biosignals, to find new information embedded in them and not easily observable in the raw data [1]. In this respect, Doppler ultrasound blood flow signal analysis could be introduced both in the graduate and undergraduate biomedical engineering programmes. Most engineering students are introduced to MATLAB and the various toolboxes at an early stage of their careers in the general areas of simulation, controls and dynamic system analysis. MATLAB is the basic ‘engine’ with add-on components called toolboxes. MATLAB and its toolboxes allow students to investigate the characteristics of the algorithm and easily design their own algorithm with its vast assortment of graphical, signal processing and simulation functions. The data or signals generated by any component of the system (software or hardware) can be displayed and/or saved for subsequent use, such as system identification or offline signal analysing.

Doppler ultrasound is a noninvasive technique which is widely used in medicine for the assessment of blood flow in vessels. The technique has improved much since Satomura first demonstrated the application of the Doppler effect to the

measurement of blood velocity in 1959 [2–5]. Doppler ultrasonography works by emitting a focused ultrasound beam with a base frequency into the body via a piezoelectric transducer and detecting the change in frequency that occurs after the beam is reflected or scattered by moving targets. This Doppler shift frequency is proportional to the speed of the moving targets:

$$f_D = \frac{2vf \cos \theta}{c} \quad (1)$$

where v is the magnitude of the velocity of target, f_D is the Doppler shift frequency, f is the frequency of transmitted ultrasound, c is the magnitude of the velocity of ultrasound in blood and θ is the angle between ultrasonic beam and direction of motion.

Doppler ultrasound has proved to be a valuable technique for investigation of arterial diseases. The results of the studies in the literature have shown that Doppler ultrasound evaluation can give reliable information on both systolic and diastolic blood velocities of arteries and have supported Doppler ultrasound as a useful tool in screening certain haemodynamic alterations in arteries [2–5].

The Doppler power spectrum has a shape similar to the histogram of the blood velocities within the sample volume and thus spectral analysis of the Doppler signal produces information concerning the velocity distribution in the artery. The estimation of the power spectral density (PSD) of the Doppler signal is performed by applying spectral

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analysis methods. By using spectral analysis methods, variations in the shape of the Doppler power spectra as a function of time are presented in the form of sonograms. In a sonogram, the horizontal axis represents time, the vertical axis frequency and the grey level intensity denotes signal power at frequency and time instant. The darker the grey level, the higher the power of the frequency component measured at time instant. By monitoring the sonogram, variation of the spectral properties of the Doppler signal and a number of extents related to the blood flow can easily be tracked [2–5].

A number of spectral estimation methods have recently been developed and compared to the more standard fast Fourier transform (FFT)–based methods for Doppler ultrasonic signal processing. FFT-based methods are known as classical (nonparametric) methods and have been widely studied in the literature [4, 6–8]. Autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) methods are model-based (parametric) methods with spectra that can be computed via different algorithms. Eigenvector methods are used for estimating frequencies and powers of signals from noise-corrupted measurements. Pisarenko, multiple signal classification (MUSIC), and Minimum-Norm methods are eigenvector methods which can be used for obtaining PSD estimates of Doppler ultrasound blood flow signals [3, 9]. Since flow in arteries is pulsatile and the red blood cells have a random spatial distribution, the Doppler signal is time-varying and random. Therefore, short-time Fourier transform (STFT) and wavelet transform (WT) can be used for spectral analysis of the arterial Doppler signals [1]. Using these spectral analysis methods, the time-dependent spectral distributions were visualized and detailed documentations of the Doppler signals were obtained [5].

COURSE DESCRIPTION

A MATLAB-based approach is one of the topics in the biomedical instrumentation course in the department of electrical and electronics engineering. It is a selective course designed to equip undergraduate and/or graduate students with necessary programming and hardware design skills and to acquaint them with the latest biomedical instruments and their relation with spectral analysis methods. These skills and knowledge are crucial in the biomedical field, which faces a constant shortage of trained engineers with digital signal processing background. The course includes biomedical instrumentation theory, design, implementation and spectral analysis methods applied to biomedical signals. Prerequisite courses before biomedical instrumentation are medical electronics and digital signal processing.

Before embarking on the formulation of a syllabus for the biomedical instrumentation course, some important questions had to be asked:

- 1) How do we begin designing a biomedical instrumentation project from specification?
- 2) How do we teach the algorithms of MATLAB functions in a fun and easy-to-absorb way?
- 3) How do we highlight the functionality of biomedical instruments and features and relate them to the signal processing algorithms?
- 4) How do we create a laboratory session that fits in with the lecture properly? How do we cover the software and hardware tools used in the design course?
- 5) How do we assess the students?
- 6) How do we evaluate the educational contribution of our course?

The biomedical instrumentation course, like the other modules among the optional courses, is a 36-hour lecture course. Course lectures are scheduled for 12 weeks (consisting of a three-hour lecture block per week), followed by two weeks of exams. The course outline consists of the following:

- Basic concepts of biomedical instrumentation;
- Basic sensors and principles;
- Biomedical signal processing;
- The origin of biopotentials;
- Biopotential electrodes;
- Biopotential amplifiers; Blood pressure and sound;
- Measurement of flow and volume of blood;
- Clinical laboratory instrumentation.

In a six-hour lecture, biomedical signal processing involving Doppler blood flow signal processing is explained. The course forms a part of computer science and is very computationally intensive. The key features of the MATLAB software and how the signal processing and wavelet toolboxes of MATLAB work with the course material are given to the students in the lecture.

THEORETICAL BASIS

Classical methods (fast Fourier transform)

The FFT-based methods such as Welch method are defined as classical methods. Welch spectral estimator can be efficiently computed via FFT and is one of the most frequently used PSD estimation methods. In the Welch method, signals are divided into overlapping segments, each data segment is windowed, periodograms are calculated and the average of periodograms is found [4,6–8]. $\{x_l(n)\}$, $l = 1, \dots, K$ are signal intervals and each interval's length equals to M . The Welch spectral estimator is defined as

$$\hat{P}_l(f) = \frac{1}{M} \frac{1}{P} \left| \sum_{n=1}^M v(n)x_l(n) \exp(-j2\pi fn) \right|^2$$

and

$$\hat{P}_W(f) = \frac{1}{K} \sum_{l=1}^K \hat{P}_l(f) \tag{2}$$

where $\hat{P}_l(f)$ is the periodogram estimate of each signal interval, $v(n)$ is the data window, P is the average of $v(n)$ given as

$$P = \frac{1}{M} \sum_{n=1}^M |v(n)|^2, \hat{P}_W(f)$$

is the Welch PSD estimate, M is the length of each signal interval and K is the number of signal intervals.

