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Atrial Fibrillation Detection Using Swarm Fuzzy Inference System and Electrocardiographic P-Wave Features

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Abstract

A new technique for detecting atrial fibrillation (AF) is proposed and investigated. The technique employs a swarm fuzzy inference system (SFIS). SFIS is fuzzy system optimized by using a particle swarm optimization (PSO). The technique introduces new inputs for the SFIS to detect AF. The inputs involve the peaks number and width of electrocardiographic P-wave. Experiments of FA detection utilizing SFIS with different inputs are conducted. On a test using clinical electrocardiographic data, SFIS performs well in AF detection with sensitivity, specificity and accuracy of 77.86 %, 60.40 % and 75.09 %, respectively.

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Keywords: Atrial fibrillation (AF), electrocardiogram, particle swarm optimization (PSO), fuzzy inference system (FIS).

1. Introduction

An atrial fibrillation or AF [1] is a premature heartbeat originating from the atrial of the heart. It disrupts normal rhythm of the heart. AF in patients with heart diseases might be associated with life-threatening. AF is associated with stroke, heart failure and mortality [2].

Different AF detection techniques have been proposed and investigated by research groups and currently are still as a research trend in heart-arrhythmic detection technologies [3, 4] [5-9] [10]. Support vector machine (SVM) for AF identification is presented in [11]. Fuzzy system has been investigated for

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AF detection by Vafaie, et al. [12]. The genetic algorithm is used for optimization of this fuzzy method. Hybrid of artificial neural network and fuzzy system has also been proposed of AF detection, as presented in [13]. Fuzzy inference system (FIS) is still need further investigations for AF detection, including efforts to find its suitable inputs, which are usually electrocardiographic features.

This article proposes a new technique to detect AF using a swarm based fuzzy inference system (SFIS). SFIS is a FIS where its parameters are optimized using a particle swarm optimization (PSO). Optimization of FIS parameters is necessary to find the optimal one. The PSO has shown a good performance to find optimal parameters in classification, rather than the parameters chosen randomly [14]. The inputs proposed for the FIS, in this article, are features of the electrocardiographic P-wave. The main reason of the P-wave utilization is that AF could be recognized using the P-wave.

The rest of this paper is organized as follows. Section II presents the proposed technique; describing inputs, FIS and PSO. Section III and IV presents the experimental results and discussion, respectively. Finally, the conclusion for this article is drawn in Section V.

2. Method

This paper presents an AF detection technique by employing SFIS, as shown in Fig. 1. The inputs in the technique are peaks number and width of electrocardiographic P-wave. The output is one of two situations: AF or normal. In the strategy, PSO is used to optimize FIS parameters.

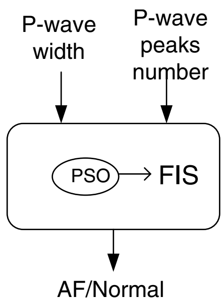

Fig. 1. The structure of AF detection using fuzzy inference system (FIS) and particle swarm optimization (PSO)

2.1. Inputs

The inputs in this technique are features of electrocardiographic P-wave, consisting of peaks number and width of P-wave. Theoretically, P-wave width is the interval between the beginning and the end of P-wave. In this article, P-wave width is measured in terms of the interval between two defined points at P-wave: a defined point in the left side of the P-wave and another point in the right side. The vertical positions of the two points are at around 80% of the peak height of the wave. The peak of P-wave is the maximum point in a defined region in the left side of the R-peak. The R-peak is referred to the data provided by the Physionet [15]. This approach is chosen to reduce the error caused by frequently error determination of the exact position of the beginning and the end of P-wave. Peaks number of P-wave is measured in terms of the number of peaks in a defined region in the left side of the R-peak. As mentioned above, The R-peak is referred to the data provided by the Physionet [15].

2.1.1. Fuzzy Inference System

We develop a fuzzy inference system (FIS) which consists of three main stages: fuzzification, inference engine and defuzzification, as described in Fig. 2. The three parts are described as follow.

