Atrial flutter and atrial tachycardia detection using Bayesian approach with high resolution time–frequency spectrum from ECG recordings

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ABSTRACT

Contemporary methods of atrial flutter (AFL), atrial tachycardia (AT), and atrial fibrillation (AF) monitoring, although superior to the standard 12-lead ECG and symptom-based monitoring, are unable to accurately discriminate between AF, AFL and AT. Thus, there is a need to develop accurate, automated, and comprehensive atrial arrhythmia detection algorithms using standard ECG recorders. To this end, we have developed a sensitive and real-time realizable algorithm for accurate AFL and AT detection using any standard electrocardiographic recording. Our novel method for automatic detection of atrial flutter and atrial tachycardia uses a Bayesian approach followed by a high resolution time–frequency spectrum. We find the TQ interval of the electrocardiogram (ECG) corresponding to atrial activity by using a particle filter (PF), and analyze the atrial activity with a high resolution time–frequency spectral method: variable frequency complex demodulation (VFCDM). The rationale for using a high-resolution time–frequency algorithm is that our approach tracks the time-varying fundamental frequency of atrial activity, where AT is within 2.0–4.0 Hz, AFL is within 4.0–5.3 Hz and NSR is found at frequencies less than 2.0 Hz. For classifications of AFL (n = 22), AT (n = 10) and normal sinus rhythms (NSR) (n = 29), we found that our approach resulted in accuracies of 0.89, 0.87 and 0.91, respectively; the overall accuracy was 0.88.

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1. Introduction

The atrial tachyarrhythmias atrial flutter (AFL), atrial tachycardia (AT), and atrial fibrillation (AF) represent the most common class of heart rhythm disorders presenting to medical attention [1–2]. Many algorithms have been developed to detect AF and can be categorized as being based on RR interval (RRI) variability [3–11]. Specifically, their aim was to quantify markedly increased beat-to-beat variability RRI time series in AF. Consequently, most algorithms showed sensitivity and specificity values higher than 90% for AF detection. On the other hand, automatic detection of AFL and AT is more challenging and has been less studied since the RRI characteristics of AFL and AT are regular, and the acquisition of the atrial signal (F-wave) is required.

AFL is an atrial dysrhythmia that generates a discernable P-wave, making it difficult to distinguish from normal sinus rhythm. Moreover, although AFL often results from distinct electrophysiological mechanisms, namely focal automaticity and macro-reentry, the RR intervals and P wave morphologies associated with these arrhythmias are often quite similar. An atrial rhythm of approximately 130–240 waves/min (i.e. 2.2–4 Hz) is referred to as AT while a regular macoreentrant atrial rhythm of approximately 240–320 waves (i.e. 4–5.3 Hz) is referred to as AFL [12]. Thus, the QRST cancelation or elimination (ventricular cancelation or elimination) in the ECG is critical for classification of AFL and AT by analyzing the atrial activity. In the TQ interval, electrical activity in the ECG is dominated by the atrial contribution while the ventricular component is a time series with missing data in the QT interval. The atrial signal is considered as a time series with missing data in the QT interval [13]. Some of the notable algorithms for QRST cancelation include spatiotemporal, the QRST cancelation technique, and average beat subtraction, but these require long ECG recordings (e.g. one minute of average beats or longer) [14–15]. Wave rectification, blind source separation, principal component analysis, and automatic mode switching are algorithms that have been developed to deal with the challenges of automated AT and AFL detection, but these methods are relatively crude, inconsistently effective, and with notable shortcomings [16–18]. Recently, Jaqueñet et al. [19] proposed a new AFL detection algorithm, which reconstructs the spectrum of the atrial component of the
ECG corresponding to TQ intervals, but they assumed that the TQ intervals are given. Hence, at present, no reliable and complete AFL detection algorithm is available because existing QRST cancelation algorithms are insufficient as described above.

