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Automated Cerebral Emboli Detection Using Adaptive Threshold and Adaptive Neuro-Fuzzy Inference System

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ABSTRACT This work proposes an automated algorithm based on adaptive threshold and adaptive neuro-fuzzy inference system (ANFIS) to couple with transcranial Doppler ultrasound in detecting cerebral embolic signal (ES). Our main objective is to support practical stroke risk monitoring in interventional procedures. Suspected ESs are captured in real time using adaptive thresholds based on 1) standard deviation, to capture suspected ESs of long duration and 2) median absolute deviation, to capture the shorts, which proved to be the key contribution of this paper. For classification using ANFIS, handcrafted feature extraction is performed and the resulting features are classified as embolic or non-embolic. The effectiveness of the classifier was evaluated over 19 subjects going under procedures generating emboli and compared with the Euclidean matrix-based indexing high-dimensional model representation system. The ANFIS-based system yielded in average of 91.5% sensitivity, 90.0% specificity, and 90.5% accuracy significantly outperformed the HDMR system and the hybrid of HDMR system and the proposed features in both detection accuracy [$F(2,57) = 10623.05$, $p < 0.0001$] and sensitivity [$F(2,57) = 10572.12$, $p < 0.0001$] at 90.0% specificity. The system using adaptive threshold to capture suspected intervals and ANFIS to identify ES has promising potential as a medical decision support in various clinical settings, e.g., real-time monitoring of cerebral emboli in carotid artery stenting procedures.

INDEX TERMS Adaptive threshold, adaptive neuro-fuzzy inference system, adaptive wavelet packet transform, embolic signal, ischemic stroke, microemboli, transcranial Doppler ultrasound.

I. INTRODUCTION

Every year, 15 million people worldwide suffer a stroke and nearly 6 million people die [1]. Ischemic stroke, accountable for 87% of all strokes, occurs when an embolus, i.e., a loose clot or plaque fragment, occludes a blood vessel and cuts off blood flow to the brain [2]. Transcranial Doppler ultrasound (TCD), a non-invasive and affordable approach (less than USD 100 per use) to measure blood flow velocity in intracranial arteries can be used to detect the circulating cerebral emboli by monitoring middle cerebral artery (MCA), allowing a fast diagnosis and treatment of embolus-related risk of stroke, especially in surgical procedures [3]. TCD is a promising technique to enter clinical routine [4]. Medical decisions can be made based on this investigation once the significance of the technique is definite and undebatable [4]. The possibilities for guiding surgical technique to reduce the frequency of emboli [5] and assessing new strategies to lessen complications [6] will significantly benefit the patients.

However, limitations of the recent cerebral emboli detection using TCD still include insufficient real-time performance and reliability of the detection result [7]. Embolic signal (ES), a signal reflected from an embolus once insonated with TCD, has similar characteristics to those of artifacts (AF), usually caused by patient's movements or motion of the TCD probe [3]. ES and AF are difficult to distinguish as both often appear as short-duration transient signals (SDTSs) [7]–[9]. The questionable result therefore needs to be verified by human experts, referred to as "Gold Standard" [9], by analyzing audio and spectral characteristics of the reflected signal [7], which are prone to human error and inter-rater reliability issue [8], [10]. The need for an efficient automated algorithm to distinguish ES is widely agreed and that it will make an impactful contribution as a medical decision support [9].

Most traditional ES detection techniques applied the fast Fourier transform (FFT) and the short-time Fourier transform (STFT) to detect ES and differentiate artifacts [8], [9], [11]. However, FFT can provide only frequency information of the signal but not directly time information, while STFT can provide both but not of good resolution at the same time and the resolution is fixed [8]. Recently, the discrete wavelet transform (DWT) has been widely used to analyze SDTSs for its multi-resolution representation of time-frequency analysis [12], [13]. Specifically, DWT provides trade-off between time and frequency resolution, i.e., it has good time but poor frequency resolution at high frequencies and has good frequency but poor time resolution at low frequencies [12], [14]. Aydin *et al*. transformed TCD signal using DWT to determine the features most accurately representing ES and proposed an ES detection system based on it [7]. Though, DWT has advantages for analyzing small signals, such as some ESs, due to its high temporal resolution at high frequency ranges, it lacks resolution in the frequency range in which ES are mostly found [7], [10]. To overcome the limitation, the adaptive wavelet packet transform (AWPT) has been used to achieve the information located in high frequency band as it can provide good frequency resolution for both high and low frequency ranges and the resolution is not fixed [10], [12], [15]. Further, best basis approach was applied for dimensionality reduction of feature vector [12]. Then, the adaptive neuro-fuzzy inference system (ANFIS), an adaptive classifier where the classification rules can be adjusted in accordance with the training data, was used. The experimental results showed impressive results with high sensitivity and specificity [10], [15].

The best claimed performance from the literature (98% accuracy, 99% sensitivity), uses the Euclidean matrix based indexing high dimensional model representation (MIHDMR) to detect ES by constructing a general polynomial model [16]. Though iterative training is not needed for this method, training data were still required to construct the model. The total number of training data was calculated from a combination of prime factors, and the total number of prime factors making the combination equals the total number of parameters used, i.e., for seven parameters in this study, 192 out of 300 episodes were randomly selected as training dataset ($3 \times 2 \times 2 \times 2 \times 2 \times 2 \times 2 = 192$) and the remaining 108 episodes were used as a testing dataset [16]. However, the construction of the model requires many steps of data preparation [16] and would not suit a system with an expanding set of data available for training [17]. That is, the number of training data depends on the number of the detection parameters and also on the combination of prime factors; both always need to be calculated before training since managing the balance of training and testing data is crucial [16].

Though it is well known that an efficient automated real-time application will essentially make cerebral ES detection with TCD practical, and is specifically needed if intended to serve as an emboli warning system in interventional procedures [18]–[20], no systems have yet been unanimously agreed to enter clinical routine [3]. We suggest that an effective real-time detection of SDTS would enhance clinical performance of TCDs. However, an automation of this part of signal pre-processing had not been focused enough in previous literature, e.g., algorithms in [9] and [11] cannot be directly used to analyze the collected TCD signals; a manual pre-processing unit is required to select SDTSs from specific locations in the TCD signals prior to ES detection. And though a candidate event detection unit with real-time ES detection was proposed in [18], scanning for such event uses a lot of overlapping information (75% overlapping window).