Model-based methods

AR method: the most frequently used model-based method because estimation of the AR parameters can be done easily by solving linear equations. The AR parameters can be estimated via different estimation methods such as the Burg method [4, 6–8]. This is computationally efficient and yields a stable AR method. It is based on minimization of the forward and backward prediction errors and estimation of the reflection coefficient.

From the estimates of the p th-order Burg AR parameters, PSD estimation is formed as

$$\hat{P}_{BURG}(f) = \frac{\hat{e}_p}{\left| 1 + \sum_{k=1}^p \hat{a}_p(k) e^{-j2\pi fk} \right|^2}, \tag{3}$$

where $\hat{e}_p = \hat{e}_{f,p} + \hat{e}_{b,p}$ is the total least squares error.

MA method: one of the model-based methods in which the signal is obtained by filtering white noise with an all-zero filter [4,6–8]. Estimation of the MA spectrum can be done by the reparameterization of the PSD in terms of the autocorrelation function. The q th-order MA PSD estimation is

$$\hat{P}_{MA}(f) = \sum_{k=-q}^q \hat{r}(k) e^{-j2\pi fk} \tag{4}$$

where $\hat{r}(k)$ is autocorrelation function estimates.

ARMA method: the spectral factorization problem associated with a rational PSD has multiple solutions, with the stable and minimum phase ARMA model being one of the model-based methods [4,6–8]. A reliable method is to construct a set of linear equations and to use the method of least squares on them. Suppose that for an ARMA of order p,q the autocorrelation sequence can be accurately estimated up to lag M , where $M > p + q$. Then the following set of linear equations can be written:

$$\begin{bmatrix} r(q) & r(q-1) & \cdots & r(q-p+1) \\ r(q+1) & r(q) & \cdots & r(q-p+2) \\ \vdots & \vdots & & \vdots \\ r(M-1) & r(M-2) & & r(M-p) \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_p \end{bmatrix} = - \begin{bmatrix} r(q+1) \\ r(q+2) \\ \vdots \\ r(M) \end{bmatrix}, \tag{5}$$

or equivalently,

$$Ra = -r. \tag{6}$$

Since the dimension of R is $(M - q)xp$ and $M - q > p$ the least squares criterion can be used to solve for the parameter vector a . The result of this minimization is

$$\hat{a} = -(R^*R)^{-1}(R^*r) \tag{7}$$

Finally the estimated ARMA power spectrum is

$$\hat{P}_{ARMA}(f) = \frac{\hat{P}_{MA}(f)}{\left| 1 + \sum_{k=1}^p \hat{a}(k) e^{-j2\pi fk} \right|^2}, \tag{8}$$

where $\hat{P}_{MA}(f)$ is estimate of the MA PSD and is given in equation (4).

Selection of AR, MA and ARMA model orders: one of the most important aspects in the use of model-based methods is the selection of the model order. Much work has been done by various investigators on this problem and many experimental results are in the literature [6–8]. One of the better known criteria for selecting the model order has been proposed by Akaike [10], called the Akaike information criterion (AIC). This is based on selecting the order that minimizes equation (9) for the AR method, equation (10) for the MA method, and equation (11) for the ARMA method.

$$AIC(p) = \ln \hat{\sigma}^2 + 2p/N, \tag{9}$$

$$AIC(q) = \ln \hat{\sigma}^2 + 2q/N, \tag{10}$$

$$AIC(p, q) = \ln \hat{\sigma}^2 + 2(p + q)/N. \tag{11}$$

where $\hat{\sigma}^2$ is the estimated variance of the linear prediction error. In the illustrative applications, model orders of the AR, MA, and ARMA methods were taken as 10 by using equations (9), (10), and (11).

Eigenvector methods

Eigenvector methods are used for estimating frequencies and powers of signals from noise-corrupted measurements. These methods are based on an eigen-decomposition of the correlation matrix of the noise-corrupted signal. Even when the signal-to-noise ratio (SNR) is low, the eigenvector methods produce frequency spectra of high resolution. These methods are best suited to signals that can be assumed to be composed of several specific sinusoids buried in noise [3, 9]. In the illustrative applications, three eigenvector methods (Pisarenko, MUSIC, and Minimum-Norm) were selected to generate the PSD estimates.

Pisarenko method: proposed by Pisarenko [11], this is particularly useful for estimating PSD which contains sharp peaks at the expected frequencies. The polynomial $A(f)$ which contains zeros on the unit circle can then be used to estimate the PSD.

$$A(f) = \sum_{k=0}^m a_k e^{-j2\pi f k} \quad (12)$$

where $A(f)$ represents the desired polynomial, a_k represents coefficients of the desired polynomial, and m represents the order of the eigenfilter, $A(f)$.

From the eigenvector corresponding to the minimum eigenvalue, the Pisarenko method determines the signal PSD from the desired polynomial [3, 9]

$$P_{PISARENKO}(f) = \frac{1}{|A(f)|^2} \quad (13)$$

MUSIC method: this is also a noise subspace frequency estimator. The MUSIC method proposed by Schmidt [12] eliminates the effects of spurious zeros by using the averaged spectra of all of the eigenvectors corresponding to the noise subspace. The resultant PSD is determined from

$$P_{MUSIC}(f) = \frac{1}{\frac{1}{K} \sum_{i=0}^{K-1} |A_i(f)|^2} \quad (14)$$

where K represents the dimension of noise subspace, $A_i(f)$ represents the desired polynomial that corresponds to all the eigenvectors of the noise subspace [3,9].

Minimum-norm method: in addition to the Pisarenko and MUSIC methods, the Minimum-Norm method was investigated [13]. In order to differentiate spurious zeros from real zeros, the Minimum-Norm method forces spurious zeros inside the unit circle and calculates a desired noise subspace vector a from either the noise or signal subspace eigenvectors. Thus, while the Pisarenko method uses only the noise subspace eigenvector corresponding to the minimum eigenvalue, the Minimum-Norm method uses a linear combination of all noise subspace eigenvectors. Using the Minimum-Norm method, the polynomial $A(f)$ is written as [13]

$$A(f) = A_1(f)A_2(f) \quad (15)$$

where

$$A_1(f) = \sum_{k=0}^L b_k e^{-j2\pi f k} \quad b_0 = 1 \quad (16)$$

$$A_2(f) = \sum_{k=0}^{m-L} c_k z^{-k} \quad c_0 = 1 \quad (17)$$

The Minimum-Norm PSD can be estimated as follows [3, 9]:

$$P_{MIN}(f, K) = \frac{1}{|A(f)|^2} \quad (8)$$

where K represents the dimension of the noise subspace.