Recently, McSharry et al. introduced a powerful dynamic ECG model, which is capable of replicating many of the important features of the human ECG by generating different morphologies for the PQQRS-complex [20]. Based on the dynamic model, Sayadi et al. [21] and Sameni et al. [22] used Kalman Filters (Extended Kalman Filter, Extended Kalman Smoother and Unscented Kalman Filter) as a Bayesian approach for ECG denoising and atrial activity analysis. Both demonstrated superior results compared to bandpass filtering, adaptive filtering, and wavelet transform over a wide range of ECG SNRs. We extended this concept to atrial signal (TQ interval) detection by using the Particle Filter (PF), which has been widely adopted in many estimation problems, as it is especially powerful for nonlinear and non-Gaussian problems [23–24]. It is widely known that the PF estimator performs better than any Kalman Filter estimator [25]. First, we modified the dynamic ECG model by generating only four waves for QRST (excluding P wave) complex, and predicted the prior density function by propagating parameters of peak amplitudes, peak widths, angular spreads and locations of each QRST wave. Since the ECG waveform itself and measurement noise are nonlinear and non-Gaussian, PF is more suitable than any Kalman Filter. Thus, our PF framework results in more accurate QRST wave detection than does a Kalman Filter algorithm. After finding the atrial signal, we use a high-resolution time-frequency method named variable frequency complex demodulation [27] in order to detect AFL and AT in the atrial signal.

2. Methods

2.1. Databases

We collected data from 22 AFL patients, 10 AT patients and 29 normal sinus rhythm (NSR) subjects. Electrocardiographic data were obtained from Holter recordings and retrospectively collected 12-lead electrocardiograms. Each ECG recording was approximately one to ten hours in duration. The University of Massachusetts Institutional Review Board approved the data collection and analysis of electrocardiographic data. Of participants with available clinical and demographic data, the mean age of participants with AFL was 69 ± 11 years of age and 57% were women. The mean age of participants with AT was 72 ± 13 years of age and 33% were women. The NSR data recordings were collected for 3 min using ScottCare RZ153 series recorders, and acquired at the sampling rate of 180 Hz with 10-bit resolution. The subjects were comprised of 15 men and 14 women, with a mean age of 24 ± 3.1 years. The NSR subjects were free from any known cardiovascular diseases.

2.2. Synthetic ECG model and TQ interval definition

Let us denote the onset of the Q wave by \( Q_{\text{on}} \), and the end of the T wave by \( T_{\text{end}} \). The TQ interval between \( T_{\text{end}} \) and \( Q_{\text{on}} \) corresponds to atrial activity. Then, the atrial activity signal \( A_{\text{TQ}}(t) \) from ECG can be formulated as shown below:

\[
A_{\text{TQ}}(t) = s(t) \cdot G_{\text{TQ}}(t),
\]

where \( s(t) \) is the measurement ECG, and \( G_{\text{TQ}}(t) \) is a gating function defined as one in the intervals between \( T_{\text{end}} \) and \( Q_{\text{on}} \) and zero otherwise.

To find the end of the T wave (\( T_{\text{end}} \)) and the onset of the Q wave (\( Q_{\text{on}} \)), we used a synthetic ECG model [20] as follows:

\[
\begin{aligned}
x &= \rho x - \frac{\rho}{y} \\
y &= \rho y + \frac{\rho}{x} \\
z &= \sum_{i \in \{P, Q, R, S, T\}} a_i \Delta \theta_i \exp \left( -\frac{(\Delta \theta_i)^2}{2 \sigma_i^2} \right)
\end{aligned}
\]

where \( x, y \) and \( z \) are the state variables, \( \rho = 1 - \sqrt{x^2 + y^2} \), \( \Delta \theta_i = (\theta - \theta_i) \mod(2\pi) \), \( \theta = \tan(2\pi y/x) \) is the four quadrant arctangent of the elements of \( x \) and \( y \) with \( 0 \leq \tan(2\pi y/x) \leq 2\pi \), and \( \sigma \) is the angular velocity of the trajectory as it moves around the limit cycle in \( x-y \) plane. The parameters \( a_i \) and \( \theta_i \) represent peak amplitudes, standard deviation (SD) and location of each PQRS wave, respectively. Then, in each one cycle of ECG, \( T_{\text{end}} \) and \( Q_{\text{on}} \) can be approximately calculated as:

\[
T_{\text{end}} = \theta_T + a_T \cdot b_T,
\]

and

\[
Q_{\text{on}} = \theta_Q - a_Q \cdot b_Q,
\]

where \( a_Q \) and \( a_T \) are multiplication factors to determine T and Q wave half-width. That is, \( T_{\text{end}} \) can be calculated by the summation of T wave peak location (\( \Delta \theta_T \)) and the half-width (\( a_T \cdot b_T \)). Similarly, \( Q_{\text{on}} \) can be calculated by the subtraction of Q wave peak location (\( \Delta \theta_Q \)) and the half-width (\( a_Q \cdot b_Q \)). Since Eq. (2) assumes each wave is Gaussian form, the onset and end locations can be determined based on a confidence level. Under the confidence level of 0.99, we set up \( a_Q \) and \( a_T \) as 2.576.

2.3. TQ interval detection with particle filter

Given one cycle of ECG signal \( s_{\text{cycle}}(t_1 : t_2) \), where \( t_1 \) and \( t_2 \) are each consecutive R peak time, we convert the time series \( s_{\text{cycle}}(t_1 : t_2) \) to phase series \( s_{\text{cycle}}(\theta, n) \), which is considered a measurement vector at the \( n \)-th cycle. The measurement vector \( s_{\text{cycle}}(\theta, n) \) can be formulated by each PQRS peak amplitude, SD and location as follows:

\[
s_{\text{cycle}}(\theta, n) = F(a_{i,n}, \theta_{i,n}, b_{i,n}, a_{u,n}, b_{u,n}, \theta_{u,n}), \quad i \in \{P, Q, R, S, T\}
\]

where \( F(\cdot) \) is a measurement function, where \( a_{i,n}, \theta_{i,n} \) and \( b_{i,n} \) form a sum of Gaussian functions with measurement noise \( a_{u,n}, b_{u,n}, \) and \( \theta_{u,n} \) at the \( n \)-th cycle. Note that the measurement noise can be positive or negative. The measurement noise distorts the ECG morphology due to physical factors such as digitization errors, noise artifact and inaccurate R peak detection. Note that \( i \) represents each PQRS wave. Then, \( s_{\text{cycle}}(\theta, n) \) can be expressed as:

\[
s_{\text{cycle}}(\theta, n) = \sum_{i \in \{P, Q, R, S, T\}} (a_{i,n} + a_{u,n}) \cdot (\Delta \theta_{i+u,n}) \cdot \exp \left( -\frac{(\Delta \theta_{i+u,n})^2}{2(b_{i,n} + b_{u,n})^2} \right)
\]

where \( \Delta \theta_{i+u,n} = (\theta - (-\theta_{i,n} + \theta_{u,n}) \mod(2\pi)) \).

The QT interval includes both ventricular depolarization and repolarization. We define the ventricular activity by \( M(n) \)

\[
M(n) = |Q(n)|R(n)|S(n)|T(n)|^T
\]

where

\[
Q(n) = [a_{Q,n}b_{Q,n}\theta_{Q,n}]
\]

\[
R(n) = [a_{R,n}b_{R,n}\theta_{R,n}]
\]

\[
S(n) = [a_{S,n}b_{S,n}\theta_{S,n}]
\]

\[
T(n) = [a_{T,n}b_{T,n}\theta_{T,n}]
\]
Let $s_{\text{cycle}}(\theta, n) = [s_{\text{cycle}}(\theta, 1), \ldots, s_{\text{cycle}}(\theta, n-1), s_{\text{cycle}}(\theta, n)]$ denote the concatenation of all measurement vectors up to the n-th cycle. The aim is to recursively estimate the conditional posterior probability density $p(M(n)|s_{\text{cycle}}(\theta, 1:n))$, from which the ventricular activity can be obtained from the mean values of the density function. We modified the dynamic ECG model by generating only four waves for QRST (excluding P wave) complex, and predicted prior density function by propagating parameters of peak amplitudes, peak widths, angular spreads and locations of each QRST wave. Details concerning the generic PF algorithm are described in [25–26].