An interesting idea is to determine signal envelope and develop the concept of adaptive threshold; a changing value (a minimum of statistical values: Mean, SD, Median, and Median Absolute Deviation) that automatically determines whether the present frame of TCD signal is a SDTS, and propose an accurate real-time cerebral microemboli detection that is compatible with any TCD device. A similar idea of statistical threshold and calculation using Mean and SD has previously been explored based on pseudo-cyclo-stationary properties of blood Doppler signals [21], but the method of a fixed threshold for this energy detector could fail if used with patients with high levels of variations in cardiac rhythm. In this work, we're determined to propose a solution for this challenge of fluctuating signal with a threshold that is adaptive to the individual's fluctuating blood flow based on Median Absolute Deviation (MAD) [22]. Specifically, we developed further from our previous work, the algorithm that continuously scans for ES using short window along the duration of TCD signal [10], [15] to one that processes further only when there is a suspected ES, achieved by adaptive thresholds [17]. The adaptive threshold is applied to capture suspected ESs, i.e., all ESs are initially singled out in real-time with some AFs and few normal (NR) intervals. Ideally, the developed adaptive thresholds should be able capture ESs of all durations, long and short. The Mean and SD adaptive threshold is expected to be able to capture long duration ESs, and the MAD the shorts. It should be noted that, to be more precise, the term ''AGC'' in our previous reports [17], [23] should be substituted with ''adaptive threshold of windowed power signal'' and the term ''AGC value'' with ''RMS value'' [24].

In our previous report on detection system with ANFIS as classifier [17], each captured ES suspect was transformed using AWPT and fast Fourier transform (FFT) such that feature extraction can be easily and efficiently performed, resulting in a vector of seven best features for the system determined with Sequential Feature Selection (SFS) technique [25]. Extracted feature values were then classified as non-ES or ES using ANFIS [17]. The performance of the proposed features and the proposed algorithm were compared to those of [16], referred to as K's features and K's algorithm. To achieve an efficient modeling process and reliability of prediction results, a data partitioning technique, leave-one-subject-out cross validation (LOSOXV) was employed. The results suggested that using a combination of adaptive threshold, ANFIS, and seven proposed features significantly outperforms a combination of K's features and K's algorithm [16]. In this paper, the proposed algorithm is explained in more detail. Moreover, we investigated further the sole efficiency of the seven proposed features by assessing their impact on the K's algorithm. In addition, each proposed feature is also discussed.

We also have investigated the potential of Deep Convolutional Neural Network (CNN) in cerebral ES detection as it can learn features while training and bypass the traditional handcrafted feature extraction and selection process [23]. Though it took considerably much less time in development, the CNN-based system, using spectrograms of the same TCD signal dataset as inputs and the same experimental setup, did not achieve better results than that of the ANFIS. We speculated it was majorly due to insufficient training data for deep learning and therefore we only propose the ANFIS-based system in this paper.

The paper is organized as follows: Section II explains TCD data preparation and suspected ES detection with adaptive threshold process used in both proposed approaches. The ANFIS-based system, the manual feature selection approach, is detailed in Section III. Section IV explains the experimental setup. Section V shows the experimental results. Section VI discusses and concludes the paper. Section VII informs on the on-going and future works.

II. REAL-TIME MICROEMBOLUS DETECTION ALGORITHM

As shown in Fig. 1, we propose an algorithm that receives TCD signal directly from TCD device as audio format and pre-processes the audio signal with DC offset removal and high pass filter (HPF). The resulting signal is passed onto the adaptive suspected ES detection step, which uses two

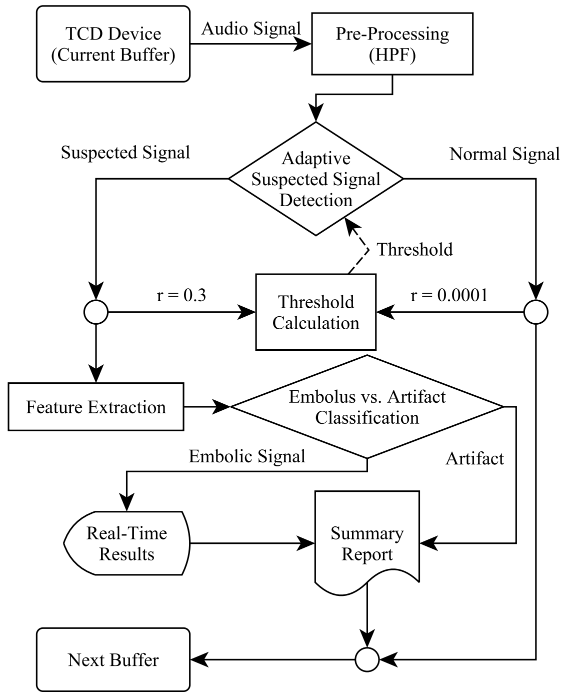

FIGURE 1. The proposed automated embolic signal detection.

adaptive thresholds to capture suspected ES intervals, while also feedbacks signal parameters onto itself to adjust the thresholds. The captured suspects proceed on to the feature extraction step before classification in ANFIS approach.

A. TCD DATA

TCD signals were collected from 19 stroke patients undergoing procedures generating emboli; cerebral angiography (six) [26], carotid artery stenting (CAS) (12) [27], and patent foramen ovale (PFO) screening (one) [11], at Thammasat University Hospital using Nicolet Pioneer TC8080 TCD system with 2 MHz transducer and fixation headgear. The included subjects of 14 men and five women were with clinical presentation of stroke or transient ischemic attack (TIA), for example, weakness, paresis, dysarthria, dysphagia, motor aphasia, or with a history of stroke, such as, a known case of stroke in the young. Their ages ranged from 16 to 88 with the mean of 57. All had adequate acoustic windows (temporal) for evaluation with TCD and were informed of the MCA monitoring during interventional procedures prior to signing their consent form. The study was conducted under the Thammasat University Human Research Ethics Committee approval no. 023/2555.

The first six subjects (one PFO and five CAS) were recorded per default setting in episodes of eight seconds (6,349 Hz sampling frequency) and the resulting signals were used to develop and assess the adaptive threshold algorithm. With regards to generalization ability of the developing algorithm, the rest of the subjects (13; six angiograms and seven CAS) were recorded for the whole session of procedures, approximately one hour per session, directly from the audio-out port of the TCD device with the same sampling frequency. The suspected ES collection from 19 subjects resulted in a total of 2,382 ESs, 1,051 AFs and 4,391 NRs, unanimously verified by three specialists. The intervals not met unanimous agreements were previously excluded from the study. Using the developed adaptive threshold algorithm, the captured suspected ES intervals from all 19 subjects were used to train and evaluate the ANFIS-based system.

