Stenosis Detection using Burg Method with Autoregressive Model for Hemodialysis Patients

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Received 1 May 2012; Accepted 13 Sep 2012; doi: 10.5405/jmbe.1173

Abstract

This paper proposes a signal processing method for the evaluation of arteriovenous (AV) shunt stenosis in hemodialysis patients. AV shunts are surgically created pathological fistulas that serve as access routes for hemodialysis. The distinct and periodic bruit of the vascular shunts is clearly audible over the access routes. Thus, a bruit spectral analysis can be a valuable noninvasive method for quantifying the severity of vascular stenosis. This study collected phonoangiographic data from thirty AV shunts obtained from an electronic stethoscope during pre- and post-percutaneous transluminal angioplasty (PTA) periods. An autoregressive (AR) model was applied to analyze the phonoangiographic signals. The AR model and a filter order of eight were chosen to estimate the characteristic frequency of the bruit. AR model results obtained from the analysis of the phonoangiographic data under the pre- and post-PTA conditions show significant changes in frequency and magnitude. Seven patients were enrolled for periodical follow-up analysis for AV shunts. The Burg AR model is used to find the characteristic frequency of phonoangiographic signals. Therefore, the variation of frequency and amplitude in power spectra analysis showed strong correlation with the severity of AV shunt stenosis.

Keywords: Arteriovenous (AV) shunt, Burg method, Phonoangiographic signal, Stenosis, Percutaneous transluminal angioplasty (PTA)

1. Introduction

Chronic kidney disease (CKD) is recognized as a major international public health problem with high morbidity and mortality [1]. CKD is an irreversible and progressive disease generally classified into five stages depending on the severity of the condition. Reports by the Department of Health indicate that Taiwan has the highest prevalence rate of end-stage renal disease (ESRD), estimated to be 2447 cases per million people [2]. Patients suffering from ESRD are usually treated with hemodialysis, peritoneal dialysis, or kidney transplant. Hemodialysis is the most common treatment choice for ESRD patients in Taiwan. Arteriovenous (AV) shunts, including fistulas and grafts, are surgically created pathological fistulas that serve as access routes for hemodialysis patients [3].

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The National Kidney Foundation Dialysis Outcomes Quality Initiative (NK-DOQI) guidelines stipulate mandatory regular monitoring and surveillance of vascular access function [3]. Clinical assessments are based on the physical examination on the AV shunt or using readily available information obtained during daily hemodialysis processes. These surveillance methods include intra-access blood flow monitoring, static dialysis venous pressure measurement, duplex ultrasound, and angiography [4]. When the vascular lumens are reduced by over 50% [5], percutaneous transluminal angioplasty (PTA) or surgical intervention is required to dilate the stenotic lesion or remove the intraluminal thrombus [6,7]. Although these surveillance methods provide a highly accurate analysis, most of them require specialized equipment or experienced staff, are time-consuming, and are unsuitable for the early detection of disease or home application.

Phonoangiography is the recording and analysis of arterial bruits to estimate the extent of arterial stenosis. It is a noninvasive method used to investigate local fluid motion in narrowed arteries and to assess arterial dysfunction [4,8,9].
Doyle et al. proposed using digital spectral analysis to detect hemodialysis vascular access stenosis [10] utilizing a computer-based bruit monitor as an easy-to-use, economical, and effective transducer device. In earlier studies, the power spectrum of diastolic heart sounds was estimated using the fast Fourier transform (FFT) method. The Fourier transform is a traditional mathematical method used to convert time-domain signals into frequency components [11]. Nonetheless, this method suffers from spectral leakage effects and cannot localize the observed frequency components in time. Numerous researchers have thus attempted to simplify the recording of biomedical signals from vascular access sites, and have developed algorithms capable of removing background noise and retaining the required features of the signals [8,9,12-16]. Akay et al. proposed a wavelet method to reduce background noise from diastolic heart sounds for the noninvasive detection of coronary artery disease. The wavelet method works as a mathematical microscope that can be used to examine different parts of the signal by adjusting the focus, offering both excellent time resolution at high frequencies and good frequency resolution at low frequencies [12]. Previous studies have found an increase in the high-frequency energy (300 Hz to 800 Hz) as the severity of AV shunt stenosis. However, when the obstruction (with > 95% occlusion) is too severe, sounds may not be produced because of low blood flow. Therefore, as an alternative method for the noninvasive acoustical detection of coronary artery disease, Akay et al. presented an autoregressive (AR) model, which track changes in signal characteristics without prior knowledge [9]. Based on the results obtained from the wavelet method, Vasquez [8] and Gram [14] developed algorithms for the reliable detection of stenosis in hemodialysis patients with AV shunts. Their findings show a significant redistribution of energy content, specifically at frequency ranges of 625-750 Hz and 875-1000 Hz [14], occurring with the development of stenosis.