Assuming that the posterior probability density at the (n-1)-th cycle is available, the posterior probability density at the n-th cycle can be found through the Chapman–Kolmogorov equation and Bayes' rule:

$$p(M(n)|s_{\text{cycle}}(\theta, 1:n-1))$$

$$= \int p(M(n)|M(n-1))p(M(n-1)|s_{\text{cycle}}(\theta, 1:n-1)) \cdot dM(n-1),$$

where $p(M(n)|s_{\text{cycle}}(\theta, 1:n-1))$ is the posterior probability density, $p(M(n)|M(n-1))$ is the state transition density, $p(M(n)|s_{\text{cycle}}(\theta, 1:n-1))$ is the prediction probability density and $p(s_{\text{cycle}}(\theta, n)|M(n))$ is the likelihood.

The first step to particle generation is to represent a prior probability density function $p(M(n)|s_{\text{cycle}}(\theta, 1:n-1))$ by a set of particles. To find the end of the T wave ($T_{\text{end}}$) and the onset of the Q wave ($Q_{\text{onset}}$), we generate particles by using a synthetic ECG model in Eq. (2) without a P wave. In each one cycle of the ECG, the parameters $a_i$, $b_i$ and $\theta_i$ are estimated and QRST waves are subsequently generated. Given the particles corresponding to the posterior probability density function of $p(M(n)|s_{\text{cycle}}(\theta, 1:n-1))$ obtained at the $(n-1)$-th cycle, new particles $M^*(n)$ are generated at the n-th cycle as:

$$p(M(n)|s_{\text{cycle}}(\theta, 1:n-1)) \cdot M^*(n)$$

$$= \left[ \begin{array}{c}
\tilde{a}_{Q,n} \\
\tilde{b}_{Q,n} \\
\tilde{\theta}_{Q,n} \\
\tilde{a}_{R,n} \\
\tilde{b}_{R,n} \\
\tilde{\theta}_{R,n} \\
\tilde{a}_{S,n} \\
\tilde{b}_{S,n} \\
\tilde{\theta}_{S,n} \\
\tilde{a}_{T,n} \\
\tilde{b}_{T,n} \\
\tilde{\theta}_{T,n}
\end{array} \right]$$

$$= \tilde{M}^*(n-1) + V_{\text{int}}(n), \quad j = (1, 2, \ldots, J)$$

where $M^*(n)$ and $\tilde{M}^*(n)$ are the j-th generated particles and resampled particles, respectively, $j = (1, 2, \ldots, J)$ for the number of particles. The generated particles $M^*(n)$ can be expressed as

$$M^*(n) = [Q(n-1)R(n-1)S(n-1)T(n-1)]^T + [V_Q(n)V_R(n)V_S(n)V_T(n)]^T$$

$$\sim \sum_{i \in \{Q,R,S,T\}} (\tilde{a}_{i,n} + \tilde{b}_{i,n}) \cdot \exp \left( -\frac{(\tilde{a}_{i,n} + \tilde{b}_{i,n})^2}{2} \right)$$

$$\sim \tilde{\delta}_{i+1,n} \cdot \exp \left( -\frac{(\tilde{a}_{i,n} + \tilde{b}_{i,n})^2}{2} \right)$$

where $\tilde{\delta}_{i+1,n} = (\theta - (\tilde{a}_{i,n} + \tilde{b}_{i,n}) + \delta(2\pi))$

