Atrial fibrillation detection using RR-interval irregularity supported by particle swarm optimization

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Abstract. Atrial Fibrillation (AF) is the most common arrhythmia. AF has increased peoples health and financial burdens. Patients with AF should be stratified according to a predictive stroke-risk score. According to the complication, risk factor and data of epidemiology, AF is always interesting to be multidisciplinary research topic, one of which is the developing algorithms for auto-detect software. In this study we use analogue recorded of electrocardiography (ECG) data who converted to digital data. Before detecting the presences of AF, we detect R-Peaks of that ECG wave using differential operating method (DOM). Then we analyse the presence of AF by determining irregularities of RR-interval. To detect the occurrence of AF we use two methods, finding anomalies beat around the mean (FAM) and comparison of each other's beat (CEO). Both of methods are optimized using Particle Swarm Optimization (PSO). The principle of FAM is to look for intervals that have a big margin compared to mean of intervals in a segment. While CEO’s principle is to compared all of intervals in the segment each other, then it find the big different to declare the presence of AF. The role of PSO is to optimize their performance by initializing and evaluating their parameters to create the threshold between normal and AF. We have used this method to test the patient’s data from MIT-BIH. The performance of FAM is presented in accuracy, sensitivity, and specificity of 90.46%, 95.81, and 84.84% respectively. The performance of CEO is presented in accuracy, sensitivity, and specificity of 85.30%, 94.46%, and 77.19% respectively.

1. Introduction
AF is a supraventricular tachycardia defined by uncoordinated electrical and mechanical activity of the atria [1]. Atrial fibrillation is the most common cardiac arrhythmia that clinicians encounter in their daily clinical practice. AF affects 1.0-1.5% of the population in the developed world. It is the most common arrhythmia [2]. AF can increase an irregular ventricular activity, which is triggering several complications including palpitations, hearth failure, and cardiomyopathy followed by tachycardia [3]. Sooner or later AF may cause stoke embolic. In addition to causing anxiety in stroke embolic and heart failure, AF also has a close relationship with several diseases such as diabetes mellitus [4], hypertension, thyroid dysfunction, and rheumatic heart [5], [6]. In some cases AF has no symptoms or complaints, so the appearance is unknown to patients or medical staff. For such cases, long-term recording is required. It’s useful to correct the diagnoses, assess electrocardiographic suppression of AF/AFL, and guide the therapy for rhythm control. To correct the diagnosis, 24 hours recording on paroxysmal AF daily may be possible to do. However in patients whose
interval is more than 24 hours, recording and readout the results will be very troublesome and become an almost impossible activity [2], [7]. We need a solution to achieve that target. The various members of the interdisciplinary team must achieve an integrated approach to primary and secondary prevention, identification, management, and progression of AF [1].

AF can be diagnosed easily if on the ECG record there is a display of fibrillation waves, absence of wave P, and the irregular RR interval [3]. Nevertheless many study of biomedicine use irregularity of irregular RR intervals as a key feature [8]. This is because on an electrocardiography (ECG) record there are at least two types of atrial fibrillation waves. Coarse AF are displayed by fibrillation’s amplitude higher than 1mm and fine AF are displayed by fibrillation’s amplitudes less than 1mm or even do not appear significantly. For such cases the diagnosis is based on the occurrence of arrhythmias or RR irregularities [9], [10].

There have been many investigations of AF automation detection using the degree of RR-irregularity interval. The used methods are CoSEN [11], [12], Detrended Fluctuation Analysis, Coefficient Variance, RMSS, Median absolute deviation, Local Dynamic Score [12] and so on.

In this study we detect AF appearance by finding anomalies beat around the mean (FAM) and comparison of each other's beat (CEO) method. The basic principle of both methods is to detect the occurrence of RR intervals that have irregular lengths. In the FAM method, the occurrence of RR-irregular is indicated by the appearance of the RR-interval whose length is too short or too long compared to the mean of the RR-interval. In the CEO method, the occurrence of RR-irregular is indicated by the appearance of RR-interval which has a big difference compared to others RR-interval. This FAM and CEO method we combine with Particle Swarm Optimization (PSO). PSO is an famous evaluating computation method. PSO is discovered by Kennedy and Eberhart at 1995. For two decades the PSO has been extensively researched, developed and used in evalutional computation programing [13]. Some cases that can be solved using PSO is a Premature Atrial Contraction detection [14], combination of nutritional doses for diet [15], schedule combinations [16], and others.