B. SUSPECTED ES DETECTION WITH ADAPTIVE THRESHOLDS

Each collected TCD signal contains both normal and abnormal intervals, and these abnormal intervals could result from either embolus or artifact, since both can have similar characteristics of transient-like short duration. To firstly identify suspected durations among the signals, the signals were first fed into the suspected ES detection algorithm, which operates with two adaptive thresholds.

As the signal proceeds, the value of each sample is pre-processed by getting subtracted with the mean value of its current buffer to remove its DC offset, and high-pass filtered at 650 Hz cut-off frequency (600 Hz stop band and −20 dB stop band magnitude) with 249$^{\text{th}}$-order FIR Chebyshev II [28] to filter out the low-frequency AF. The use of 650 Hz cut-off frequency was derived from our investigation using this dataset based on a previous work exploring the frequency range of solid emboli [9]. An RMS value is then determined by

$$O[n] = \sqrt{\frac{1}{M}\sum_{i=0}^{M-1} S^2[n-i]}, \tag{1}$$

where $O[n]$ is an RMS value, $S[n]$ is pre-processed input value, and M is the moving average window (80 samples). To attempt to achieve real-time signal processing, each buffer takes over 1,024 samples, equivalent to 161.29 ms. Each resulting RMS value is then defined whether it is a suspected ES value by a threshold that is adaptive to the individual's fluctuating blood flow; especially in interventional procedures, where the volume and pressure of the injected contrast and the unstable heart rate contribute to the rise of RMS values. These values would falsely be identified as suspected ES if a fixed threshold was used. Here, an initial threshold value is set above the highest RMS value of the previously verified normal (not ES or AF) initial buffer. The threshold to define the next buffer's RMS values is calculated as a summation of the adaptive mean (μ) and standard deviation (SD; σ) of RMS values up to current. The SD coefficient, k_1, is 4 to cover the highest possible value of normal RMS signal (99.7% of normal distribution) and achieve 100% suspected ES detection sensitivity with more than 50% specificity, i.e.,

$$Th_{SD} = \mu + k_1\sigma. \tag{2}$$

The threshold is adapted by the changing values of RMS mean and SD, which are both factored by r; under the condition that, if the current RMS value is identified as suspected ES, r is 0.0001, but if identified as normal, r is 0.3. This enables the adaptive threshold to closely keep up with the rise of RMS signal and accurately identify SDTSs, i.e.,

$$\mu = \mu_p + r(\mu_c - \mu_p) \tag{3}$$

and

$$\sigma = \sqrt{\sigma_p^2 + \mu_p^2 + r(\sigma_c^2 - \sigma_p^2 + \mu_c^2 - \mu_p^2) - \mu^2}, \tag{4}$$

where μ_p and σ_p are the previous mean and SD, μ_c and σ_c are the current mean and SD, respectively. However, we found that this threshold could effectively capture long suspected ES intervals but not the short ones, which results from the mean and SD's sensitivity to SDTSs, e.g., the method using mean ± 3SD cannot distinguish 1,000 from the group of 1, 3, 3, 6, 8, 10, 10, and 1,000 [22]. To efficiently detect SDTSs among a small number of samples and capture small ES, another threshold using absolute deviation around the median (the Median Absolute Deviation: MAD) [22] is used, which can be expressed as

$$Th_{MAD} = \tilde{x} + k_2 MAD, \tag{5}$$

where

$$MAD = \text{median}(|x_i - \tilde{x}|) \tag{6}$$

and $\tilde{x}$ is the median of the current buffer, while the MAD coefficient, k_2, is 8.5 from preliminary experiments (varying values of k_2 from 5 to 10). The experiments with k_1 and k_2 parameters were done on our dataset of approximately 14 hours in total duration, which we believed sufficed for generalization ability. Therefore, to effectively capture the wide variation of suspected ES, we manipulated both threshold algorithms and determine from their minimum (see Fig. 2. and Fig. 3), i.e., threshold can be expressed as

$$\text{Threshold} = \min(Th_{SD}, Th_{MAD}). \tag{7}$$

Based on six subjects, the proposed adaptive threshold algorithm can detect suspected ES intervals with 100% sensitivity and 76.19% specificity. It should be noted that the algorithm was developed to achieve 100% sensitivity so that it is able to capture all pre-verified ES at this step. Adaptive thresholds could initially neglect a considerable amount of the pre-verified non-ES (normal and AF intervals) and the specificity was satisfactorily achieved at 76.19% as the false positive detection could later be filtered out at the classification model. The average duration (from t_{on} to t_{off}, see Fig. 3) of the included suspected ES intervals was of 62.5 ms with standard deviation of 47.9 ms.

III. ANFIS-BASED SYSTEM FOR MICROEMBOLUS DETECTION

A. FEATURE EXTRACTION

Once a suspected ES is detected, important characteristics information of it are extracted to construct features potentially best representing embolic signal. The resulting feature vector

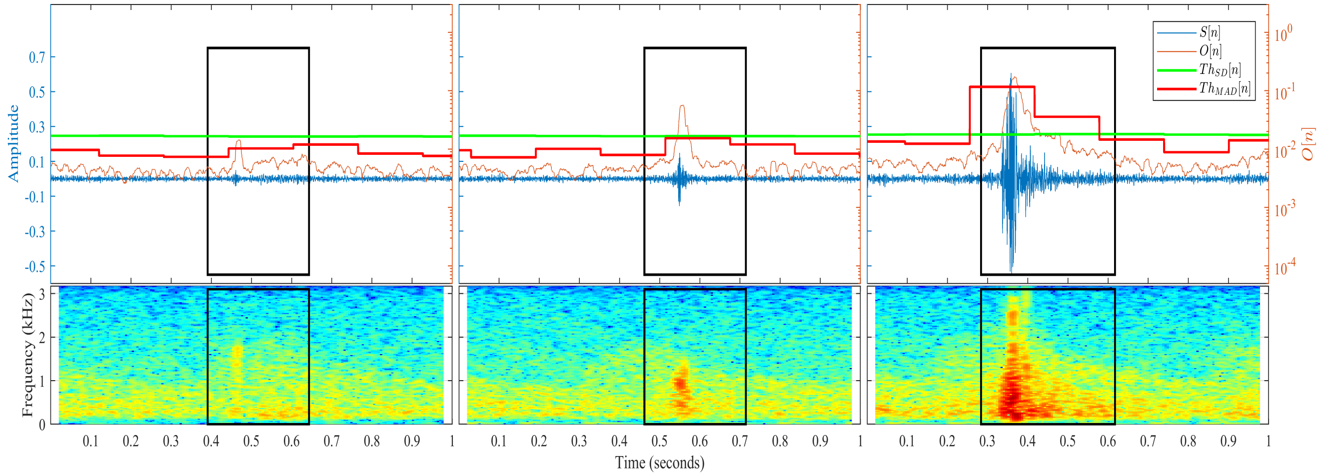

FIGURE 2. Time domain and spectrogram of some suspected ES variation from a CAS subject the proposed suspected ES detection algorithm is able to capture. Green and red lines respectively represent Th_{SD} and Th_{MAD}. The captured intervals are later classified as ES or non-ES at ANFIS.