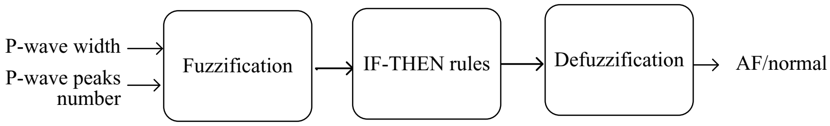

Fig. 2. Fuzzy inference system with three main stages: fuzzification, IF-THEN rules and defuzzification

2.1.1.1. Fuzzification

The first stage of the FIS is fuzzification. Fuzzification maps a real-world space to a fuzzy space [16]. The inputs of the fuzzification are the P-wave features and the output is their associated degrees of membership function.

The fuzzification applies a Gaussian membership function. The membership function as $\mu_{N_j^k}$ is expressed as [17]

$$\mu_{N_j^k}(x_j) = e^{-\left(x-m_j^k\right)^2/2\sigma_j^k} \quad (1)$$

where x_j, consists of the two FIS inputs, which are the width and peaks number of P-wave; m_j^k and σ_j^k are the mean and the standard deviation of the Gaussian membership function, respectively; k denoted the membership function term, such as low, medium or high.

2.1.1.2. Inference Engine

The second stage of the FIS is an inference engine. The inference engine converts a fuzzy input to a fuzzy output using a fuzzy rule employing IF-THEN type. The rule consists of antecedence (IF part) and consequence (THEN part). The rule is given as the following [18]:

Rule ρ: **IF** x_1 is N_1^k **AND** x_2 is N_2^k **AND … AND** x_n is N_n^k **THEN** η is h_ρ (2)

where N_j^k (j = 1, 2, …, n) is the fuzzy term of the associated input x_j. Rule ρ = 1, 2, …, r denotes the rule number; r denotes the number of rules. The number of rule is $(m_f)^n$; m_f is the number of membership functions and n is the number of inputs. h_ρ is a fuzzy singleton to be optimized.

2.1.1.3. Defuzzification:

The third stage of the FIS is defuzzification. This part is used to translate the outputs of the fuzzy rules into a real world value [16]. The output of the defuzzification η is given by

$$\eta = \sum_{\rho=1}^{r} s_\rho h_\rho \quad (3)$$

$$s_\rho = \frac{\mu_{N_1^\rho}(x_1)\times\mu_{N_2^\rho}(x_2)\times\ldots\times\mu_{N_n^\rho}(x_n)}{\sum_{\rho=1}^{r}\left(\mu_{N_1^\rho}(x_j)\times\mu_{N_2^\rho}(x_j)\times\ldots\times\mu_{N_n^\rho}(x_n)\right)} \quad (4)$$

2.1.1.4. FIS parameters:

The mean m_j^k, the standard deviation σ_j^k and the consequent part h_ρ are determined using an optimization. Thus, the FIS parameters to be optimized are m_j^k and σ_j^k in (1) and h_ρ in (2).

2.1.2. Particle swarm optimization

In this article, the FIS parameters mentioned above are optimized using a particle swarm optimization (PSO). Using the optimized parameters, FIS could perform well. PSO performed optimization using an evolutionary technique. The technique is based on movement of swarms and is inspired by social behavior of bird flocking and fish schooling [19].

The pseudo code of the PSO is described in Fig. 3. Firstly, a swarm $Z(t)$ which represents FIS parameter is defined. A defined fitness function utilizing $Z(t)$ is evaluated. Essentially, the objective of the optimization is to minimize a fitness function $f(Z(t))$ iteratively. The swarm evolves from iteration t to $t+1$ by a repeating procedure.

