Hemodialysis Arteriovenous Shunts Dysfunction Screening with a Fractional-order Feature and Non-cooperative Game Based Decision-making Model

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Abstracts Early clots and thrombosis to the progress of stenosis leading to arteriovenous shunt dysfunction occurs at the venous anastomosis site or the outflow vein. To prevent vascular access complications, such as inflow or outflow stenosis, this study proposes a computerized decision support system combining feature extraction methods and a non-cooperative game (NCG)-based decision-making model to evaluate arteriovenous shunt stenosis in clinical usages. Feature extraction methods, including the Burg autoregressive (AR) method and the fractional-order self-synchronization error formulation, are used to estimate the characteristic frequencies and to quantify the differences between the reference data and the routine examination data, in terms of the degree of stenosis (DOS). For 42 long-term follow-up patients, a less parameterized NCG model is then used to identify the possible level of stenosis. A novel screening model might be further built on an embedded system, for portable medical screening applications.

Keywords Non-Cooperative Game (NCG), Decision-Making Model, Degree of Stenosis (DOS)

Maintenance of proper function of the intra-graft blood flow (IBF), 600 - 1000 ml/min, is the most important issue for dialysis care, and the flow threshold should be < 600 ml/min for AVF and < 400 - 500 ml/min for AVG [1].

Computerized decision support system provides useful information and allows improved screening performance in a clinical setting. It uses an information process, qualitative analysis, and a decision support algorithm to deal with clinical examinations [2]. In this research, phonoangiography (PCG) provides a non-invasive to acquire the blood sounds from the interior of the vascular access. The frequency domain and time-frequency techniques, such as the maximum entropy method [3-4], Fourier transform, wavelet transform, and Burg-autoregressive method [5-7], are used to extract the specific high or low frequency components and the magnitude of the characteristic frequencies. As previous studies, these information processes are useful for the specific feature extraction. However, there is no automatic screening function and there is a requirement for a physician's judgment. The confidence in any human decision depends on experience and expert knowledge [2, 8-9]. To analyze broad frequency ranges of PCG signals, the Burg AR method and the fractional-order self-synchronization error formulation are used to quantify the differences between normal and abnormal PCG signals, in terms of the degree of stenosis (DOS).

In addition, decision-making methods, such as rule-based decision support systems, support vector machines, or artificial neural networks, consist of a multi-layer mechanism that uses a mathematical or a computational algorithm for automated information analysis and pattern recognition [8-9]. The multi-layer mechanisms are non-linear statistical data modeling methods that model complex relationships in order to identify out-of-range results between the normal ranges and abnormal ranges. If the examination data is in two classes or more classes, a dichotomy hyper-plane is used to separate the examination

1. Introduction

Chronic renal failure is an irreversible and progressive end-stage disease. In Taiwan, more than 77 thousand people require hemodialysis treatment and this number is increasing yearly. An arteriovenous access, such as Brescia-Cimino arteriovenous fistulas (AVFs) or politetrafluoroethylene grafts (AVGs), provides vital access for hemodialysis therapy. If there is repeated puncturing of this access (three days per week), narrowing of the access is caused by thrombosis, intimal hyperplasia, cellular deposits, or aneurysm. This produces turbulent flow, pulsatile flow, inadequate arterial inflow, or venous outflow occlusion.

data into one class or none. They also provide a good basis for tasks that involve decision making. However, an effective diagnosis relies on the assignment of network parameters, the amount of training data, iteration computing and the convergent conditions.

In clinical applications, event variables describe the probabilities or the criterion possibilities that class / state changes are interesting to patients themselves, physicians and to nurses' care decisions. Additionally, current techniques use a built-in digital signal processor (DSP) to support signal preprocessing functions, hence frequency spectra of PCG signals can be easily to obtain [5]. However, above mentioned decision-making algorithms are difficult to implement in a field-programmable gate array chip or an embedded system. Therefore, the aim of this study is to designs a decision-making model that allows: (1) PCG signals feature extraction, and (2) less parameterized

decision reasoning. The Burg AR method [5-7] overcomes spectral leakage and is used to smooth the frequency spectra, and to estimate the characteristic frequencies. Fractional-order self-synchronization error formulation [6] is then used to quantify the differences between the reference data and the routine examination data. The qualitative criteria are bounded in relation to the degree of stenosis. Finally, the problem of dysfunction screening is formulated as non-cooperative games [10-11] based novel inference framework between normal and dysfunction conditions. A likelihood indicator [12] is used to maximize the probability of predictive model to observe the trends of progressive stenosis levels, where there is no iteration for updating inference parameters and no objective function is specified. For long-term follow-up patients, the results show that the proposed decision-making model is more efficient for dysfunction screening.