The above-mentioned methods, such as the Fourier transform and wavelet analysis, give promising results for the evaluation of AV shunt stenosis. The Fourier transform is a non-parametric method for estimating the power spectra. However, it is not an optimal method because it suffers from spectral leakage effects due to the sampling window. Wavelet analysis is a parametric method that provides better time-frequency resolution than non-parametric methods. However, significant frequencies are extracted at specific wavelet coefficients with different types of wavelets and sampling frequency through trial procedures of wavelet decomposition [17]. Therefore, the Burg AR method is a parametric method for time-domain and frequency-domain signal processing. It can smooth spectra in comparison with frequency-based methods to find the characteristic frequencies by fitting an AR model of a given order [17]. To assess the AV shunt in patients undergoing PTA, this study adopts the AR model. An AV shunt stenosis detector was applied to estimate the frequency spectrum characteristics and to compare the spectral energy distributions. In addition, the longitudinal functional performance of AV shunts was measured using power spectral density (PSD) analysis during the regular follow-up period.

This study develops an AR-modeling-based detection method to evaluate the severity of stenosis in AV shunts.

2. Materials and methods

2.1 AV shunt stenosis detector

2.1.1 Experimental setup

This study recruited 30 patients with AV shunts who were eligible for PTA and consented to undergo a noninvasive examination. Seven patients agreed to participate in the follow-up program and allowed further data collection based on monthly follow-up reports. The Institutional Review Board of National Cheng Kung University Hospital (ER-99-186) approved this study. The phonoangiographic signals in AV shunts were acquired using an electronic stethoscope (Littmann 4100, 3M, USA) with a sampling rate of 4000 Hz. Auscultations were performed with a digital stethoscope at four recording sites, namely the arterial anastomosis site (A-site), arterial puncture site, vein puncture site, and venous anastomosis site (V-site). The AV shunt stenosis detector was used to track changes in the recorded signal. The block diagram in Fig. 1 shows the process of bruit recording and data acquisition, the frequency spectrum estimation obtained using the Burg method, the AR frequency spectrum comparison before and after PTA, and the estimation of the AV shunt stenosis.

![Diagram](image-url)

**Figure 1.** Block diagram of proposed AV shunt stenosis detector.

2.1.2 Signal preprocessing

After the bruit was obtained, the digital stethoscope continued to record for 8 seconds at each measurement site. Before the envelope of the phonoangiographic signals was calculated, a high-pass filter with a cut-off frequency of 25 Hz
was used to remove the baseline wander and then a low-pass filter with a cut-off frequency of 200 Hz was used. The envelope of the signal was calculated using the Hilbert transform and filtered with a 5-Hz low-pass filter. The durations of the data window were determined using the basic command-line function for finding valleys and the envelope of the periodic phonoangiographic signals was obtained as shown in Fig. 2(a). The frequency spectra were normalized between 0 and 1, as shown in Fig. 2(b). Therefore, the characteristic frequencies of various sound can be found easily in the frequency spectra.

![Graph](image_url)

**Figure 2.** (a) Segmentation of wave at two minimum points. (b) Characteristic frequency spectra obtained using Burg method with AR model.

### 2.2 Autoregressive model for frequency spectrum analysis

A turbulent blood flow is expected to cause an audible bruit and to generate high-frequency signals at the stenosis site [8]. The frequency spectrum changes depend on the location and severity of stenosis. The frequency spectra were estimated using the power spectrum method, as shown in Fig. 3(a). However, it is difficult to detect and identify the main characteristic frequencies using spectral leakage. Due to the involvement of additional spectra, the peak amplitudes in the main spectra are lower than the theoretical values. The Burg method with an AR model can smooth frequency spectra and is susceptible to frequency shifts. Thus, the Burg AR method is used here to find the characteristic frequencies of phonoangiographic signals. Depending on frequency-based parameters, the method provides key information for the evaluation of AV shunt stenosis in hemodialysis patients.

