A Rule-Based Decision-Making Diagnosis System to Evaluate Arteriovenous Shunt Stenosis for Hemodialysis Treatment of Patients Using Fuzzy Petri Nets

Wei-Ling Chen, Chung-Dann Kan, Chia-Hung Lin, and Tainsong Chen

Abstract—This paper proposes a rule-based decision-making diagnosis system to evaluate arteriovenous shunt (AVS) stenosis for long-term hemodialysis treatment of patients using fuzzy petri nets (FPNs). AVS stenoses are often associated with blood sounds, resulting from turbulent flow over the narrowed blood vessel. Phonoangiography provides a noninvasive technique to monitor the sounds of the AVS. Since the power spectra changes in frequency and amplitude with the degree of AVS stenosis, it is difficult to make a human-made decision to judge the degree using a combination of those variances. The Burg autoregressive (AR) method is used to estimate the frequency spectra of a phonoangiographic signal and identify the characteristic frequencies. A rule-based decision-making method, FPNs, is designed as a decision-making system to evaluate the degree of stenosis (DOS) in routine examinations. For 42 long-term follow-up patients, the examination results show the proposed diagnosis system has greater efficiency in evaluating AVS stenosis.

Index Terms—Arteriovenous shunt (AVS), Burg autoregressive (AR) method, degree of stenosis (DOS), fuzzy petri net (FPN), phonoangiography.

I. INTRODUCTION

End-stage renal disease (ESRD) is an irreversible disease with high rates of morbidity and mortality [1]. Patients suffering ESRD are treated with hemodialysis, peritoneal dialysis, or kidney transplant. Hemodialysis is one choice for ESPD patients, but arteriovenous shunt (AVS) occlusion and failure lead to thrombosis, resulting in repeated puncturing of the arteriovenous accesses and long-term use. Therefore, the interior of the vascular accesses can cause intimal hyperplasia and aneurysmal deformability. Any narrowing of the interior of the access increases the physical stress on the vascular wall and produces vibrations, turbulent flow, and high blood pressure [2]. A greater than 50% narrowing of the lumen diameter in the vascular access may result in a need for percutaneous transluminal angioplasty (PTA) or surgical intervention [3], [4].

In clinical evaluation, angiography (X-ray), Doppler ultrasound, intravascular ultrasound imaging, and phonoangiography (PCG) are used to detect the presence of a stenosis within these vascular accesses [5], [6]. Stationary instruments provide reliable techniques and high accuracy in clinical applications. However, they need to appreciate the operational principles and need extra learning for limitations by the patients themselves. They are not suitable for early detection or homecare applications by the patients themselves. Therefore, this paper proposes a noninvasive measurement, free of irradiation technique, and decision-making method to evaluate the DOS, purporting for screening the degree of AVS senosis.

As an early detection tool, phonoangiography provides a noninvasive technique to monitor the sounds of the AVS. In software applications, studies [7]–[10] have shown the stenosis produces higher frequency components in the frequency spectra, and spectral changes in frequency and magnitude. Frequency analysis methods, such as Fourier transform (FT) and wavelet transform (WT), used the frequency spectra of the phonoangiographic signals to determine the specific parameters for stenosis evaluation. However, traditional FT has spectral leakage effects and cannot localize the observed characteristic frequency because of the size of the sampling window. The wavelet method has both time and frequency resolutions to decompose the low- and high-frequency components using a trial procedure of wavelet decomposition. In hardware applications, an embedded system (ES) can be applied to design a portable diagnosis system, as shown in Fig. 1. The current technique uses a built-in digital signal processor (DSP) to support signal preprocessing and digital filters to obtain the frequency spectra. However, it lacks an automatic diagnosis function.

To overcome the above-mentioned limitations, the Burg method was used to estimate the frequency spectra by fitting an autoregressive (AR) model of a given specific AR order [10], [11]. It produces smoother spectra than the FT method and is used to find the characteristic frequencies. For DOS evaluation, artificial intelligence methods have been applied to evaluate the degree of AVS stenosis.
perform classification tasks, such as support vector machines (SVMs) and neural networks. They provide promising solutions, but the algorithms are not easy to implement in hardware, due to the need to assign many parameters and tune network parameters. The fuzzy petri net (FPN) [12]–[15] is a dynamic and marked graphical system, and extends to develop an algorithm to deal with fuzzy reasoning problems and multicriteria decision-making applications. It is used for representing fuzzy inference rules in the knowledge base system, and can perform fuzzy reasoning to evaluate the degree of specified proposition. The reasoning capability of FPN allows computers to perform reasoning in a more flexible manner and is easy to program into the ES and field-programmable gate array (FPGA) chip. For 42 long-term follow-up patients, the results show the proposed diagnosis system is more efficient in evaluating AVS stenosis.

II. EXPERIMENTAL SETUP AND METHOD DESCRIPTION

A. EXPERIMENTAL SETUP

Hemodialysis patients were chosen for clinical examination at the Department of Surgery, National Cheng Kung University Hospital (Tainan City, Taiwan). The Institutional Review Board (IRB, under contract number: ER-99-186) approved this study. The phonoangiographic signals in AVS were acquired using an electronic stethoscope (3M LITTLMANN 4100 Series, Minnesota, USA), with a sample rate of 4 kHz. Auscultations were performed with a digital stethoscope at four recording sites, including the arterial anastomosis site (A-site), arterial puncture site, vein puncture site, and venous anastomosis site (V-site, in AVG means after graft region, in AVF means leaving anastomosis at least 10 cm), as shown in Fig. 1.

The advantage of the electronic consumer stethoscope is its good ability to remove unwanted noises. Then, Hildbert transform and a 5 Hz low-pass digital filter smoothed phonoangiographic signals were utilized to find those peaks. The envelope of the periodic PCG signals was obtained, and the distribution of energy content with each envelope. The segmentation process was used to find the minimum value before and after the detected peaks [10]. Each signal segment could then be determined between continuous two minimum values in the time-domain, providing a reliable acquisition window to perform segmentation of the PCG signals. Before analyzing the envelope of each PCG signal, the high-pass filter with the cut-off frequency 25 Hz was implemented to remove the baseline wander and after that a low-pass filter with 200 Hz [10]. The spectral peaks of frequency spectra, the region of 25 to 800 Hz, can be identified and are normalized between zero and one by a Burg AR method.

B. Burg AR Method

The Burg AR method is applied to estimate the characteristic frequency spectra from each segment of the phonoangiographic signals. With a discrete set of t sampling points of the frequency spectrum from 0.0 kHz to 0.8 kHz, P coefficients were used to approximate the original data of $x_i$, where $i = 1, 2, 3, \ldots, n$, presented as [10], [11]

$$x_i = - \sum_{p=1}^{P} a_p x_{i-p} + r e s_i$$  \hspace{1cm} (1)

where $x_i$ represents the samples, $P$ is the AR model order, $p = 1, 2, 3, \ldots, P$, and $a_p$ stands for the model coefficients of the AR model.

This method uses the optimal parameters $a_p$ to minimize the square error between the original and the approximated data. Forward and backward linear prediction requires the minimization of $F_p$ and $B_p$, as [11]

$$F_p = \sum_{i=p}^{n} (x_i - w_i)^2 = \sum_{i=p}^{n} \left( a_0 x_i - \left( - \sum_{j=1}^{p} a_j x_{i-j} \right) \right)^2$$  \hspace{1cm} (2)

$$B_p = \sum_{i=p}^{n} (x_i - z_i)^2 = \sum_{i=0}^{n-p} \left( a_0 x_i - \left( - \sum_{j=1}^{p} a_j x_{i+j} \right) \right)^2$$  \hspace{1cm} (3)

where $w_i, i \in [p, n]$, is a linear weighted combination of $p$ previously known data, and $z_i, i \in [0, n-p]$, is a linear weighted combination of $p$ next known data. The sum of the residual energies at stage $p$ is $E_p = F_p + B_p$. The Levinson–Durbin recursion algorithm [10], [11] is used to minimize the sum of the residual energy (SORE), $E = \sum [r e s_i]^2 \leq \varepsilon$, for estimating the AR model coefficients. To obtain the suitable parameters, a final prediction error criterion (FPEC) is used to select the AR model orders and coefficients [10].

