Graph Search-Based Detection of Periodic Activations in Complex Periodic Signals: Application in Atrial Fibrillation Electrograms

Rupin Dalvi, Adrian Suszko, Vijay S. Chauhan

***Abstract*— A novel method for automatic detection of peaks corresponding to the periodic activations in complex periodic signals is proposed. The approach involves dominant frequency based periodicity detection combined with a graph search algorithm to identify periodic peaks of interest. The performance of the proposed method is demonstrated in human atrial fibrillation electrograms with simulated periodicity corrupted by complex aperiodic signal features. The proposed method is compared to two state-of-the-art peak detection algorithms and is shown to be more accurate in detecting periodic peaks.**

***Index Terms*— peak detection, periodicity detection, periodic signal, graph search**

I. Introduction

Many signals in nature, medicine and technology exhibit periodicity. It is frequently important not only to determine the cycle length (CL) of this periodicity, but also the locations of the corresponding periodic peaks. For instance, in atrial fibrillation (AF), a cardiac arrhythmia characterized by seemingly irregular electrical activation of the atrium, both animal and human studies [1] have suggested that AF is maintained by discrete high-frequency periodic sources. Catheter ablation of these sources is considered an important treatment strategy for patients suffering from AF. However, finding these sources remains challenging. While methods that attempt to find these sources by detecting the presence or absence of high frequency periodicity in the AF signal do exist [2], being able to identify the individual periodic activations may allow sources to be identified with greater accuracy. Indeed, Gizurarson et al [3] recently proposed that AF focal sources can be identified by their periodic activity as well as the specific morphology of their periodic activations or peaks in the unipolar AF electrogram (EGM).

Most traditional methods have focused either on finding the periodicity CL alone, or finding all valid peaks (excluding noise according to a given criterion) and then estimating the periodicity CL based on the peak locations. The peak detection methods are based on a variety of properties and techniques, including window-thresholding [4,5], wavelet transform [6], Hilbert transform [7], linear prediction and higher-order statistics analysis [8,9], K-Means clustering [10], Empirical Mode Decomposition [11], and hidden Markov models [12]. Recent peak detection methods, such as [13] and [14], use non-parametric approaches to improve the robustness and reproducibility of the peak detection process.

A limitation of most periodic peak detection algorithms available is that all valid peaks are assumed to be part of the periodic activity. However, in various real applications, such as [3], periodic activations are often surrounded by aperiodic complex, multiphasic components. These components are not part of the periodic activity of interest, but may still arise from other physiologic processes. Another problem is that most of these algorithms assume that the peak validity is directly proportional to its amplitude. Thus, they are likely to miss genuine peaks that are not local maxima in favour of higher magnitude, aperiodic peaks. These algorithms are prone to performance degradation if periodic activity is embedded in other, aperiodic physiologic signal.

In this paper, we present a peak detection method specifically designed to identify periodic peaks in complex signals with both periodic and aperiodic components of varying magnitude. The method relies on a robust periodicity detection algorithm to determine the periodicity CL and then a graph search method to identify the corresponding periodic peaks with high accuracy. The method is general in its scope and application; however, our implementation and validation have been confined to human AF bipolar EGM recordings.

II. Methods

Our method consists of two parts. Firstly, a preprocessing step finds the CL of the periodic signal. Second, peaks corresponding to this periodic CL are found using a graph search approach which is the novel aspect of this paper.

Preprocessing

The preprocessing step identifies the periodicity present in the signal and its periodicity CL. The most widely used methods for periodicity detection can be broadly classified as spectral analysis-based and autocorrelation-based, though there are a wide variety of other approaches such as periodicity transform [15], wavelet-based periodicity detection [16], and maximum likelihood-based periodicity detection [17]. In this paper, we use the widely adopted dominant frequency (DF) analysis [18] in order to determine the periodicity in the signal. DF analysis first preprocesses the input signal to enhance the dominant sinusoidal waveform and to elucidate its periodicity. It then performs a Fast Fourier Transform on the processed signal and considers the frequency with the highest amplitude in its power spectral density distribution to be the 'dominant' frequency (corresponding to the 'dominant' periodicity CL).