Figure 1. A Block diagram of the proposed screening model

2. Technological Support

2.1. Feature Extraction Method

Phonography is a non-invasive and inexpensive method for monitoring the vascular access functions in clinical applications. Turbulent flow and high-pressure pulsatile flow cause high pitched sounds that are recorded by an electric stethoscope. Feature extraction methods include signal preprocessing and segmentation, frequency spectral analysis, and fractional-order self-synchronization error formulation, as a step-by-step guide in Figure 1. As Step 1, PCG signals are acquired using an electronic stethoscope with a sampling rate of 4 kHz (3M LITTMANN® 4100 Series, Minnesota, USA). The electronic stethoscope provides an amplifier (eighteen times the amplification, 25dB), filtering, and recording functions, as well wireless (infrared transmission) data transfers to a tablet PC for further analysis. In the signal preprocessing stage, digital filters are used to remove the baseline wander and unwanted ambient noises. The Hilbert transform and a 5Hz low-pass digital filter smoothes each PCG signal and then obtains the peaks of the envelope of the periodic PCG signals with the 9 PCG waves. The segmentation process was used to find the minimum value before and after the detected peaks in the time domain, as Step 1 in Figure 1. A band-pass filter was implemented to maintain the main characteristic frequencies in the region of 25Hz to 800Hz. Therefore, the spectral peaks of frequency spectra can be identified using the Burg autoregressive (AR) method [5-7], as Step 2 in Figure 1. An AR model parameters and model orders can be determined by the Levinson-Durbin recursion. The recursion algorithm is used

to minimize the final prediction error criterion (PEC). We suggested the AR model order 8 for constructing the Burg AR model with prediction coefficients [5-6].

2.2. Phonography Quantitative Analysis

The fractional-order feature extraction method is designed to extract the differences of frequency spectra between normal and abnormal PCG signals. According to the Grünwald-Letnikov definition [6, 14], the fractional-order error is expressed as

$$D_e^\alpha e^m \approx \frac{\Gamma(m+1)}{\Gamma(m+1-\alpha)} e^{m-\alpha} \quad (1)$$

where $e = (x - y)$ is the dynamic error for all α and m is any real number, x represents the data sequence for the frequency spectra for the reference data after percutaneous transluminal angioplasty treatment (stored in Database), y represents the data sequence for the further collection of data from routine examinations, and Γ is a Gamma function. Therefore, a self-synchronization error system using Chen-Lee system [6] can be described as

$$\begin{bmatrix} \dot{e}_1 \\ \dot{e}_2 \\ \dot{e}_3 \end{bmatrix} = \begin{bmatrix} a & -e_3 & 0 \\ e_3 & b & 0 \\ \frac{1}{3}e_2 & 0 & c \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} = \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + \begin{bmatrix} -e_3e_2 \\ e_1e_3 \\ \frac{1}{3}e_1e_2 \end{bmatrix} \quad (2)$$

where error states $e = [e_1, e_2, e_3]^T$ as $e_1 = (x_1 - y_1)$, $e_2 = (x_2 - y_2)$, and $e_3 = (x_3 - y_3)$. The first-order differential system (2) can be modified by the fractional-order derivatives as

$$\frac{d}{dt} \frac{d^{-\alpha}}{dt^{-\alpha}} \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} \approx \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \frac{d^{-\alpha}}{dt^{-\alpha}} \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} + \frac{d^{-\alpha}}{dt^{-\alpha}} \begin{bmatrix} -e_2e_3e_1^0 \\ e_1e_3e_2^0 \\ \frac{1}{3}e_1e_2e_3^0 \end{bmatrix} \Rightarrow \begin{bmatrix} D^q e_1 \\ D^q e_2 \\ D^q e_3 \end{bmatrix} \approx \begin{bmatrix} a' & 0 & 0 \\ 0 & b' & 0 \\ 0 & 0 & c' \end{bmatrix} \begin{bmatrix} e_1^{1+\alpha} \\ e_2^{1+\alpha} \\ e_3^{1+\alpha} \end{bmatrix} + \begin{bmatrix} \frac{-\Gamma(1)e_2e_3e_1^\alpha}{\Gamma(1+\alpha)} \\ \frac{\Gamma(1)e_1e_3e_2^\alpha}{\Gamma(1+\alpha)} \\ \frac{\Gamma(1)e_1e_2e_3^\alpha}{3\Gamma(1+\alpha)} \end{bmatrix} \quad (3)$$

where $m = 1$ and $q = (1 - \alpha)$ is the fractional order that satisfies, $0 < q \leq 1$; and α is the value rounded up to the nearest integer 1 [6]. In order to design the discrete formulation in Step 3, a Chen-Lee system that consists of a master system (MS) and a slave system (SS) [6, 15] is modified as a fractional-order discrete error system. The error states, $e_1[i] = x[i] - y[i]$, $e_2[i] = x[i+1] - y[i+1]$, and $e_3[i] = x[i+2] - y[i+2]$, $i = 1, 2, 3, \dots, n-2$, and $\Phi_1[i]$, $\Phi_2[i]$, and $\Phi_3[i]$ are defined, as