Time-frequency methods

Short-time Fourier transform: spectral analysis of the Doppler signal is performed using the STFT, in which the signal is divided into small sequential or overlapping data frames and FFT is applied to each one. The output of successive STFTs can provide a time-frequency representation of the signal. To accomplish this, the signal is truncated into short data frames by multiplying it by a window so that the modified signal is zero outside the data frame. To analyse the whole signal, the window is translated in time and then reapplied to the signal [1, 5].

In STFT analysis, the signal is multiplied by a window function $w(t)$ and the spectrum of this signal frame is calculated using the Fourier transform. Thus

$$STFT(t, f) = \left| \int_{-\infty}^{+\infty} x(\tau) w(\tau - t) e^{-j2\pi f \tau} d\tau \right|^2 \quad (19)$$

where $x(t)$ represents the analysed signal.

Wavelet transform (WT): addresses the problem of fixed resolution by using base functions that can be scaled. The wavelets act in a similar way to the windowed complex exponentials that are used in the STFT, except that with the WT the length of signal being analysed is not fixed. It is known that wavelets are better suited to analysing nonstationary signals, since they are well localized in time and frequency. The property of time and frequency localization is known as compact support and is one of the most attractive features of the WT. The WT of a signal is the decomposition of the signal over a set of functions obtained after dilatation and translation of an analysing wavelet. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges. Furthermore, owing to the fact that windows are adapted to the transients of each scale, wavelets lack of the requirement of stationarity. Therefore, the WT has become a powerful alternative to the STFT in analysis of the Doppler signals [1,5].

Continuous wavelet transform (CWT) is defined by

$$CWT(a, b) = \int_{-\infty}^{+\infty} x(t) \psi_{a,b}^*(t) dt \quad (20)$$

where $x(t)$ represents the analysed signal, a and b

represent the scaling factor (dilatation/compression coefficient) and the time (shifting coefficient), respectively, and the superscript asterisk denotes the complex conjugation.

$\psi_{a,b}(\bullet)$ is obtained by scaling the wavelet at time b and scale a .

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) \quad (21)$$

where $\psi(t)$ represents the wavelet.

ILLUSTRATIVE APPLICATIONS

Hardware

The data acquisition system used in the illustrative applications had five components as shown in Fig. 1. These are ultrasonic transducer (5 MHz for internal carotid artery, 10 MHz for ophthalmic artery), analogue Doppler unit, analogue tape recorder (Sony), analogue/digital interface board (Sound Blaster Pro-16 bit), a personal computer with a printer. The analogue Doppler unit was equipped with an imaging facility that made it possible to focus the sample volume at a desired location. The beam of ultrasound transfixed the vessel axis at an angle of around 60 degrees. The output of the analogue Doppler unit was transferred to a PC via a 16-bit sound card on an analogue/digital interface board.

Doppler power spectra and sonograms

Doppler power spectra describe the distribution of power with frequency. In the illustrative applications, internal carotid and ophthalmic arterial Doppler signals were processed to achieve Doppler PSDs and sonograms. In order to achieve Doppler PSDs and sonograms, the signal processing and wavelet toolboxes of MATLAB were used. Clinically useful information can be extracted from the Doppler PSDs and sonograms. Since the velocity components are proportional to the Doppler frequency shifts, the Doppler PSDs giving the shape of the velocity distribution within the artery. PSDs of internal carotid arterial, Doppler signals were obtained using the FFT, AR, MA, and ARMA methods [4]. Sample PSDs of the internal carotid arterial Doppler signals for an unhealthy subject having artery stenosis are presented in Fig. 2.

The FFT has large variance and is a poor

spectral estimator, as can be observed in Fig. 2. The assumption that the autocorrelation estimate is zero outside the window severely limits the frequency resolution and the quality of the PSD estimates that are achieved using the FFT method. Owing to the limitations of the FFT method, model-based spectral estimation methods are extremely valuable for Doppler signal analysis. The AR method avoids the problem of leakage and provides better frequency resolution than the FFT method. The AR equation may model spectra with narrow peaks and this is an important feature since narrowband spectra are quite common in practice. The MA method is valuable when the PSD is characterized by broad peaks and/or sharp nulls. As is apparent from Fig. 2, smooth internal carotid arterial Doppler PSDs are obtained by the MA method. Because the MA method is not a high resolution spectral estimator for processes with narrowband spectral features, the MA method has been found inappropriate for obtaining internal carotid arterial Doppler PSDs. Spectra with both sharp peaks and deep nulls can be modelled by the ARMA method. By combining poles and zeros, the ARMA method provides a more efficient representation, from the viewpoint of the number of model parameters, of the spectrum of a random process. It is clearly shown in Fig. 2 that both the AR and ARMA methods generate similar PSD estimates. The AR and ARMA method's performance characteristics (determining peak frequencies and power levels of Doppler PSDs and correlation coefficients between the methods calculated from Doppler PSDs) have been found to be superior to the FFT and MA methods, as can be observed in Fig. 2 [4].

The Doppler shift signal contains a wealth of information about blood flow occurring within the sample volume of the Doppler ultrasonography. The most complete way to display this information is to perform spectral analysis and present the results in the form of a sonogram. The variation in the shape of Doppler power spectrum as a function of time can be presented in the form of a sonogram. A number of parameters related to the blood flow may be extracted from the sonograms and these are of high clinical value. The indices derived from the sonograms defined as resistivity index (RI), pulsatility index (PI) and used for the evaluation of arterial Doppler sonograms. RI and PI are defined as

$$RI = (S - D)/S \quad (22)$$

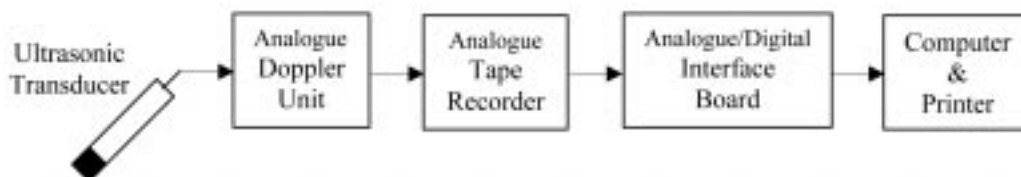


Fig. 1. Block diagram of measurement system.