Manuscript submitted July 21, 2014. This work was supported by the Don and Carol Pennycook Arrhythmia Research Fund. Address correspondence to V. Chauhan MD, Peter Munk Cardiac Center, University Health Network, 150 Gerrard St. W., Toronto, ON, Canada, M5G 2C4 (e-mail: {rupin.dalvi, adrian.suszko, vijay.chauhan}@uhn.ca).

Figure 1 shows the ability of the method to identify the DF from a synthetic signal with periodic activation corrupted with several aperiodic activations or peaks. Details of DF analysis may be found in [18].

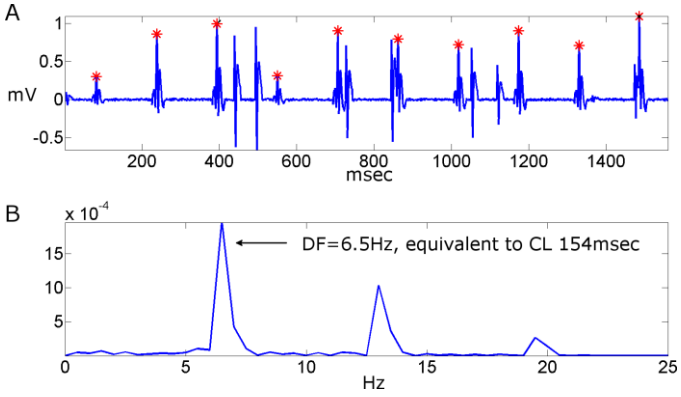

Figure 1 A. Synthetic AF bipolar EGM with periodic activations (CL 154 msec, marked by asterisks) along with multiple large amplitude, aperiodic activations. **B.** Power spectral density distribution of A. after processing showing a dominant frequency at 6.5Hz corresponding to a periodic CL of 154 msec.

Proposed Method

The proposed method utilizes graph search methods in order to specifically find the peaks corresponding to a given periodic CL.

A. We correct the DC shift in the signal S and then find the set ($Peak_{EGM}$) of all peaks in S whose gradient is greater than a threshold τ and whose absolute amplitude is greater than ρ. We then calculate the distance matrix, i.e., the matrix of the absolute values of the differences of all peak locations with respect to each other. Thus,

$$Peak_{Distances} = \begin{bmatrix} |P(1)-P(1)| & \cdots & |P(1)-P(N)| \\ \vdots & \ddots & \vdots \\ |P(N)-P(1)| & \cdots & |P(N)-P(N)| \end{bmatrix} \quad \ldots(1)$$

where P(N) refers to the Nth peak location in $Peak_{EGM}$

B. From this matrix, we compute the cost matrix which is $Peak_{Cost} = Peak_{Dist} - CL$. Thus,

$$Peak_{Cost} = \begin{bmatrix} |Peak_{Dist}(1,1)-CL| & \cdots & |Peak_{Dist}(1,N)-CL| \\ \vdots & \ddots & \vdots \\ |Peak_{Dist}(1,N)-CL| & \cdots & |Peak_{Dist}(N,N)-CL| \end{bmatrix} \quad \ldots(2)$$

where $Peak_{Dist}(n,m)$ is the distance from node n to node m in $Peak_{EGM}$

C. We then apply Dijkstra's shortest path algorithm on $Peak_{Cost}$ to find the shortest cost path between the first and last peaks in $Peak_{EGM}$ and find the set of peaks (P') corresponding to that path.

The rationale behind doing so is that the costs in $Peak_{Cost}$ indicate how much the distance between any two peaks differs from the CL. Hence, the shortest cost path will be the one that returns a set of peaks (P') which are as periodic as possible (with a periodicity = CL).