Narrowing of the lumen diameter required PTA to clear the residual thrombus and dilate the stenotic segment (site Trk – site Trk2), as shown in Fig. 2. An electric stethoscope can be used to record the PCG signals originating from the arteriovenous fistula (AVF) or arteriovenous graft (AVG). Using this information, the frequency spectra are estimated for stenosis evaluation. The frequency spectra are normalized between zero and one, as a
color bar in Fig. 3. So the characteristic frequencies of the PCG signals are easily found in the frequency spectra. The frequency spectra for AVS stenosis and the normal condition at the two sites are shown in Fig. 3(a) and (b), respectively. It can be seen the frequency components occupy different frequency bands. The frequency-domain parameters for these bands provide indices for detecting of AVS stenosis before PTA and after PTA.

C. Fuzzy Petri Net

A set of fuzzy IF–THEN rules is commonly used to represent linguistic inference rules. Let inference rule \( R = \{ R_1, R_2, R_3, \ldots, R_j, \ldots, R_J \} \), the form of the \( j \)th rules be presented as:

\[
\text{IF } f_j \text{ THEN } C \quad (\text{CF} = \mu_j)
\]

where \( f_j \) and \( C \) are propositions, each proposition is a real value, and \( \mu_j \) is the value of the certainty factor (CF), \( \mu_j \in [0,1] \). The CF can indicate the grade of membership of \( \mu_j \), \( j = 1, 2, 3, \ldots, J \), in the fuzzy set. A triangular membership function can be parameterized by a triplet \( (a_j, b_j, c_j) \), is defined by [14]:

\[
\mu_j = \begin{cases} 
0, & \text{for } f_j < a_j \\
\frac{f_j - a_j}{b_j - a_j}, & \text{for } a_j \leq f_j < a_j \\
1, & \text{for } f_j = a_j \\
\frac{b_j - f_j}{b_j - c_j}, & \text{for } a_j < f_j \leq b_j \\
0, & \text{for } f_j > b_j
\end{cases}
\]

The larger the value of \( \mu_j \), the more confidence is conformed.

We can use a FPN to represent the fuzzy IF–THEN rules of a rule-based system, as shown in Fig. 4(a). The FPN is a marked graphical system, containing two types: places (Pl) and transitions (Tr), where circle symbols represent places, and bar symbols represent transitions. Each transition is associated with a CF value between zero and one. In this study, the definition of the FPN is as follows [13]–[15]:

\[
\text{FPN} = (P_I, T_r, D, F, C, \mu, \theta, \beta, W)
\]

where \( P_I = \{ p_1, p_2, p_3, \ldots, p_M \} \) is a finite set of places, \( T_r = \{ t_1, t_2, t_3, \ldots, t_S \} \) is a finite set of transitions, \( D = \{ d_1, d_2, \ldots, d_S \} \) is a finite set of directed arcs, \( F = \{ \mu_1, \mu_2, \mu_3, \ldots, \mu_J \} \) is a finite set of CF values, \( C = \{ c_1, c_2, c_3, \ldots, c_S \} \) is a finite set of confidence factors, and \( \theta, \beta, W \) are additional attributes.
\[ C = \{ C_1, C_2, C_3, \ldots, C_K \} \]

where value \( p_m \), \( 0 \leq p_m \leq 1 \), can determine the output of function \( \theta_m \), and the larger value, the more likely output goal proposition will occur. Its solution list is monotone decreasing, and the degree can be divided into three levels: “very likely (VL),” “likely (L),” and “unlikely (UL).”

The rule-based FPNs database was collected from physical records at the National Cheng Kung University Hospital, Institutional Review Board (IRB), under contract number: ER-99-186 (Dr. C.-D. Kan). We used the long-term hemodialysis treatment of patients database to set up the FPNs. The next section will describe the implementation of the proposed diagnosis system.

### III. Diagnosis System Implementation

#### A. Preliminary Diagnosis and Classification

In clinical research, the degree of narrowing of the normal vessel is an index for the degree of AVS in patients, the so-called degree of stenosis (DOS). Examination results have confirmed the specific degrees from X-ray images or angiographic images. For a measurement segment Trk1–Trk2, as shown in Fig. 2(a), the definition is [4], [18]

\[ \text{DOS\%} = \left(1 - \frac{d^2}{D^2}\right) \times 100\% \]  

where \( D \) is the diameter of the normal graft or vessel in the direction of blood flow and \( d \) is the diameter of the stenosis lesion. The results of clinical experiences have been confirmed by professional physicians, including Class I: DOS\% < 50\%, Class II: 50\% < DOS\% < 70\%, and Class III: DOS\% > 70\% (DOS\% = 0%: no stenosis, DOS\% = 100%: total occlusion), as shown in Table I [10]. When the DOS is greater than 50\%, PTA or surgical intervention is required to dilate the stenotic lesion or remove the thrombus.

From our previous study [10], we determined the suitable AR model order to minimize the SORE using the FPEC. Generally, low AR orders result in poor spectral estimates, and high AR orders result in better spectral estimates, but increased computational tasks. For the convergent condition, we considered \( E \leq \varepsilon = 10^{-1} \) to stop the Burg AR algorithm. Considering the nonstationary nature of PCG signals, we could obtain the reliable frequency spectra using the AR order between 5 and 9 and could guarantee to reach the residual flatness. Therefore, the diagnosis system will be applicable for the other commercially available electronic stethoscopes. We suggest that the AR model
order \( P = 8 \) to construct the Burg AR method with prediction coefficients. The frequency spectra are estimated before PTA (pre-PTA) and after PTA (post-PA). The characteristic frequencies of the phononangiographic signals are easily found in the frequency spectra between 0 and 800 Hz. For the specific AR model order, there are three peaky spectra, defining the first, second, and third characteristic frequency. For 42 hemodialysis treatment patients, the peaky spectra fall into different frequency bands. Depending on these frequency bands and DOS%, frequency-base parameters provide key information for evaluating the degree of AVS stenosis, as shown in Table I.

### B. Design of FPN-Based Diagnosis System

According to Table I, a triangular membership function can be parameterized by a triplet (minimum value, mean value, maximum value) using (5), we have nine membership functions \( \mu_j, j = 1, 2, 3, \ldots, 9 \), with specific ranges \( f_j, j = 1, 2, 3, \ldots, 9 \), as shown Fig. 10 (a) in the Appendix. The CF of each input in the different ranges typically distributes in the universe of discourse \([0,1]\). In this study, the FPN can perform fuzzy inference to evaluate the degree of AVS stenosis of each proposition specified by the professional physician. Assume the degree of proposition \( C_k \) (Class I–Class III), \( k = 1, 2, 3 \), place \( p_m \) is associated with the proposition \( d_m = \theta_m(p_m), m = 1, 2, 3, \ldots, 13 \). The FPN performs min and max composite operations, the so-called “multivalued logic (Boolean rule of C. G. Looney [16])”, to generate the goal proposition \( C, C = \max\{C_1, C_2, C_3\} \). The rule connectivity matrix of FPN is shown, as seen Fig. 1 (b) in the Appendix. The algorithm is summarized as follows:

**Step 1)** IF \( f_j \) THEN \( t_j, C F = \mu_j, \) where \( t_j = \mu_j(f_j), j = 1, 2, 3, \ldots, 9 \).

**Step 2)** IF \( (\mu_1 \text{ and } \mu_2 \text{ and } \ldots \text{ and } \mu_j) \) THEN \( p_m, p_m = \min \{(\mu_1 \times \beta), (\mu_2 \times \beta), \ldots, (\mu_j \times \beta)\}, m = 1, 2, 3, \ldots, 13 \).