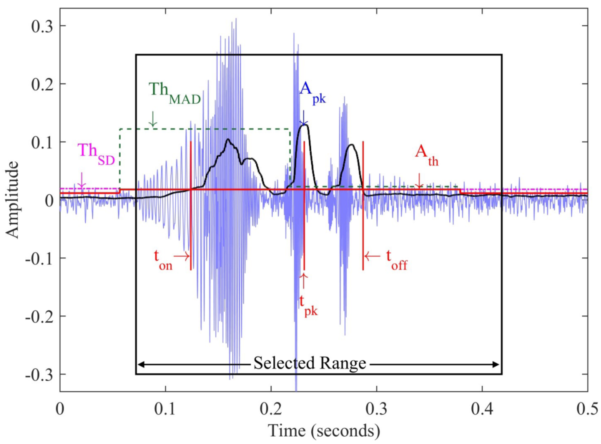

FIGURE 3. Illustration of parameters: Th_{SD} is the minimum among Th_{SD} and Th_{MAD} and is therefore the threshold amplitude (A_{th}) determining suspected ES intervals. A_{th} is then used to construct features (*RR* and *P2TR*) later classified as ES or non-ES at ANFIS. A_{pk} and t_{pk} are peak amplitude and its corresponding time. t_{on} and t_{off} indicate the beginning and the end of the captured interval duration.

is then fed to the proposed classification model to determine if the suspected ES is ES or non-ES.

In order for the proposed model to accurately identify the type of the detected signal, it has to be trained with the most proper and efficient features. To do so, we thoroughly reviewed features used in previous literature of similar attempts [7], [10], [16], [29] to detect embolic signals with TCD and tried implementing them with the proposed algorithm through the help of various feature selection methods (detailed in Section III-C) in pre-selecting the potentially most suitable features for such problem. After multiple preliminary experiments, several new features were developed to test together with the pre-selected features from literature in anticipation of their impact on the efficiency of the model (see Table 1). Such features were extracted from the pre-verified ES intervals in time-frequency domain using AWPT with the best basis algorithm; namely, maximum and mean entropy of leaf nodes, maximum and mean energy of leaf nodes, maximum standard deviation (SD) of level-3 frequency index (one to eight)'s WPT leaf node coefficients, frequency index of such maximum SD, % similarity to the complete tree, and % similarity to the low-frequency and high-frequency best tree. While candidate features from literature were extracted in three fashions; in time domain, in frequency domain with FFT, and also in time-frequency domain using AWPT and best basis.

TABLE 1. List of candidate features.

Feature
Time Domain
Fall Rate[a] and Rise Rate[a]
Total Power to Threshold Ratio[a]
Maximum Peak to Threshold Ratio[a]
Energy Centroid[a] and Energy Spreading[a]
Spectral Domain
Spectral Centroid[a] and Spectral Spreading of squared magnitude[a]
Spectral Centroid[b] and Spectral Spreading of absolute magnitude[b]
Spectral Rolloff[b]
Spectral Entropy[b]
Best Basis Wavelet Packet
SD of each level-3 frequency index (1-8)'s WPT leaf node coefficients[c]
Maximum SD of level-3 frequency index's WPT leaf node coefficients[d]
Frequency Index of the Maximum SD of leaf node coefficients[d]
Maximum Energy[d] and Mean Energy of leaf nodes[d]
Maximum Entropy[d] and Mean Entropy of leaf nodes[d]
% Similarity to the complete tree[d]
% Similarity to the low-[d] and high-frequency best tree[d]

[a] [7], [16] [b] [29] [c] [10] [d] New feature

B. ADAPTIVE WAVELET PACKET TRANSFORM (AWPT)

AWPT could benefit embolic signal detection in this study. WPT generates a full decomposition tree. Unlike WT, the detail signals will be further decomposed in WPT, so the information located in a high frequency band can be achieved [12], [14]. The wavelet packet coefficients show the energy distribution of the signal in time and frequency, which could be used to represent the TCD signal. The wavelet packet coefficients for each node (j, n) of a function $x(t)$ can be calculated as

$$x_{j,n}(p) = \langle x(t), \psi_{j,n}(t - 2^j p) \rangle, \tag{8}$$

where j is the scale parameter, n is the number of node at the same scale j, and p is the position parameter.

Occasionally, the number of decomposition by WPT is redundant. Therefore, we need to determine an optimal decomposition scale based on the characteristics of the signal or the problems to be treated. The best tree can be selected by using a convenient algorithm, namely the best basis algorithm [30], which compares entropy of two children nodes with their parent node to determine whether it is worthwhile to further decompose. In this study, the Shannon entropy-cost function [30] is used defined as

$$Entropy = -\sum_{n} p_n \log p_n, \tag{9}$$

where

$$p_n = \left(\frac{x_n}{\sqrt{\sum_{n=1}^{m} x_n^2}} \right)^2 \tag{10}$$

and x_n is the n^{th} coefficient generated by the WPT for $n = 1, 2, \ldots, m$.

C. FEATURE SELECTION

To determine the best features for the study, candidates from literature and from our development were compared and selected with methods such as sequential feature selection (SFS) [25], sequential floating feature selection (SFFS) [31], InfoGain [16], and manual selection [17]. Since our data were very limited, for the sake of simplicity and comparibility, the concept of cross validation utilizing the test set, was employed in this process. Through trial and error, we found that features from the SFS method provided the most promising classification results.

In this study, the sequential search was manipulated in forward direction. All candidates were firstly compared against each other on their ability to distinguish the pre-verified ES in the proposed algorithm. The best performer was then paired up with each of the rest of the candidates to compare their performance in pairs. The best pair went on to add a third candidate in the same fashion to compare in groups of three, and so forth, until there was no improvement in performance [25]. After multiple experiments, the best features selected by SFS consisted of seven features (detailed in Section III-D). It should be noted that we proposed two new features which are Mean Entropy of leaf nodes and Maximum SD of frequency indexes' leaf node coefficients.