Briefly, Dijkstra's algorithm finds the shortest path between two nodes (vertices) of a graph (directed or undirected), provided the weights on the edges of the graph are all non-negative. Consider a graph G with V vertices (corresponding to the peaks in $Peak_{EGM}$) and E edges having non-negative edge weights $\{\Theta_{edge}: edge \in E\}$ corresponding to the elements of $Peak_{Cost}$. Let $s \in V$ be the source node (i.e. first peak) from which the shortest cost path to some other node in V is to be determined. Let *dist(u)* be the distance of node *u* from *s*. Let *traceback(u)* contain the node in the path from *s* to *u* immediately preceding *u*. Then, Dijkstra's algorithm may be summarized as follows:

Set $dist(s)=0$ & $dist(u)=Inf\ \forall u!=s$
Let *N* be the queue of all searchable vertices (initially all vertices in the graph)
Let *P'* be the set of all vertices searched so far. Set *P=[]*
Then, while *length(P')<length(V)*
  select $u \in N$ *s.t.* $dist(u) = min(dist(v)),\ \forall v \in N$
  P' -> P' union u
  $\forall$ *edges* $(u, v) \in E$
    if $dist(v)>dist(u)+\Theta(u,v)$
      $dist(v)=dist(u)+\Theta(u,v)$
      N->N-v
      traceback(v)=u

D. While P' will mainly contain peaks corresponding to the periodic CL, it may also contain some that don't which were selected to obtain a better cost. To remove the latter, only those peaks in P' that are within 10% of CL from another peak are included in the final set of peaks (P). This ensures that P contains peaks with periodicity CL (i.e. their distance from their nearest neighbor is within a tolerance band of CL).

E. Since the first and last peaks in $Peak_{EGM}$ may not be part of the periodic sequence, we re-implement Steps C and D considering the first n peaks in $Peak_{EGM}$ as starting peaks and the last n peaks in $Peak_{EGM}$ as ending peaks. Using n=3, we finally choose the final set of points (Ψ) for those starting/ending peaks whose cost for P is least.

Figure 2 shows the result of the method on an AF bipolar EGM with visually apparent periodicity. Figure 3 shows the result of the method on a more complex AF bipolar EGM. Details of AF EGM acquisition from patients are provided in the subsection, *Validation using Simulated Periodic Signal.*

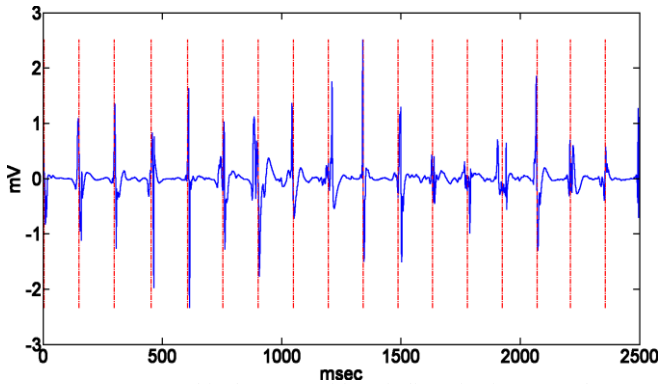

Figure 2 Human AF bipolar EGM with periodic activations or peaks (CL 154 msec). Vertical dashed lines indicate activations detected by the proposed method which correspond to all visually apparent periodic activations.

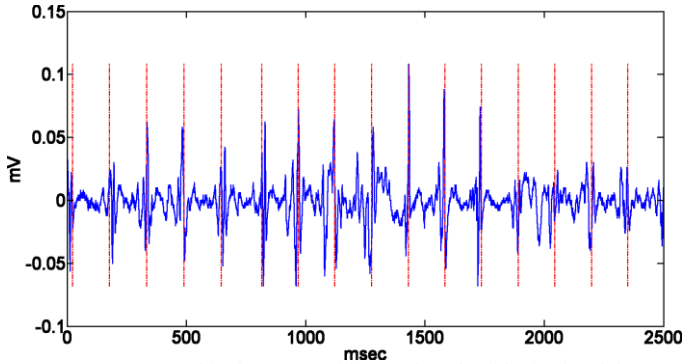

Figure 3 Human AF bipolar EGM with complex physiologic signal features amidst periodic activations or peaks (CL 154 msec). Vertical dashed lines indicate activations detected by the proposed method which correspond to all visually apparent periodic activations. Note the method's detection of periodic activation at the far right where the peaks become visually less apparent.