We have 13 AND operations in this step.

**Step 3)** Compute the proposition \( d_m = \theta_m(p_m), m = 1, 2, 3, \ldots, 13 \).

**Step 4)** IF \( (d_1 \text{ or } d_2 \text{ or } \ldots \text{ or } d_m) \) THEN \( C_k, C_k = \max \{(\theta_1(p_1) \times W, \theta_2(p_2) \times W, \ldots, \theta_m(p_m) \times W)\}, k = 1, 2, 3 \).

We have 3 OR operations in this step.

**Step 5)** Final output \( C = \lambda_k \times \max\{C_1, C_2, C_3\} \) where \( \lambda_1 = 1 \) for Class I, \( \lambda_2 = 2 \) for Class II, and \( \lambda_3 = 3 \) for Class III. The goal proposition \( C \) indicates the possible degree of AVS senosis and also subdivides into three levels “VL,” “L,” and “UL.” We have the following degrees: Class I (UL, L, VL), Class II (UL, L, VL), and Class III (UL, L, VL). The proposed diagnosis system is tested for diagnostic accuracy with long-term follow-up patients, as detailed in Section IV.

### IV. Experimental Results and Discussion

Using a digital stethoscope, the auscultation method was used to obtain the phononangiographic signals at the measurement sites, including the arterial anastomosis site (A-site) and the venous anastomosis site (V-site). The proposed diagnosis system with the Burg AR method and FPNs was developed on a PC AMD Athlon II x2 245 2.91 GHz with 1.75 GB RAM and MATLAB software. To demonstrate the effectiveness of the proposed model for detecting AVS senosis, 42 subjects were tested (IRB, under contract number: ER-99-186), the participants comprised 23 females and 19 males with a mean age of 63 ± 10.2 years (49–81 years). The AVS types included 22 AVGs and 20 AVFs to surgically connect the artery and vein. The participants’ mean duration of long-term hemodialysis therapy was 48 ± 31 months. Preliminary diagnosis results confirmed the specific degrees by ultrasonic image examination and professional physicians. Case studies of long-term hemodialysis patients were validated the proposed diagnosis system, as detailed below.

**A. Feasibility Tests with the Proposed Diagnosis System**

The study records from 42 subjects were divided into two groups, with 21 patients being used to design the rule-based decision-making diagnosis system. Using 42 testing data from other 21 patients, the overall testing results are shown in Fig. 6(a) and (b), comparison with the DOS%, the accuracy is 85.71% with six failures. The measurement sites, quantification errors, and undetected senosis could affect the efficiency of the
Compute the proposition \( \theta^{m} \), \( i = 1, 2, 3 \), \( j = 1, 2, 3 \), \( k = 1, 2, 3 \), \( l = 1, 2, 3 \), \( m = 1, 2, 3 \).

Perform AND operations with 13 combinations of triplet transitions, then place \( P \) = \([p_{1}, p_{2}, p_{3}, ..., p_{13}] = [0.0000, 0.0000, 0.4588, 0.0000, 0.0000, 0.3679, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.6154, 0.0000, 0.6364, 0.3800, 0.0167] \).

Perform OR operations with 13 combinations of three groups of places, then goal proposition \([C_{1}, C_{2}, C_{3}] = [0.3679, 0.5821, 0.5379] \).

The final output \( C \triangleq \lambda_{2} \times \max[0.3679, 0.5821, 0.5379] = 1.1641 \).

The final output is 1.1641, and place value \( p_{3} \) is near 0.4588, indicating the degree of truth of the goal proposition \( \text{"Class II (L: } p_{3} = 0.4588, C = 1.1641\text{"} } \). The FPNs also agree with the \( \text{"Class II"} \) degree. This confirms the FPNs based diagnosis system provides promising results for evaluating the degree of AVG stenosis.

Following multiple PTA treatment, the vessel developed severely fibrous soft tissue and sclerotic. An immediate elastic recoil can occur after PTA, graft thrombosis, or loss of the available graft puncture area, which contributing to blood flow resistance, so the 1st and 2nd characteristic frequencies shift to lower frequency components from 170 to 68 Hz and 425 to 303 Hz, respectively, and the 3rd characteristic frequency is 644 Hz. The proposed system has evaluated the \( \text{"Class II (VL: } \theta^{3}(f_{3}) \text{"} } \).

For example, a female hemodialysis patient, aged 54 years, AVG type (Right Forearm Loop), agreed to participate in a long-term examination and allowed further monthly data collection from observation from June 25, 2011, to July 11, 2012. In a routine monitoring cycle, a monthly examination was used to evaluate the AVG function. The first characteristic frequency also gradually increased from 68 to 170 Hz over three months of observation, as shown in Fig. 7. On September 6, 2011, the female patient had a severe AVG occlusion, and the professional physician confirmed the \( \text{"Class II"} \) using the ultrasonic image examination, the DOS\% = 66% was found at the measurement site, and received PTA treatment. The three characteristic frequencies were 170, 425, and 681 Hz. The diagnostic procedures of the FPNs are:

1. Compute the CFs of \( \mu_{j}(f_{j}) \), then transition \( T_{r} = \{t_{1}, t_{2}, t_{3}, ..., t_{6}\} = [0.0000, 0.3846, 0.4588, 0.0000, 0.6154, 0.0000, 0.6364, 0.3800, 0.0167] \).
2. Perform AND operations with 13 combinations of triplet transitions, then place \( P = [p_{1}, p_{2}, p_{3}, ..., p_{13}] = [0.0000, 0.0000, 0.4588, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.6154, 0.0000, 0.6364, 0.3800, 0.0167] \).
3. Compute the proposition \( D = [d_{1}, d_{2}, d_{3}, ..., d_{13}] = [\theta_{1}, \theta_{2}, \theta_{3}, ..., \theta_{13}] = [0.3679, 0.3679, 0.5821, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.5379, 0.3679, 0.3679] \).
4. Perform OR operations with 13 combinations of three groups of places, then goal proposition \([C_{1}, C_{2}, C_{3}] = [0.3679, 0.5821, 0.5379] \).
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B. Long-Term Examination: Monthly Examination

For example, a female hemodialysis patient, aged 54 years, AVG type (Right Forearm Loop), agreed to participate in a long-term examination and allowed further monthly data collection from observation from June 25, 2011, to July 11, 2012. In a routine monitoring cycle, a monthly examination was used to evaluate the AVG function. The first characteristic frequency also gradually increased from 68 to 170 Hz over three months of observation, as shown in Fig. 7. On September 6, 2011, the female patient had a severe AVG occlusion, and the professional physician confirmed the \( \text{"Class II"} \) using the ultrasonic image examination, the DOS\% = 66% was found at the measurement site, and received PTA treatment. The three characteristic frequencies were 170, 425, and 681 Hz. The diagnostic procedures of the FPNs are:

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2. Perform AND operations with 13 combinations of triplet transitions, then place \( P = [p_{1}, p_{2}, p_{3}, ..., p_{13}] = [0.0000, 0.0000, 0.4588, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.6154, 0.0000, 0.6364, 0.3800, 0.0167] \).
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4. Perform OR operations with 13 combinations of three groups of places, then goal proposition \([C_{1}, C_{2}, C_{3}] = [0.3679, 0.5821, 0.5379] \).
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CHEN et al.: RULE-BASED DECISION-MAKING DIAGNOSIS SYSTEM TO EVALUATE ARTERIOVENOUS SHUNT STENOSIS

Fig. 8. Ultrasonic image for stenosis AVG at measurement V site, date: November 2, 2011.