Particles flies through a search space with adjusted velocity $v(t)$ and position $y(t)$. The velocity $v(t)$ is adjusted as

$$v(t) = q\left(\varphi v(t-1) + c_1 r_1 (z_p - z(t-1)) + c_2 r_2 \left(z_g - z(t-1)\right)\right) \tag{5}$$

and

$$y(t) = y(t-1) + v(t) \tag{6}$$

where z_p is the best previous position of a particle, and z_g is the best particle position among the all particle. r_1 and r_2 are random functions in the range [0 1], and φ is inertia weight factor. c_1 and c_2 are acceleration constants. q is a constriction factor to ensure the optimization to be converged, but not prematurely.

The fitness function of the optimization is defined in the following

$$f = -(Se_t + Sp_t) \tag{7}$$

where Se_t and Sp_t are the sensitivity and specificity, respectively. Sensitivity is defined as the ratio of the correct detection of AF to the actual number of AF cases; specificity is defined as the ratio of the correct detection of non-AF to the actual number of non-AF cases. The training is the optimization process to find the optimal FIS parameters.

```
begin
    t→0                // iteration number
    Initialize Z(t)    // Z(t): swarm for iteration t
    Evaluate f(Z(t)) // f(·): fitness function
while (not termination condition) do
     begin
         t→t+1
         Update velocity v(t) and position of each particle z(t) based on (12) – (15) respectively
             if v(t)>v_max , v(t)= v_max end
             if v(t)<−v_max, v(t)= − v_max end
         Evaluate f(Z(t))
         Update z̃ if the new position is better than the previous z̃
         Update ẑ if the new position is better than the previous ẑ
     end
end
```

Fig. 3. The Pseudocode of particle swarm optimization (PSO) used to optimize FIS parameters

3. Result

We have developed and investigated the proposed technique for detection of AF as presented in the method section. The inputs of the detection are the width and peaks number of the electrocardiographic P-wave. The inputs are extracted from a clinical electrocardiogram. The electrocardiogram is collected from MIT-BIH database [15]. The electrocardiograms of six patients are used. The patients are with the record numbers of 201, 203, 210, 217, 219 and 221. The electrocardiogram data of these record numbers are chosen as they contain AF beats.

Example of AF and normal beats are presented in Fig 4. As it can be seen in the figure, in the area of P-wave, AF beat is wavier than the normal one. In other words, the peaks number of AF beats is more than the normal one. In addition, the normal electrocardiogram shows a clear P-wave which is not clear in the AF beat. In the normal one, the P wave is wider and higher. Thus, this article applies peaks number and width of P-wave as features of electrocardiogram. These features are used for the inputs of FIS.

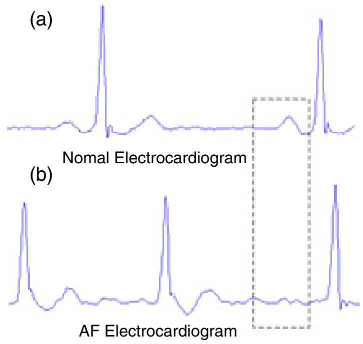

Fig. 4. Electrocardiogram beats of (a) normal and (b) AF. The P-wave region is shown by the square

Membership functions of the inputs –the width and peaks number of P-wave – are shown, respectively, in Fig. 5. The functions are presented with the range of 0 to 1. The inputs are normalized to 0 to 1. The mean and standard deviation of the membership functions are found from the optimization using PSO.