Comparator Methods

We compared the performance of the proposed method with two recent state-of-the-art algorithms designed for peak localization, one of which has been specifically applied to AF bipolar EGMs. The first is an iterative algorithm [13], the second makes use of a multiscale technique to detect local maxima which it then analyses for peaks [14]. A brief description of the two methods follows:

Cycle Length Iteration (CLI) Algorithm

This iterative method begins by finding the highest magnitude peak. It then iteratively finds the next highest peak after applying a blanking window around the peaks already detected. The process continues until the mean CL calculated from the detected peaks falls below 275 msec and either the (mean CL - median CL) < 5 msec or the peak under consideration has a magnitude 20% less than the magnitude of the previously detected peaks. Once this step is completed, the signal is searched for maxima in windows of 1.5*median CL. If a maximum is present and not within a blanking window, it is added to the list of detected peaks. This step iterates until no further peaks are found. It should be noted that this method is specifically designed to detect AF peaks or activations. Accordingly, the 275 msec threshold as well as the other thresholds used in the stopping criteria is chosen based on the characteristics of human AF bipolar EGMs.

Automatic Multiscale Peak Detection (AMPD) Algorithm

The signal (n) of length N is first detrended using a linear detrend function. A 'local maxima scalogram' (LMS) is then generated. This is a matrix whose rows are equal to the length of the signal being processed. It is generated as follows:

A moving window is used to calculate the local maxima for n. The width of this window w_k is varied as

$w_k = 2k|k=1,2,...,L$, where L = ceil(N/2)-1

The LMS matrix ($M = (m_{k,i})$) is then populated as follows:

$$m_{k,i} = \begin{cases} 0, x_{i-1} > x_{i-k-1} \& x_{i-1} > x_{i+k-1} \\ r + \alpha, otherwise \end{cases} \quad \ldots(3)$$

for i = k+2,...,N-k+1 where *r* is a random number between 0 and 1, and α is a constant (usually 1).

The elements of the matrix not populated using the above rule are then assigned values of $r + \alpha$, where *r* and α are defined as before.

M is then summed rowwise and the index of its global minimum (λ) indicates the scale with the most local maxima. M is then truncated to keep only the first λ rows, resulting in a truncated matrix, MT. The standard deviations of the columns of MT are then calculated and the peak locations in n are identified as the indices of those columns for which the standard deviation is 0.

Validation using Simulated Periodic Signal

Human AF bipolar EGMs signals with known periodicity CL were used to evaluate the accuracy of the proposed method in detecting periodic peaks compared to CLI and AMPD. Simulated periodicity of known CL was added to real AF bipolar EGMs recorded from 6 patients undergoing AF catheter ablation as follows:

1. The patient's femoral vein was cannulated. The left atrium was accessed via a trans-septal puncture. A steerable multielectrode recording catheter was maneuvered to various regions of the left atrium. At each location, bipolar EGMs were recorded (bandwidth 30-150Hz) for 2500 msec during AF at a sampling rate of 1 kHz.

2. Each of the 600 periodic EGM signals generated in Step 3 were then contaminated with randomly allocated aperiodic peaks or activations that could potentially introduce false "peaks" in the periodic EGM signal. These aperiodic activations were derived from the 18 AF bipolar templates as described in Step 2. Their amplitudes were randomly selected as 0 to 125% of the template EGM amplitude. Please see Figure 6D illustrates an example of a simulated aperiodic signal with 10 peaks. for a sample corrupting signal and Figure 6E for a signal with both the periodic and aperiodic signals.

