IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 6, 2019, accepted September 17, 2019, date of publication September 24, 2019, date of current version October 9, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2943453

Estimating the Ankle Angle Induced by FES via the Neural Network-Based Hammerstein Model

H. Y. ZHOU[1,2], L. K. HUANG[1,2], Y. M. GAO[1,2], Ž. LUČEV VASIĆ[3], M. CIFREK[3], AND M. DU[1,4]

[1]College of Physics and Information Engineering, Fuzhou University, Fuzhou 350116, China
[2]Key Laboratory of Medical Instrumentation and Pharmaceutical Technology of Fujian Province, Fuzhou 350116, China
[3]Faculty of Electrical Engineering and Computing, University of Zagreb, 10000 Zagreb, Croatia
[4]Fujian Provincial Key Laboratory of Eco-Industrial Green Technology, Wuyi University, Nanping 354300, China

Corresponding author: Y. M. Gao (fzugym@gmail.com)

This work was supported in part by the National Natural Science Foundation of China under Grant U1505251, in part by the Project of Chinese Ministry of Science and Technology under Grant 2016YFE0122700, and in part by the Project of S&T Department of Fujian Province under Grant 2018I0011.

ABSTRACT Functional electrical stimulation (FES) has been widely used in limb rehabilitation. The first step for the precision rehabilition is to clarify the variation of limb angle induced by FES. In this study, an electric stimulator and an inertial sensor are used to build a human body experimental platform. Motion characteristics of ankle angle induced by electrical stimulation pulse variation are obtained through experiment. The obtained ankle angle characteristics are used to train a neural network-based Hammerstein (H) model and the model parameters are identified by the genetic algorithm, which can effectively predict the ankle angle change induced by electrical stimulation. The structural parameters of the H model are adjusted according to the normalized root mean square error value (*NRMSE*) of the training data. The 10-fold cross-validation is used to verify the feasibility and effectiveness of the model. Experimental results show that the neural network-based H model can effectively predict the output change of the ankle angle induced by the electrical stimulation pulse, and its root mean square error (*RMSE*) and *NRMSE* are $2.78 \pm 0.33°$ and $23.70 \pm 1.77\%$, respectively. Therefore, the proposed model can provide a theoretical basis for predicting ankle angle change in an electrical stimulation closed-loop control system.

INDEX TERMS Functional electrical stimulation, ankle angle, Hammerstein model, neural network, genetic algorithm.

I. INTRODUCTION

The foot drop is a gait abnormality caused by damage to the central nervous system and suppression of advanced motor function dominated by the cerebral cortex, thereby resulting in the release of primitive reflexes from the lower central nervous system. The incidence of foot drop is increasing annually. Patients often exhibit specific spastic patterns. Spasms are usually caused by the contracture of the Achilles tendon due to the lack of stretching in the triceps of the calf muscle [1]. When the anterior tibial muscle and lateral muscle groups of the calf are insufficiently activated, the patient experiences long-term braking, which leads to difficulty in ankle dorsiflexion and disused muscle atrophy [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Le Hoang Son.

Most of the foot drop patients are associated with ankle dyskinesia. The main rehabilitation methods for ankle dorsiflexion are passive exercise [3] and functional electrical stimulation (FES) [4]. Passive exercise refers to rehabilitation training with the help of artificial apparatus or instrumentation. Such a method has a long treatment period and is highly dependent on a rehabilitator. Patients can easily become overtired, and secondary muscle injury can even occur during the rehabilitation process [5]. FES is a technique that uses low-energy electrical pulses for muscle stimulation. It stimulates muscles through pre-programmed procedures, induces muscle contraction or simulates normal autonomous movement to improve or restore the voluntary function of patients [4]–[6]. FES effectiveness depends on the precise control of stimulation time and intensity [7], [8]. Thus, establishing a reliable model between the FES signal and induced ankle angle output is important. An accurate and reliable ankle model can be used for exploring not only ankle movement characteristics induced by different electrical stimulation parameters, but also for adjustments and optimization of the electrical stimulation configuration parameters to maximise the electrical stimulation effect.

The existing FES joint angle model studies are mainly divided into two aspects. The first aspect is modelling by using the nonlinear system identification method. Munih *et al.* [9] used pseudorandom binary sequence data for the identification model, and the model of ankle dorsiflexion and plantar flexion is equivalent to a second-order function with zero and time delay. The recursive least squares algorithm was applied in the identification of model structure parameters to establish the relationship between pulse width (PW) and ankle dorsiflexion force. Li *et al.* [10] established a muscle excitation model with PW and evoked electromyography as the input and output, respectively, through the H model. Model predictive control is adopted to compute the PW based on H model which can online update its output parameters. Schauer and Vrontos [11] established the reference of the FES-induced muscle recruitment serves and the voluntary muscle activity extracted from EMG signals as input, joint angle as the model of output. the model was identified by least squares method. The second aspect involves the construction of H models, such as neural network [12], extreme learning machine [13], and fuzzy algorithm [14], from an artificial intelligence perspective. Błażkiewicz and Wit [15] developed an artificial neural network able to accurately simulate the changes in the angle of the ankle, knee and hipjoints during the gait cycle. Rahmatian *et al.* [16] used neural networks to design joint models with surface EMG as input and ankle joint angle and velocity as output. The model approximated velocities of the joint opening and closing by time-delayed artificial neural network. Janczak [17] described the dynamic linear and static nonlinear parts of the H model by using neural network methods to train the study via the backpropagation algorithm. However, this algorithm is sensitive to the initial value and easily falls into the local optimum, thereby causing failure in identification training.

The ankle angle model induced by the FES is a complex system with many unknown variables, and its nonlinearity and time-variability complicate its quantification in the model [18]–[20]. In this study, the relationship between electrical stimulation parameters and ankle angle is established by using the ''black box'' nonlinear model [21]. This model can establish a direct connection between parameter input and angle output without considering the changes in internal parameters. The FES equipment with inertial sensor is selected to construct the experimental test system with the electrical stimulation pulse width and ankle angle as the input and output, respectively, simplifying the data measurement process. For a neural network with feedback and feedforward links, the ''sawtooth phenomenon'' occurs when the error back-propagation algorithm results in an inefficient algorithm. Updating the calculated error gradient information during training is difficult, thus making it difficult for the algorithm to converge. Therefore, the genetic algorithm is applied to the H-model on the basis of the neural network due to its remarkable flexibility and convergence [22]–[25]. This algorithm can optimize the neural network structure and transform the model parameter optimization problem into an optimization problem of weight and threshold on the neural network structure.