$P_1 = 0.8752, C = 1.7503$’’ degree on October 13, 2011. This examination provides a recommendation of increasing surveillance and confirming analysis. It can be seen the occlusion level will perhaps develop into the “Class III (UL)” degree. Further monthly examination using the ultrasonic image examination, on November 2, 2011, found DOS% = 89%, $d = 0.178$ cm and $D = 0.556$ cm, at the V site, as shown in Fig. 8.

In clinical applications, the following conditions indicate the patient needs to receive PTA treatment and surgical revision: 1) DOS% > 50% and more than one abnormalities, 2) intragraft blood flow (IBF) < 600 mL/min for AVF, 3) intragraft blood flow (IBF) < 400–500 mL/min for AVG, 4) venous segment static pressure ratio > 0.50, 5) arterial segment static pressure ratio > 0.75.

The aforementioned testing results have confirmed the proposed diagnosis system can also be used for early detection and monthly examination. Cooperating with the recommended clinical conditions, it provides a reliable and noninvasive method to monitor AVS conditions.

C. Performance Tests

Table II shows comparison performances using the proposed method and a SVM-based classifier [11]. Updating of network parameters was performed after the network topology had been decided. For a SVM topology 3-3-3, 42 sets of training data from input–output pairs (three characteristic frequencies—three classes) were used to train the SVM. The swarm-intelligence algorithm (SIA), as a particle swarm optimization (PSO) [21], is an evolutionary optimization technique, which provides more efficiency in solving multiple optimal solutions, high dimensionality, featuring nonlinearity, and nondifferentiability problems. The evolution computations of PSO technique were used to minimize the mean squared error function (MSEF), as shown in Fig. 9. It can be seen the solution list of the SVM based classifier is decreasing with less than 30 iteration training, and the slight improvement in the optimal parameters, $\gamma$, $\sigma$, and $b$, was obtained by increasing the number of iteration training and population sizes ($G = 10–40$). In addition, the SVM topology is slightly less than FPN (topology 9-13-3-1); however, it needs iteration computations for updating parameters. It also trains a classifier under the high-dimensional and complexity pattern space. Although the multilayer network provides promising solutions to perform classification tasks, but the
algorithm is difficult to implement in hardware devices. The proposed screening system provides a rule-based mechanism and automatic weighted fuzzy reasoning. Thus, it could overcome the complexity of adjustable mechanism design and shorten a design cycle.

D. Discussion

An ES is a computer system that can be designed to perform specific functions, including control, diagnosis applications, signal processing, etc. [22]–[24]. It contains processing cores, such as micro-controllers or DSP, and also contains analog and digital input/output (I/O), memory, and application specific integrated circuits (ASICs). An FPGA chip is a high-level ES that can be configured by engineers designers or customers. It has an array configuration of logical elements, which can be used to design any logical operation function to implement the given applications. The FPGA is also a programmable device, and has an inherent parallel and distributed configuration, allowing designers to execute multiple inputs and control loops simultaneously. Its development environment can simulate and verify the logic designs [25].

Under the ES development environment, we used four fundamental operations of arithmetic and logical reasoning to configure the combinational logics or ASICs, and then embed intelligent algorithms on the compact chip. The proposed diagnosis system provides rule-based configuration and automatic weighted fuzzy reasoning. A flexible and intelligent manner needs no iteration for updating system weights. Therefore, it can overcome the complex configuration design, and the prototype device can be implemented, tested, debugged, and modified as needed in a short design cycle. Of the current techniques, the graphical user interface for windows application has repro-grammability and flexibility to quickly develop a specific ASIC. The proposed FPNs’ algorithm can be implemented using four fundamental operations with specific storage data. In addition, an exponent function, as (7), can be expanded into a Maclaurin series as

\[
\exp(1-p_m))^{-1} \approx \left[ \sum_{n=0}^{\infty} \frac{(\Delta)^n}{n!} \right]^{-1}
\]

\[
\cong [1 + (\Delta) + \frac{1}{2!}(\Delta)^2 + \frac{1}{3!}(\Delta)^3 + \cdots + \frac{1}{(Z)!}(\Delta)^Z]^{-1}
\]

\[
\cong [1 + z_0(\Delta) + z_1(\Delta)^2 + z_2(\Delta)^3 + \cdots + z_S(\Delta)^Z]^{-1}
\]

where \(\Delta = (1-p_m)\), series coefficient \(z_s, s = 0, 1, 2, 3, \ldots, S\), is the number of series term, and series coefficient are constant values. The series term verified the expanded function accuracy, and \(S = 6\) was recommended. The special equation can be computed with multiplication, addition, and division. Related constant data can be computed and stored in the memory elements. The accuracies of the expanded function have been verified, as follows:

1) \(\text{VL: } \exp(-0.0) = [1.0 + 0.0 + \frac{1}{2!}(0.0)^2 + \cdots + \frac{1}{6!}(0.0)^6]^{-1} = 1.0000\)
2) \(\text{L: } \exp(-0.5) = [1.0 + 0.5 + \frac{1}{2!}(0.5)^2 + \cdots + \frac{1}{6!}(0.5)^6]^{-1} \approx 0.6065\)
3) \(\text{UL: } \exp(-1.0) = [1.0 + 1.0 + \frac{1}{2!}(1.0)^2 + \cdots + \frac{1}{6!}(1.0)^6]^{-1} \approx 0.3679\)

The proposed ES within the FPGA chip. Therefore, designers can quickly develop a specific ES within the FPGA chip.

V. CONCLUSION

According to reports from the Department of Health (DOH), the rate of ESRD in Taiwan is 2447 per million. ESRD is an irreversible and progressive chronic disease. More than 66,000 people need to receive the hemodialysis treatment, and this number is increasing year by year. For long-term use, AVF or AVG accesses must be punctured every two days. Maintenance of proper function at IBF 600–2000 mL/min is the most important issue for ESRD patients. This study has provided a flexible, intelligent, and FPGA chip design method to develop a portable early detection medical device. With noninvasive phonoangiographic signals, the Burg AR method was used to estimate the characteristic frequency spectra, including the first, second, and third characteristic frequencies. To observe three main characteristic frequencies, it provides information to evaluate the degree of AVS stenosis. Then, we implemented the human diagnosis work to present a fuzzy inference algorithm for a rule-based system using FPNNs, and the degree subdivides into nine scales to survey the occlusion levels. We also used some case studies to verify the feasibility of the proposed diagnosis system. Under advanced ES techniques, an automatic diagnosis system could be easy to implement for hemodialysis patients needs.
Fig. 10. (a) FPNs based diagnosis system for evaluating AVS stenosis. (b) Rule connectivity matrix of FPN.
Fig. 11. ASIC configurations of triangular membership function, exponent function, and FPNs.

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REFERENCES


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Q1. Author: Figures A and B appearing in the Appendix have been renumbered as Figs 10 and 11, respectively, to maintain the sequential order. Please check.