The resampled particles $\tilde{M}^*(n)$ can be expressed as:

$$\tilde{M}^*(n) = [Q(n-1)R(n-1)S(n-1)T(n-1)]^T + [V_Q(n)V_R(n)V_S(n)V_T(n)]^T$$

$$\sim \sum_{i \in \{Q,R,S,T\}} (\tilde{a}_{i,n} + \tilde{b}_{i,n}) \cdot \exp \left( -\frac{(\tilde{a}_{i,n} + \tilde{b}_{i,n})^2}{2} \right)$$

where $\tilde{\delta}_{i+1,n} = (\theta - (\tilde{a}_{i,n} + \tilde{b}_{i,n}) + \delta(2\pi))$

We assume that $s_{\text{cycle}}(\theta, n)$ is a stationary process denoted as $s_{\text{cycle}}(\theta, n) = s_{\text{cycle}}(\theta, 1:n)$. After the new particles corresponding to the prior probability density function in (13) and (14) are generated, each particle weight should be evaluated based on the measurement vector $s_{\text{cycle}}(\theta, n)$. The weighted particles represent the posterior probability density function of $p(M(n)|s_{\text{cycle}}(\theta, 1:n))$. For the particle weight $w(n)$ evaluation, we calculated correlation between $M^*(n)$ and $s_{\text{cycle}}(\theta, n)$ for $j = 1, 2, \ldots, J$:

$$w(n) = \text{Corr}(\tilde{M}^*(n), s_{\text{cycle}}(\theta, n))$$

where Corr(·) is the function of correlation. To find the TQ interval, we normalized the particle weight as

$$\tilde{w}(n) = \left( \frac{w(n)}{\sum_{j=1}^{J} w(n)} \right)$$
and calculated the mean values as in (18), which estimate the TQ interval based on (3) and (4).

$$\hat{a}_{T,n} = \sum_{j=1}^{J} q_{T,n} \cdot \tilde{w}(j)$$  \hspace{1cm} (18-1)$$

$$\hat{b}_{T,n} = \sum_{j=1}^{J} b_{T,n} \cdot \tilde{w}(j)$$  \hspace{1cm} (18-2)$$

$$\hat{a}_{Q,n} = \sum_{j=1}^{J} a_{Q,n} \cdot \tilde{w}(j)$$  \hspace{1cm} (18-3)$$

$$\hat{b}_{Q,n} = \sum_{j=1}^{J} b_{Q,n} \cdot \tilde{w}(j)$$  \hspace{1cm} (18-4)$$

Based on the weighted particles, we resample them to generate new particles at the next cycle \(n+1\) [25]. The overall algorithm is summarized below

1. Initial step \((n=1)\)
   i) Predict the new set of particles \(\mathbf{M}^{(1)}\), where \(j=1,2,\ldots,J\) for the number of particles \(J\).
   \[
   \mathbf{M}^{(1)} = [\tilde{Q}^{(0)} \mathbf{R}^{(0)} S^{(0)} T^{(0)}]^T + [v^{(1)}_{Q} (1) v^{(1)}_{R} (1) v^{(1)}_{S} (1) v^{(1)}_{T} (1)]^T,
   \]
   where \(\tilde{Q}^{(0)} \mathbf{R}^{(0)} S^{(0)} T^{(0)}\) is given in Table 1 [20].
   ii) Detect two adjacent R peaks and obtain measurement vector \(s_{cycle}(\theta, 1)\).
   iii) Evaluate each particle weight \(w^{(1)}(1) = \text{Corr}(\mathbf{M}^{(1)}, s_{cycle}(\theta, 1))\)
   iv) Normalize the particle weight \(\tilde{w}^{(1)}(1) = w^{(1)}(1)/\left(\sum_{j=1}^{J} w^{(1)}(1)\right)\)
   v) Calculate mean values and estimate TQ interval
   \[
   T_{end} = \bar{\theta}_{T,n} + 2.576 \cdot b_{T,n}
   \]
   \[
   Q_{on} = \bar{\theta}_{Q,n} - 2.576 \cdot b_{Q,n}
   \]
   vi) Resample particles \(\tilde{\mathbf{M}}^{(1)}\)