![Graph](image_url)

**Figure 3.** (a) Frequency content of murmurs determined using Burg algorithm. (b) Variation of normalized residual energy as function of model order for each murmur. (c) Spectrum obtained with final prediction criterion criterion for AR model with order of 8 for one patient.

The AR parameters can be determined from the solution of a set of linear equations [13]. Each signal sample is represented by a linear combination of the previous samples and residual values $r(n)$, which are assumed to be independent of the previous samples [2,8]. With a discrete set of $N$ sampling points, $K$ coefficients are used to approximate the original data of $x(n)$, where $n=1, 2, 3, \ldots, N$, presented as:

$$x(n) = \sum_{k=0}^{K} a_k x(n-k) + r(n)$$

(1)

where $x(n)$ represents the estimated frequency spectrum of a phonoangiographic signal in this study, $K$ is the AR model order, $k = 1, 2, 3, \ldots, K$, and $a_k$ represents the model coefficients of the AR model. The model coefficients are calculated by minimizing the total energy of the residual $E = \sum_{n=1}^{N} r(n)^2$.

The Burg algorithm is based on minimizing the total sum of the forward prediction errors $F_1$ and backward prediction errors $B_1$. Generally, the optimal parameters $a_k$ are chosen to minimize the squared error between the original and estimated data, whereas the forward and backward linear prediction equations attempt to minimize $F_1$ and $B_1$. Defining $a_0=1$ gives:

$$F_1 = \sum_{n=0}^{N} \left( a_0 x_n + \left( \sum_{i=1}^{K} a_i x_{n-i} \right) \right)^2 = \sum_{n=0}^{N} \left( \sum_{i=0}^{K} a_i x_{n-i} \right)^2 = \sum_{n=0}^{N} (f_k(n))^2$$

with

$$f_k(n) = \sum_{i=0}^{K} a_i x_{n-i}$$

(2)
where \( y_{kr} \) defined for \( n \in [k, N] \), is a linear weighted combination of the \( k \) previous known data, and \( z_{nk} \), defined for \( n \in [0, N-k] \), represents a linear weighted combination of the \( k \) next known data. The sum of residual energies in the stage \( k \) is \( E_k = F_k + B_k \). In the original Levinson-Durbin recursion, \( a_k \) defined for \( k \in [1, K] \), is stored in a vector \( A_k = [a_1 a_2 ... a_k ]^T \) and in an inverted vector \( V_1 = [0 \ a_k ... a_k \ a_1]^T \). Therefore, the recursion formula is \( A_k = A_{k-1} + \mu V_k \).

The Burg method adjusts the parameter \( \mu \) to minimize the sum of residual energies \( E_k \). The AR coefficients \( a_k \) can then be obtained from the parameter \( \mu \) using the Levinson-Durbin algorithm:

\[
a_k' = a_k + j \mu a_{k+1-k}
\]

where \( a_{k+1-k} \) is defined to be \( a_{k+1} \) and \( a_{k+1} \) is defined to be \( a_k \), \( k \in [1, K+1] \), can be calculated using optimization methods and gradient (steepest-descent) methods.

### 2.3 Determination of AR coefficients

Assuming that \( A_k \) has been found, Eqs. 2 and 3 are used to calculate \( \mu \). The residual energy \( E_{k+1} = F_{k+1} + B_{k+1} \) can be presented as:

\[
F_{k+1} + B_{k+1} = \sum_{n=0}^{N-k-1} (f_{k+1}(n))^2 + \sum_{n=0}^{N-k} (b_{k+1}(n))^2
\]

(4)

The optimal parameter \( \mu \) tends to minimize the residual energy \( E_{k+1} \). Finding when the derivative of \( \mu \) is zero helps to achieve this object. The first partial derivatives of residual energy \( E_{k+1} \) can be obtained as:

\[
\frac{\partial(E_{k+1})}{\partial \mu} = 0
\]

(5)