3. Thus, a total of 600 AF bipolar EGM signals were generated with complex signal features, including periodic signal and random aperiodic peaks or activations. These EGMs were divided into 6 categories (ie. 100 EGMs per category) based on the presence of 0, 2, 4, 6, 8 or 10 aperiodic peaks. Figure 6 shows an example of a complex AF bipolar EGM with periodic signal which is corrupted by 10 aperiodic peaks of varying amplitude.

The CLI, proposed method and AMPD were programmed using MATLAB 2012b (MathWorks Inc., Natick, Massachusetts, USA) on a computer with a Core i7-3930K CPU operating at 3.2 GHz and with 16 GB of RAM. All three methods generated output within 1 sec per EGM signal for the 600 EGM signals (2500 samples per signal).

III. Results

In order to evaluate the performance of the 3 methods in detecting periodic peaks in the 600 AF bipolar EGMs, each method's annotated peaks were compared to the location of known periodic peaks. If the known peak location and annotated peak location was within 10 msec of one another, the method's annotation was considered accurate. The performance of each method was described in terms of specificity (true negative / (true negative + false positive)) and sensitivity (true positive / (true positive + false negative).

As shown in Figures 4 and 5, the proposed method was more specific and more sensitive than CLI and AMPD in annotating periodic peaks. While the performance in the absence of any aperiodic EGM signal was nearly identical (and very good) for all 3 methods, the presence of an increasing number of aperiodic activations significantly degraded the performance of CLI and AMPD whereas the proposed method maintained high accuracy.

For illustrative purposes, Figure 6 compares periodic peak annotation using the 3 methods for an AF bipolar EGM containing periodic signal (CL 154 msec) as well as 10 aperiodic peaks. In this example, the proposed method correctly identifies all periodic activations corresponding to the periodicity CL (defined by the DF algorithm described above). In contrast, CLI and AMPD often misclassify the aperiodic activations as periodic activations, since they coincide with local signal maxima. On some occasions, CLI and AMPD do so at the expense of annotating true periodic activation.

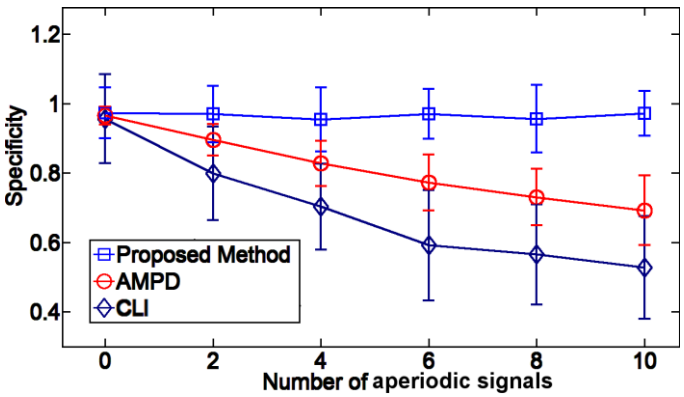

Figure 4 The specificity of annotating periodic peaks is presented for the proposed method, AMPD and CLI as a function of increasing number of aperiodic peaks. These peaks were introduced randomly into a complex AF bipolar EGM with simulated periodic peaks of known periodicity CL.

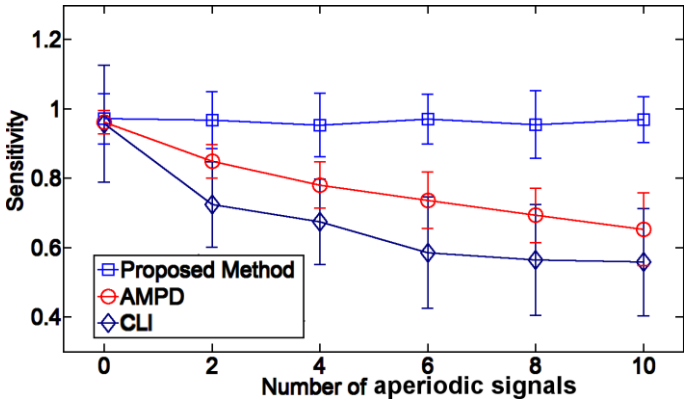

Figure 5 The sensitivity of annotating periodic peaks is presented for the proposed method, AMPD and CLI as a function of increasing number of aperiodic peaks. These peaks were introduced randomly into a complex AF bipolar EGM with simulated periodic peaks of known periodicity CL.