$$\begin{bmatrix} \Phi_1[i] \\ \Phi_2[i] \\ \Phi_3[i] \end{bmatrix} = [A] \begin{bmatrix} (e_1[i])^{1+\alpha} \\ (e_2[i])^{1+\alpha} \\ (e_3[i])^{1+\alpha} \end{bmatrix} + \begin{bmatrix} \frac{-\Gamma(1)e_2[i]e_3[i](e_1[i])^\alpha}{\Gamma(1+\alpha)} \\ \frac{\Gamma(1)e_1[i]e_3[i](e_2[i])^\alpha}{\Gamma(1+\alpha)} \\ \frac{\Gamma(1)e_1[i]e_2[i](e_3[i])^\alpha}{3\Gamma(1+\alpha)} \end{bmatrix}, \quad \text{matrix: } [A] = \frac{\Gamma(2)}{\Gamma(2+\alpha)} \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \quad (4)$$

where α is a parameter that satisfies, $0.0 < \alpha < 0.2$, within $0.0 < \alpha < 1.0$ equal difference values are dominated for quantification and scaling applications [6], the system parameters are any nonzero constants, satisfying with an inequality: $0 < a < -(b + c)$ [15], and n is the integer number of the frequency. The fractional-order discrete error system is used to quantify the differences between the reference data and the incoming collected data, in terms of the degree of stenosis (DOS). The specific degrees are confirmed using ultrasonic images and X-ray images and are defined as [5-6]

$$DOS = (1 - \frac{d^2}{D^2}) \quad (5)$$

where D is the diameter of the normal graft or vessel in the direction of blood flow, d is the diameter of the stenosis lesion. Refer to the DOS, a fractional-order self-synchronization error formulation, Ψ , is the norm of (Φ_1, Φ_2, Φ_3) , and this index is represented as [6]

$$\Psi = \sqrt{(\max\{\Phi_1[i]\})^2 + (\max\{\Phi_2[i]\})^2 + (\max\{\Phi_3[i]\})^2} \quad (6)$$

where $\Phi_1 \in R^{n-2}$, $\Phi_2 \in R^{n-2}$, and $\Phi_3 \in R^{n-2}$ are fractional-order dynamic errors, as Step 3 in Figure 1.

For 42 subjects (22 AVGs and 20 AVFs), clinical data was used to construct a prediction model to monitor the function of a vascular access at a venous anastomosis site. This study is approved by the National Cheng Kung University Hospital research ethics committee and the Institutional Review Board (IRB), under contract number: ER-99-186. Equations (2) and (4) are used to calculate the fractional-order dynamic errors, Ψ , with the nonzero parameters, $a=2$, $b=-4$, $c=-3$, $m=1$, and $\alpha=0.1$, which are used to quantify the relationship between the fractional-order dynamic errors, Ψ , and the DOS, as $DOS = 0.1 \times \exp(0.3677 \times \Psi)$ ($R^2 = 0.6846$), as seen in Figure 2. The specific ranges are used to evaluate the stenosis degree. Given the certainty factors (CFs), the suggested specific ranges are determined for stenosis screening in terms of the order of severity, with Class III: $DOS > 0.65$, Class II $\rightarrow$ III: $0.45 < DOS < 0.65$, Class II: $0.3 <$

$DOS < 0.45$, Class I $\rightarrow$ II: $0.25 < DOS < 0.3$, and Class I: $DOS < 0.25$ [5-6], as shown in Figure 3.

Figure 2. The degree of stenosis and the certainty factor versus the fractional-order dynamic errors

Figure 3. The fractional-order dynamic errors bounds versus the degrees of the stenosis

Game I			Game II		
Follow-up Reference	Class I	Class II	Follow-up Reference	Class II	Class III
Class I	$s_1 = f_I^*(\Psi)$ $\times p_1(\Psi)$ $\times (1 - q_2(\Psi))$	$s_2 = f_I^*(\Psi)$ $\times p_1(\Psi)$ $\times q_2(\Psi)$	Class II	$s_1 = f_{II}^*(\Psi)$ $\times q_2(\Psi)$ $\times (1 - r_3(\Psi))$	$s_2 = f_{II}^*(\Psi)$ $\times q_2(\Psi)$ $\times r_3(\Psi)$
Class I $\rightarrow$ II	$s_3 = f_{I-II}^*(\Psi)$ $\times (1 - p_1(\Psi))$ $\times (1 - q_2(\Psi))$	$s_4 = f_{I-II}^*(\Psi)$ $\times (1 - p_1(\Psi))$ $\times q_2(\Psi)$	Class II $\rightarrow$ III	$s_3 = f_{II-III}^*(\Psi)$ $\times (1 - q_2(\Psi))$ $\times (1 - r_3(\Psi))$	$s_4 = f_{II-III}^*(\Psi)$ $\times (1 - q_2(\Psi))$ $\times r_3(\Psi)$
	$S_I^d = s_1 + s_3$	$S_{II}^d = s_2 + s_4$		$S_{II}^{II} = s_1 + s_3$	$S_{III}^{II} = s_2 + s_4$

- **Note:** (Reference, Follow-up) $\rightarrow$ Rational Outcome
- **Action Combinations for Game I:** (Class I, Class I), (Class I, Class II), (Class I $\rightarrow$ II, Class I), (Class I $\rightarrow$ II, Class II)
- **Action Combinations for Game II:** (Class II, Class II), (Class II, Class III), (Class II $\rightarrow$ II, Class II), (Class II $\rightarrow$ II, Class III)

Figure 4. Normal-form representations for stenosis screening

3. The Game Theoretical Model for Screening Applications

3.1. Game Theoretical Concept

The game theory is a mathematical method, including non-cooperation and cooperative models. It consists of a set of agents and characteristic functions specifying the strategies created by the agents in a game. The game in strategic form is represented by a matrix or a table that shows the overall actions and payoffs. The normal-form game represents any associated payoff for each agent with every possible combination of actions. For a non-cooperative game [10-12], a compound strategy allows a likelihood indicator to be assigned for each pure strategy. It is described by a set of agents and each agent independently chooses a feasible strategy. Payoffs depend not only on individual strategy, but also on the other agents' strategy choices.