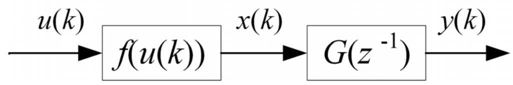

FIGURE 1. Block diagram of the Hammerstein model.

The response characteristics of hysteresis, nonlinearity and time-variation of the ankle angle induced by electrical stimulation pulse, which provides theoretical and supporting data for establishing the H-model on the basis of the neural network structure, are investigated. The genetic algorithm is applied to the H model for parameter identification training. Lastly, 10-fold cross-validation is used to verify the effectiveness of the model in predicting the ankle angle change induced by electrical stimulation. The rest of this paper is arranged as follows. Section II establishes the experimental platform for adjusting the ankle angle with different electrical stimulation variables. The H model structure based on the neural network is established, and the global optimal solution is determined by using the genetic algorithm. Section III obtains the experimental data induced via different electrical stimulation variables through the built-in *in vivo* experimental platform, which is used to train the neural network-based H model, determine the H model structural parameters and verify the H model reliability. Section IV discusses the phenomena in the experiments and models. Lastly, Section V presents the conclusion of this study.

II. METHODS

A. HAMMERSTEIN MODEL OF NEURAL NETWORK

1) HAMMERSTEIN MODEL

The H model [26], [27] consists of a static nonlinear function followed by a linear dynamic subsystem, as shown in Fig. 1.

In the H model, $u(k)$, $x(k)$, and $y(k)$ represent the input, intermediate signal and the output of the system at instant k, respectively. $f(u)$ is the nonlinear function, $G(z^{-1})$ is the transfer function of the linear dynamic part. The H model can be expressed by the Eq. (1–3):

$$x(k) = f(u(k)), \tag{1}$$

$$y(k) = G(z^{-1})x(k), \tag{2}$$

$$G(z^{-1}) = \frac{B(z^{-1})}{A(z^{-1})} = \frac{b_0+b_1z^{-1}+b_2z^{-2}+\cdots+b_{n_b}z^{-n_b}}{1+a_1z^{-1}+a_2z^{-2}+\cdots+a_{n_a}z^{-n_a}}. \tag{3}$$

2) STRUCTURE DETERMINATION OF HAMMERSTEIN MODEL BASED ON NEURAL NETWORK

The H model based on neural network was established on the basis of the ankle motion response characteristics induced by electrical stimulation. The use of a neural network as the

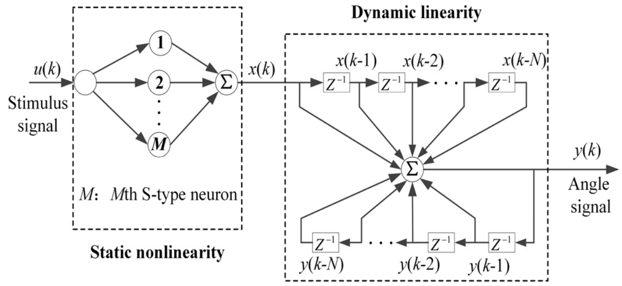

FIGURE 2. Block diagram of the H model based on neural network.

model structure transforms the model parameter optimisation problem into the training problem of the neural network model. The genetic algorithm is utilised to determine the training parameters and the neural network model structural parameters. The H model comprises a series of nonlinear static and linear dynamic parts. This model does not depend on past data and involves a small amount of computation, which is widely used in models [28], [29].

The model of ankle angle change induced by FES is designed as the H model based on the neural network. The type of neural network is Multi-Layer Perceptron (MLP), which consists of two parts, as shown in Fig 2. The first part is a static nonlinear part, which is a single hidden layer feed-forward neural network [30]. The single-layer neural network with feedback hysteresis constitutes the dynamic linear part of the second part. The effect of electrical stimulation pulse width on activation is linearly and non-linearly correlated within and outside the threshold range, respectively. The potential recruitment curve in the process that starts from the electrical stimulation to the muscle activation state is equivalent to the static nonlinear part. By contrast, the process of dynamic muscle contraction induced by electrical stimulation is equivalent to the dynamic linear part.

The input signal $u(k)$ represents the electrical stimulation frequency and the pulse width, the intermediate signal $x(k)$ is the activation function and $y(k)$ marks the ankle angle signal of the model output. Z^{-1} is the the unit delay. Neural network neurons in static nonlinear part are S-type neurons. The activation function is $g(x) = (1-e^{-2x})/(1+e^{-2x})$, which is the type of the Tanh. In the S-type nonlinear activation function, the TanH overcomes the shortcomings of non-zero mean output in the Sigmoid. It delays the saturation period with the better fault tolerance. N is the order of delay and M represents the number of static nonlinear hidden layer neurons. The model relation expression obtained from the connection relationship of the neural network, as shown in Eq. (4–5):

$$x(k) = \sum_{m=1}^{M} \beta_m g(\omega_m \cdot u(k) + \eta_m), \tag{4}$$

Substituting the Eq.(4) into the Eq.(2), and then joining the Eq.(3) to obtain the Eq.(5).

$$y(k) = -\sum_{i=1}^{N} a_i y(k-i) + \sum_{j=1}^{N} \sum_{m=1}^{M} b_j \beta_m g(\omega_m u(k-j) + \eta_m). \tag{5}$$

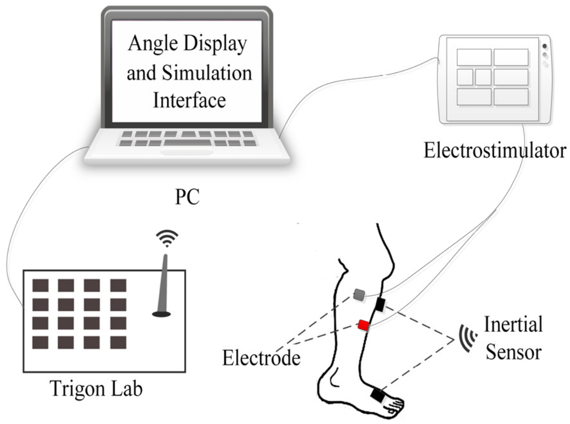

FIGURE 3. Experimental platform for obtaining input signal parameters of the H model.