IV. Discussion

The difference in accuracy between the proposed method, CLI and AMPD in annotating periodic peaks is most pronounced when aperiodic, albeit physiologic, activations are frequent, and in cases where the periodic peaks vary widely in amplitude. The latter becomes particularly relevant when the periodic activations do not represent the local signal maxima. CLI and AMPD are prone to detecting aperiodic peaks which are not part of the periodic signal whereas the proposed method is designed to find only peaks satisfying a periodic constraint, namely the periodicity CL derived independently. Hence, the proposed method is more robust in avoiding aperiodic peak detection regardless of peak amplitude.

It should be pointed out that the proposed method is specifically designed under the assumption that there is genuine periodicity in the signal and that, furthermore, the peaks of interest are only those belonging to the periodic component in the signal. Therefore, it is not unexpected that the proposed method outperforms other algorithms which attempt to detect all valid peaks in the EGM. Notwithstanding this, most peak detection algorithms are designed to do just that (detect all peaks), and are unlikely to perform adequately in signals with complex features, such as those with periodic and aperiodic peaks of varying magnitude where the goal is to find periodicity- related activations.

One limitation of the proposed method is its assumption that at least one of the first n and at least one of the last n peaks are part of the periodic sequence (See step D of Proposed Method description). This is not a concern when the signal has sustained periodicity. However, the assumption becomes problematic in the special circumstance where the periodicity is non-sustained, or where the periodic train of activations start well after the beginning, or terminate well before the end of the sample recording. We are currently developing an algorithm to overcome this limitation, which will be an

important step towards applying the proposed method to a larger variety of real-world periodic signals.