PSO is used to solve the problem on giant data. The basic principle of how PSO works is to find the best solution for fitness function to reach the minimum point. The procedure is repeated until the fitness goals achieved [13], [17].

Before entering on the irregularity detection RR-interval of course we have to detect R peak first. Because the samples we use are ECG records of analog recordings that are converted into digital data with a frequency of 250 samples per second.

In this research we detect R peak by using Differential Operation Method (DOM) method. DOM was developed by Yun Chi Yeh and Wen June Wang in 2007. To find the point R its method is applying the different equation operation to an ECG signal. [18]

2. Numerical Methods

In this study, we use data from MIT-BIH published by Physionet. The ECG data is an analog recording that is converted into digital data with a sample frequency of 250 Hz [19]. The length of data we use more than 200 hours of recording.

To start the feature extraction process, the data to be used should be RR interval. Therefore, we have to detect the QRS complex of the samples. In this study we use the differential operation method (DOM) to do that job. Then we get the RR-Interval, for the extraction process the series of RR-Interval is segmented with length 40 of them.

2.1. DOM (Differential Operation Method)

Differential Operation Method is a proposed method by Yun Chi Yeh and Wen June Wang in 2007 to detecting QRS complex [18]. They have claimed that the method is quite simple and fast algorithm because it does not require complicated mathematical calculations like Fourier and cross transformations -correlation. Overall this method is able to detect the point of Q, R, and S [18]. But since our research is only requires R peaks, we only use the DOM until the method of determining R. This consists of two
steps of DOM, Differential Operation Processed (DOP) and Wave's Detection Process. The equation used in DOP is presented by eq.1.

$$x_d(n) = x(n) - x(n - 1)$$ (1)

After that we apply low pass filter to signal $X_d$. It aims to eliminate the signals that have frequencies greater than 100 Hz and low amplitude. The next stage is applying the Thresholds 1 ($T_1$) and Thresholds 2 ($T_2$) to obtain the final signals ($X_{df}$), it’s according to equation 2. $T_1$ is 2MVp and $T_2$ is 2MVn. MVp is the mean of all positive amplitude and MVn is the mean of all negative amplitude.

$$x_{df} = f(x) = \begin{cases} 
0, & \text{if } 0 < X_{df} < T_1, \text{or } T_2 < X_{df} < 0 \\
X_{df}, & \text{if } X_{df} \geq T_1, \text{or } X_{df} \leq T_2
\end{cases}$$ (2)

The last stage is to find the R-peak. The way to get R-peaks is to scan the $X_{df}$ wave. The criterion is the extreme point that has a distance of each other between 0.4 to 12 seconds. For a sampling frequency of 250Hz, 0.4 seconds is equivalent to 100 sample points. Actually DOM still has several stages to detect points Q and S. Because we only need R, then we do not do that stage.

2.2. FAM (Finding Anomalies Beat around the Mean)

FAM is a method for determining the status of AF based on RR interval irregularity. This method is quite simple and short because it only consists of 3 easy steps. It’s presented on figure 1. The first step is to determine the average of the interval ($i$) on the segment being worked on.

| $i_1$ = first interval |
| $i_2$ = second interval |
| $i_n$ = nth interval |
| $\bar{i}$ = mean |
| $\sigma_{fam}$ = threshold |
| $\tau_{fam}$ = tolerance |
| $\delta_{an}$ = abnormal difference |

Input $i_1, i_2, i_3, \ldots, i_{40}$

$$\delta_{an} = \text{find}(i_{n+n} > (\sigma_{fam} + \bar{i})||i_{n+n} < (\bar{i} - \sigma_{fam}))$$

If amount of $\delta_{an} > \tau_{ceo}$

Segment = AF

Else segment = normal

| Figure 1. Pseudo-code of FAM |

The second step is to determine the threshold. This threshold is used to determine whether a given interval-RR ($i_n$) in the segment is normal or abnormal. An interval when compared to the mean ($i$) has a margin that exceeds the threshold ($\sigma_{fam}$) is called an abnormal interval ($i_{an}$), so that the interval whose margin does not exceed the threshold ($\sigma_{fam}$) is called the normal interval ($i_{nor}$). The threshold ($\sigma_{fam}$) we use is derived by the equation 3.