Assume subsequent stenosis and dysfunction be possible, if there is repeated puncturing of the pathologic accesses. This results in inadequate arterial inflow or occlusion of the venous outflow. In clinical examinations, the order of severity is divided into three main classes, depending on the DOS. In terms of the DOS, the norm of fractional-order dynamic errors, $\Psi = \text{norm}(\Phi_1, \Phi_2, \Phi_3)$, described are divided into three ranges, to screen the dysfunction levels from Class I to Class III. For a reference state, the dysfunction level could be increase as stenosis becomes gradually severe, the class can be subdivided into Class I to Class II and Class II to Class III, represented by "Class I $\rightarrow$ II" and "Class II $\rightarrow$ III", respectively, as shown in Figure 3. The action may maintain current condition or gradually become dysfunctional. The follow-up actions are a combination of the decreased probability of current conditions and the increased probability of dysfunction. Therefore, these phenomena could be described a non-cooperative game model, as shown in Figure 4. If there are changes in the fractional-order dynamic errors, the two classes are against and do not compromise.

3.2. Non-cooperative Game for Dysfunction Screening

In establishing a reference data after surgical revision or percutaneous transluminal angioplasty (PTA), the trend is determined during a routine examination. For the normal-form representations, games use the combination of actions (reference, follow-up) and rational outcomes to make decisions. In a non-cooperative game (NCG), the individual action and their influence on follow-up actions are considered, along with the other actions that could occur. Therefore, the combinations of two games are shown in Figure 4.

For two agents, each agent has two actions, $S_j = \{1, 2\}$ for reference and follow-up actions in a game, respectively, where S_j , $j = 1, 2$, is the action set of a game, S , is $S_1 \times S_2$. Therefore, we have four action combinations, $S = \{s_1, s_2, s_3, s_4\}$, as shown in Figure 4. For assumptions made in the action space, S , the payoff functions could be continuous and

be bounded on S . Depending on the value of the certainty factors (CFs) versus fractional-order dynamic errors, each action is a payoff function that represents the degree of truth as an extension of the valuation, such as a trapezoidal function or a sigmoidal function, as shown in Figure 3. For simplicity of computation and implementation, the various trapezoidal functions, $p_1(\Psi)$, $q_2(\Psi)$, and $r_3(\Psi)$, are taken to represent the payoffs, as [11]:

$$\begin{aligned} p_1(\Psi) &= \begin{cases} 1 & , 0 \leq \Psi \leq \gamma \\ \frac{\beta - \Psi}{\beta - \gamma} & , \gamma \leq \Psi \leq \beta \\ 0 & , \beta \leq \Psi \leq \rho \end{cases} \\ q_2(\Psi) &= \begin{cases} 0 & , 0 \leq \Psi \leq \gamma \\ \frac{\Psi - \gamma}{\beta - \gamma} & , \gamma \leq \Psi \leq \beta \\ 1 & , \beta \leq \Psi \leq \rho \\ \frac{\delta - \Psi}{\delta - \rho} & , \rho \leq \Psi \leq \delta \\ 0 & , \Psi \geq \delta \end{cases} \\ r_3(\Psi) &= \begin{cases} 0 & , 0 \leq \Psi \leq \rho \\ \frac{\Psi - \rho}{\delta - \rho} & , \rho \leq \Psi \leq \delta \\ 1 & , \delta \leq \Psi \leq \infty \end{cases} \end{aligned} \quad (7)$$

The $p_1(\Psi)$, $q_2(\Psi)$, and $r_3(\Psi)$, are payoff functions for denoted main three classes, and against payoff functions are $(1 - p_1(\Psi))$, $(1 - q_2(\Psi))$, and $(1 - r_3(\Psi))$. For two games, the overall payoffs have the following two definitions:

- Game I: the action payoffs for changes from Class I to Class II are given by $S_{I \rightarrow II}$

$$\begin{bmatrix} s_1 & s_2 \\ s_3 & s_4 \end{bmatrix} = \begin{bmatrix} p_1(\Psi) \times (1 - q_2(\Psi)) & p_1(\Psi) \times q_2(\Psi) \\ (1 - p_1(\Psi)) \times (1 - q_2(\Psi)) & (1 - p_1(\Psi)) \times q_2(\Psi) \end{bmatrix} \quad (8)$$

- Game II: the action payoffs for changes from Class II to Class III are given by $S_{II \rightarrow III}$

$$\begin{bmatrix} s_1 & s_2 \\ s_3 & s_4 \end{bmatrix} = \begin{bmatrix} q_2(\Psi) \times (1 - r_3(\Psi)) & q_2(\Psi) \times r_3(\Psi) \\ (1 - q_2(\Psi)) \times (1 - r_3(\Psi)) & (1 - q_2(\Psi)) \times r_3(\Psi) \end{bmatrix} \quad (9)$$

Each action payoff reflects the possibility of an outcome to a class and is weighted with its probability, $S \in [0, 1]$.