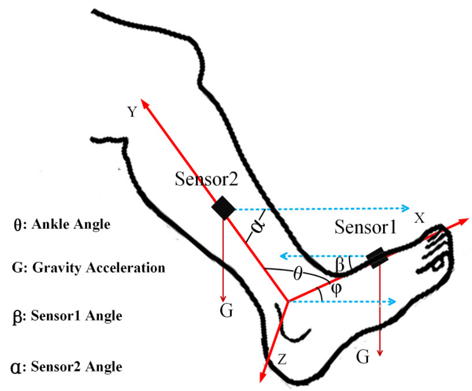

FIGURE 4. Set the reference coordinate system on the ankle to calculate the ankle angle.

All parameters that must be determined in the model include the following: ω_m, β_m, a_i, b_j are the connection weight of each layer. η_m are the threshold of each layer. Where $m = 1, 2, \ldots, M$; $i = 1, 2, \ldots, N$; $j = 1, 2, \ldots, N$. These model parameters need to be determined by training the neural network with experimental data.

B. EXPERIMENTAL PLATFORM

The input signal parameters of the H model are obtained via the experimental platform shown in Fig. 3, which comprises of an electrostimulator, inertial sensor and a PC. The inertial sensor comprises of the Trigon Lab wireless base station and two inertial sensor modules.

The inertial sensor calculates the angle by using the ground as the reference system. The origin of the reference coordinate system is set on the ankle and considers it as two connecting rods, and the calf and the foot are considered to be a rigid body. The directions of the foot and the calf are set as the x- and y-axes, respectively, as shown in Fig. 4. The calculation of the ankle angle requires application of a sensor on the instep and the shank to avoid errors in ankle angle measurement due to changes in human posture.

TABLE 1. General characteristics of subjects.

	Gender	Age	Weight (kg)	Height (cm)	BMI (kg/ m^2)
1	Male	24	52	167	18.47
2	Male	26	66	172	22.31
3	Female	25	43	159	17.01
4	Female	26	46	153	19.65

After the initial angle is measured, the relative ankle angle θ is calculated by using Eq. (6). In the post-experimental process, the ankle dorsiflexion angle is obtained by subtracting the relative angle θ produced by the experimental stimulus from the measured initial state angle.

Table 1 lists the four subjects with no history of any lower limb injury that were selected for the experiment. A 4 cm × 4 cm physiotherapy electrode was used in this study. The electrical stimulation instrument was a Motion-Stim 8 electrostimulation device (Medel, Germany). The optimal electrode placement position on the tibialis anterior muscle fibres was determined via the neuromuscular locator. Given the purpose of the experiment, the electrical stimulation output sequence programme was compiled, and the ankle angle was corrected. During the experiment, the crus of the subject naturally bent, and the knee and hip joints were maintained at a 90° angle from the horizontal plane, thereby showing a relaxed state. Each electrical stimulation did not exceed 20 s. Considering the contingency factor of the experiment, each group of experiments was repeated thrice to obtain the average. The interval between the two groups was 30 min to reduce the subjective memory effect, adaptability and voluntariness of the subject.

$$\theta = 180^{\circ} - (\alpha + \beta), \tag{6}$$

C. OPTIMAL SOLUTION BASED ON GENETIC ALGORITHM

The training of the H model parameters based on the neural network structure can be transformed into the problem of determining optimal weight and thresholds, and the process is a complex function optimisation process. The application of the genetic algorithm to neural network training has been widely used. This algorithm was proposed by Professor Holland of the Michigan University in the United States; genetic algorithm, a type of optimisation method with a solid biological basis, is used for obtaining the optimal solution in the process search by simulating the natural genetic mechanism and biological evolution theory [31], [32]. This method can automatically find global optimal solutions in accordance with the changes in the environment and optimise the weight and threshold parameters of the neural network in the H model structure. Fig. 5 shows the flowchart of genetic algorithm, consisting of five steps.

Step 1 *Generating the Initial Population:*

The initial population mainly depends on the size of the population and the initialising individual parameters. The number of population size is d, and the length of each individual is defined as n, which represents the total number of weight and threshold in the model, as shown in Eq. (7):

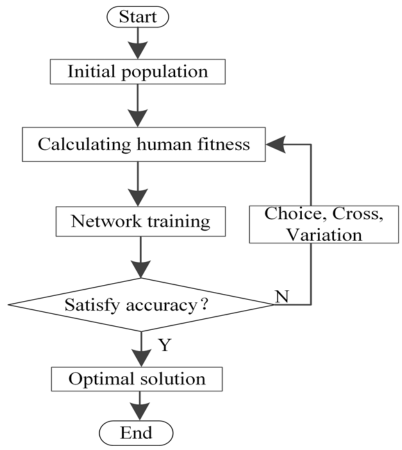

FIGURE 5. Flowchart of genetic algorithm.

$$n = rq_1 + q_1 + q_1q_2 + q_2 + q_2q_3N + q_3 + q_3q_3N, \tag{7}$$

where r represents the number of nodes in each input layer of the static nonlinear part of the H model, q_1 refers to the number of each hidden layer of static nonlinearity in the H model, q_2 is the number of static nonlinear output layers in the H model, q_3 denotes the number of medium dynamic linear neurons in the H model and N represents the delay order of the feed forward and feedback links in the model structure.

Step 2: Fitness Evaluation:

Fitness is the criterion by which an individual is chosen or not, and the optimal solution is the one with the largest fitness criteria. F is expressed as fitness, as shown in Eq. (8):

$$F = \sum_{i=1}^{n} |(y_i - o_i)|, \tag{8}$$

where y_i is the expected output of the i-th node in the model structure, o_i is the predicted output of the i-th node in the network structure and n is the number of output nodes in the model structure.

Step 3 *Select Operation*

The optimised individual will be passed on to the next generation through the roulette selection on the basis of individual fitness evaluations. The probability of each individual being selected is calculated as shown in Eq. (9):

$$P_i = f_i \Big/ \sum_{j=1}^{N_1} f_j, \tag{9}$$

where f_i is the fitness of each individual, and N_1 is the number of populations. Individuals with high selection probability are directly inherited to the next generation.

Step 4 *Crossover and Mutation Operations:*

Cross-operation aims to maintain the stability of the population and facilitates movement toward the optimal direction.