$$\sigma_{fam} = \frac{\beta}{100} \bar{i}$$ (3)

Where $\beta$ constant is parameter which is will be initiated and evaluated at PSO process later. The third step is to count the amount of abnormal intervals ($i_{an}$). It’s because we use the number of normal intervals ($i_{nor}$) and abnormal intervals ($i_{an}$) to classify normal and abnormal segments. The status of
segment is abnormal if the number of abnormal intervals is more than the tolerance ($\tau_{\text{num}}$). The tolerance we use is 10% of the segment’s length. This means if 10% interval abnormal ($i_{\text{an}}$) then the segment is AF.

2.3. CEO (Comparison of Each Other’s Beat)

The CEO is a method for determining AF status based on RR interval irregularities by interval’s length comparison. Each interval is compared to each other to produce many comparative values. This method is the same as the method we proposed in the previous journal [8]. In this research we call it CEO because it is easier to remember and so that different term is not confused in the mentioning. In this study we modified the length of segments and thresholds. The length of the segment we use is 41 R-Peaks or 40 intervals.

The first step of this method is to comparing each other all the intervals in the segment. The first RR-interval ($i_1$) is compared with 39 subsequent RR-Intervals ($i_2 - i_{40}$), it’s resulting in 39 values of difference ($\delta$). Furthermore, the second interval ($i_2$) compared with 38 subsequent RR-interval ($i_3 - i_{40}$) and resulting in 38 values of the difference. The second interval ($i_2$) is not compared with the first interval ($i_1$) again, because it has been compared. Next the third interval ($i_3$) compared to 37 of subsequent RR-intervals ($i_4 - i_{40}$), and so on. Until at the end of the process we get as many as 782 comparative results we call the row of difference ($i_{82}$). This method is presenting with pseudo code at figure number 2.

![Figure 2. Pseudo-code of CEO](image)

The second step is to determine the normal threshold ($\sigma_{\text{CEO}}$). In the next process, $\sigma_{\text{CEO}}$ as the parameters that initiating and evaluating by PSO. The third step is to calculate the amount of $\delta$ whose value exceeds the normal threshold ($\sigma_{\text{CEO}}$). For the difference ($\delta$) smaller than the normal threshold ($\sigma_{\text{CEO}}$) we symbolize with ($\delta_{\text{nor}}$) normal difference. For the difference ($\delta$) exceeding the normal threshold we symbolize ($\delta_{\text{an}}$) or abnormal difference. If the amount of abnormal difference $\delta_{\text{an}}$ in a segment is exceeds the tolerance ($\tau_{\text{CEO}}$), then that segment is abnormal or AF segment. The tolerance we use is 10% of the segment length. This means the AF segment must be contain abnormal intervals at least 10%.
2.4. PSO (Particle Swarm Optimization)
PSO is an evaluating computation method found through simulation of simplified social model. It inspired by animal movement like bird flocking and fish schooling. This optimization model is discovered by Kennedy and Eberhart at 1995. The PSO methodology is illustrated by the movement of birds as particles on their way to food [13]. Every bird in the group has the same goal, that is food, and they work together. But not all birds know the route to food and not all birds get food. The birds that get the food, the route they through is not the same. Some of birds are through an effective route, but some aren’t. Then the other birds will follow the most effective route their members found. For the next-period of food searches, these birds will use the best route they had found the day before. The movement through the most effective route to the most food is not only becomes the movement of some individual birds, but the movement of the swarm.

The PSO algorithm consists of three steps. First, evaluate the fitness of each particle. Second, update individual and global best fitness and positions. Third, update velocity and position of each particle. The steps are repeated until stopping condition is found [20].