According to the Neyman-Pearson theory [12], the optimal detection test maximizes the probability of detection between two measurement points, hypotheses H^* : $\mu = \mu_0$ and H : $\mu = \mu_1$. It is found that the optimal function $f^*(\Psi)$ and is given by [12, 16]

$$\Lambda(\Psi) = \frac{f^*(\mu_0 | \Psi)}{f(\mu_1 | \Psi)} \stackrel{H^*}{\geq} \varepsilon, \quad \mu_0 = 0.50 \quad (10)$$

where $\Lambda(\Psi)$ is a decreasing function of parameter, Ψ , with the mean, $\mu_0 = 0.5$. The likelihood ratio is defined as

$$f^*(\Psi) = \frac{f(\Psi) \Lambda(\Psi)}{\int f(\Psi) e^{-\mu_0 \Psi} d\Psi}, \quad \Lambda(\Psi) = e^{-\mu_0 \Psi} \quad (11)$$

where $f(\Psi)$ is an any payoff function, the mean μ_0 is known.

The likelihood ratio is computed and the $f(\Psi)$ is rejected if parameter, Ψ , is sufficiently large within the finite bounds. The rejection threshold, ε , depends on the size of the test. The test statistic is scaled as a distributed function or an exact critical value, the so called “Nash equilibrium [10]”, between both classes. The likelihood indicator, $f^*(\Psi)$, can be computed using equation (11) and be a probability mass function. The likelihood indicator is then obtained using the following two definitions:

- Game I: the likelihood indicators, $f^*_I(\Psi)$ and $f^*_{I-II}(\Psi)$, for changes from Class I to Class II are given by

$$f^*_I(\Psi) = \frac{p_1(\Psi)e^{-\mu_0\Psi}}{\int_{\gamma-\Delta}^{\gamma} e^{-\mu_0\Psi} d\Psi + \int_{\gamma}^{\beta} \left(\frac{\beta-\Psi}{\beta-\gamma}\right) e^{-\mu_0\Psi} d\Psi}$$

$$= \frac{p_1(\Psi)e^{-\mu_0\Psi}}{\frac{1}{\mu_0}(e^{-\mu_0(\gamma-\Delta)}) + \frac{1}{\mu_0^2}(\mu_0(\beta-\gamma))(e^{-\mu_0\beta} - e^{-\mu_0\gamma})} \quad (12)$$

$$f^*_{I-II}(\Psi) = \max_{0 \leq \Psi \leq \rho} (f^*_I(\Psi)) - f^*_I(\Psi) \quad (13)$$

where the lower limit of integral is the term, $(\gamma - \Delta)$, and $\Delta = \frac{(\gamma-0)}{2} = \frac{\gamma}{2}$; $(\gamma - \Delta)$ is an initial measurement point. The action payoffs, $S^I_I(\Psi)$ and $S^I_{II}(\Psi)$, will mix the likelihood indicators, and the action profiles of Game I are modified as

$$\begin{bmatrix} S^I_I(\Psi) \\ S^I_{II}(\Psi) \end{bmatrix} = \begin{bmatrix} f^*_I \times p_1(\Psi) \times (1 - q_2(\Psi)) + f^*_{I-II} \times (1 - p_1(\Psi)) \times (1 - q_2(\Psi)) \\ f^*_I \times p_1(\Psi) \times q_2(\Psi) + f^*_{I-II} \times (1 - p_1(\Psi)) \times q_2(\Psi) \end{bmatrix} \quad (14)$$

For two opposing classes, the compound actions are the sum of pure actions and combined actions, using the additive axiom. Thus, it is to reject the Class I (hypothesis H^*) when the compound actions, $S^I_I(\Psi) < S^I_{II}(\Psi)$, and then the Class II is accepted (hypothesis H).

- Game II: the likelihood indicators, $f^*_{II}(\Psi)$ and $f^*_{II-III}(\Psi)$, for changes from Class II to Class III are given by

$$f^*_{II}(\Psi) = \frac{q_2(\Psi)e^{-\mu_0\Psi}}{\int_{\rho-\Delta}^{\rho} e^{-\mu_0\Psi} d\Psi + \int_{\rho}^{\delta} \left(\frac{\delta-\Psi}{\delta-\rho}\right) e^{-\mu_0\Psi} d\Psi}$$

$$= \frac{q_2(\Psi)e^{-\mu_0\Psi}}{\frac{1}{\mu_0}(e^{-\mu_0(\rho-\Delta)}) + \frac{1}{\mu_0^2}(\mu_0(\delta-\rho))(e^{-\mu_0\delta} - e^{-\mu_0\rho})} \quad (15)$$