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A Rule-Based Decision-Making Diagnosis System to Evaluate Arteriovenous Shunt Stenosis for Hemodialysis Treatment of Patients Using Fuzzy Petri Nets

Wei-Ling Chen, Chung-Dann Kan, Chia-Hung Lin, and Tainsong Chen

Abstract—This paper proposes a rule-based decision-making diagnosis system to evaluate arteriovenous shunt (AVS) stenosis for long-term hemodialysis treatment of patients using fuzzy petri nets (FPNs). AVS stenoses are often associated with blood sounds, resulting from turbulent flow over the narrowed blood vessel. Phonoangiography provides a noninvasive technique to monitor the sounds of the AVS. Since the power spectra changes in frequency and amplitude with the degree of AVS stenosis, it is difficult to make a human-made decision to judge the degree using a combination of those variances. The Burg autoregressive (AR) method is used to estimate the frequency spectra of a phonoangiographic signal and identify the characteristic frequencies. A rule-based decision-making method, FPNs, is designed as a decision-making system to evaluate the degree of stenosis (DOS) in routine examinations. For 42 long-term follow-up patients, the examination results show the proposed diagnosis system has greater efficiency in evaluating AVS stenosis.

Index Terms—Arteriovenous shunt (AVS), Burg autoregressive (AR) method, degree of stenosis (DOS), fuzzy petri net (FPN), phonoangiography.

I. INTRODUCTION

END-STAGE renal disease (ESRD) is an irreversible disease with high rates of morbidity and mortality [1]. Patients suffering ESRD are treated with hemodialysis, peritoneal dialysis, or kidney transplant. Hemodialysis is one choice for ESPD patients, but arteriovenous shunt (AVS) occlusion and failure lead to thrombosis, resulting in repeated puncturing of the arteriovenous accesses and long-term use. Therefore, the interior of the vascular accesses can cause intimal hyperplasia and aneurysmal deformability. Any narrowing of the interior of the access increases the physical stress on the vascular wall and produces vibrations, turbulent flow, and high blood pressure [2]. A greater than 50% narrowing of the lumen diameter in the vascular access may result in a need for percutaneous transluminal angioplasty (PTA) or surgical intervention [3], [4].

In clinical evaluation, angiography (X-ray), Doppler ultrasound, intravascular ultrasound imaging, and phonoangiography (PCG) are used to detect the presence of a stenosis within these vascular accesses [5], [6]. Stationary instruments provide reliable techniques and high accuracy in clinical applications. However, they need to appreciate the operational principles, and need extra learning for limitations by the patients themselves. They are not suitable for early detection or homecare applications by the patients themselves. Therefore, this paper proposes a noninvasive measurement, free of irradiation technique, and decision-making method to evaluate the DOS, purporting for screening the degree of AVS senosis.

As an early detection tool, phonoangiography provides a noninvasive technique to monitor the sounds of the AVS. In software applications, studies [7]–[10] have shown the stenosis produces higher frequency components in the frequency spectra, and spectral changes in frequency and magnitude. Frequency analysis methods, such as Fourier transform (FT) and wavelet transform (WT), used the frequency spectra of the phonoangiographic signals to determine the specific parameters for stenosis evaluation. However, traditional FT has spectral leakage effects and cannot localize the observed characteristic frequency because of the size of the sampling window. The wavelet method has both time and frequency resolutions to decompose the low- and high-frequency components using a trial procedure of wavelet decomposition. In hardware applications, an embedded system (ES) can be applied to design a portable diagnosis system, as shown in Fig. 1. The current technique uses a built-in digital signal processor (DSP) to support signal preprocessing and digital filters to obtain the frequency spectra. However, it lacks an automatic diagnosis function.

To overcome the above-mentioned limitations, the Burg method was used to estimate the frequency spectra by fitting an autoregressive (AR) model of a given specific AR order [10], [11]. It produces smoother spectra than the FT method and is used to find the characteristic frequencies. For DOS evaluation, artificial intelligence methods have been applied to
perform classification tasks, such as support vector machines (SVMs) and neural networks. They provide promising solutions, but the algorithms are not easy to implement in hardware, due to the need to assign many parameters and tune network parameters. The fuzzy petri net (FPN) [12]–[15] is a dynamic and marked graphical system, and extends to develop an algorithm to deal with fuzzy reasoning problems and multicriteria decision-making applications. It is used for representing fuzzy inference rules in the knowledge base system, and can perform fuzzy reasoning to evaluate the degree of specified proposition. The reasoning capability of FPN allows computers to perform reasoning in a more flexible manner and is easy to program into the ES and field-programmable gate array (FPGA) chip. For 42 long-term follow-up patients, the results show the proposed diagnosis system is more efficient in evaluating AVS stenosis.

II. EXPERIMENTAL SETUP AND METHOD DESCRIPTION

A. Experimental Setup

Hemodialysis patients were chosen for clinical examination at the Department of Surgery, National Cheng Kung University Hospital (Tainan City, Taiwan). The Institutional Review Board (IRB, under contract number: ER-99-186) approved this study. The phonoangiographic signals in AVS were acquired using an electronic stethoscope (3M LITTMANN 4100 Series, Minnesota, USA), with a sample rate of 4 kHz. Auscultations were performed with a digital stethoscope at four recording sites, including the arterial anastomosis site (A-site), arterial puncture site, vein puncture site, and venous anastomosis site (V-site, in AVG means after graft region, in AVF means leaving anastomosis at least 10 cm), as shown in Fig. 1.

The advantage of the electronic consumer stethoscope is its good ability to remove unwanted noises. Then, Hilbert transform and a 5 Hz low-pass digital filter smoothed phonoangiographic signals were utilized to find those peaks. The envelope of the periodic PCG signals was obtained, and the distribution of energy content with each envelope. The segmentation process was used to find the minimum value before and after the detected peaks [10]. Each signal segment could then be determined between continuous two minimum values in the time-domain, providing a reliable acquisition window to perform segmentation of the PCG signals. Before analyzing the envelope of each PCG signal, the high-pass filter with the cut-off frequency 25 Hz was implemented to remove the baseline wander and after that a low-pass filter with 200 Hz [10]. The spectral peaks of frequency spectra, the region of 25 to 800 Hz, can be identified and are normalized between zero and one by a Burg AR method.

B. Burg AR Method

The Burg AR method is applied to estimate the characteristic frequency spectra from each segment of the phonoangiographic signals. With a discrete set of sampling points of the frequency spectrum from 0.0 kHz to 0.8 kHz, $P$ coefficients were used to approximate the original data of $x_i$, where $i = 1, 2, 3, \ldots, n$, presented as [10], [11]

$$x_i = -\sum_{p=1}^{P} a_px_{i-p} + res_i$$

where $x_i$ represents the samples, $P$ is the AR model order, $p = 1, 2, 3, \ldots, P$, and $a_p$ stands for the model coefficients of the AR model.

Forward and backward linear prediction requires the minimization of $F_p$ and $B_p$, as [11]

$$F_p = \sum_{i=p}^{n} (x_i - w_i)^2$$

$$= \sum_{i=p}^{n} (f_p(i))^2$$

$$B_p = \sum_{i=0}^{n-p} (x_i - z_i)^2$$

$$= \sum_{i=0}^{n-p} (b_p(i))^2$$

where $w_i, i \in [p, n]$, is a linear weighted combination of $p$ previously known data, and $z_i, i \in [0, n-p]$, is a linear weighted combination of $p$ next known data. The sum of the residual energies at stage $p$ is $E_p = F_p + B_p$. The Levinson–Durbin recursion algorithm [10], [11] is used to minimize the sum of the residual energy (SOE), $E = \sum [res_i]^2 \leq \varepsilon$, for estimating the AR model coefficients. To obtain the suitable parameters, a final prediction error criterion (FPEC) is used to select the AR model orders and coefficients [10].

Narrowing of the lumen diameter required PTA to clear the residual thrombus and dilate the stenotic segment (site Trk – site Trk2), as shown in Fig. 2. An electric stethoscope can be used to record the PCG signals originating from the arteriovenous fistula (AVF) or arteriovenous graft (AVG). Using this information, the frequency spectra are estimated for stenosis evaluation. The frequency spectra are normalized between zero and one, as a
CHEN et al.: RULE-BASED DECISION-MAKING DIAGNOSIS SYSTEM TO EVALUATE ARTERIOVENOUS SHUNT STENOSIS

Fig. 2. (a) X-ray image for abnormality in blood vessel (near the wrist) and (b) X-ray image for PTA.