Each candidate solution in PSO is called a “particle” \( Z(t) \). The particle is represented in a \( \mathcal{D} \)-dimensional space, which \( \mathcal{D} \) is the number of parameters to be optimized [21]. Each particle has the position and velocity determined by the representation of the solution at that time. The direction and displacement of particles is determined by the velocity (\( v \)) adjusted by eq.4. The changes in velocity are held at every iterations process to improve the position of the original particles. The position is defined by equation 5 [22].

\[
v(t) = q \left( \varphi v(t-1) + c_1 r_1 (z_p - z(t-1)) + c_2 r_2 (z_g - z(t-1)) \right) \tag{4}
\]

\[
z(t) = z(t-1) + v(t) \tag{5}
\]

Personal best (\( z_p \)) is the best position of the particle has ever achieved by comparing the fitness to the present particle position with the previous particle. Personal best prepared to get the best solution. Global best (\( z_g \)) is the best position of the particles obtained by calculating the best fitness value of the whole particle in the swarm. \( q \) is constriction factor, \( \varphi \) is inertia factor, \( r_1 \) and \( r_2 \) is random number in the range [0 1], then \( c_1 \) and \( c_2 \) are acceleration constant [22].

PSO work by initializing and evaluating the swarm particle \( Z(t) \) by the fitness function. The fitness function is a particular type of objective function that is used as an optimization criterion [21], how close the design solution is to achieve the set target. In this study fitness function is performance of method that we targeted.

We use PSO to optimize parameter of \( \beta \) of FAM and optimize parameter \( \sigma_{ceo} \) in CEO method. This procedure is upgrading the performance of methods which is indicated by an increasing of accuracy. Parameter \( \beta \) and \( \sigma_{ceo} \) are represented by \( Z(t) \) or particle of swarm. Fitness function is represented by performance function that defined by eq.3 [14].

\[
f = -(Sen + Spec) \tag{6}
\]

Sensitivity (Sen) is the ability of a test to correctly identify those with the disease (true positive rate), specificity (Spec) is the ability of the test to correctly identify those without the disease (true negative rate).

3. Result and Discussion
A series of experiments has been completed. Starting from detecting R-Peaks using DOM until detecting the appearance of AF using FAM and CEO. Both of FAM and CEO are modified using PSO. The inputs we use are analog recording data that has been converted into digital with a sample frequency of 250 Hz. In this study DOM successfully detects R-Peaks from all samples. The failed detection rate of this method is 4.4%.
The R-Peaks that obtained from the previous process are used as inputs for the next process. The entire data is aggregated into the big one. In the process of operating the R-Peaks, data in a segmentation of 40 RR Intervals. Both FAM and CEO use the same input data.

We separate the input data into 2 groups. The first set is a training data consisting of 30% of all randomly selected data. The second is testing data consisting of 70% of all randomly selected input data, it is the rest of the training data. This means that there is no training data which also becomes test data.

Both FAM and CEO are developed using training data and optimized using PSO. After optimization is complete, FAM and CEO are ready to be applied to the test data. The goal of this optimization in the FAM program is to get the best value of the $ \beta $ parameter, so that the fitness function reaches the minimum point. Likewise CEO, optimization aims to get the best value from the threshold $ \sigma_{ceo} $ for fitness function to reach its minimum point.

| Table 1. Performance of FAM and CEO |
|------------------------------------|
| FAM-PSO                           | CEO-PSO                        |
| Sensitivity                       | Training (%)   | Testing (%) | Training (%)   | Testing (%) |
|                                  | 84.61          | 84.84       | 77.39          | 77.19       |
| Specificity                       | 95.47          | 95.81       | 94.59          | 94.46       |
| Accuracy                          | 90.18          | 90.46       | 85.48          | 85.30       |

At Training process, the $ \beta $ parameter of FAM we get is 18.62, followed by fitness function achievement -90%, then for CEO method the threshold ($ \sigma_{ceo} $) obtained is 52, followed by fitness function achievement -85%.

DOM provide us a good performance in detecting R-Peak. In addition DOM has a simple algorithm. This makes the computing process run quickly and does not burden the device. In this study we did not use complete DOM as they proposed [18]. There are two differences of DOM between our and theirs steps. First we only use DOM to the stage of R Peak detection. Secondly, we made a slight modification to the threshold. We raised the threshold to 2 times higher, but this is only done during the final process, which is a scan process for R-Peaks identification. The reason we raise the threshold is because on the previous threshold usage R-Peaks can’t be detected yet. At the end of process the R-Peaks detection gives a good result with failed detection rate of 4.4%

Based on table number 1 we can see that FAM has a higher performance than the CEO. Both FAM and CEO work by finding the presence of irregular RR-Interval within each segment. The differences between them are processing the irregularities and the indicators of irregularity.