2. From \(n=2\)
   i) Predict the new set of particles \(\mathbf{M}^{(2)}\), where \(j=1,2,\ldots,J\) for the number of particles \(J\).
   \[
   \mathbf{M}^{(2)} = [\tilde{Q}^{(n-1)} \mathbf{R}^{(n-1)} S^{(n-1)} T^{(n-1)}]^T + [v^{(1)}_{Q} (n) v^{(1)}_{R} (n) v^{(1)}_{S} (n) v^{(1)}_{T} (n)]^T
   \]
   ii) Detect two adjacent R peaks and obtain measurement vector \(s_{cycle}(\theta, n)\).
   iii) Evaluate each particle weight \(w^{(2)}(n) = \text{Corr}(\mathbf{M}^{(2)}, s_{cycle}(\theta, n))\)
   iv) Normalize the particle weight \(\tilde{w}^{(2)}(n) = w^{(2)}(n)/\left(\sum_{j=1}^{J} w^{(2)}(n)\right)\)
   v) Calculate mean values and estimate TQ interval
   \[
   T_{end} = \bar{\theta}_{T,n} + 2.576 \cdot b_{T,n}
   \]
   \[
   Q_{on} = \bar{\theta}_{Q,n} - 2.576 \cdot b_{Q,n}
   \]
   vi) Resample particles \(\tilde{\mathbf{M}}^{(2)}\)
Fig. 1. Example (AFL): (a) generated QRST complex-particles (thick and red: AFL measurement, thin and blue: particles); (b) estimated wave for P wave extraction (thick and red: AFL measurement, thin and blue: final estimation). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 2 shows the resultant time-frequency spectrum of AFL and AT atrial activity. In Fig. 2(a), we used the AFL atrial activity wave obtained from Fig. 1(b), and the dominant frequencies were found around 4.8 Hz. Fig. 2(b) shows the time–frequency spectrum of AT atrial activity wave, and the dominant frequencies were found around 3 Hz.

Fig. 3. Distribution of atrial activity wave dominant frequencies (sample to sample) on AFL, AT, and NSR databases. The diamonds above and below represent the 5th and the 95th percentiles of each different dataset, and the squares above and below represent the 90th and the 10th percentiles. Whiskers above and below represent the 75th and the 25th percentiles, respectively. The circle indicates the median value.

3. Results

3.1. Results from clinical database

Fig. 3 shows the sample-to-sample distribution of atrial activity wave dominant frequencies on AFL \( (n = 22) \), AT \( (n = 10) \) and NSR \( (n = 29) \) databases. For the simulation, we used 100 particles \( (J = 100) \). The diamonds above and below represent the 5th and the 95th percentiles of each different dataset, and the squares above and below represent the 90th and the 10th percentiles. Whiskers above and below represent the 75th and the 25th percentiles, respectively. The circles indicate the median value. For AFL, the median frequency was 4.64 Hz and the interquartile range was 0.54 Hz; the 25th percentile and the 75th percentile were 4.44 Hz and 4.98 Hz, respectively. For AT, the median frequency was 2.54 Hz and the interquartile range was 1.56 Hz; the 25th percentile and the 75th percentile were 2.30 Hz and 3.86 Hz, respectively. For NSR, the median frequency was 0.39 Hz and the interquartile range was 1.37 Hz; the 25th percentile and the 75th percentile were 0.29 Hz and 1.66 Hz, respectively.