Fig. 3. (a) Frequency spectra of before PTA at sites Trk1 and Trk2. (b) Frequency spectra after PTA at sites Trk1 and Trk2.

Color bar in Fig. 3. So the characteristic frequencies of the PCG signals are easily found in the frequency spectra. The frequency spectra for AVS stenosis and the normal condition at the two sites are shown in Fig. 3(a) and (b), respectively. It can be seen the frequency components occupy different frequency bands. The frequency-domain parameters for these bands provide indices for detecting of AVS stenosis before PTA and after PTA.

C. Fuzzy Petri Net

A set of fuzzy IF–THEN rules is commonly used to represent linguistic inference rules. Let inference rule $R = \{R_1, R_2, R_3, \ldots, R_J\}$, the form of the $j$th rules be presented as

$$\text{IF } f_j \text{ THEN } C (\text{CF} = \mu_j) \quad (4)$$

where $f_j$ and $C$ are propositions, each proposition is a real value, and $\mu_j$ is the value of the certainty factor (CF), $\mu_j \in [0, 1]$. The CF can indicate the grade of membership of $\mu_j$ $j = 1, 2, 3, \ldots, J$, in the fuzzy set. A triangular membership function can be parameterized by a triplet $(a_j, a_j, b_j)$, is defined by [14]

$$\mu_j = \begin{cases} 
0, & \text{for } f_j < a_j \\
\frac{f_j - a_j}{a_j - a_j}, & \text{for } a_j \leq f_j < a_j \\
1, & \text{for } f_j = a_j \\
\frac{b_j - f_j}{b_j - b_j}, & \text{for } a_j < f_j \leq b_j \\
0, & \text{for } f_j > b_j
\end{cases} \quad (5)$$

The larger the value of $\mu_j$, the more confidence is conformed.

We can use a FPN to represent the fuzzy IF–THEN rules of a rule-based system, as shown in Fig. 4(a). The FPN is a marked graphical system, containing two types: places (Pl) and transitions (Tr), where circle symbols represent places, and bar symbols represent transitions. Each transition is associated with a CF value between zero and one. In this study, the definition of the FPN is as follows [13]–[15]:

$$\text{FPN} = (\text{Pl}, \text{Tr}, D, F, C, \mu, \theta, \beta, W)$$

$$\text{Pl} \cap \text{Tr} \cap D = \emptyset \text{ and } |\text{Pl}| = |D| \quad (6)$$

where $\text{Pl} = \{p_1, p_2, p_3, \ldots, p_M\}$ is a finite set of places, $\text{Tr} = \{t_1, t_2, t_3, \ldots, t_S\}$ is a finite set of transitions, $D = \{d_1, d_2, \ldots, d_T\}$
\[ \theta W = \{ \theta_1, \theta_2, \theta_3, \ldots, \theta_B \} \]

\[ \mu = \{ \mu_1, \mu_2, \mu_3, \ldots, \mu_J \} \]

The graphical structure of FPN can be represented by a rule connectivity matrix. For an example of Fig. 4(a), the rule matrix is given by Fig. 4(b). In this study, inference functions contain “AND” and “OR” operators with min and max composite operators [16], [17] and can be divided into the following rule types:

1) IF \( f_j \) THEN \( t_j \), CF = \( \mu_j \), where \( t_j = \mu_j(f_j), j = 1, 2, 3, \ldots, J \).

2) IF \( (\mu_1 \). \( \mu_2 \) and \( \ldots \) and \( \mu_i \)) THEN \( p_m, p_m = \min\{ (\mu_1 \times \beta), (\mu_2 \times \beta), (\mu_3 \times \beta), \ldots, (\mu_J \times \beta) \}, m = 1, 2, 3, \ldots, M \).

3) IF \( (p_1 \) or \( p_2 \) or \( \ldots \) or \( p_m \)) THEN \( d_m, d_m = \max\{ \theta_1(p_1), (\theta_2(p_2), \ldots, \theta_m(p_m)), m = 1, 2, 3, \ldots, M \).

4) Final output \( C = \lambda_k \times \max\{ C_1, C_2, C_3, \ldots, C_K \} = \lambda_k \times \max\{ (d_1 \times W), (d_2 \times W), (d_3 \times W), \ldots, (d_K \times W) \} \).

where \( \lambda_k \) is a real number, \( k = 1, 2, 3, \ldots, K \), function \( \theta_m(p_m) \) is a nonlinear approximator, as shown in Fig. 5, and is defined by

\[ \theta_m = \exp(-(1 - p_m)), \quad 0 < \theta_m \leq 1 \]  

where value \( p_m \), \( 0 \leq p_m \leq 1 \), can determine the output of function \( \theta_m \), and the larger value, the more likely output goal proposition will occur. Its solution list is monotone decreasing, and the degree can be divided into three levels: “very likely (VL),” “likely (L),” and “unlikely (UL).” The rule-based FPNs database was collected from physical records at the National Cheng Kung University Hospital, Institutional Review Board (IRB), under contract number: ER-99-186 (Dr. C.-D. Kan). We used the long-term hemodialysis treatment of patients database to set up the FPNs. The next section will describe the implementation of the proposed diagnosis system.

### III. DIAGNOSIS SYSTEM IMPLEMENTATION

#### A. Preliminary Diagnosis and Classification

In clinical research, the degree of narrowing of the normal vessel is an index for the degree of AVS in patients, the so-called degree of stenosis (DOS). Examination results have confirmed the specific degrees from X-ray images or angiographic images. For a measurement segment Trk1–Trk2, as shown in Fig. 2(a), the definition is [4], [18]

\[ \text{DOS\%} = \left(1 - \frac{d^2}{D^2} \right) \times 100\% \]  

where \( D \) is the diameter of the normal graft or vessel in the direction of blood flow and \( d \) is the diameter of the stenosis lesion. The results of clinical experiences have been confirmed by professional physicians, including Class I: DOS\% < 50%, Class II: 50% < DOS\% < 70%, and Class III: DOS\% > 70% (DOS\% = 0%: no stenosis, DOS\% = 100%: total occlusion), as shown in Table I [10]. When the DOS is greater than 50%, PTA or surgical intervention is required to dilate the stenotic lesion or remove the thrombus.

From our previous study [10], we determined the suitable AR model order to minimize the SORF using the FPEC. Generally, low AR orders result in poor spectral estimates, and high AR orders result in better spectral estimates, but increased computational tasks. For the convergent condition, we considered \( E \leq 10^{-1} \) to stop the Burg AR algorithm. Considering the nonstationary nature of PCG signals, we could obtain the reliable frequency spectra using the AR order between 5 and 9 and could guarantee to reach the residual flatness. Therefore, the diagnosis system will be applicable for the other commercially available electronic stethoscopes. We suggest that the AR model...
order $P = 8$ to construct the Burg AR method with prediction coefficients. The frequency spectra are estimated before PTA (pre-PTA) and after PTA (post-PA). The characteristic frequencies of the phonoangiographic signals are easily found in the frequency spectra between 0 and 800 Hz. For the specific AR model order, there are three peaky spectra, defining the first, second, and third characteristic frequency. For 42 hemodialysis treatment patients, the peaky spectra fall into different frequency bands. Depending on these frequency bands and DOS%, frequency-base parameters provide key information for evaluating the degree of AVS stenosis, as shown in Table I.