FAM is works by finding RR-intervals that have a large margin when compared to the mean of the RR-interval in that segment, either too long or shorter. An RR-interval is said to be too long or too short if it has a margin that exceeds the FAM threshold ($ \sigma_{fam} $). $ \sigma_{fam} $ is derived from $ \beta % $ of the mean of the RR-interval. This has been defined by the eq.3. The role of PSO in FAM is to get the best value from $ \beta $, so FAMs method gets the best performance. In the PSO, $ \beta $ is a particle of swarm. And the performance of the method is a fitness function that is optimized. In this study we presented was 18.62. This means the threshold $ \sigma_{fam} $ we set as 18.62% of the average RR interval, or is presented in the number eq. 7

$$ \sigma_{fam} = \frac{18.62}{100} x \bar{f} $$

Furthermore, an RR-interval whose margin exceeds the threshold we call an abnormal interval ($ \bar{f}_{an} $). If in a segment the number of abnormal intervals ($ \bar{f}_{an} $) reaches 2.5% then it can be said that AF has appeared in the segment. The best performance that we got for FAM is 90.16% on the 12th PSO iteration. Actually it is rather surprising, but although we continue to iterating, the performance has not changed. FAM’s performance when testing process is 90.46%, It’s 0.3% better than during the training process. The basis of CEO’s work concept is to comparing each other all of the RR-interval in a segment. An RR-interval is not only compared to the RR-interval neighbors, but also compared with all the intervals in that segment. To obtain the threshold CEO was optimized using PSO. In this method, the threshold $ \sigma_{ceo} $
obtained is 52, followed by fitness function achievement 85%. This is achieved after the process was iterated seven times. In the next of iteration the result has not changed. For the testing process, CEO performance has not changed.

In the duration of running time, CEOs is spend more time than FAM. For ones iteration, modified FAM using PSO takes approximately 2 minutes, whereas modified CEO using PSO is takes 20-25 minutes. This is because in the FAM method, the number of values compared is only 40 items. While at CEO that numbers is reach until 782 items, it's 19 times more than FAM. When compared to previous studies [8], the accuracy of the CEO did not experience a significant change, they both only reached 85%. Although in this study the CEO has been optimized using PSO. The difference between the two is in sensitivity and specificity. The sensitivity of CEO without optimization is reaches 91%, this is better than the CEO using optimization. But in terms of specificity, CEO using optimization is better. Without optimization the specificity is reaches 77.85%, whereas using optimization reaching 94.46%. This performance change may be due to differences in segment length. In the previous study, the segment length used was 10 intervals, while in this study the segment was 4 times longer.

Overall it can be concluded that FAM modified using PSO give us better performance than unmodified FAM. In addition FAM also provides higher performance than CEO, whether optimized using PSO or not. In terms of algorithms, FAM has a simpler algorithm than the CEO. Even in terms of time usage, FAM is much faster than the CEO.

In this research, PSO performs a very good task in optimizing both methods. Although the accuracy of CEO is does not change, but the processing time is faster. It’s because, without PSO finding the threshold must be done by manually testing repeatedly as in previous studies.

4. Conclusion
This paper presents methods to detect AF. The methods are FAM and CEO which are both optimized using PSO. FAM is a method for detecting AF by finding RR-intervals that have large margins with mean of RR-intervals on a segment. The CEO is the detection of irregularity by comparing each other throughout the RR-Interval in the segment and finding a large RR-Interval difference. Both methods are optimized using PSO. FAM provides higher performance with accuracy, sensitivity, and specificity of 90.46%, 84.84%, and 95.81% respectively.