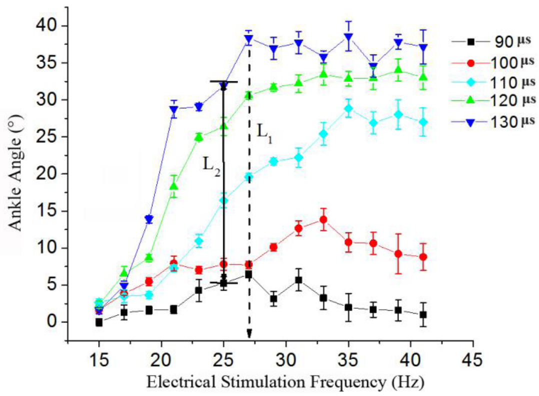

FIGURE 6. Relationship between different electrical stimulation frequency and induced ankle angle.

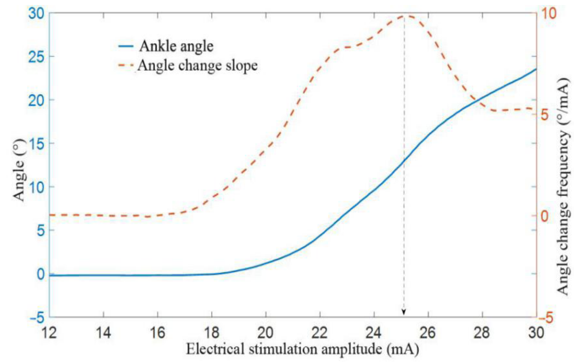

FIGURE 7. Effect of different electrical stimulation amplitudes on ankle angle.

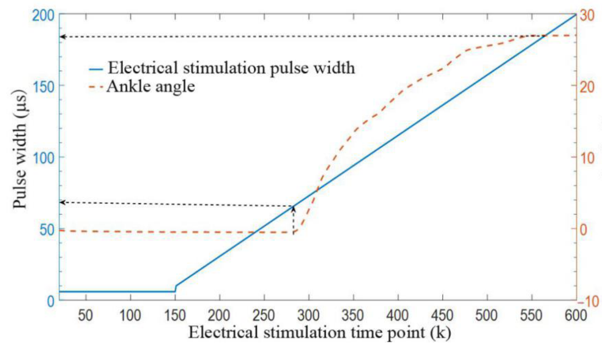

FIGURE 8. Effect of different electrical stimulation pulse width on ankle angle.

Different chromosomes are cross-operated in the same location through individual coding as shown in Eq. (10):

$$\begin{cases} a_{kj} = a_{kj}(1-b) + a_{lj}b \\ a_{lj} = a_{lj}(1-b) + a_{kj}b \end{cases}, \tag{10}$$

where b is a random number between 0 and 1. Variation prevents the partial convergence of the crossover and ensures the diversity of the population. The specific operation modifies the j gene in the i-th individual as shown in Eq. (11):

$$a_{ij} = \begin{cases} a_{ij} + \left(a_{ij} - a_{\max}\right) * f(g) & r > 0.5 \\ a_{ij} + \left(a_{\min} - a_{ij}\right) * f(g) & r \le 0.5 \\ f(g) = r_2\left(1 - g/G_{\max}\right)^2 \end{cases}, \tag{11}$$

where $a_{\max}$ and $a_{\min}$ are the upper and lower bounds of the gene a_{ij}, respectively; $G_{\max}$ is the maximum reproductive evolution algebra; g is the current iteration number; r is the random number between 0 and 1; and r_2 is a random number.

Step 5 Repeat Steps 2 to 4:

The above steps are repeated until the weight of network connection and the training index of threshold reach the precision requirement.

III. RESULTS

A. DETERMINATION OF ELECTRICAL STIMULATION INPUT PARAMETERS

On the basis of the above experimental platform for the ankle angle acquisition, the effects of different electrical stimulation parameters (frequency, amplitude and pulse width) on the angular motion characteristics of the ankle were investigated.

1) The amplitude of electrical stimulation current was set to 25 mA and the electrical stimulation pulse width increased from 90 μs to 130 μs in steps of 10 μs. Average and standard deviation of the induced ankle angle measured at different electrical stimulation frequencies for each pulse width are shown in Fig. 6. To avoid musle fatigue effect, FES frequency should be as low as possible. Therefore, according to Fig. 6, a 25 Hz was selected as the input frequency to avoid muscle fatigue and maintain the electrical stimulation time and pulse width at the maximum adjustable linear range.
2) The electrical stimulation pulse width and frequency were set to 100 μs and 25 Hz, respectively, and amplitude of the stimulation current changed. When the amplitude of electrical stimulation current reached 31 mA, the subjects developed a tingling sensation. Therefore the amplitude range was limited to 12–31 mA in advance (Fig. 7). The experimental results showed that the ankle angle increased with amplitude and the highest ankle angle derivation was achieved for 25 mA stimulation current. Thus, the stimulus input amplitude was set to 25 mA.
3) The experimental setting of the electrical stimulation amplitude and frequency was 25 mA and 25 Hz, respectively, and the pulse width increased linearly. Fig. 8 illustrates the experimental results of the subject 2, which indicates that the minimum threshold of the ankle was obtained at for the pulse width of 70 μs. The maximum threshold of pulse width was set to 110 μs due to the prickling sensation of subject no. 3 when the pulse width reached 110 μs.

The threshold change of pulse width of different subjects measured under the same electrical stimulation experiment conditions is shown in Table 2. The results provide a data reference for the input parameters of the neural network-based H model.

TABLE 2. Threshold of the electrical stimulation pulse width for different subjects.

Pulse width threshold (μs)	Subject number				Value of other parameters	
	1	2	3	4	Amplitude (mA)	Frequency (Hz)
Start threshold	50	70	50	40	25	25
Saturation threshold	160	180	110	120		

TABLE 3. Functional electrical stimulation parameter settings.

Parameter type	Parameter
Stimulation output mode	Bidirectional current pulse
Stimulation current amplitud	25 mA
Stimulation frequency	25 Hz
Stimulation pulse width	40–110 μs
Stimulation site	Tibialis anterior muscle

4) The experimental study was conducted based on the experimental platform described in Section II.B, using the related input parameters are shown in Table 3. Variations in the electrical stimulation pulse width affect the subsequent model identification. In this study, filtered random noise (FRN) was used as the model identification data, which were applied as the electrical stimulation input variation pulse (Fig. 9), and its influence on the joint angular motion characteristics was analysed. In Fig. 9(a) and 9(b) results for pulse sequences lasting two and one seconds respectively are presented. It is shown that the ankle output angle significantly lagged behind the electrical stimulation input pulse in both cases. However, Fig. 9(b) also shows that the time-varying characteristics of the random pulse variation are not proportional to the change in its joint angle and the non-uniformity of decline characteristics.