### B. Design of FPN-Based Diagnosis System

According to Table I, a triangular membership function can be parameterized by a triplet (minimum value, mean value, maximum value) using (5), we have nine membership functions $\mu_j$, $j = 1, 2, 3, \ldots, 9$, with specific ranges $f_j$, $j = 1, 2, 3, \ldots, 9$, as shown Fig. 10 (a) in the Appendix. The CF of each input in the different ranges typically distributes in the universe of discourse $[0, 1]$. In this study, the FPN can perform fuzzy inference to evaluate the degree of AVS stenosis of each proposition specified by the professional physician. Assume the degree of proposition $C_k$ (Class I–Class III), $k = 1, 2, 3$, place $p_m$ is associated with the proposition $d_m = \theta_m(p_m)$, $m = 1, 2, 3, \ldots, 13$. The FPN performs min and max composite operations, the so-called “multivalued logic (Boolean rule of C. G. Looney [16])” to generate the goal proposition $C$.

$C = \max\{C_1, C_2, C_3\}$. The rule connectivity matrix of FPN is shown, as seen Fig. 1 (b) in the Appendix. The algorithm is summarized as follows:

**Step 1)** IF $f_j$ THEN $t_j$, CF $= \mu_j$, where $t_j = \mu_j(f_j)$, $j = 1, 2, 3, \ldots, 9$.

**Step 2)** IF ($\mu_1$ and $\mu_2$ and ... and $\mu_j$) THEN $p_m$, $p_m = \min\{(\mu_1 \times \beta), (\mu_2 \times \beta), \ldots, (\mu_j \times \beta)\}$, $m = 1, 2, 3, \ldots, 13$.

We have 13 AND operations in this step.

**Step 3)** Compute the proposition $d_m = \theta_m(p_m)$, $m = 1, 2, 3, \ldots, 13$.

**Step 4)** IF ($d_1$ or $d_2$ or ... or $d_m$) THEN $C_1$, $C_k = \max\{\theta_1(p_1) \times W, \theta_2(p_2) \times W, \ldots, \theta_m(p_m) \times W\}$, $k = 1, 2, 3$.

We have 3 OR operations in this step.

**Step 5)** Final output $C = \lambda_k \times \max\{C_1, C_2, C_3\}$, where $\lambda_1 = 1$ for Class I, $\lambda_2 = 2$ for Class II, and $\lambda_3 = 3$ for Class III. The goal proposition $C$ indicates the possible degree of AVS stenosis and also subdivides into three levels “VL,” “L,” and “UL.” We have the following degrees: Class I (UL, L, VL), Class II (UL, L, VL), and Class III (UL, L, VL). The proposed diagnosis system is tested for diagnostic accuracy with long-term follow-up patients, as detailed in Section IV.

### IV. Experimental Results and Discussion

Using a digital stethoscope, the auscultation method was used to obtain the phonoangiographic signals at the measurement sites, including the arterial anastomosis site (A-site) and the venous anastomosis site (V-site). The proposed diagnosis system with the Burg AR method and FPNs was developed on a PC AMD Athlon II x2 245 2.91 GHz with 1.75 GB RAM and MATLAB software. To demonstrate the effectiveness of the proposed model for detecting AVS stenosis, 42 subjects were tested (IRB, under contract number: ER-99-186), the participants comprised 23 females and 19 males with a mean age of 63 ± 10.2 years (49–81 years). The AVS types included 22 AVGs and 20 AVFs to surgically connect the artery and vein. The participants’ mean duration of long-term hemodialysis therapy was 48 ± 31 months. Preliminary diagnosis results confirmed the specific degrees by ultrasonic image examination and professional physicians. Case studies of long-term hemodialysis patients were validated the proposed diagnosis system, as detailed below.

### A. Feasibility Tests with the Proposed Diagnosis System

The study records from 42 subjects were divided into two groups, with 21 patients being used to design the rule-based decision-making diagnosis system. Using 42 testing data from other 21 patients, the overall testing results are shown in Fig. 6(a) and (b), comparison with the DOS%, the accuracy is 85.71% with six failures. The measurement sites, quantification errors, and undetected stenosis could affect the efficiency of the...
**IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 00, NO. 00, 2013**

### Perform AND operations with 13 combinations of three

- $p_{13}$ can determine the similarity level, and more likely closes to value 1, 2, or 3 for the goal proposition. If place $p_{13}$ is only partially similar, its value is less than 1 and gradually decays to 0. From these results, we observed the function of AVS could be evaluated by the proposed diagnosis system.

Due to variations in frequency spectra for different classes and even for patients, the characteristic frequencies occupy different frequency bands, and some characteristic frequencies are distributed into overlapping bands or crossing bands. The physicians decided on the final degree using a combination of the variances in frequency and magnitude. However, it required offline analysis to obtain diagnosis results. Traditional petri nets (PNs) used the constant transitions and constant weighted parameters ($\beta$ and $W$). It is difficult to deal with the varying frequency spectra. PNs were suitable to process binary data in truth–false decisions, on–off switching, and automatic control applications [19], [20]. Comparing the FPNs with PNs, the inference rules in the knowledge base of the rule-based system are both modeled. FPNs use the CFs of the fuzzy inference rules and the weights of the propositions using numerical and binary data and can automatically perform weighted fuzzy reasoning for varying spectra analysis. It allows the proposed rule-based diagnosis system to perform fuzzy inference in a flexible and intelligent manner.

#### B. Long-Term Examination: Monthly Examination

For example, a female hemodialysis patient, aged 54 years, AVG type (Right Forearm Loop), agreed to participate in a long-term examination and allowed further monthly data collection from observation from June 25, 2011, to July 11, 2012. In a routine monitoring cycle, a monthly examination was used to evaluate the AVG function. The first characteristic frequency also gradually increased from 68 to 170 Hz over three months of observation, as shown in Fig. 7. On September 6, 2011, the female patient had a severe AVG occlusion, and the professional physician confirmed the “Class II.” Using the ultrasonic image examination, the DOS% = 66% was found at the measurement site, and received PTA treatment. The three characteristic frequencies were 170, 425, and 681 Hz. The diagnostic procedures of the FPNs are:

**Step 1** Compute the CFs of $\mu_j(f_j)$, then transition $T_r = [t_1, t_2, t_3, \ldots, t_9] = [0.0000, 0.3846, 0.4588, 0.0000, 0.6154, 0.0000, 0.6364, 0.3800, 0.0167]$.

**Step 2** Perform AND operations with 13 combinations of triplet transitions, then place $Pl = [p_1, p_2, p_3, \ldots, p_{13}] = [0.0000, 0.0000, 0.4588, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000]$.

**Step 3** Compute the proposition $D = [d_1, d_2, d_3, \ldots, d_{13}] = [\theta_1, \theta_2, \theta_3, \ldots, \theta_{13}] = [0.3679, 0.3679, 0.5379, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679, 0.3679]$.

**Step 4** Perform OR operations with 13 combinations of three groups of places, then goal proposition $[C_1, C_2, C_3] = [0.3679, 0.5821, 0.5379]$.

**Step 5** Final output $C = \lambda_2 \times \max(0.3679, 0.5821, 0.5379) = 1.1641$.

The final output is 1.1641, and place value $p_3$ is near 0.4588, indicating the degree of truth of the goal proposition “Class II (L: $p_3 = 0.4588$, $C = 1.1641$).” The FPNs also agree with the “Class II” degree. This confirms the FPNs based diagnosis system provides promising results for evaluating the degree of AVS stenosis.