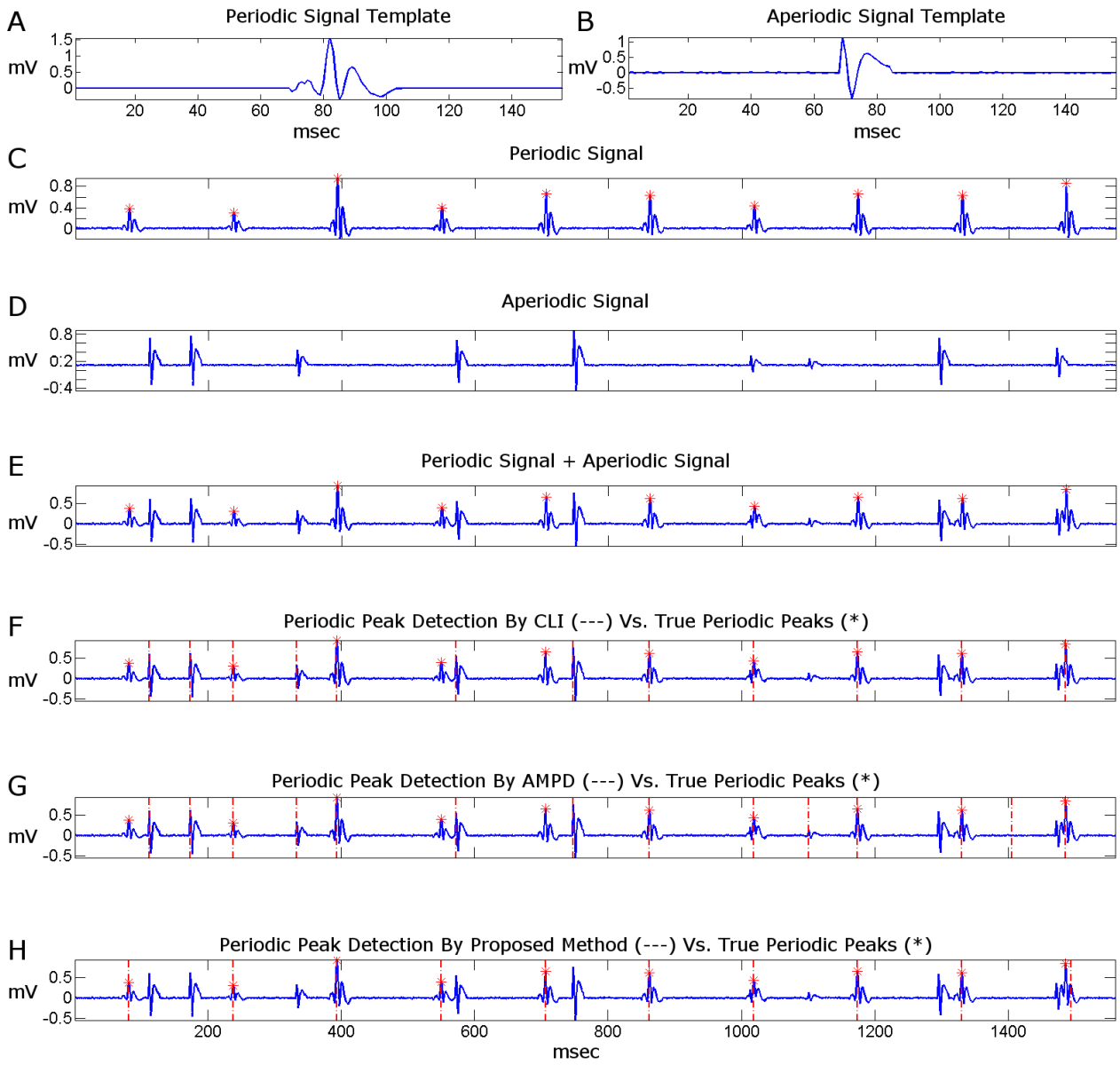

Figure 6 Complex AF bipolar EGM with simulated periodic (periodicity CL 156 msec) and 10 aperiodic peaks. (a) Template for the periodic signal peaks. (b) Template for the aperiodic signal peaks. (c) Train of 10 periodic signal peaks. (d) Train of 10 aperiodic signal peaks. (e) Combination of periodic and aperiodic signal (ie. c+d). (f) Annotations of periodic peaks detected by CLI (dashed lines) compared to true periodic peaks (asterisks). (g) Annotation of periodic peaks detected by AMPD (dashed lines) compared to true periodic peaks (asterisks). (h) Annotation of periodic peaks detected by Proposed Method (dashed lines) compared to true periodic peaks (asterisks). Note the tendency of the CLI and AMPD to annotate aperiodic peaks corresponding to local maxima at the expense of the true periodic peaks of lower magnitude. These annotations represent false positive periodic peaks.

V. Conclusion

A method for detecting peaks corresponding to the periodicity CL of a periodic signal is proposed. The method was compared against two state-of-the-art peak detection algorithms using human AF bipolar EGMs containing simulated periodic signal, and was shown to perform more accurately. Future work will involve applying the proposed method to human AF bipolar EGMs in order to locate periodic electrical sources in the atrium that may provide therapeutic targets for AF catheter ablation.

References

[1] M. Vaquero, D. Calvo, and J. Jalife, "Cardiac fibrillation: from ion channels to rotors in the human heart," *Heart Rhythm*, vol. 5, no. 6, pp. 872–879, Jun. 2008.

[2] P. Sanders, O. Berenfeld, M. Hocini, P. Jaïs, R. Vaidyanathan, L.-F. Hsu, S. Garrigue, Y. Takahashi, M. Rotter, F. Sacher, C. Scavée, R. Ploutz-Snyder, J. Jalife, and M. Haïssaguerre, "Spectral analysis identifies sites of high-frequency activity maintaining atrial fibrillation in humans," *Circulation*, vol. 112, no. 6, pp. 789–797, Aug. 2005.