D. THE SELECTED FEATURES

The best candidates selected by SFS consist of features from literature as well as from our development, i.e.,

1) Maximum Peak to Threshold Ratio (P2TR) [7]

$$P2TR = 10 \log \frac{A_{pk}}{A_{th}} \quad \text{(dB)} \tag{11}$$

The ratio of the maximum peak amplitude to the threshold amplitude, where A_{th} is the threshold determined at the suspected ES detection process; $Threshold = \min(Th_{SD}, Th_{MAD})$, and A_{pk} is the maximum peak amplitude above such threshold (see Fig. 3).

2) Rise rate (RR) [7]

$$RR = \frac{P2TR}{t_{pk} - t_{on}} \quad \text{(dB/ms)} \tag{12}$$

The ratio of $P2TR$ to the duration between t_{on} and t_{pk} determines the rise rate of the interval, where t_{pk} is the time at the maximum peak amplitude above the threshold and t_{on} is the time where the interval starts to rise above the threshold (see Fig. 3).

3) Spectral rolloff [29]

$$\sum_{f=1}^{m} S(f) = C \sum_{f=1}^{W_{f_L}} S(f) \tag{13}$$

Spectral rolloff, m, is the frequency position, where the respective spectral energy is equal to a certain percentage, C, of the total energy of the interval [29]. $S(f)$ is the discrete Fourier transform (DFT) coefficient of a frequency position f, m is the frequency position satisfying the above equation, and W_{f_L} is the normalization factor (length of the FFT) [29].

4) Spectral centroid of absolute magnitude [29]

$$f_c = \frac{2}{F_s} \frac{\sum_{f=1}^{W_{F_L}} f\,|S(f)|}{\sum_{f=1}^{W_{F_L}} |S(f)|} \tag{14}$$

This feature is also calculated from the magnitude distribution of the spectrum. Spectral centroid, f_c, is the center of gravity of the spectrum, a simple measure of spectral position [29], where F_s is the sampling frequency acting as the overall normalization factor in this equation.

5) Standard Deviation (SD) of frequency index 7's leaf node coefficients based on [10]

After decomposing the interval with WPT to the third level and using the Shannon entropy cost function to determine the best tree, we derive the WPT leaf node coefficients of each frequency index (one to eight). Calculating the SD of such and using SFS, we found that the SD of the seventh frequency index and the maximum SD among all frequency indexes were two of the top performers.

6) Maximum SD of frequency index 1–8's leaf node coefficients

It is explained in 5).

7) Mean entropy of leaf nodes

$$\bar{H} = \frac{\sum_{l=1}^{L} H(l)}{L} \tag{15}$$

The level-3 WPT leaf nodes coefficients could be used to calculate another effective feature, the mean entropy, where $\bar{H}$ is mean entropy of leaf nodes, L is total number of leaf nodes, and $H(l)$ is entropy of leaf node l^{th}.

E. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

As discussed earlier, we believe that the characteristics of ANFIS would efficiently work with TCD for ES classification because the fuzzy rules can be constructed by using a given input/output data set; the membership function parameters and the coefficients of the first order polynomial in each constructed rule can be adjusted according to the data they are modeling [32]. In this study, to generate the fuzzy rules, we applied the subtractive clustering method [33], [34] after experimenting with grid clustering [15] and FCM clustering [10]; provided that it could significantly reduce the complexity of the algorithm, which affects the processing time, but still provided high detection accuracy as in [10] and [15].

In subtractive clustering, the data is divided into homogeneous groups and only one particular rule is defined to each group (details are as in [34]). The important factor is the radius r_a, which can affect the number of clusters. We found that the best value of r_a is 0.6, and the radius r_b was chosen as $1.5r_a$ to avoid close clusters, resulting in two clusters of fuzzy rules being produced.

Prior to using the ANFIS model, it was trained with a hybrid learning method, including the gradient descent and the least squares estimator (LSE) [32], for finding the optimal parameters. The membership function parameters were adjusted for finding the optimal point and the best fuzzy rules were generated. These parameters were updated in each training epoch until the maximum number of training epochs or a least square error was reached [32]. In this study, the maximum training epoch number was set at 500 and the training error goal at 0. The initial step size was 0.01 with the decrease rate of 0.9 and the increase rate of 1.1.

F. LEAVE-ONE-SUBJECT-OUT CROSS VALIDATION (LOSOXV)

To obtain a predictive model, its algorithm has to be trained to achieve the best weights and tested with such weights. The best weights can be determined from its ROC curve at the best sensitivity and specificity. For a model to make efficient predictions on new datasets, it has to be improved and assessed on its predictive performance with techniques such as cross validation (CV), where dataset was randomly partitioned into two groups for each round of algorithm training and testing.

However, applying such CV in this study by rotating test intervals regardless of their source subject could allow the model to overfit; it could recognize patterns possibly hidden in intervals of the test subject if some of their intervals were trained earlier, and cause the falsely high accuracy of test result. Instead, we manipulated the LOSOXV approach [35] to rotate the test subject in order to avoid such bias and achieve a more realistic outcome. Partitioning was carried out over subjects in place of randomized intervals; a set of intervals from one subject was considered one fold, the test set was rotated such that each subject was used only in testing, not in training, for each round of LOSOXV. To determine overall performance, weighted average was applied as each fold did not contain the same proportion of ES to non-ES.

IV. EXPERIMENTAL SETUP

The aims of this study are to compare the efficiency of our developed algorithm to that of [16], which outperformed 29 various well-known methods in literature including nearest neighbour based methods, decision tree based methods, regression methods, and fuzzy logic, etc. [16], and to evaluate the impact of our set of proposed features over such algorithm.

The study comprised of three experiments. First, to establish baseline results, the K's algorithm was implemented with the K's algorithm's features (K's features) [16], namely, f_s/F_s, T_s^2, B_s^2/F_s, $TP2TR$, t_s, $P2TR$, and RR, where F_s is the sampling frequency, RR is the rise rate, $TP2TR$ shows the total power to the threshold ratio, $P2TR$ is the scale with maximum peak to threshold ratio, T_s^2 stands for the time spreading term, B_s^2 is corresponding to the frequency spreading term, t_s is the average time of the signal, and f_s is the average frequency of the signal, using our dataset previously detailed. Second, our proposed features based on those of [7]and [16], and SFS (see Section III-D) were tested on our proposed ANFIS algorithm to validate the efficiency of such combination. Lastly, the K's algorithm was tested with the proposed features to determine whether the proposed features could significantly enhance its detection performance and to compare the result to our proposed system. The dataset was prepared into training and testing sets using LOSOXV per Section III-F. Data from the first six subjects (five CAS, one PFO) were fixed as training data in the LOSOXV process since their short sessions (8 s) and low ratio of ES per subject did not suit testing a model aimed to serve the continuous clinical monitoring of TCD.