B. PARAMETERS DETERMINATION OF THE H MODEL

The model parameters are divided into structural and training parameters. The structural parameters include the nonlinear static partial hidden layer point number M in the H model and the delay order N in the linear dynamic equation. The training parameters include population size and evolutionary algebra of genetic algorithm.

1) DETERMINATION OF POPULATION SIZE AND EVOLUTIONARY ALGEBRA

The two-second period change of FRN data in Fig. 9(a) was used as the pulse variation sequence of electrical stimulation model. The ankle angles of 10 groups of different random sequences were collected, of which 9 groups were selected as the training data, and 1 group was used as the test data. The 10 groups of data obtained in the experiment were used for testing and network training through the 10-fold cross-validation. When the population size was determined, the optimal fitness of an individual was fixed within a certain range. The population size was set to 12 and the genetic optimisation had 20 generations to ensure that the best fitness of individuals could be achieved under each calculation of the genetic algorithm, thereby indicating the fitness change in the optimisation process (Fig. 10). The evolutionary algebra converged upon reaching the eighth generation, and the fitness did not decrease. The same data set was trained 10 times, and the evolutionary algebraic values were recorded under the same population size (Table 4). Table 4 shows that evolutionary algebra takes 10 generations to guarantee the best training effect.

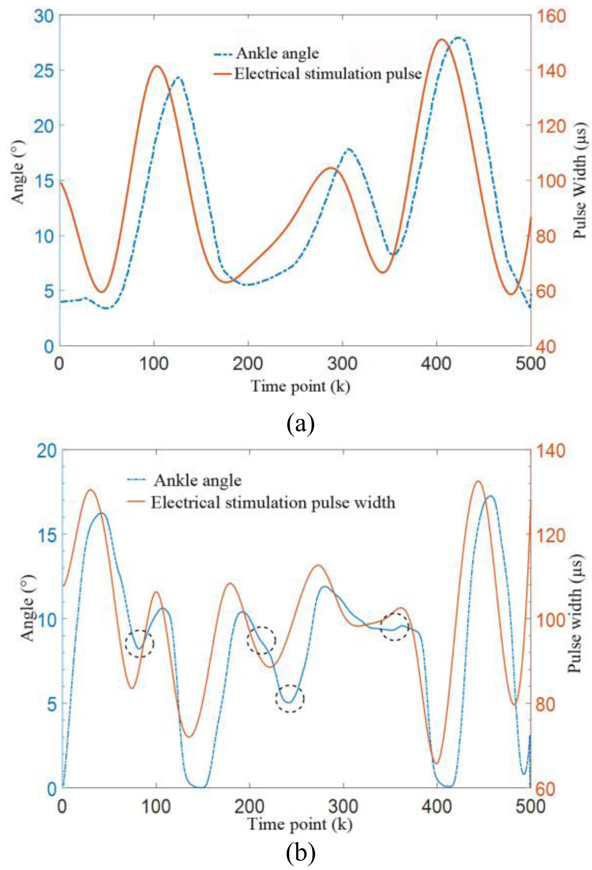

FIGURE 9. FRN electrical stimulation pulse width sequence: (a) two-second period change, (b) one-second period change.

TABLE 4. Convergence algebraic value under the same population size.

Number of times	1	2	3	4	5	6	7	8	9	10	Max
Convergence algebra	6	10	4	3	8	8	5	5	6	5	10

2) DETERMINATION OF STRUCTURAL PARAMETERS OF THE NEURAL NETWORK MODEL

The experimental data were used in the simulation test by applying the genetic algorithm in MATLAB and changing the H model parameters. The root mean square error (*RMSE*) and the normalised root mean square error (*NRMSE*) between the

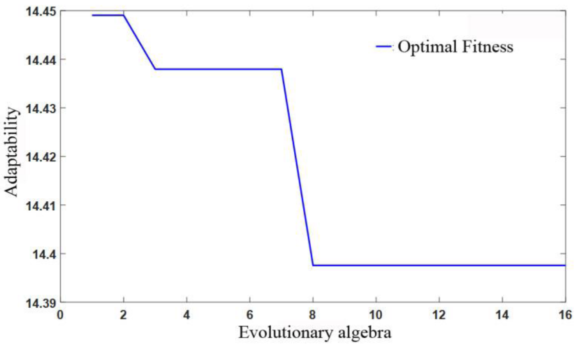

FIGURE 10. The change of fitness in the process of individual optimization under the calculation of genetic algorithm.

model output angle and the *in vivo* measured ankle angle were calculated as the evaluation indices for estimating the ankle angle of the H model as shown in Eq. (12−13):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=0}^{N}(\theta_m - \theta_s)^2}, \tag{12}$$

$$NRMSE = \frac{1}{\bar{\theta}_m}\sqrt{\frac{1}{N}\sum_{t=0}^{N}(\theta_m - \theta_s)^2}, \tag{13}$$

where θ_m is the actual measured ankle angle, $\bar{\theta}_m$ is the average of the actual angle, θ_s is the theoretical model output angle and N is the number of time sampling points. By using the identical electrical stimulation angle data as in training, one set was randomly selected from the 10 data sets for testing whilst the 9 remaining sets were used for training. The experiment was repeated, and each experiment changed the delay order or the number of hidden layer points. The delay order N was 1, 2 and 3, and the number of hidden layer points M was 5, 10 and 15, which were combined into 12 different parameter combinations. The *RMSE* and *NRMSE* values of the samples were calculated. The results show that *RMSE* and *NRMSE* are the smallest when the hidden layer number M and the delay order N are 15 and 2, respectively. Therefore, the number of hidden layer point M of the H model and delay order N are set to 15 and 2, respectively.

3) HAMMERSTEIN MODEL VERIFICATION

After determining the parameters of the H model via the genetic algorithm, 10-fold cross-validation was applied to the *in vivo* experiment data to verify the error effect of the H model. The two-second pulse variation FRN sequence shown in Fig. 9(a) was considered to be the model training sample. Nine groups were randomly selected as the training data, and the last group was considered the test data. A total of 90 random fluctuation sequences were sufficient to activate all angular motion characteristics of the ankle induced by the electrical stimulation waveform. Figs. 11(a) and 11(b) present the test results of a training and non-training sample, respectively. The curve in Fig. 11 shows that the model output data can track the actual data. The experiment was repeated 20 times for comparison. Figs. 11(c) and 11(d) illustrate the obtained relative error curves.