Finally, the parameter \( \mu \) can be computed as:

\[
\mu = -2 \sum_{n=0}^{N-k-1} f_k(n + k + 1)b_k(n)
\]

\[
\mu = \frac{\sum_{n=0}^{N-k-1} f_k(n)^2 + \sum_{n=0}^{N-k} b_k(n)^2}{\sum_{n=0}^{N-k-1} f_k(n)^2 \sum_{n=0}^{N-k} b_k(n)^2}
\]

(6)

The vector \( A_{k+1} \) and AR coefficients \( a_k' \) are updated using Eq. 6. Then, \( f_k(n) \) and \( b_k(n) \) are updated as follows:

\[
f_{k+1}(n) = f_k(n) + \mu \sum_{i=0}^{k+1} a_{k+1-k-x_{n-i} = f_k(n) + j \mu b_k(n-k-1)
\]

(7)

\[
b_{k+1}(n) = b_k(n) + \mu \sum_{i=0}^{k+1} a_{k+1-k-x_{n-i} = b_k(n) + j \mu f_k(n+k+1)
\]

(8)

If the sum of residual energies \( E_{k+1} \) is less than the pre-specified value, the algorithm is terminated under the convergence condition. The recursive formulas in Eqs. 4 and 6 can be used to achieve quicker and more efficient results.

This study uses the Burg AR method to estimate the characteristic frequencies of phonoangiographic signals. After the phonoangiographic signals are obtained, the segmentation algorithm is employed to obtain the period length as the time between two minimum values, as shown in Fig. 2(a). Each record has at least ten segments, with a time interval of 668.2 ± 16 ms, for the segmentation of the phonoangiographic signals. An AR model with optimal coefficients tends to estimate peak spectra. The PSD can be used to identify the characteristic frequencies and magnitudes. For instance, for a Burg AR method with model order \( P = 8 \), there are three peak spectra, defining the 1st, 2nd, and 3rd characteristic frequencies, respectively, as shown in Fig. 2(b). The three characteristic frequencies are 246.6 ± 7.1, 410.3 ± 9.9, and 645.8 ± 12.2 Hz, respectively. The peak spectra fall into different frequency bands. Reproducibility experiments show that these characteristic frequencies provide reliable and promising results for the evaluation of AV shunt stenosis.

### 3. Results and discussion

#### 3.1 Order determination in AR models

The study obtained 240 records from 30 hemodialysis patients. All patients provided four records before and four records after the PTA procedure at each marked site. Fourier-transform-based spectral estimation methods have some drawbacks, such as spectral leakage into sidelobes and characteristic spectral broadening, as shown in Fig. 3(a). In order to determine the characteristic frequency for the diagnosis of AV shunt stenosis, the Burg AR method is used to identify the characteristic frequencies. However, the accuracy, precision, and severity of stenosis for the evaluation of AV shunt stenosis depend on the selection of the AR model order. Generally, high-order models give reduced spectral broadening and better spectral estimates, but require more computation. Conversely, low-order models give poor spectral estimates, but require less computation. Therefore, a sufficiently high model order should be selected for good analysis [18]. To obtain reliable characteristic frequencies, the order determination in
3.2 Power spectral density pre- and post-PTA

Doppler ultrasound and angiograms are typically used to supervise the AV shunt in clinical assessments. The degree of stenosis (DOS) was used as an index to classify the AV shunt stenosis, and was determined by the narrowing percentage of the normal vessels. We classified residual DOS into three groups: Class I: DOS < 50%, Class II: 50% ≤ DOS < 70%, and Class III: DOS ≥ 70%. When the DOS is higher than 50%, patients are considered serious candidates for PTA [5]. A total of 30 patients referred for angioplasty were enrolled in this study. The DOS values for these patients varied from 81% to 99% before PTA, as measured from angiographic data. After PTA, the DOS values for these patients were evaluated from the final angiographic images. The degree of residual stenosis was found to range from 8% to 72%. Figures 4(a) and 4(b) show results for patients with high and low improvement rates, respectively. For a post-PTA residual DOS of lower than 40% (high improvement rates), the frequency spectrum distribution significantly fell and shifted to a lower frequency zone. As shown in Fig. 4(a), three characteristic frequencies that peaked at central frequencies of 177, 327 (main frequency), and 597 Hz before PTA shifted to 113 (main frequency), 324, and 638 Hz after PTA. The changes in frequency and amplitude depended on the severity of the stenosis. Conversely, with higher residual DOS post-PTA, as shown in Fig. 4(b), the frequency spectrum distribution remained nearly the same as that before PTA. The statistical analyses of frequency distributions and three groups of DOS were shown in Table 1.