$$f^*_{II-III}(\Psi) = \max_{\beta \leq \Psi \leq \infty} (f^*_{II}(\Psi)) - f^*_{II}(\Psi) \quad (16)$$

where the lower limit of integral is the term, $(\rho - \Delta)$, and $\Delta = \frac{(\rho-\beta)}{2}$. The action profiles, $S^{II}_{II}(\Psi)$ and $S^{II}_{III}(\Psi)$, of Game II are modified as

$$\begin{bmatrix} S^{II}_{II} \\ S^{II}_{III} \end{bmatrix} = \begin{bmatrix} f^*_{II} \times q_2(\Psi) \times (1 - r_3(\Psi)) + f^*_{II-III} \times (1 - q_2(\Psi)) \times (1 - r_3(\Psi)) \\ f^*_{II} \times q_2(\Psi) \times r_3(\Psi) + f^*_{II-III} \times (1 - q_2(\Psi)) \times r_3(\Psi) \end{bmatrix} \quad (17)$$

It is also to reject the Class II (hypothesis H^*) when the compound actions, $S^{II}_{II}(\Psi) < S^{II}_{III}(\Psi)$, and then the Class III (hypothesis H) is accepted. In dysfunction screening, logic inference with maximum composite operations is used to evaluate the possible class, S^+ as

$$S^+ = \max_{0 \leq \Phi \leq \text{Max}} [\max_{0 \leq \Phi \leq \rho} (S^I_I(\Psi), S^I_{II}(\Psi)), \max_{\beta \leq \Phi \leq \text{Max}} (S^{II}_{II}(\Psi), S^{II}_{III}(\Psi))] \quad (18)$$

4. Experimental Results

4.1. Implementations of NCG Based Screening Models

The auscultation method was used to acquire and record the PCG signals at the venous anastomosis sites (V sites), using an electric stethoscope. Each subject provided at least 2 PCG records for 8seconds at the V sites. The recording data of 42 subjects were used to design the NCG-based screening models. The proposed feature extraction and screening methods were developed on a tablet PC, using the LabVIEW graphical programming (National Instruments TM Corporation, Austin, Texas, U.S.) and the MATLAB software (MathWork, Natick, Massachusetts, U.S.). For two NCGs, the inference procedures are shown below:

Step 1) Given recording data of three main classes, the mean values and standard deviations of fractional-order dynamic errors are employed to estimate the parameters of payoff functions, as shown in Table 1. These parameters are used to establish the payoff functions, $p_1(\Psi)$, $q_2(\Psi)$, and $r_3(\Psi)$, using equation (7). The against payoff functions are $(1 - p_1(\Psi))$, $(1 - q_2(\Psi))$, and $(1 - r_3(\Psi))$.

Step2) The pure action profiles and against action profiles are combined using equations (8) and (9).

Step3) The likelihood indicator is obtained using equations (12) and (13) for Game I and equations (15) and (16) for Game II.

Step 4) The continuity functions for the compound action profiles, (S^I_I, S^I_{II}) and $(S^{II}_{II}, S^{II}_{III})$, are expressed using equations (14) and (17).

The compound action profiles for dysfunction screening are shown in Figure 5. It can be seen that these continuity functions do not remain constant if there are changes in the fractional-order dynamic errors, Ψ . In order to determine the fixed points, ξ_1 and ξ_2 , the denominators of the left-hand side of the action functions, S^I_I and S^{II}_{II} , decrease as the against actions, S^I_{II} and S^{II}_{III} , increase. The fixed points (Nash equilibrium points), $(\Psi, \xi_1) = (3.41, 0.36)$ and $(\Psi, \xi_3) = (4.95, 0.35)$, were represented by “circles”, as shown in Figure 5, and were defined as the points of class changes, while maximize the payoffs of the current classes. Thus, the two classes are against and do not compromise. This is defined as a critical point of the compound action profiles, so the index, Ψ , represents the best decision for the separation of the two classes in Game I and Game II, respectively. The dysfunction screening rules are then established in Table 2.

Table 1. Related parameters of mixed action profiles

Action Profile	γ	β	ρ	δ	Max	μ_0	Δ
S^I_I	3.0	4.0	4.5	—	7	0.5	1.5
S^I_{II}							
S^{II}_{II}	—	4.0	4.5	5.5	7	0.5	0.25
S^{II}_{III}							

4.2. Experimental Results and Discussion

Table 2 shows the suggested screening rules, which are divided into five levels. For two games, the fixed point, $(\Psi, \xi_2) = (3.98, 1.27)$, is also defined as a point of class change

between level II and level II→III. The trends for compound action profiles are used to identify the possible degree, as shown in Figure 5. Another group of 42 recording data was used to verify the proposed NCG-based screening models. The overall experimental results are shown in Figures 6. A computer-assisted decision-making, including auscultation record, signal preprocessing, frequency spectral analysis, feature extraction, and NCG-based decision-making model, is shown in Figure 7(a). The related parameters can be input and stored for further analysis, as shown in Table 1.