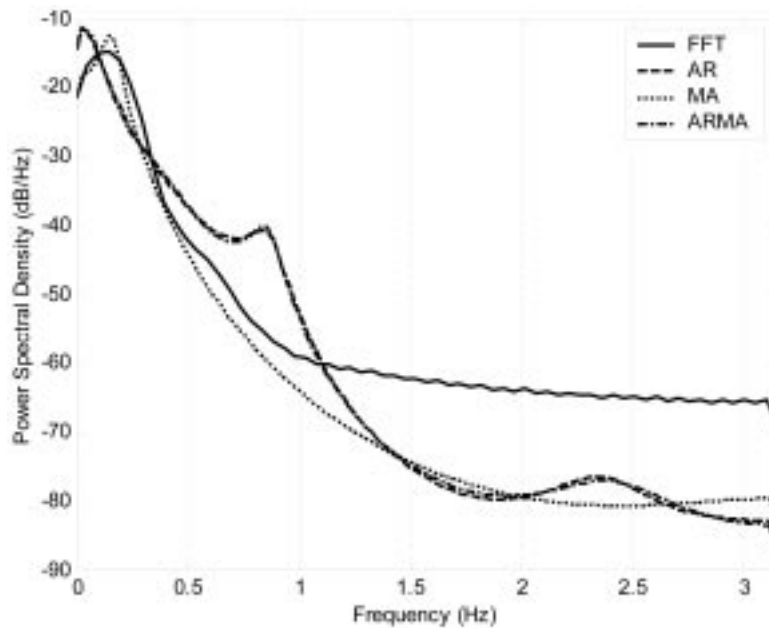


Fig. 2. Internal carotid arterial Doppler PSDs recorded from an unhealthy subject having artery stenosis: FFT, AR, MA, ARMA methods.

$$PI = (S - D)/M \quad (23)$$

where S is maximum systolic height, D is end diastolic height and M is mean height of the sonogram (Fig. 3).

In Fig. 4, internal carotid artery flow sonograms recorded from an unhealthy subject having artery stenosis are given. Internal carotid artery flow sonogram in (a) is obtained using the FFT method, in (b) using the AR method, in (c) using the MA method, and in (d) using the ARMA method. As is seen from Fig. 4, in the FFT sonogram spurious frequencies are seen and systole and diastole are not clear. The sonogram obtained using the MA method has very low frequency resolution. Internal carotid arterial Doppler sonograms of unhealthy subject obtained using the AR and ARMA methods are more clear and have higher spectral resolution compared with the FFT and MA methods' sonograms [4].

The calculations of RI and PI from internal carotid arterial Doppler sonograms obtained using the FFT and MA methods are difficult since systole and diastole are not clear as seen in Figs 4(a), 4(c). On the other hand, internal carotid arterial Doppler sonograms obtained using the AR and ARMA methods (Figs 4(b) and 4(d)) are clearer so that the calculation of RI and PI from these two methods' sonograms will not be difficult. There is a distinct qualitative improvement in the Doppler sonograms obtained using the AR and ARMA methods over the FFT and MA methods, which is in agreement with other published results [4].

Eigenvector methods are based on an eigen-decomposition of the correlation matrix of the noise-corrupted signal. Even when the SNR is low, the eigenvector method produces a frequency

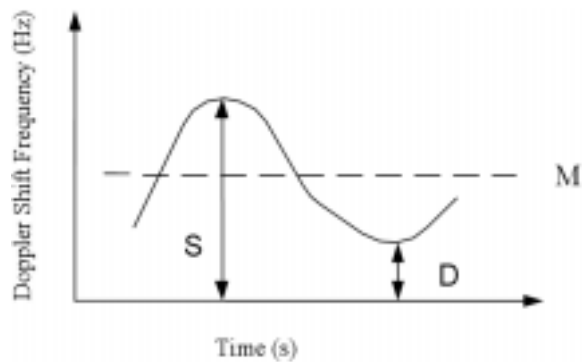


Fig. 3. Diagram illustrating variables involved in definitions of RI and PI. S is maximum systolic height, D is end diastolic height and M is mean height of waveform

spectrum of high resolution. These methods provide sufficient resolution to estimate the sinusoids from the data. Hence, to gain some noise immunity it is reasonable to retain only the principal eigenvector components in the estimation of the autocorrelation matrix. The Pisarenko, MUSIC, and Minimum-Norm methods were employed to determine PSDs of the internal carotid arterial Doppler signals [3]. Using the frequency estimations provided by any one of these methods, the power levels of the signal can be determined from the power matrix.

In the Pisarenko method, the eigenvector associated with the minimum eigenvalue of the estimated autocorrelation matrix is used to calculate the PSD. This method may produce spurious zeros and has a relatively poor statistical accuracy [3,9,11]. In all cases, the Pisarenko PSD showed extra peaks as compared to PSDs obtained from the MUSIC or Minimum-Norm methods (Fig. 5).