To discriminate among AFL, AT, and NSR, we followed the procedure below:

- If \( TH(\text{AT}, \text{AFL}) \leq \text{frequency} \leq 5.4 \) Hz, then declare as AFL
- If \( TH(\text{NSR}, \text{AT}) \leq \text{frequency} < TH(\text{AT}, \text{AFL}) \), then declare as AT
- If frequency \( < TH(\text{NSR}, \text{AT}) \), then declare as NSR
- Increment \( TH(\text{AT}, \text{AFL}) \) from 3.0 to 5.0 Hz with an interval of 0.1 Hz
- Increment \( TH(\text{NSR}, \text{AT}) \) from 1.0 to 3.0 Hz with an interval of 0.1 Hz
- Find ROC curves and the best pair of \( TH(\text{AT}, \text{AFL}) \) and \( TH(\text{NSR}, \text{AT}) \) providing the best accuracy
3.2. Analysis with synthesized ECG signals

To further analyze our algorithm, we used the synthetic ECG model in (2) to generate 50 realizations of AT and AFL signals. The sampling frequency was set to 200 Hz, mean heart rate to 150 bpm, standard deviation of heart rate to 1 bpm, and LF/HF ratio to 0.5. In addition, $a_p$, $b_p$ and $\theta_p$ were set to [1.2 1.2], [0.25 0.25] and [3\pi/2 11\pi/6], respectively for AT, and $a_p$, $b_p$ and $\theta_p$ were set to [1.2 1.2], [0.25 0.25 0.25] and [3\pi/2 2\pi 3\pi/2 11\pi/6], respectively for AFL [12,20,30]. Each ECG signal realization was 1 min in duration and 100 particles were used for PF. Fig. 6 shows the resultant sample-to-sample distribution of atrial dominant frequencies of the synthesized AT and AFL signals. As shown in Fig. 6, for AT, the median frequency was 3.6 Hz, the 25th percentile was 3.1 Hz and the 75th percentile was 3.9 Hz. For AFL, the median frequency was 4.8 Hz, the 25th percentile was 4.4, and the 75th percentile was 5.0 Hz. Using the threshold values obtained from the clinical database, the classification accuracies of AT and AFL were 92.3% and 93.1%, respectively.

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**Fig. 4.** Accuracy of AFL, AT, and NSR detection according to $TH(AT,AFL)$ and $TH(NSR,AT)$. It shows that $TH(AT,AFL)=4.0$ and $TH(NSR,AT)=2.0$ provided the best accuracy.

**Fig. 5.** Accuracy and computation time according to model orders.

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**Fig. 6.** Distribution of atrial activity wave dominant frequencies (sample to sample) of simulated AFL and AT signals. The diamonds above and below represent the 5th and the 95th percentiles of each different dataset, and the squares above and below represent the 90th and the 10th percentiles. Whiskers above and below represent the 75th and the 25th percentiles, respectively. The circles indicate the median values.
3.3. Analysis of noise effect on P wave frequencies

Fig. 7 shows the estimated dominant frequency effect from additive Gaussian white noise (GWN). For the analysis, we generated a clean synthetic ECG signal with 5 Hz atrial activity wave, and corrupted the signal by adding GWN. The simulation was performed 100 times for each SNR from −50 to 50 dB with an interval of 10 dB, and the estimated dominant frequency distribution was plotted in Fig. 7. The diamonds above and below represent the 5th and the 95th percentiles of each different dataset, and the squares above and below represent the 90th and the 10th percentiles. Whiskers above and below represent the 75th and the 25th percentiles, respectively. The circles indicate the median values. When the signal-to-noise ratio (SNR) was 20 dB or higher, all estimated dominant frequencies were 5 Hz. With 10 dB, 90% of dominant frequencies were 5 Hz. However, when SNR decreased to zero or below, the estimated dominant frequencies tended to be random.

4. Discussion and conclusion

In this paper, we presented a novel AFL and AT detection method by using particle filtration followed by the VFCDM method. The overall accuracy value was 0.88; 0.89 for AFL, 0.87 for AT and 0.91 for NSR. The most attractive feature of our approach is that it can be used to accurately find TQ intervals and detect AFL and AT in each R–R interval. In addition, our method is applicable for a Holter system as it is real-time realizable. Based on the average of multiple trials, the computation time was approximately 110 ms for 100 particles on Matlab 2011b on a 2.80 GHz Intel Core2 processor; 80 ms for PF and 30 ms for VFCDM. Our method works for ECG signals measured from at least 2 leads. However, it is known if our method works with single lead data.

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