<table>
<thead>
<tr>
<th>Degree of stenosis (DOS %)</th>
<th>Class I &lt; 50%</th>
<th>Class II 50% - 70%</th>
<th>Class III &gt; 70%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Characteristic frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st (Hz)</td>
<td>Mean 160</td>
<td>65</td>
<td>65</td>
</tr>
<tr>
<td></td>
<td>Min-max 100-230</td>
<td>0-120</td>
<td>0-120</td>
</tr>
<tr>
<td></td>
<td></td>
<td>195</td>
<td>195</td>
</tr>
<tr>
<td></td>
<td></td>
<td>130-260</td>
<td>130-260</td>
</tr>
<tr>
<td>2nd (Hz)</td>
<td>Mean 380</td>
<td>445</td>
<td>445</td>
</tr>
<tr>
<td></td>
<td>Min-max 320-450</td>
<td>250-370</td>
<td>250-370</td>
</tr>
<tr>
<td></td>
<td></td>
<td>390-500</td>
<td>390-500</td>
</tr>
<tr>
<td>3rd (Hz)</td>
<td>Mean 640</td>
<td>640</td>
<td>600-700</td>
</tr>
<tr>
<td></td>
<td>Min-max 550-720</td>
<td>550-720</td>
<td>730</td>
</tr>
<tr>
<td></td>
<td></td>
<td>650</td>
<td>680-800</td>
</tr>
</tbody>
</table>

Note: DOS = 1 - \( \frac{d^2}{D^2} \), where d is the diameter of the stenosis lesion and D is the diameter of a normal vessel.

phenomena were observed in 95% of the 120 samples. However, several factors possibly affected the results of this study. The stenotic lesions repeatedly experienced multiple PTA procedures, and could develop severe fibrosis and recoiled soon after PTA. Therefore, the characteristic frequencies were distributed in overlapping zones. For Class II and Class III
stenosis. In addition, a turbulent murmur at the anastomosed sites could interfere with the real stenotic bruit. An AV shunt with multiple stenosis sites or undetected stenosis could also affect the final results of the study.

3.3 Reproducibility tests using long-term examination

Seven patients were used to validate the reproducibility of frequency-based parameters for the evaluation of AV shunt stenosis. All of them were undergoing PTA procedures, and received the regular follow-up analysis for their AV graft functions. In this case, a 54 years old female patient had severe AV graft occlusion, Class III (DOS% = 92), received the PTA treatment. After the PTA, the spectrum M0 regards as reference level, as shown in Fig. 5. However, routine monitoring revealed an upward and rightward shift in the central frequencies of the spectral components. The first characteristic frequency shifted from 100 Hz (spectrum M1) to 185 Hz (spectrum M3). The power magnitudes of the 2nd and 3rd characteristic frequencies also gradually increased. When another severe occlusion was noted and after successful PTA, the central frequencies of three spectral components (spectrum M0') returned to reference levels. These findings show that long-term frequency spectrum variations can be used as an indicator for the severity of AV shunt stenosis.

4. Conclusion

Phonoangiographic signals obtained from an electronic stethoscope were used to determine the state of AV shunts. Analyzing bruit on a daily basis could provide good guidance for healthcare providers and patients in AV shunt maintenance. The AR model was applied in this study for AV shunt analysis. The Burg method with an AR model was developed to analyze the PSD of phonoangiographic signals. The method was then applied to 30 patients to detect changes of the central frequencies of the spectral components. To find long-term tendencies, seven patient cases were received regular follow-up analysis. This algorithm was demonstrated to be useful in estimating the longitudinal follow-up of AV shunts. In the future, the research team plans to further develop the AV shunt stenosis detector, develop an automatic diagnosis system based on multiple decision-making models, and provide patients with the ability to examine their AV shunts at home.

Acknowledgments

This study was supported, conducted, and completed by the Multidisciplinary Center of Excellence for Clinical Trials and Research at National Cheng Kung University Hospital. Additionally, this study was supported by Medical Device Innovation Center and Department of Biomedical Engineering, National Cheng Kung University.

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