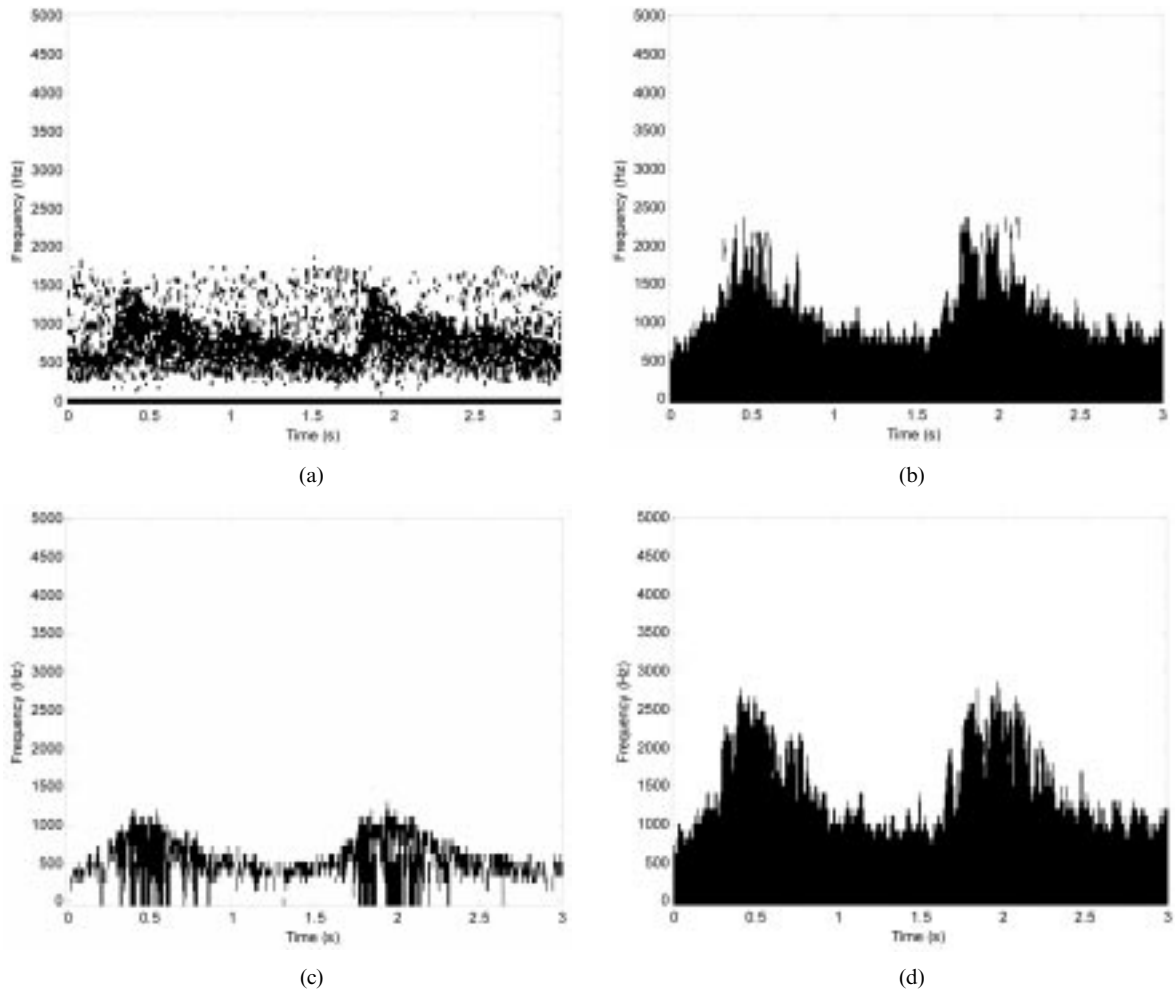


Fig. 4. Internal carotid arterial Doppler sonograms recorded from an unhealthy subject having artery stenosis: (a) FFT, (b) AR, (c) MA, (d) ARMA methods

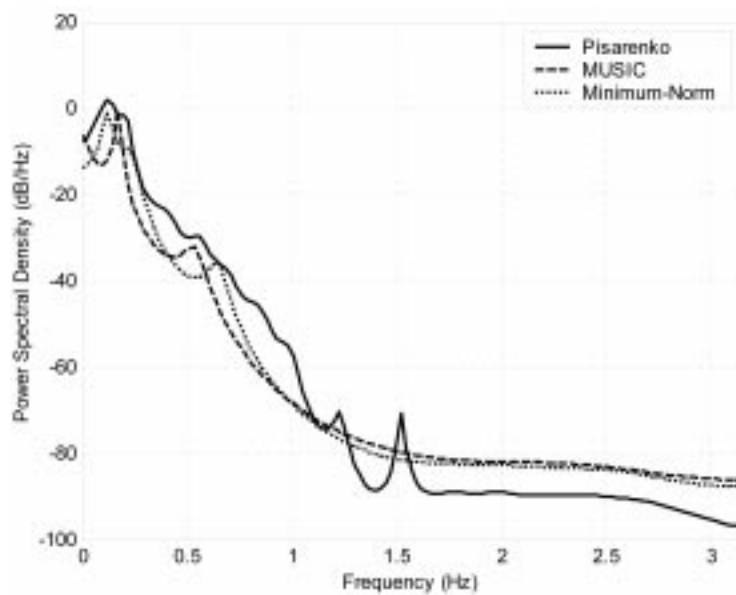


Fig. 5. Internal carotid arterial Doppler PSDs recorded from an unhealthy subject having artery stenosis: Pisarenko, MUSIC, Minimum-Norm methods.

Since the Pisarenko method showed a tendency to generate spurious zeros, the Pisarenko was considered inappropriate for the internal carotid arterial Doppler signals. The MUSIC method eliminates these spurious zeros by averaging the spectra from all of the eigenvectors corresponding to noise subspace. The MUSIC method is the most widely studied, computationally simple, high-resolution eigenvector method [3,9, 12]. From Fig. 5, it is apparent that the MUSIC method is the most suitable method for the internal carotid arterial Doppler signals. The Minimum-Norm method treats the problem of spurious zeros by forcing them inside the unit circle (Fig. 5). Both the MUSIC and Minimum-Norm methods produce similar spectral characteristics with nearly identical peak frequencies. This similarity held for all internal carotid arterial Doppler signals obtained from healthy and unhealthy subjects having artery stenosis and occlusion indicating that the frequency peaks can be accurately estimated using either method [3]. Variance of the MUSIC spectra is smaller than the Minimum-Norm method's variance. The MUSIC method provides asymptotically unbiased estimates of a general set of signal parameters approaching the Cramer-Rao accuracy bound. According to statistical analysis, the MUSIC method's performance characteristics have been found to be superior to the Minimum-Norm method [3].

In Fig. 6, ophthalmic artery flow sonograms recorded from an unhealthy subject having ophthalmic artery stenosis are given. Ophthalmic arterial Doppler sonogram in Fig. 6(a) is obtained using the STFT, in Fig. 6(b) using the WT. As is seen from Fig. 6, there is a distinct qualitative improvement in the sonograms obtained using the WT over the STFT. In the STFT analysis, taking the FFT of a short data frame of the Doppler signal leads to a distortion of the spectral estimate and leakage of signal energy into spurious side lobes due to the sharp truncation of the signal. Therefore, the STFT sonograms have spurious

frequencies and the STFT does not produce clear sonograms. The advantage of the WT over the STFT is the optimization of the time-frequency resolution [5].