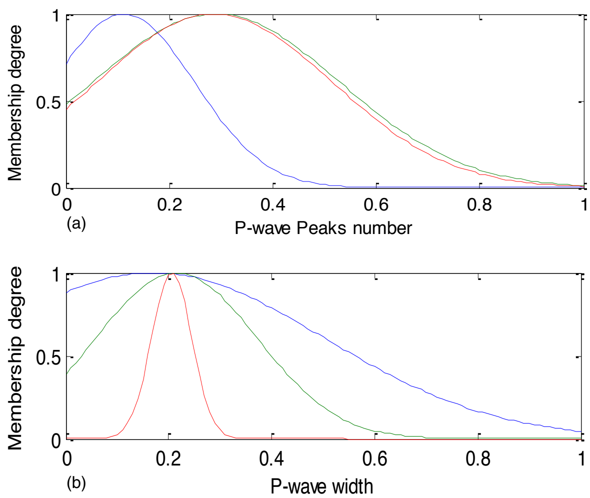

Fig. 5. Membership functions of a) P-wave peaks number and b) P-wave width

The performances of SFIS with different inputs are presented in Table 1. Three types SFIS are investigated to find the best one. The three types are the SFIS with the input of the P-wave width (SFISw), P-wave peaks number (SFISp) and both width and peaks number (SFISwp) of the P-wave. The performances are presented in terms of sensitivity (*Se*), specificity (*Sp*) and accuracy (*Ac*).

As indicated in Table 1, the performance of SFISwp, which is the SFIS with the inputs of the width and peaks number of the P-wave, is higher compared to the other two methods, SFISw and SFISp. SFISw and SFISp are the SFIS with the input of the width and the peaks number of the P-wave, respectively. In the testing, the performance of SFISwp is 77.86%, 60.40% and 75.09% in terms of sensitivity, specificity and accuracy. SFISw performs the worst in both training and testing. The performance of SFISp is slightly lower than SFISwp but is higher than SFISw.

Table 1. The performances of SFIS with different inputs for AF detection

Method	Training			Testing		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
SFISw	68.84	52.24	66.21	69.02	56.76	67.07
SFISp	72.14	51.76	68.91	72.63	48.77	68.84
SFISwp	78.04	62.47	75.09	77.86	60.40	75.09

4. Discussion

The proposed technique for detecting AF using SFIS has been presented. The inputs of SFIS are the electrocardiographic P-wave features. Feature extraction of the P-wave is conducted to find the features. SFIS with different inputs are compared to find the best one.

The FIS optimization using PSO could work as desired. It is indicated by the high sensitivity and high specificity obtained by the SFIS algorithms. In the optimization, the PSO applies sensitivity and specificity for its objective function, as defined in (7). It means that the PSO conduct an effort to find a high sensitivity and specificity. A high sensitivity of a health problem detector means that it has a high true positive. The high true positive in an AF detection means that AF beats could be detected properly. A high specificity in an AF detector minimizes a false alarm, which is a normal beat recognized as an AF beat.

The computing time required by the FIS optimization using PSO depends to the iteration number and the time consumed by every iteration. Every iteration creates n FIS models; n is the particles number of PSO. The iteration number applied in this article is 100 and the particle number is 300. Hence, after 100 iterations the optimization terminates and the best FIS model is obtained.

The SFIS utilizing both the width and the peaks number of the P-wave performs higher than which applying the single input, either the width or the peaks number. The performance of the SFIS applying the peaks number is higher than which applying the width. It could imply that the peaks number contributes more significantly than the width in the AF detection.

The P-wave features –the width and peaks number– are in the form of normalized value 0 to 1. The normalization is essential to reduce the effects of alteration of P-wave amplitudes. It could also be useful to minimize the effects of baseline wander.

A FIS model for AF detection is obtained by the optimization. The optimization applies electrocardiographic clinical data. The FIS model could be used to indicate whether the electrocardiogram in the input belongs to AF or normal. Thus, the proposed strategy could have an opportunity to be applied for an AF detection.

5. Conclusion

This paper presents a new technique for detecting atrial fibrillation (AF), a serious arrhythmic heart problem. The method applies fuzzy inference system (FIS) optimized using particle swarm optimization (PSO). The method is called SFIS (swarm fuzzy inference system). The inputs for the SFIS are the features of the electrocardiographic P-wave. The SFIS is developed and tested using clinical data. Using the width and the peaks number of the P-wave, the SFIS found the best performances, for AF detection, with of 77.86 %, 60.40 % and 75.09 %, in terms of sensitivity, specificity and accuracy.

Acknowledgements

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