5. References
[1] Faisal Rahman and Emelia J Benjamin, "Classification and Epidemiology of Atrial Fibrillation," in Atrial Fibrillation: A Multidisciplinary Approach to Improving Patient Outcomes, Mark Estes and Albert L Waldo, Eds. Minneapolis, Minnesota, USA: Cardiotext Publishing, 2015, vol. 4, ch. 1.
[2] Yee Guan Yap and A John Camm, Essentials of Atrial Fibrillation. London: Springer Healthcare, 2014.
[3] Attila Roka, "Atrioventricular Conduction in Atrial Fibrillation: Pathophysiology and Clinical Implications," in Atrial Fibrillation - Basic Research and Clinical Applications. Rijeka, Croatia: InTech, 2011.
[4] M Yazici, K Ozdemir, and BB Altunkeser, "The effect of diabetes mellitus on the P-wave," vol. 71, no. 6, pp. 880-883, 2007.
[5] Mohammad Shenasa and A John Camm, Management of Atrial Fibrillation. Oxford: Oxford University Press, 2015.
[6] Jennifer Cruz and Paul Dorian, "Clinical Evaluation of the Atrial Fibrillation Patient," in Atrial Fibrillation: A Multidisciplinary Approach to Improving Patient Outcomes. Minneapolis, Minnesota, USA: Cardiotext Publishing, 2015, vol. 4, ch. 2.
[7] D George Wyse and Laurie Burland, "Rhythm Management: Making the Choice Between Rate and Rhythm Control," in Atrial Fibrillation: A Multidisciplinary Approach to Improving Patient Outcomes. Minneapolis, Minnesota, USA: Cardiotext Publishing, 2015, vol. 4, ch. 3.

[8] Mufida Eliana and Nuryani, "Identification of atrial fibrillation using electrocardiographic RR-interval difference," in ICSAS, vol. 909, Surakarta, 2017.

[9] M.K. Das and D.P. Zipes, Electrocardiography of Arrhythmias: A Comprehensive Review. Philadelphia: Elsevier Saunders, 2012.

[10] M. Munawar and H. Sutandar, Buku Ajar Kardiologi, A. Tjokronegoro, Ed. Jakarta: Gaya Baru, 2003.

[11] D.E. Lake and J.R. Moorman, "Accurate Estimation of Entropy in very Short Physiological Time Series: The Problem of Atrial Fibrillation Detection in Implanted Ventricular Devices," Hearth Circ, pp. 19-25, 2011.

[12] M. Carrara et al., "Heart rate dynamics distinguish among atrial fibrillation, normal sinus rhythm, and sinus rhythm with frequent ectopy," Physiological Measurement, vol. 36, no. 9, p. 2873, 2015.

[13] James Kennedy and Russel C. Eberhart, "Particle Swarm Optimization," pp. 1942-1948, 1995.

[14] Nuryani Nuryani, Iwan Yahya, and Anik Lestari, "Hybrid Particle Swarm Optimization-Fuzzy Inference System for Premature Atrial Contraction Detection," in 7th International Conference on Physics and Its Applications, Surakarta, 2014, pp. 153-156.

[15] Dong Sheng Xu, Feng Zhang, and Yong Heng Zhang, "Multi-objective Optimization Model of Nutritional Ingredients for Poultry Based on Particle Swarm Optimization Algorithm," vol. 39, no. 3, pp. 286 - 293, 2016.

[16] Andreas C. Nearchou and Sotiris L. Omirou, "A Particle Swarm Optimization Algorithm for Scheduling Against Restrictive Common Due Dates," International Journal of Computational Intelligence Systems, vol. 6, no. 4, pp. 684-699, July 2013.

[17] C., Eberhart Russel and Shi Yuhui, "Partice Swarm Optimization: Development, Applications, and Resources," pp. 81-86, 2001.

[18] Yun Chi Yeh and Wen June Wang, "QRS complexes detection for ECG signal: The Difference Operation Method," Computer Methods and Programs in Biomedicine, vol. 91, pp. 245-254, 2008.

[19] AL Goldberger et al., "PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals," Circulation Electronic, 2000.

[20] James Blondin, "Particle Swarm Optimization: A Tutorial," September 4 2009.

[21] Federico Marini and Beata Walczak, "Particle swarm optimization (PSO). A tutorial," Chemometrics and Intelligent Laboratory Systems, no. 149, pp. 152-165, 2015.

[22] Nuryani, Iwan Yahya, and Anik Lestari, "Premature Ventricular Contraction Detection using Swarm-based Support Vector Machine and QRS Wave Features," International Journal of Biomedical Engineering and Technology, vol. 16, pp. 306-316, Desember 2014.