Signal processing and wavelet toolboxes of MATLAB

Command windows of MATLAB taken from students' projects related to the acquisition of Doppler power spectra and sonograms are presented in Figs 7 and 8. The signal processing toolbox functions are algorithms, expressed mostly in M-files, that implement a variety of signal processing tasks. These toolbox functions are specialized extension of the MATLAB computational and graphical environment [14]. The selected functions in MATLAB's signal processing toolbox are listed in Table 1. The students can read the explanations of the listed functions and can obtain the spectra and sonograms of their own signals. The listed functions can be used in order to perform application of the signal analysis methods mentioned above to biomedical signals. The performance characteristics of the signal analysis methods can vary according to the signal under study. In this paper, we emphasized the superiority of the AR, ARMA methods among the model-based methods, the superiority of the MUSIC method among the eigenvector methods and the superiority of the WT among the time-frequency methods for the Doppler ultrasound blood flow signals.

The signal processing toolbox is a collection of tools built on the MATLAB numeric computing environment. The toolbox supports a wide range of signal processing operations, from waveform generation to filter design and implementation, parametric modelling, and spectral analysis. The toolbox provides two categories of tools.

Command line functions in the following categories:

- Analogue and digital filter analysis;
- Digital filter implementation;

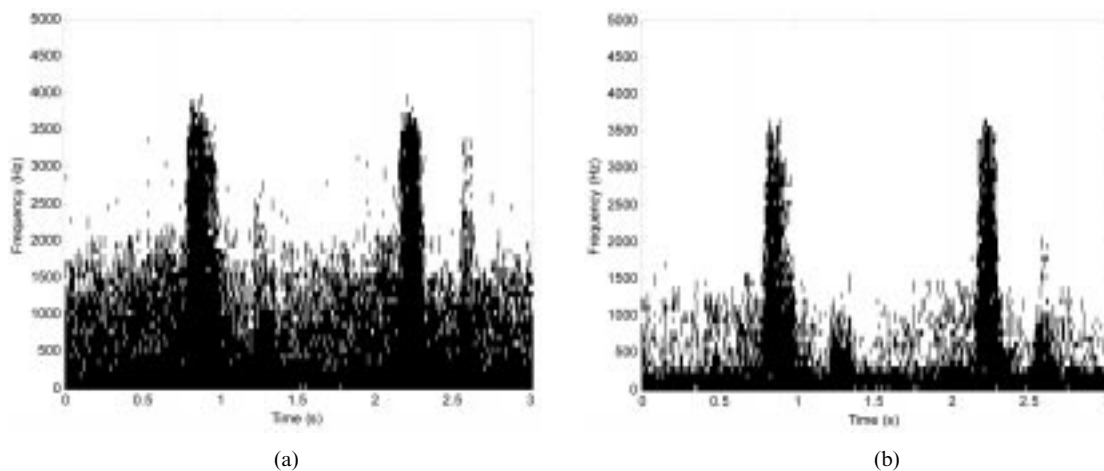


Fig. 6. Ophthalmic arterial Doppler sonograms recorded from an unhealthy subject having ophthalmic artery stenosis: (a) STFT, (b) WT

- FIR and IIR digital filter design;
- Analogue filter design;
- Filter discretization;
- Spectral windows transforms;
- Cepstral analysis;
- Statistical signal processing and spectral analysis;
- Parametric modelling;
- Linear prediction;
- Waveform generation.

A suite of interactive graphical user interfaces for

- Filter design and analysis;
- Window design and analysis;
- Signal plotting and analysis;
- Spectral analysis;
- Filtering signals.

The wavelet toolbox is a collection of functions built on the MATLAB technical computing environment. It provides tools for the analysis and synthesis of signals and images, also tools for statistical applications, using wavelets and wavelet packets within the framework of MATLAB [15]. The selected functions that are available in MATLAB's wavelet toolbox are listed in Table 2.

The toolbox provides two categories of tools:

- Command line functions;
- Graphical interactive tools.

The first category of tools is made up of functions that you can call directly from the command line

or from your own applications. Most of these functions are M-files, series of statements that implement specialized wavelet analysis or synthesis algorithms. The second category is a collection of graphical interface tools that afford access to extensive functionality. The wavelet toolbox provides a complete introduction to wavelets and assumes no previous knowledge. The toolbox allows you to use wavelet techniques on your own data immediately and develop new insights. You can change the way any toolbox function works by copying and renaming the M-file, then modifying your copy. You can also extend the toolbox by adding your own M-files.

EVALUATION AND ASSESSMENT

Student interaction with MATLAB toolboxes

To keep sustainable interest in the education process and with many students enrolling in colleges with some computer literacy, it is essential to reinforce the engineering education curriculum with computer-aided teaching tools that are interactive as well as educational [16]. At the beginning of the biomedical instrumentation course, the students receive a handout showing the key features of MATLAB software and how the signal processing and wavelet toolboxes work with the course material. The practicality of students using MATLAB functions is that they