Table 2. The proposed dysfunction screening rules

Class, DOS Parameter	I < 0.25	I → II 0.25~0.30	II 0.30~0.45	II → III 0.45~0.65	III > 0.65
Ψ	0.00 ~ 1.50	1.50 ~ 3.41	3.41 ~4.50	3.98 ~4.95	4.95 ~7.00
Action Profile	1.33 ~0.77	0.77 ~0.36	0.36 ~1.33	1.27 ~0.35	0.35 ~1.29
Fixed Point	(Ψ, ξ ₁)=(3.41, 0.36)		(Ψ, ξ ₂) = (3.98, 1.27)		(Ψ, ξ ₃)=(4.95, 0.35)
Final Decision	max(S ^I _I , S ^I _{II})			max(S ^{II} _{II} , S ^{II} _{III})	
	S [*] =max[max(S ^I _I , S ^I _{II}), max(S ^{II} _{II} , S ^{II} _{III})]

Figure 5. Compound action profiles for dysfunction screening

Figure 6. Overall experimental results

In a clinical case, a patient agreed to participate and allowed monthly data collection, as shown in Figure 7(b). In a routine examination, she had a severe AVG occlusion and the physician initially confirmed the condition as “Class II”. After ultrasonic image examination, a $DOS=0.66$ ($D=0.556$ cm and $d=0.178$ cm) was found at the measurement site. She also received PTA treatment. In contrast, the result of PCG quantitative analysis is the index, $\Psi = 3.79$. The decision-making with two NCGs is detailed, as the following normal-form representations:

Game I		Class I	Class II	Game II		Class II	Class III
Class I	$s_1 =$	0.0027	0.0102	Class II	$s_1 =$	0.0000	0.0000
	$s_3 =$	0.2106	0.7923		$s_3 =$	0.0000	0.0000
	$S_I' =$	0.2133	0.8025		$S_{II}'' =$	0.0000	0.0000
Class I $\rightarrow$ II	$s_2 =$			Class II $\rightarrow$ III	$s_2 =$		
	$s_4 =$				$s_4 =$		
	$S_{II}'' =$				$S_{III}'' =$		

Here, there are two pure actions: the current class is Class I or Class II and it is seen that $s_1 = 0.0027$ and $s_4 = 0.7923$. Because the index, Ψ , is in the intersection between Class I and II, a combination of actions, s_3 and s_2 , consists of the I and II, a combination of actions, s_3 and s_2 , consists of the probability of a change from the Class I to Class II. For two against events, the compound actions for disjointed events are the sum of the pure actions and the combined actions using the additive axiom. Given a fixed point, $\xi_1 = 0.33$, there is a compound action, $S_{II}^I(\Psi, \xi_1) = 0.8025 \geq S_I^I(\Psi, \xi_1) = 0.2133$, and the decision $\max(S_I^I, S_{II}^I) = 0.8025$ for Game I. It is seen that the event set for Game II is empty (null event), so the decision $\max(S_{II}^I, S_{III}^I) = 0.0000$. The final decision, $S^+ = 0.8025$, is between the fixed points, ξ_1 and ξ_2 , as seen a red dashed ellipse in Figure 6. The proposed screening model also agrees with the “Class II” level. This confirms that the NCG-based screening model provides an accurate evaluation of the degree of AVG stenosis. Hence, the risk of AVG dysfunction can be identified.

Figure 7. (a) The graphic user interface of feature extraction and NCG-based screening method, (b) A clinical case, female, aged 54, AVG type, July 13, 2011

5. Conclusions

The proposed fractional-order feature and NCG-based screening model uses an auscultating method to assess an arteriovenous shunt stenosis. Using the non-invasive phonoangiography technique, the Burg AR method is used to analyze PCG signals and to estimate the characteristic frequency spectra. Therefore, the sounds of normal and stenosis conditions can be identified. Using fractional calculation with fractional orders, $0.0 < \alpha < 0.2$, the self-synchronization error formulations are used to quantify the relationship between the fractional-order dynamic errors and the DOS, which are used to subdivide into five suggested classes. The screening procedure is formulated as two NCGs, in order to solve the automatic decision-making task. The likelihood indicator is used to determine the pure action and against action profiles and the payoff of screening is maximized, to separate the two classes with an equilibrium point for class change. Forty-two subjects were used to evaluate the risk of arteriovenous access dysfunction, in order to verify the feasibility of the proposed screening model.

By comparison with the multi-layer networks [6, 9, 13], seen in Table 3, their structures were determined using the input-output training data. Network parameters assignment was performed by optimization methods, such as the gradient descent method, least-square algorithm, and evolutionary optimization algorithm. The proposed NCG-based screening model has a general formulation to express the less parameterized decision reasoning. It uses a straightforward mathematical computation to produce inference results by directly alternating the specific parameters, and the reasoning accuracy was raised by the proposed dysfunction screening rules, seen in Tables 1 and 2, especially in Class I $\rightarrow$ II and Class II $\rightarrow$ III. The proposed method needs (1) minor parameters assignment; (2) no training data (statistics based method); (3) no an objective function assignment; (4) no iteration computing to update parameters; and (5) no convergent condition assignment. The screening model is established within a short design cycle. Less parameterized decision-making method

overcomes the complexity of adjustable mechanisms, and the prototype model is easily implemented in an embedded system or a field programmable gate array chip [5]. A comprehensive performance evaluation indicates that the proposed model is better than existing ones.