In training step, for both K's algorithm experiments, the LOSOXV was performed in accordance with the algorithm's condition; several data from the training set were excluded uniformly at random to meet a proper number of training data that satisfied the prime factor combination constructing the algorithm's index space [16]. For the proposed algorithm experiment, data from the training set were reduced in order to obtain the fastest training process possible that still enabled the model to result with the highest detection sensitivity at an acceptable specificity of more than 90% (false positive detection less than 10%), aiming towards our goal of clinical application. To do so, several non-ES (NR and AF) data were excluded uniformly at random from the training set and the amount of ES was maintained the same to meet a proper proportion of training ES to non-ES, so that the model could achieve such accuracy with the least generalization error.

The LOSOXV was performed 13 rounds (six fixed training subjects, 13 rotating test subjects) to determine overall sensitivity, specificity, and accuracy for each experiment. As different randomization in data preparation yielded different test result, all three experiments were carried out with such steps 20 times to determine average sensitivity, specificity, and accuracy, respectively.

The same ANFIS-based experiment with the two new features excluded was also performed to investigate the effect of the two new features.

V. EXPERIMENTAL RESULTS

Based on 90% detection specificity for all experiments as discussed earlier, the baseline experiment founded with K's algorithm and K's features resulted in 67.9% average detection sensitivity (SD = 0.6%) and 83.5% average detection accuracy (SD = 0.2%). Our proposed algorithm and features yielded an average sensitivity of 91.5% (SD = 0.6%) and an average accuracy of 90.5% (SD = 0.2%), higher than that of the baseline experiment 23.6% and 7%, respectively. Determining the impact of our proposed features over K's algorithm, the experiment with our proposed features yielded an average sensitivity of 86.7% (SD = 0.4%) and an average accuracy of 89.1% (SD = 0.1%), higher than that of the K's features 18.8% and 5.6%, respectively.

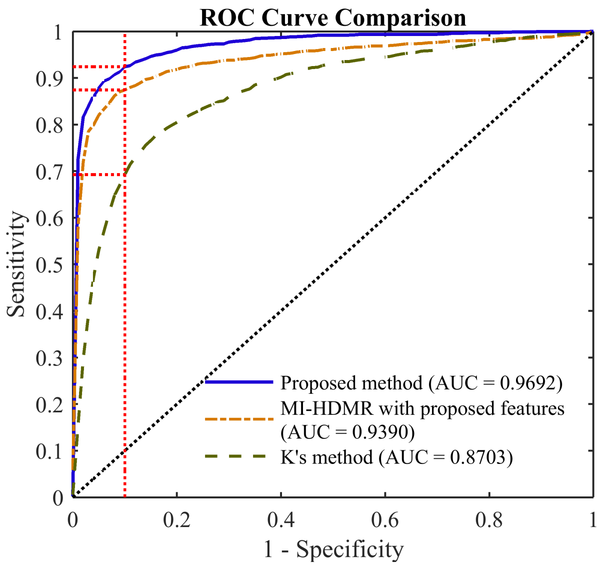

FIGURE 4. Comparison of ROC curves. The ANFIS-based method outperforms the K's method. Higher sensitivity is achieved at 90% specificity. Note that several averaging steps done over the results could cause the smoothness of the ROC curves.

Running ANOVA, where n is the number of times each experiment was performed ($n = 20$), not the number of subjects, the proposed algorithm and features significantly outperformed the other two experiments in both detection accuracy [$F(2,57) = 10623.05$, $p < 0.0001$] and sensitivity [$F(2,57) = 10572.12$, $p < 0.0001$] at 90.0% specificity (see Fig. 4 and Table 2).

The results of the same ANFIS-based experiment investigating the effect of the two new features proposed showed that, without the two new features, the average AUC dropped from $96.58 \pm 0.19\%$ to $96.26 \pm 0.17\%$.

TABLE 2. Average efficiency of ANFIS-based system, HDMR system (K's), and hybrid system; K's algorithm with proposed features.

Algorithm	ANFIS		K's			
Features	Proposed		Proposed		K's	
Results	Avg	SD	Avg	SD	Avg	SD
Accuracy*	**90.5%**	0.2%	**89.1%**	0.1%	83.5%	0.2%
Sensitivity**	**91.5%**	0.6%	**86.7%**	0.4%	67.9%	0.6%
Specificity	90.0%	0%	90.0%	0%	90.0%	0%
AUC	96.6%	0.2%	93.5%	0.2%	86.5%	0.3%

*[$F(2,57) = 10623.05$, $p<0.0001$] **[$F(2,57) = 10572.12$, $p<0.0001$]

VI. DISCUSSION AND CONCLUSION

An accurate real-time cerebral microemboli detection system has been developed to couple with any TCD model for clinical monitoring of ES. An algorithm to detect suspected embolic intervals using adaptive threshold and an approach to classify ESs using ANFIS have been proposed.

The performance was compared to Euclidean MI-HDMR (K's), the latest and most efficient method to date [16]. The impact of our proposed features was also determined over K's algorithm to assess if they could significantly enhance its detection performance. The proposed system using adaptive thresholds, ANFIS, and a set of features, partly derived from AWPT and selected by SFS, obtained 90.5% accuracy and 91.5% sensitivity at 90.0% specificity, which significantly outperformed the experiments on K's method in both detection sensitivity ($p < 0.01$ and accuracy ($p < 0.01$). Further, the proposed set of features manifested its own effectiveness by enhancing the K's algorithm's performance by 18.8% in sensitivity and 5.6% in accuracy. Two key contributions accounted for the success of the development were 1) the adaptive threshold approach that was manipulated in the detection of suspected ES and made possible real-time ES detection 2) the set of most effective features to work with the developed model in obtaining the least classification error.

The suspected ES detection part was designed to keep only the suspected ES for later operation and neglect the positive non-ES at this step, which immensely reduces the information to be fed further onto the classification process, and hence the fast processing time and possible online detection. Moreover, it was developed to capture all pre-verified ES regardless of their duration (100% sensitivity); the use of adaptive thresholds could swiftly capture the dynamic-length nature of suspected ES and keep all possible ES. The K's and A's algorithms [7], on the other hand, used segments of fixed duration from pre-verified signals in the modeling process (1, 5, and 5 s for training, validating, and testing, respectively). The width of the RMS moving average window is narrow enough to capture the transient occurrence of an ES and wide enough to gather sufficient characteristics information of it for the modeling of classifier. Further, the wide variation of ES could be accurately determined with two adaptive thresholds developed based on SD and Median.