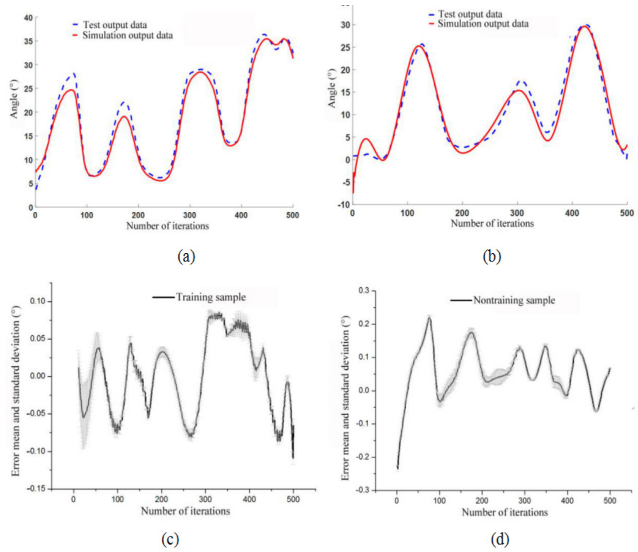

FIGURE 11. Model test results: (a) training sample input, (b) non-training sample input, (c) average relative error and standard deviation of training samples, (d) average error and standard deviation of non-training samples.

TABLE 5. Different individual simulation error results.

Subject number	1	2	3	4	Average ± Standard deviation
NRMSE (%) ± S	20.50 ± 1.66	19.50 ± 1.35	28.30± 1.44	26.50 ± 2.62	23.70 ± 1.77
RMSE (°) ± S	2.40 ± 0.56	2.29 ± 0.43	3.31 ± 0.22	3.11 ± 0.12	2.78 ± 0.33

Figs. 11(c) and 11(d) show that the relative error of the electrical stimulation waveform with the training sample as input is within ±10% and that of the electrical stimulation data input with the non-training sample is ±25%, respectively. The model could accurately track the changing trend of actual data. Table 5 lists the mean and standard deviation of *RMSE* and *NRMSE* for four subjects. The *RMSE* and *NRMSE* are 2.78 ± 0.33° and 23.70 ± 1.77%, respectively, indicating the feasibility of this model.

Klauer *et al.* [33] proposed to construct a feedback control model through an H-model and an artificial neural network based on radial basis functions. The model uses an EMG as the input to the model and the output is the angle of the shoulder abduction joint. The model was validated in two healthy subjects with *RMSE* values for joint angle errors of 3.56° and 3.44°, respectively. The average value of the *RMSE* value of the joint angle error herein is 2.59 ± 0.35 °.

IV. DISCUSSIONS

A. ANALYSIS AND DISCUSSION OF THE ANKLE MOTION CHARACTERISTICS INDUCED BY FES

The hysteresis, time-varying, nonlinear and other motion characteristics of the ankle angle can be summarised on the basis of the ankle angle acquisition experiment induced by electrical stimulation. The physiological function response of the ankle induced by electrical stimulation is not a mechanical or physical process. The hysteresis shows that the ankle angle lags behind the electrical stimulation signal. Starting from the muscle biomechanical bone model, the process of electrical stimulation-induced muscle contraction is a process of gradually collecting potentials per unit time. Thus, muscle contraction will lag behind the electrical stimulation sequence. The time-varying and nonlinear characteristics are observed in electrical stimulation therapy possibly due to the effects of electrical stimulation fatigue, stiffness and antagonistic muscle synergy. When the electrical stimulation time is extremely long, the muscle will gradually enter the state of fatigue. When the muscle is continuously contracted, its physiological characteristics change; its excitability, contractility and conductivity decrease [34], and the same electrical stimulation intensity cannot reach the same angle. With the change in stimulation time, angular jitter, non-linearity and other problems arise due to muscle fatigue, and even muscle stiffness and angle invariance due to excessive stimulation are also observed. From the analysis of the stiffness effect, the ankle has different stiffness coefficients at different angles. Therefore the activation of the same angle requires electrical stimulation of different intensities. Under the same electrical stimulation intensity, the large current angle causes a minimal increase in the angular amplitude, resulting in the nonlinearity of the ankle joint angle and electrical stimulation intensity. From the perspective of antagonistic muscle synergy, a large number of electrical signals are induced in a unit time. The change rate of the electrical signal exceeds the recruitment speed of the tibialis anterior muscle fibres and triggers the involuntary reflex mechanism of the central nervous system [35], thereby prompting the dorsiflexion of the gastrocnemius, soleus and other antagonistic muscles [31].

Selecting the proper input data form for the complex motion characteristics of the ankle and the identification of angle model parameters of the ankle induced by electrical stimulation is crucial. The appropriate electrical stimulation pulse sequence can ensure that the electrical stimulation intensity is within the range of the muscle contraction of the subject. The input electrical stimulation signal can gradually collect additional potentials per unit time instead of instantaneously exciting a large number of electrical signals. Hence, the problem of abnormal physiological reactions, such as physical discomfort caused by triggering the involuntary reflex mechanism of the human body, is avoided [36].

B. DISCUSSION AND ANALYSIS OF THE H MODEL

The H model based on the neural network is a ‘‘black box’’ model suitable for complex and time-varying nonlinear systems [18]–[20]. The model combines the advantages of the Hammerstein and neural networks and embodies the characteristics of static nonlinearity and dynamic linearity of the system. The H model trains the parameters of the model by using the genetic algorithm, mining the laws from the data itself and applying the laws to other data. However, the law between the electrical stimulation parameters of the H model and the angle of the ankle has poor versatility because of the hysteresis, time variation and nonlinearity of the ankle motion angle induced by FES and the individual differences between the subjects. Therefore, the phenomenon of large model error occurs.

The pulse sequence of FRN electrical stimulation (Fig. 9) shows that the stimulation effect of the pulse sequence lasting for one and two seconds is different. The data of stimulation time for two seconds can clearly track the angular motion characteristics of the ankle possibly due to the slow ankle system induced by electrical stimulation. The change of the electrical stimulation pulse for one second exceeds the reaction time of the joint mechanism, thereby indicating the occurrence of an error. Tables 1, 2, and 3 show that the *NRMSE* and *RMSE* values of subject2 are relatively small. The pulse width threshold and body mass index (BMI) of subject2 were higher than those of the three other subjects as shown in table 1. Therefore, the H model is found to be effective for subjects with large BMI.