Following multiple PTA treatment, the vessel developed severely fibrous soft tissue and sclerotic. An immediate elastic recoil can occur after PTA, graft thrombosis, or loss of the available graft puncture area, which contributing to blood flow resistance, so the 1st and 2nd characteristic frequencies shift to lower frequency components from 170 to 68 Hz and 425 to 303 Hz, respectively, and the 3rd characteristic frequency is 644 Hz. The proposed system has evaluated the “Class II (VL:...
Fig. 8. Ultrasonic image for stenosis AVG at measurement V site, date: November 2, 2011.

$p_3 = 0.8752, C = 1.7503$” degree on October 13, 2011. This examination provides a recommendation of increasing surveillance and confirming analysis. It can be seen the occlusion level will perhaps develop into the “Class III (UL)” degree. Further monthly examination using the ultrasonic image examination, on November 2, 2011, found DOS% = 89%, d = 0.178 cm and $D = 0.556$ cm, at the V site, as shown in Fig. 8. In clinical applications, the following conditions indicate the patient needs to receive PTA treatment and surgical revision: 1) DOS% > 50% and more than one abnormalities, 2) intragraft blood flow (IBF) < 600 mL/min for AVF, 3) intragraft blood flow (IBF) < 400–500 mL/min for AVG, 4) venous segment static pressure ratio > 0.50, 5) arterial segment static pressure ratio > 0.75.

The aforementioned testing results have confirmed the proposed diagnosis system can also be used for early detection and monthly examination. Cooperating with the recommended clinical conditions, it provides a reliable and noninvasive method to monitor AVS conditions.

**C. Performance Tests**

Table II shows comparison performances using the proposed method and a SVM-based classifier [11]. Updating of network parameters was performed after the network topology had been decided. For a SVM topology 3-3-3, 42 sets of training data from input–output pairs (three characteristic frequencies—three classes) were used to train the SVM. The swarm-intelligence algorithm (SIA), as a particle swarm optimization (PSO) [21], is an evolutionary optimization technique, which provides more efficiency in solving multiple optimal solutions, high dimensionality, featuring nonlinearity, and nondifferentiability problems. The evolution computations of PSO technique were used to minimize the mean squared error function (MSEF), as shown in Fig. 9. It can be seen the solution list of the SVM based classifier is decreasing with less than 30 iteration training, and only slight improvement in the optimal parameters, $\gamma$, $\sigma$, and $b$, was obtained by increasing the number of iteration training and population sizes ($G = 10$–$40$). In addition, the SVM topology is slightly less than FPN (topology 9-13-3-1); however, it needs iteration computations for updating parameters. It also trains a classifier under the high-dimensional and complexity pattern space. Although the multilayer network provides promising solutions to perform classification tasks, but the
algorithm is difficult to implement in hardware devices. The proposed screening system provides a rule-based mechanism and automatic weighted fuzzy reasoning. Thus, it could overcome the complexity of adjustable mechanism design and shorten a design cycle.

D. Discussion

An ES is a computer system that can be designed to perform specific functions, including control, diagnosis applications, signal processing, etc. [22]–[24]. It contains processing cores, such as micro-controllers or DSP, and also contains analog and digital input/output (I/O), memory, and application specific integrated circuits (ASICs). An FPGA chip is a high-level ES that can be configured by engineering designers or customers. It has an array configuration of logical elements, which can be used to design any logical function operation to implement the given applications. The FPGA is also a programmable device, and has an inherent parallel and distributed configuration, allowing designers to execute multiple inputs and control loops simultaneously. Its development environment can simulate and verify the logic designs [25].

Under the ES development environment, we used four fundamental operations of arithmetic and logical reasoning to configure the combinational logics or ASICs, and then embed intelligent algorithms on the compact chip. The proposed diagnosis system provides rule-based configuration and automatic weighted fuzzy reasoning. A flexible and intelligent manner needs no iteration for updating system weights. Therefore, it can overcome the complex configuration design, and the prototype device can be implemented, tested, debugged, and modified as needed in a short design cycle. Of the current techniques, the graphical user interface for windows application has reprogrammability and flexibility to quickly develop a specific ASIC.

The proposed FPNs’ algorithm can be implemented using four fundamental operations with specific storage data. In addition, an exponent function, as (7), can be expanded into a Maclaurin series as shown in the Appendix, so it can also be implemented with the four fundamental operations. Combining the FPNs and logical operation functions, the proposed diagnosis system provides a promising way to implement a portable monitor for AVS condition evaluation in daily home care.

V. CONCLUSION

According to reports from the Department of Health (DOH), the rate of ESRD in Taiwan is 2447 per million. ESRD is an irreversible and progressive chronic disease. More than 66,000 people need to receive the hemodialysis treatment, and this number is increasing year by year. For long-term use, AVF or AVG accesses must be punctured every two days. Maintenance of proper function at IBF 600–2000 mL/min is the most important issue for ESRD patients. This study has provided a flexible, intelligent, and FPGA chip design method to develop a portable early detection medical device. With noninvasive phonoangiographic signals, the Burg AR method was used to estimate the characteristic frequency spectra, including the first, second, and third characteristic frequencies. To observe three main characteristic frequencies, it provides information to evaluate the degree of AVS stenosis. Then, we implemented the human diagnosis work to present a fuzzy inference algorithm for a rule-based system using FPNs, and the degree subdivides into nine scales to survey the occlusion levels. We also used some case studies to verify the feasibility of the proposed diagnosis system. Under advanced ES techniques, an automatic diagnosis system could be easy to implement for hemodialysis patients needs.

\[ \exp(1 - m \cdot s) \approx 1 + (\Delta) + \frac{1}{2!}(\Delta)^2 + \frac{1}{3!}(\Delta)^3 + \cdots + \frac{1}{z!}(\Delta)^z \]  

where \( \Delta = (1 - m \cdot s) \); series coefficient \( z_s \), \( s = 0, 1, 2, 3, \ldots, S \), is the number of series term, and series coefficient are constant values. The series term verified the expanded function accuracy, and \( S = 6 \) was recommended. The special equation can be computed with multiplication, addition, and division. Related constant data can be computed and stored in the memory elements. The accuracies of the expanded function have been verified, as follows:

1) VL: \( \exp(-0.0) = [1 + 0.0 + \frac{1}{2!(0.0)^2} + \cdots + \frac{1}{6!(0.0)^6}]^{-1} = 1.0000 \)
2) L: \( \exp(-0.5) = [1 + 0.5 + \frac{1}{2!(0.5)^2} + \cdots + \frac{1}{6!(0.5)^6}]^{-1} \approx 0.6065 \)
3) UL: \( \exp(-1.0) = [1 + 1.0 + \frac{1}{2!(1.0)^2} + \cdots + \frac{1}{6!(1.0)^6}]^{-1} \approx 0.3679 \)

Fig. 11 shows the ASICs’ configuration of special functions, in which adders, multipliers, and dividers are required to implement each special function, such as triangular membership functions and exponent functions. Its ASIC can design the function with combinational logical operation elements, and constant parameters are stored in the memory elements. The advantage of each ASIC is a simplified module that can be examined before programming into the FPGA chip. In addition, each ASIC of special function has the same configuration, it only assigns triplet parameters for a triangular membership function and series coefficients for an exponent function. Most can be used repeatedly. Therefore, designers can quickly develop a specific ES within the FPGA chip.
Fig. 10. (a) FPNs based diagnosis system for evaluating AVS stenosis. (b) Rule connectivity matrix of FPN.
Fig. 11. ASIC configurations of triangular membership function, exponent function, and FPNs.

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REFERENCES


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Q1. Author: Figures A and B appearing in the Appendix have been renumbered as Figs 10 and 11, respectively, to maintain the sequential order. Please check.

Q2. Author: Please check the edited sentence “More than . . . year.” for intended meaning.

Q3. Author: Please verify the changes made and the information presented in the Acknowledgment section.

Q4. Author: Please provide all the names of authors in Refs. [1] and [2].

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