[3] S. Gizurarson, Rupin Dalvi, A. Ha, L. Sugavaneswaran, S. Krishnan, and V. S. Chauhan, "Focal sources identified by Periodic Component Analysis predicts the need for ablation outside the pulmonary veins in patients

undergoing atrial fibrillation catheter ablation," presented at *Heart Rhythm*, San Francisco, USA, 2014, vol.11, pp. S27-S28.

[4] A. L. Jacobson, "Auto-threshold peak detection in physiological signals," presented at *Engineering in Medicine and Biology Society*, 2001, vol. 3, pp. 2194–2195.

[5] G. Vivó-Truyols, J. R. Torres-Lapasió, A. M. van Nederkassel, Y. Vander Heyden, and D. L. Massart, "Automatic program for peak detection and deconvolution of multi-overlapped chromatographic signals part I: peak detection," *J Chromatogr A*, vol. 1096, no. 1–2, pp. 133–145, Nov. 2005.

[6] O. Singh and R. K. Sunkaria, "Article: A robust R-peak detection algorithm using wavelet packets," *International Journal of Computer Applications*, vol. 36, no. 5, pp. 37–43, Dec. 2011.

[7] D. Benitez, P. A. Gaydecki, A. Zaidi, and A. P. Fitzpatrick, "The use of the Hilbert transform in ECG signal analysis," *Computers in Biology and Medicine*, vol. 31, no. 5, pp. 399–406, Sep. 2001.

[8] K. P. Lin and W. H. Chang, "QRS feature extraction using linear prediction," *IEEE Trans Biomed Eng*, vol. 36, no. 10, pp. 1050–1055, Oct. 1989.

[9] K. I. Panoulas, L. J. Hadjileontiadis, and S. M. Panas, "Enhancement of R-wave detection in ECG data analysis using higher-order statistics," presented at *Engineering in Medicine and Biology Society*, 2001, vol. 1, pp. 344–347.

[10] S. S. Mehta, D. A. Shete, N. S. Lingayat, and V. S. Chouhan, "K-means algorithm for the detection and delineation of QRS-complexes in electrocardiogram," *IRBM*, vol. 31, no. 1, pp. 48–54, Feb. 2010.

[11] Z.-E. Hadj Slimane and A. Naït-Ali, "QRS complex detection using Empirical Mode Decomposition," *Digital Signal Processing*, vol. 20, no. 4, pp. 1221–1228, Jul. 2010.

[12] D. A. Coast, R. M. Stern, G. G. Cano, and S. A. Briller, "An approach to cardiac arrhythmia analysis using hidden Markov models," *IEEE Trans Biomed Eng*, vol. 37, no. 9, pp. 826–836, Sep. 1990.

[13] J. Ng, V. Sehgal, J. K. Ng, D. Gordon, and J. J. Goldberger, "Iterative method to detect atrial activations and measure cycle length from electrograms during atrial fibrillation," *IEEE Trans Biomed Eng*, vol. 61, no. 2, pp. 273–278, Feb. 2014.

[14] F. Scholkmann, J. Boss, and M. Wolf, "An efficient algorithm for automatic peak detection in noisy periodic and quasi-periodic signals," *Algorithms*, vol. 5, no. 4, pp. 588–603, Nov. 2012.

[15] W. A. Sethares and T. W. Staley, "Periodicity transforms," *Signal Processing, IEEE Transactions on*, vol. 47, no. 11, pp. 2953–2964, 1999.

[16] J. Benedetto and G. Pfander, "Wavelet detection of periodic behavior in EEG and ECG data," *15th IMACS World Congress,* Berlin, vol. 1, 1997.

[17] R. Dalvi, L. Sugavaneswaran, V. S. Chauhan, and S. Krishnan, "Reviving the maximum likelihood method for detecting dominant periodicities from near-periodic signals," presented at the *Digital Signal Processing and Signal Processing Education Meeting (DSP/SPE),* San Francisco, 2013, pp. 256–261.

[18] J. Ng and J. J. Goldberger, "Understanding and Interpreting Dominant Frequency Analysis of AF Electrograms," *Journal of Cardiovascular Electrophysiology*, vol. 18, no. 6, pp. 680–685, Jun. 2007.