At present, most of the treatment products for patients with ankle dyskinesia are open-loop type electrostimulators. The output parameters of this electrostimulator are single, and the output parameters cannot be adjusted in real time according to the degree of muscle fatigue. Therefore, in the course of treatment, the phenomenon of insufficient stimulation or excessive stimulation may lead to the situation that the patient's condition cannot be improved or even muscle damage occurs. In order to solve the problems in the above FES treatment, the researchers began to focus on the FES closed-loop feedback control system. The neural network-based H model established in this study can be used as the control model of the FES closed-loop feedback control system. The control system can optimize and adjust the electrical stimulation output parameters in real time, which greatly improves the treatment effect of patients with ankle dyskinesia. The development of this control system is also our main goal in the later period.

V. CONCLUSION

In this study, the human ankle dorsiflexion motion angle is considered the research object, and an experimental platform is built by using an inertial sensor and an electrical stimulator to conduct experiments on the changes in ankle angle. Different threshold values of electrical stimulation, including amplitude, frequency and pulse width, are experimentally studied. Simultaneously, the angular hysteresis, nonlinearity and time-varying motion characteristics of the ankle induced by the input sequence of FRN electrical stimulation are obtained. According to the motion characteristics of ankle angle, an H model based on the neural network structure is established. The FRN electrical stimulation pulse sequence is selected as the model input, and the data are trained via the genetic algorithm that transforms the model parameter optimisation problem into the training problem of the neural network model. According to the *RMSE* of the training results, the structure and training parameters of the H model are adjusted. Establish a model relationship with the FES pulse width sequence as the input and the ankle control angle as the output. Lastly, the 10-fold cross-validation is used to verify the feasibility and effectiveness of the model. The experimental results show that the neural network-based H model can effectively predict the angle change induced by FES, its *RMSE* and *NRMSE* are $2.78 \pm 0.33^{\circ}$ and $23.70 \pm 1.77\%$, respectively. Therefore, applying the genetic algorithm to the neural network-based H model can provide a model basis for the closed-loop control strategy of the FES system.

This paper studies the ankle angle modeling and achieves certain achievements, but there are still some shortcomings and improvements. Firstly, the experimental studies on the motor characteristics of the ankle under electrical stimulation are all carried out in healthy subjects. There was no experimental study on stroke patients or patients with spinal cord injury. Secondly, the controller should be designed to match the ankle model, and further study how to compensate for the lack of stimulation angle induced by muscle fatigue under electrical stimulation.

REFERENCES

[1] V. Dietz, "Interaction between central programs and afferent input in the control of posture and locomotion," *J. Biomechanics*, vol. 29, no. 7, pp. 841–844, Jul. 1996.

[2] C. A. Johnson, J. H. Burridge, P. W. Strike, D. E. Wood, and I. D. Swain, "The effect of combined use of botulinum toxin type A and functional electric stimulation in the treatment of spastic drop foot after stroke: A preliminary investigation," *Arch. Phys. Med. Rehabil.*, vol. 85, no. 6, pp. 902–909, Jun. 2004.

[3] P. Langhorne, J. Bernhardt, and G. Kwakkel, "Stroke rehabilitation," *Lancet*, vol. 377, no. 9778, pp. 1693–1702, 2011.

[4] P. H. Peckham and J. S. Knutson, "Functional electrical stimulation for neuromuscular applications," *Annu. Rev. Biomed. Eng.*, vol. 7, no. 1, pp. 327–360, 2005.

[5] M. L. van der Linden, J. E. Hooper, P. Cowan, B. B. Weller, and T. H. Mercer, "Habitual functional electrical stimulation therapy improves gait kinematics and walking performance, but not patient-reported functional outcomes, of people with multiple sclerosis who present with foot-drop," *PLoS ONE*, vol. 9, no. 8, Aug. 2014, Art. no. e103368.

[6] C. L. Lynch and M. R. Popovic, "Functional electrical stimulation," *IEEE Control Syst. Mag.*, vol. 28, no. 2, pp. 40–50, Apr. 2008.

[7] S. Qiu, F. He, J. Tang, J. Xu, L. Zhang, X. Zhao, H. Qi, P. Zhou, X. Cheng, B. Wan, and D. Ming, "Intelligent algorithm tuning PID method of function electrical stimulation using knee joint angle," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2014, pp. 2561–2564.

[8] Q. Zhang, M. Hayashibe, and C. Azevedo-Coste, "Evoked electromyography-based closed-loop torque control in functional electrical stimulation," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 8, pp. 2299–2307, Aug. 2013.

[9] M. Munih, M. Mihelj, and M. Ponikvar, "Control of FES standing," in *Proc. Eur. Control Conf. (ECC)*, Sep. 2015, pp. 3935–3938.

[10] Z. Li, D. Guiraud, D. Andreu, A. Gelis, C. Fattal, and M. Hayashibe, "Real-time closed-loop functional electrical stimulation control of muscle activation with evoked electromyography feedback for spinal cord injured patients," *Int. J. Neural Syst.*, vol. 28, no. 6, 2018, Art. no. 1750063.

[11] T. Schauer and A. Vrontos, "Modeling of mixed artificially and voluntary induced muscle contractions for controlled functional electrical stimulation of shoulder abduction," *IFAC-PapersOnLine*, vol. 51, no. 34, pp. 284–289, 2019.

[12] R. Tian, Y. Yang, F. C. T. van der Helm, and J. P. A. Dewald, "A novel approach for modeling neural responses to joint perturbations using the NARMAX method and a hierarchical neural network," *Frontiers Comput. Neurosci.*, vol. 12, p. 96, Dec. 2018.

[13] G. Huang, G.-B. Huang, S. Song, and K. You, "Trends in extreme learning machines: A review," *Neural Netw.*, vol. 61, pp. 32–48, Jan. 2015.

[14] G. Chen, Z. Shen, Y. Zhuang, I. Wang, and I. Song, "Intensity- and duration-adaptive functional electrical stimulation using fuzzy logic control and a linear model for dropfoot correction," *Frontiers Neurology*, vol. 9, p. 165, Mar. 2018.

[15] M. Błażkiewicz and A. Wit, "Artificial neural network simulation of lower limb joint angles in normal and impaired human gait," *Acta Bioeng. Biomech.*, vol. 20, no. 3, pp. 43–49, 2018.

[16] S. Rahmatian, M. J. Mahjoob, and M. R. Hanachi, "Continuous estimation of ankle joint angular position based on the myoelectric signals," in *Proc. Artif. Intell. Robot. (IRANOPEN)*, Apr. 2016, pp. 158–163.