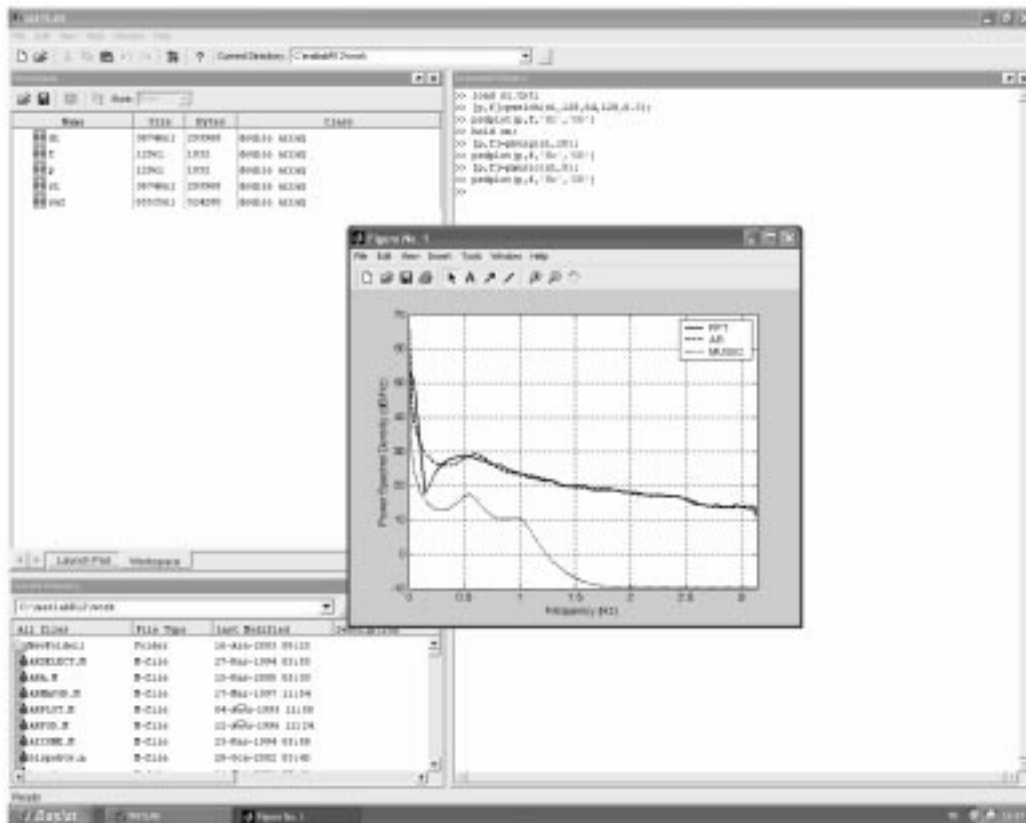


Fig. 7. Command window of MATLAB taken from students' project to obtain Doppler power spectra

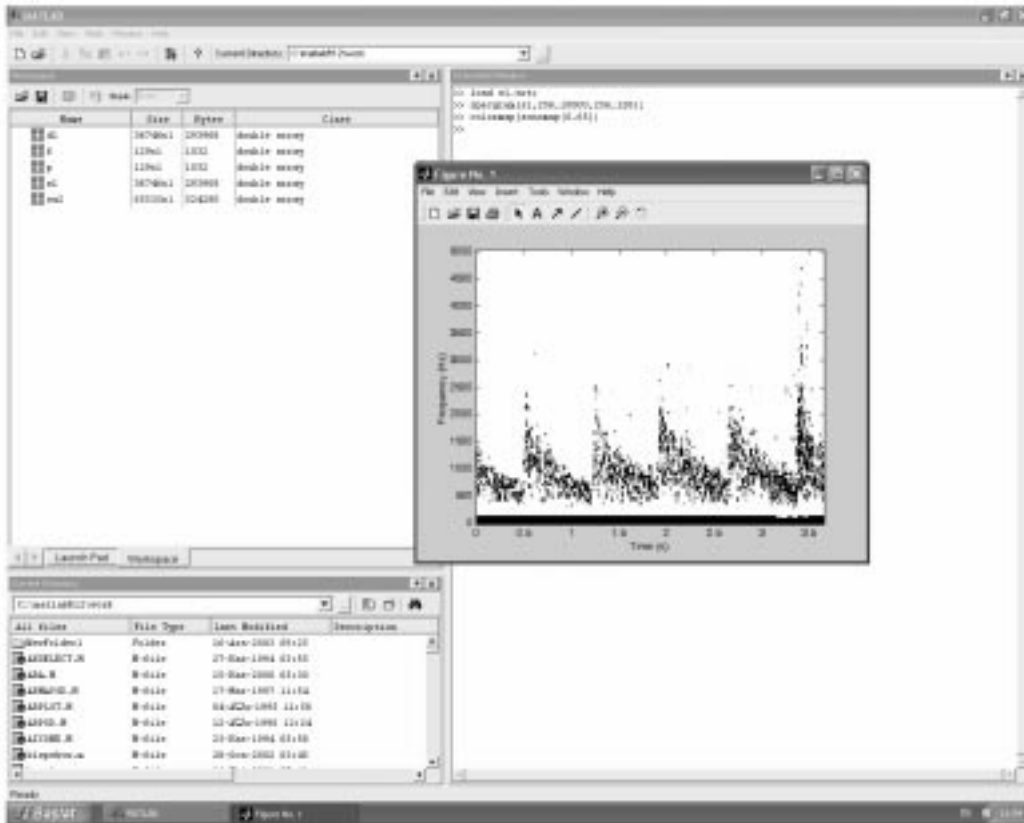


Fig. 8. Command window of MATLAB taken from students' project to obtain sonograms

will be able to develop their own functions by modifying MATLAB functions. The use of MATLAB functions in an interactive and easy way to analyse the Doppler blood flow signals (or signals under study) by the whole spectral analysis methods rather than one spectral analysis method will be more informative for the students. The examples stored for the students in the electronic handbook database of the course generate complete analysis of the whole spectral analysis methods allowing the students to examine the parameters and estimate the values of the parameters involved in the various methods.

There are several main benefits of computer-aided teaching as it relates to the distance-learning environment:

- Self-placed learning is available, suitable for all abilities.
- Graphics, animation and simulations are easily incorporated.
- Using hypertext, there can be many ways to access the same piece of information, with the caveat that some parts may never be accessed, and students may be left unsure whether they have covered all the necessary material.
- Computer-based testing can easily be integrated with a computer-aided teaching package, giving students instant feedback, either directed or undirected.

Table 1. Selected functions available in MATLAB's signal processing toolbox

Function	Explanation
pburg	Power Spectral Density Estimate via Burg's method
pcov	Power Spectral Density Estimate via the Covariance method
peig	Power Spectral Density Estimate via the Eigenvector method
periodogram	Power Spectral Density Estimate via the periodogram method
pmcov	Power Spectral Density Estimate via the Modified Covariance method
pmusic	Power Spectral Density Estimate via the MUSIC method
pwelch	Power Spectral Density Estimate via Welch's method
pyulear	Power Spectral Density Estimate via the Yule-Walker AR method
arburg	AR parametric modeling via Burg's method
arcov	AR parametric modeling via covariance method
armcov	AR parametric modeling via modified covariance method
aryule	AR parametric modeling via the Yule-Walker method
specgram	Calculates spectrogram from signal
corrmtx	Autocorrelation matrix
sptool	Signal processing tool—Graphical user interface
fdatool	Filter design and analysis tool—Graphical user interface

Table 2. Selected functions available in MATLAB's wavelet toolbox

Function	Explanation
wmaxlev	Maximum wavelet decomposition level
wfilters	Wavelet filters
cwt	Real or Complex continuous wavelet coefficients 1-D
dwt	Single-level discrete 1-D wavelet transform
wavedec	Multi-level 1-D wavelet decomposition
waverec	Multi-level 1-D wavelet reconstruction
dwt2	Single-level discrete 2-D wavelet transform
wavedec2	Multi-level 2-D wavelet decomposition
waverec2	Multi-level 2-D wavelet reconstruction
waveinfo	Information on wavelets
wavedemo	Wavelet toolbox demonstrations

- On a more subtle level, computer-aided teaching offers relative freedom from discrimination because of physical characteristics which may arise in the traditional classroom. (It also provides a solution for those with physical disabilities for whom attending and navigating a university campus might prove too difficult.)