Table 3. Comprehensive performance evaluation

Method Task	NCG	ANN [6]	SVM [9, 13]
Features	fractional-order dynamic errors	fractional-order dynamic errors	fractional-order dynamic errors
Architecture	table or matrix	multi-layer network	multi-layer network
Training Data	×	✓ (major)	✓ (major)
Parameter Assignment	✓ (minor)	✓ (major)	✓ (major)
Adjustable Parameter	×	✓ (major)	✓ (moderate)
Iteration Training	×	✓ (moderate)	✓ (moderate)
Convergent Assignment	×	✓	✓
Accuracy (%)	100% (42/42)	95% (40/42)	69% (29/42)

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REFERENCES

- [1] J. H. M. Tordoir, R. Dammers, and F. M. van der Sande, "Upper extremity ischemia and hemodialysis vascular access," *Eur. J. Vasc. Endovasc. Surg.*, vol. 27, 2004, pp. 1-5.
- [2] S. R. Raghavan, V. Ladik, and K. B. Meyer, "Developing

- decision support for dialysis treatment of chronic kidney failure, "IEEE Trans. on Information Technology in Biomedicine, vol. 9, no. 2, June 2005, pp. 229-238.
- [3] Y. Suzuki, M. Fukasawa, T. Mori, O. Sakata, A. Hattori, and T. Kato, "Elemental study on auscultating diagnosis support system of hemodialysis shunt stenosis by ANN," IEEJ Trans. on Electronics Information and Systems, vol. 130, no. 3, January 2010, pp. 401-406.
 - [4] Y. Suzuki, M. Fukasawa, T. Mori, O. Sakata, A. Hattori, and T. Kato, "An auscultating diagnosis support system for assessing hemodialysis shunt stenosis by using self-organizing map," IEEJ Trans. on Electronics Information and Systems, vol. 131, January 2011, pp. 160-166.
 - [5] W.-L. Chen, C.-D. Kan, C.-H. Lin, and T. Chen, "A rule-based decision-making diagnosis system to evaluate arteriovenous shunt stenosis for hemodialysis treatment of patients using Fuzzy Petri nets," IEEE J. Biomedical and Health Informatics, vol. 18, no. 2, March 2014 pp. 703-713.
 - [6] Y.-C. Du, C.-D. Kan, W.-L. Chen, and C.-H. Lin, "The Estimation of Residual Stenosis for an Arteriovenous Shunt Using a Flexible Fuzzy Classifier based on a Curve Approximation Function," IEEE Computing in Science & Engineering, Article in Press, September 2014.
 - [7] K. Roth, I. Kauppinen, P. A. A. Esquef, and V. Valimaki, "Frequency warped Burg's method for AR-modeling," 2003 IEEE Workshop on Applications of Signal Processing to Audio and Acoustics, October 19-22, 2003, pp. 5-8.
 - [8] C. Cornalba, R. G. Bellazzi, and R. Bellazzi, "Building a normative decision support system for clinical and operational risk management in hemodialysis," IEEE Trans. on Information Technology in Biomedicine, vol. 12, September 2008, pp. 229-238.
 - [9] S. Osowski, R. Siroic, T. Markiewicz, and K. Siwek, "Application of support vector machine and genetic algorithm for improved blood cell recognitions," IEEE Trans. on Information Technology in Biomedicine, vol. 58, July 2009, pp. 2159-2168.
 - [10] John Nash, "Non-cooperative games," The Annals of Mathematics, Second Series, vol. 54, no. 2, September 1951, pp. 286-295.
 - [11] D. Garagic and J. B. Cruz, "An approach to Fuzzy non-cooperative games," J. Optimization Theory and Applications, vol. 118, no. 3, September 2003, pp. 475-491.
 - [12] A. A. Cardenas, S. Amin, G. Schwartz, R. Dong, and S. Sasry, "A game theory model for electricity theft detection and privacy-aware control in AMI systems," Allerton Conference 2012, pp. 1830-1837.
 - [13] O. Pablo Vasquez, M. Marco Munguia, and B. Mandersson, "Arterio-venous fistula stenosis detection using wavelets and support vector machines," 31st Annual International Conference of the IEEE EMBS, Minneapolis, Minnesota, USA, September 2-6, 2009, pp. 1298-1301.
 - [14] Igor Podlubny, Fractional differential equations, Mathematics in Science and Engineering, vol. 198, New York, Academic Press, 1999.
 - [15] J.-H. Chen, "Controlling chaos and chaotification in the Chen-Lee system by multiple time delays," Chaos, Solitons & Fractals, vol. 36, no. 4, 2008, pp. 843-852.
 - [16] C.-H. Lin, S.-J. Chen, C.-L. Kuo, and J.-L. Chen, "Non-cooperative game model applied to an advanced metering infrastructure for non-technical loss screening in micro-distribution systems," IEEE Transactions on Smart Grid, vol. 5, no. 5, September 2014, pp. 2648-2649.