[17] A. Janczak, "Neural network approach for identification of Hammerstein systems," *Int. J. Control*, vol. 76, no. 17, pp. 1749–1766, 2003.

[18] F. Previdi and E. Carpanzano, "Design of a gain scheduling controller for knee-joint angle control by using functional electrical stimulation," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 3, pp. 310–324, May 2003.

[19] M. Ferrarin, F. Palazzo, R. Riener, and J. Quintern, "Model-based control of FES-induced single joint movements," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 3, pp. 245–257, Sep. 2001.

[20] N. Kirsch, N. Alibeji, and N. Sharma, "Nonlinear model predictive control of functional electrical stimulation," *Control Eng. Pract.*, vol. 58, pp. 319–331, Jan. 2017.

[21] F. Previdi, "Identification of black-box nonlinear models for lower limb movement control using functional electrical stimulation," *Control Eng. Pract.*, vol. 10, no. 1, pp. 91–99, 2002.

[22] D. E. Goldberg and K. Deb, "A comparative analysis of selection schemes used in genetic algorithms," *Found. Genetic Algorithms*, vol. 1, no. 1, pp. 69–93, 1991.

[23] J. Genlin, "Survey on genetic algorithm," *Comput. Appl. Softw.*, vol. 2, pp. 69–73, Feb. 2004.

[24] G. Syswerda, "A study of reproduction in generational and steady-state genetic algorithms," *Found. Genetic Algorithms*, vol. 1, pp. 94–101, Jan. 1991.

[25] C. A. Ankenbrandt, "An extension to the theory of convergence and a proof of the time complexity of genetic algorithms," *Found. Genetic Algorithms*, vol. 1, pp. 53–68, Jan. 1991.

[26] O. Naeem and A. E. M. Huesman, "Non-linear model approximation and reduction by new input-state Hammerstein block structure," *Comput. Chem. Eng.*, vol. 35, no. 5, pp. 758–773, May 2011.

[27] K. P. Fruzzetti, A. Palazoğlu, and K. A. McDonald, "Nolinear model predictive control using Hammerstein models," *J. Process Control*, vol. 7, no. 1, pp. 31–41, 1997.

[28] K. J. Hunt, M. Munih, N. Donaldson, and F. M. D. Barr, "Optimal control of ankle joint moment: Toward unsupported standing in paraplegia," *IEEE Trans. Autom. Control*, vol. 43, no. 6, pp. 819–832, Jun. 1998.

[29] H. Yang, X. Gao, Y. Chen and L. Hao, "Hammerstein adaptive impedance controller for bionic wrist joint actuated by pneumatic muscles," *IEEE Access*, vol. 7, pp. 47–56, 2018.

[30] Y. Xue, T. Tang, and A. X. Liu, "Large-Scale feedforward neural network optimization by a self-adaptive strategy and parameter based particle swarm optimization," *IEEE Access*, vol. 7, pp. 52473–52483, 2019.

[31] J. P. Giuffrida and P. E. Crago, "Reciprocal EMG control of elbow extension by FES," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 4, pp. 338–345, Dec. 2001.

[32] K. Sastry, D. Goldberg, and G. Kendall, "Genetic algorithms," in *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques*. Boston, MA, USA: Springer, 2005, pp. 97–125.

[33] C. Klauer, M. Irmer, and T. Schauer, "A muscle model for hybrid muscle activation," *Current Directions Biomed. Eng.*, vol. 1, no. 1, pp. 386–389, Sep. 2015.

[34] T. Marqueste, F. Hug, P. Decherchi, and Y. Jammes, "Changes in neuromuscular function after training by functional electrical stimulation," *Muscle Nerve*, vol. 28, no. 2, pp. 181–188, 2003.

[35] J. H. Burridge and M. Ladouceur, "Clinical and therapeutic applications of neuromuscular stimulation: A review of current use and speculation into future developments," *Neuromodulation, Technol. Neural Interface*, vol. 4, no. 4, pp. 147–154, Oct. 2001.

[36] N. A. Maffiuletti, "Physiological and methodological considerations for the use of neuromuscular electrical stimulation," *Eur. J. Appl. Physiol.*, vol. 110, pp. 223–234, Sep. 2010.

H. Y. ZHOU received the B.S. degree from the College of Physics and Electronic Information Engineering, Minjiang University, Fuzhou, China, in 2017. She is currently pursuing the M.S. degree with the College of Physical and Information Engineering, Fuzhou University. Her current research interests include intra-body communication and biomedical signal detecting technology.

L. K. HUANG received the B.S. degree from the College of Electronic Information and Electrical Engineering, Fujian University of Technology, Fuzhou, China, in 2017. He is currently pursuing the M.S. degree with the College of Physical and Information Engineering, Fuzhou University. His current research interests include neural networks and biomedical signal detecting technology.

Y. M. GAO received the Ph.D. degree in electrical engineering from Fuzhou University, Fuzhou, China, in 2010. He is currently a Professor with the College of Physical and Information Engineering, Fuzhou University. Since 2004, he has been involved in research in the areas of bioelectromagnetism and biomedical signal detecting technology.

Ž. LUČEV VASIĆ received the Dipl.Ing. and Ph.D. degrees in electrical engineering from the University of Zagreb, Zagreb, Croatia, in 2007 and 2014, respectively, where she is currently an Assistant Professor with the Department of Electronic Systems and Information Processing, Faculty of Electrical Engineering and Computing. Her research activities are in the field of biomedical electronic instrumentation and human-body signal transmission. She is a member of IFMBE and CROMBES. She also serves as the Vice-President of the IEEE EMB Croatian Section.

M. CIFREK received the Dipl.Ing., M.Sc., and Ph.D. degrees in electrical engineering from the Faculty of Electrical Engineering and Computing, University of Zagreb, Zagreb, Croatia, in 1987, 1992, and 1997, respectively, where he is currently a Professor of electrical engineering with the Department of Electronic Systems and Information Processing. His research interests are focused on the design of biomedical instrumentation and biomedical signal analysis for research and clinical applications. He is a member of the IFMBE, CROMBES, KoREMA, and HMD. Since 2005, he has been a Collaborating Member of the Croatian Academy of Engineering.

M. DU received the Ph.D. degree in electrical engineering from Fuzhou University, Fuzhou, China, in 2005. Since 2007, she has been the Associate Director of the Fujian Provincial Key Laboratory of Eco-Industrial Green Technology, Nanping, China. She is currently a Professor and a Doctoral Supervisor with Fuzhou University. Her research interests include smart instrument and photoelectric.