Student evaluation and grading

Grading in the class was initially based on quizzes (short answer, 15%), two midterm exams (one of them is open-book exam, 40%), final exam (40%) and final report (5%). All students are required to prepare a final report on a topic that is of particular interest to them. To discourage procrastination, sample topics and details regarding the report format are distributed with the class syllabus. Students are required to select their topic and identify several relevant references by midterm. The early literature search helps students determine the abundance or paucity of resources for their topic. Students must then meet the instructor to discuss their potential topic and obtain official approval. The full report, which is 10–15 text pages, is then due on the last day of class. The report is evaluated by the instructor in terms of content (60%), discussion with respect to class material (30%), spelling, grammar and length (5%). The remaining 5% of the project grade is based on the student's preparedness for the preliminary project meetings with the instructor. The same instructor taught all of the offerings of the

course and assigned the final grades for all of the students using essentially the same criteria. Consequently, it is felt that the potential variations in grades among offerings tend to even out, making the average grade for each group a reasonable metric for comparing their overall performance.

Course evaluation

To assess and evaluate the students' impressions of course structure, discussions were held with them and a brief questionnaire was developed for distribution and collection at the end of each session. The course evaluation form contains ten multiple choice questions and other comments of the students. The multiple choice questions are graded 1 to 5, with 5 indicating full agreement. A sample size of 30 students + 42 students was available over two years of the programme. Table 3 shows responses to the multiple choice questions, indicating that, in general, students find the experience a very positive one, with particular emphasis on the presentation quality, course navigation, MATLAB examples and the notes related to course contents. The main recommendation was the inclusion of more real-world applications and implementations of biomedical instruments. In general, the authors were very encouraged with the overall student reaction to the course, both in terms of formal evaluation and informal comments from students over the duration of the course. The authors believe that these results demonstrate that the course contents do enhance the students' understanding of spectral analysis of Doppler blood flow signals and that students recognize the importance of signal processing training and experience in their professional futures.

Future modifications

Usually, a course must be modified on a regular basis to stay current and to keep the interest of the students. Based on feedback from students, alumni and industry representatives, potential topics that may be added in the future include functional electrical stimulation (technology, status and applications), augmentative and alternative communication (assessment, current products and engineering opportunities). Finally, we determine several tools that provide data with which this

Table 3. Responses to multiple choice questions

Course aspect	Year 1 (30 students)	Year 2 (42 students)
Presentation quality	4.35	4.42
Ease of access to course notes	4.57	4.48
Ease of navigation through course	4.34	4.41
Usefulness of MATLAB examples	4.56	4.62
Usefulness of weekly summaries	4.05	4.23
Usefulness of quizzes	3.46	3.89
Giving opportunity to demonstrate individual initiative and creativity	4.53	4.25
Valuable to professional future	4.32	4.47
Recommending this course to other students	4.78	4.83
Sufficiency of examples	4.26	4.34

course and programme are evaluated. These tools include:

- 1) student performance (grades);
- 2) course portfolios;
- 3) student involvement in cooperative education and interdisciplinary programmes;
- 4) student research experience;
- 5) student preparation and matriculation into postgraduate studies;
- 6) student involvement in engineering honour societies and organizations;
- 7) student surveys;
- 8) industry and advisory boards.

Educational contribution

The main goal of the tool was the development of an educational platform allowing students to improve their knowledge about new trends in signal processing. A number of suggestions about the contribution to education were made. Several features have been taken into account:

- The students were asked to use the signal processing and wavelet toolboxes of MATLAB. They not only save time by calling these M-files but also have time to explore other practical issues. By analysing the functions of the toolboxes, students are given a good platform on which they can learn how to write their own optimized functions. From the feedback, students benefited most by working with these efficient programming templates.
- It was found that students who did well in the practical session also performed well during their open-book examination. The reason is obvious: these students have tried out and understood the process of modelling signals, and examination questions are normally based on these practical issues. Some questions also tested the students' creativity, that is ability to come up with a novel solution to a problem. The real benefit of open-book examinations is that they test the students' ability to solve a particular engineering problem in a real-life situation, not the facility with which they remember long equations, formulas, benchmarking tables, etc., as in the traditional closed-book examination.
- The system allows students to apply fundamental techniques for Doppler ultrasound blood flow signals. The main goal is to let students gain confidence before attempting to tackle more complex problems. These projects are

also open-ended, allowing students to broaden the assignment; good students will attempt these parts and gain extra bonus marks.

- Evidence from the feedback demonstrates that most students expressed their strong support and keenness in working on these projects. Some students who had a good project involvement experience stayed on for their graduate study.

CONCLUSION

A theoretical basis of signal processing methods was presented starting with the basic equations and performing applications of these methods to arterial Doppler signals. The signal processing methods were used to obtain the Doppler power spectra and sonograms which were given as illustrative examples. The intent of analysis of the Doppler ultrasound blood flow signals was to serve as an introduction to the use of the signal processing methods and thus motivate their teaching with the help of MATLAB in the classroom. We emphasized the performance characteristics of the signal processing methods (classical, model-based, eigenvector and time-frequency methods) for applications to the arterial Doppler signals. The drawn results can be helpful to the students.

However, analysing their own signals with various signal processing methods will be better because the performance characteristics of the methods can vary according to the signal under study. MATLAB was introduced in this concept because of its ease in building mathematical functions and its powerful graphical user interface for displaying the results. The students can undertake the projects related with signal processing as a part of their homework assignments, making it easy to visualize the intricacies and understand the relationship between the different parameters involved in the methods. We believe that the hands-on experiences allowed the undergraduate and/or graduate students to understand signal processing theory and applications better, particularly when they had the opportunity to hear and see real signals being processed and to observe the impact of mathematical operations on these signals. Our experience has shown that this teaching platform and methodology have clearly heightened student interest in the learning of signal processing methods and applications.

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