Manipulating such algorithm greatly comes to benefit in operating room, where patients' blood flow fluctuates during procedures. Especially when contrast medium injection is required to derive diagnostic images, the surge of blood flow could falsely be identified as ES intervals by available algorithms of current TCD devices. By means of using this statistical approach, only SDTSs among the resulting continuous rise of RMS values will be distinguished as suspected ES. It should be emphasized here that our algorithm distinctively solves this problem in clinical situations and offers a more practical and accurate approach to clinical monitoring of brain emboli, which could make a concrete difference to the market.

As for the classification features, they were determined from a thorough feature selection process. Only seven features were chosen from the SFS after exploring and experimenting with various features and feature selection methods. As our intention was to reduce the model complexity and utilize the lowest resource possible, the least number of features that could still enable the model to achieve the highest detection accuracy was required. This condition aligned with the direction of the K's algorithm development, where initially only eight features were considered over 12 candidates [16]. It is interesting to investigate further why features from SFS yielded better results than those from InfoGain and SFFS. An additional experiment was also performed to investigate the effect of the two new features proposed. Without the new features, the same ANFIS-based experiment using only the selected five features from literature resulted approximately 0.32% less in average AUC (96.58 $\pm$ 0.19% compared to 96.26 $\pm$ 0.17%). Further, in an investigation exploring the advantage of using ANFIS instead of other well-known classifiers, experiments using SVM and ANN yielded 95.85$\pm$0.1% and 96.20 $\pm$ 0.2% in average AUC, respectively, lower than that using ANFIS, which is 96.58 $\pm$ 0.19%. The result shows SVM to be a simpler alternative to ANFIS when accompanied with our seven selected features.

The K's algorithm presented a few drawbacks while being implemented with our dataset in the experiments. The condition of prime factor combination caused some data from the set to be cut off in each round of training and testing, which is not practical for the modeling process of algorithm aiming to serve growing clinical data. It would always raise the question of which data to cut off and by how, and the valuable dataset could not be wholly utilized. In addition, the transformation matrix used resource in proportion to the training data, which is also not practical for clinical use. Our proposed algorithm only requires resource to store information of means and variances of the Gaussian membership functions—a lot lower in number than that of the K's when the same amount of features are used. Despite such limitations, the K's algorithm has an advantage in deriving only a polynomial equation after transformation, while our proposed algorithm requires processing data through many fuzzy layers of ANFIS, which results in a more complex model. Moreover, the poorest performance of the baseline experiment could probably result from using a different dataset than that from the literature [16]. We've developed a system that showed better performance than that of the K's, but this is entirely based on our dataset. Additionally, in this work, the K's is not perceived as a standard of the field, but rather a state-of-the-art, which should always be compared to newer methods to promote further contribution.

Nevertheless, there are more configurations, which helped made the development successful and are also worth mentioning. One is the ANFIS based classification model, which based on the specificity of 90% (91.5% sensitivity and 90.5% accuracy) rather than the highest accuracy of 92.11% (84.08% sensitivity and 95.45% specificity) at ROC curve. The 10% false positive detection was traded off for a higher sensitivity, which is more crucial in this study as the proposed system was developed for clinical use. Another is the use of LOSOXV, which increased the volume of training and testing data in the modeling process. The method prevented the model from bias and overfitting by rotating the test subject, enabling a robust and realistic, yet highly accurate prediction.

With all contributions combined, clinical use effectiveness could be achieved with such high detection performance and real-time detection factor of less than 1, i.e., processing for an ES (from pre-processing to classification) takes less than 1 buffer (1,024 samples) or approximately only 161 ms.

In conclusion, since interventional procedures such as ones in this study (cerebral angiogram and carotid artery stenting) inevitably cause emboli, the monitoring procedure, as an add-on protocol, could identify probable occasions of recurrent stroke from embolism and support medical decisions, e.g., the management of anti-clotting medication during and after procedures. It could also help assess the likelihood of emboli formation in each step of interventional procedures. In this study, we found that the steps of catheter insertion and radiopaque injection caused the highest amount of emboli. Interventionists could consider preventive measures, such as, increasing precaution during performing such steps, determining the more proper amount of medication in each step, identifying the probable sites of recurrent stroke, etc.

VII. ON-GOING AND FUTURE WORK

The proposed algorithm has already been used with a commercial TCD in clinical environment at Thammasat University Hospital, Thailand to collect training data and determine amount of ES possibly formed during angiography and CAS procedures (Thailand patent pending, filing no. 1601001107, to be made affordable under USD 118 per use). Interventionists could utilize the system to optimize the treatment benefits and support clinical decisions in reducing the frequency of emboli formation, and therefore, the rate of disability and death, during and after the procedures. We are also studying the correlation of the detection results and the treatments that patients receive post interventional procedures to evaluate the system's possibility and validity in 24-hour post-interventional monitoring and treatment plan decision support. We will look further into statistical analysis of cerebral ES and continue the development of more robust adaptive thresholds for our suspected ES detection algorithm.

Moreover, we are also investigating the use of color (RGB) spectrogram to assess the benefit over grayscale as input to the CNN. As our TCD signal database is growing, we anticipate that together with our developing CNN algorithm, we could come up with a much better outcome than those of our previous works. A wearable application is one of our determined future works. The learnable features of the CNNs, as opposed to the fixed features of the ANFIS-based system, will well serve the demographic differentials of population at risk of stroke, e.g., patients with atrial fibrillation. A holistic mobile medical application for early detection and management of NCDs (Non-communicable diseases, e.g., diabetes mellitus, hypertension, stroke, and kidney disease) is included in our long-term plan to serve aging society.

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REFERENCES

[1] World Campaign. (Jun. 30, 2018). *Facts and Figures—World Stroke Campaign*. [Online]. Available: https://www.worldstrokecampaign.org/learn/facts-and-figures.html
[2] (Jun. 2016). *2015 World Stroke Day Fact Sheet*. [Online]. Available: http://www.strokeassociation.org/idc/groups/stroke./ucm_478390.docx
[3] E. M. Chung, "Transcranial Doppler embolus detection: A primer," *Ultrasound*, vol. 14, no. 4, pp. 202–210, 2006.
[4] R. Dittrich, M. A. Ritter, and D. W. Droste, "Microembolus detection by transcranial Doppler sonography," *Eur. J. Ultrasound*, vol. 16, nos. 1–2, pp. 21–30, 2002.
[5] M. Gorman, "Transcranial Doppler assessment of cerebral embolic disorders," *Prog. Cardiovascular Diseases*, vol. 43, no. 2, pp. 135–150, 2000.
[6] M. R. Azarpazhooh and B. R. Chambers, "Clinical application of transcranial Doppler monitoring for embolic signals," *J. Clin. Neurosci.*, vol. 13, no. 8, pp. 799–810, 2006.
[7] N. Aydin, F. Marvasti, and H. S. Markus, "Embolic Doppler ultrasound signal detection using discrete wavelet transform," *IEEE Trans. Inf. Technol. Biomed.*, vol. 8, no. 2, pp. 182–190, Jun. 2004.
[8] N. Aydin, S. Padayachee, and H. S. Markus, "The use of the wavelet transform to describe embolic signals," *Ultrasound Med. Biol.*, vol. 25, no. 6, pp. 953–958, 1999.
[9] G. Devuyst *et al.*, "Automatic classification of HITS into artifacts or solid or gaseous emboli by a wavelet representation combined with dual-gate TCD," *Stroke*, vol. 32, no. 12, pp. 2803–2809, 2001.
[10] C. Lueang-On, C. Tantibundhit, and S. Muengtaweepongsa, "Processing time improvement for automatic embolic signal detection using fuzzy c-mean," in *Proc. IEEE ECTI-CON*, May 2013, pp. 1–5.
[11] G. A. Darbellay *et al.*, "Solid or gaseous circulating brain emboli: Are they separable by transcranial ultrasound?" *J. Cerebral Blood Flow Metabolism*, vol. 24, no. 8, pp. 860–868, 2004.
[12] Y. Chen and Y. Wang, "Doppler embolic signal detection using the adaptive wavelet packet basis and neurofuzzy classification," *Pattern Recognit. Lett.*, vol. 29, no. 10, pp. 1589–1595, 2008.
[13] J.-M. Girault, "Cerebral microembolism synchronous detection with wavelet packets," in *Signal and Image Multiresolution Analysis*. Hoboken, NJ, USA: Wiley, 2013.
[14] S. Mallat, *A Wavelet Tour of Signal Processing*. New York, NY, USA: Academic, 1999.
[15] C. Lueang-On, C. Tantibundhit, and S. Muengtaweepongsa, "Automatic embolic signal detection using adaptive wavelet packet transform and adaptive neuro-fuzzy inference system," *Stroke*, vol. 44, no. 2, p. 60, 2013.
[16] A. Karahoca and M. A. Tunga, "A polynomial based algorithm for detection of embolism," *Soft Comput.*, vol. 19, no. 1, pp. 167–177, 2015.
[17] P. Sombune, P. Phienphanich, S. Muengtaweepongsa, A. Ruamthanthong, and C. Tantibundhit, "Automated embolic signal detection using adaptive gain control and classification using ANFIS," in *Proc. IEEE EMBC*, Aug. 2016, pp. 3825–3828.
[18] L. Fan, D. H. Evans, A. R. Naylor, and P. Tortoli, "Real-time identification and archiving of micro-embolic Doppler signals using a knowledge-based DSP system," *Med. Biol. Eng. Comput.*, vol. 42, no. 2, pp. 193–200, 2004.
[19] M. Cullinane *et al.*, "Evaluation of new online automated embolic signal detection algorithm, including comparison with panel of international experts," *Stroke*, vol. 31, no. 6, pp. 1335–1341, 2000.
[20] A. G. Munts, W. H. Mess, E. F. Bruggemans, L. Walda, and R. G. Ackerstaff, "Feasibility and reliability of on-line automated microemboli detection after carotid endarterectomy. A transcranial Doppler study," *Eur. J. Vascular Endovascular Surg.*, vol. 25, no. 3, pp. 262–266, 2003.
[21] J.-M. Girault and Z. Zhao, "Synchronous detector as a new paradigm for automatic microembolus detection," *Int. J. Biomed. Eng. Technol.*, vol. 14, no. 1, pp. 60–70, 2014.
[22] C. Leys, C. Ley, O. Klein, P. Bernard, and L. Licata, "Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median," *J. Exp. Social Psychol.*, vol. 49, no. 4, pp. 764–766, 2013.
[23] P. Sombune, P. Phienphanich, S. Phuechpanpaisal, S. Muengtaweepongsa, A. Ruamthanthong, and C. Tantibundhit, "Automated embolic signal detection using deep convolutional neural network," in *Proc. IEEE EMBC*, Jul. 2017, pp. 3365–3368.
[24] K. Küpfmüller, "Über die Dynamik der selbsttätigen Verstärkungsregler," *Elektrische Nachrichtentechnik*, vol. 5, no. 11, pp. 459–467, 1928.
[25] MathWorks. (Jun. 2016). *Sequential Feature Selection*. [Online]. Available: http://www.mathworks.com/help/stats/sequentialfs.html
[26] M. Bendszus, M. Koltzenburg, R. Burger, M. Warmuth-Metz, E. Hofmann, and L. Solymosi, "Silent embolism in diagnostic cerebral angiography and neurointerventional procedures: A prospective study," *Lancet*, vol. 354, no. 9190, pp. 1594–1597, 1999.
[27] H. S. Ng *et al.*, "Embolic Doppler ultrasound signal detection using continuous wavelet transform to detect multiple vascular emboli," *J. Neuroimaging*, vol. 18, no. 4, pp. 388–395, 2008.
[28] A. V. Oppenheim and R. W. Schafer, *Discrete-Time Signal Processing*. London, U.K.: Pearson Education, 2010.
[29] T. Giannakopoulos and A. Pikrakis, *Introduction to Audio Analysis: A MATLAB Approach*. New York, NY, USA: Academic, 2014.
[30] R. R. Coifman and M. V. Wickerhauser, "Entropy-based algorithms for best basis selection," *IEEE Trans. Inf. Theory*, vol. 38, no. 2, pp. 713–718, Mar. 1992.
[31] D. Ververidis and C. Kotropoulos, "Fast and accurate sequential floating forward feature selection with the Bayes classifier applied to speech emotion recognition," *Signal Process.*, vol. 88, no. 12, pp. 2956–2970, 2008.
[32] J.-S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Trans. Syst., Man, Cybern.*, vol. 23, no. 3, pp. 665–685, May/Jun. 1993.
[33] S. M. Berneti, "Design of fuzzy subtractive clustering model using particle swarm optimization for the permeability prediction of the reservoir," *Int. J. Comput. Appl.*, vol. 29, no. 11, pp. 33–37, 2011.
[34] S. L. Chiu, "Fuzzy model identification based on cluster estimation," *J. Intell. Fuzzy Syst.*, vol. 2, no. 3, pp. 267–278, 1994.
[35] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

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