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A Dempster-Shafer Approach for Corrupted Electrocardiograms Signals

Nicholas J. Napoli, and Laura E. Barnes
University of Virginia, Charlottesville Va
Department of Systems and Information Engineering
{napoli, lbarnes} @ virginia.edu

Abstract

Continuous streaming Electrocardiogram (ECG) data in the Intensive Care Unit (ICU) is highly susceptible to noise artifacts and signal corruption. Currently, the publicized algorithms for QRS detection do not account for unreliable lead information; waveform detection is typically contingent upon information from a single lead; and uncertainty metrics are not provided regarding the detection accuracy. We propose a cross-correlation fusion method for multi-component ECG templates using Dempster-Shafer (DS) Theory. Our experiments using clinical data were compared to benchmark non-syntactic detection algorithms where the detection accuracy was comparable at high signal-to-noise ratio (SNR). However, the fusion approach demonstrated a superior increase in accuracy when the SNR degraded. Addressing these downfalls for the detection of QRS complexes and other waveforms has potential to improve patient risk prediction in the ICU.

Introduction

Intensive Care Units (ICUs) have started looking toward the future with real-time data predictive models to aid physicians at the bedside. These algorithms are intended to detect latent physiological indicators that provide information to the physician about the patient's trajectory and imminent risk (Costa, Peng, and Goldberger 2008). The most commonly used information for determining a patient's trajectory is the analysis of electrocardiogram (ECG) signals. Methods such as Heart Rate Variability (HRV) and Heart Rate Complexity (HRC) have been demonstrated to be predictive of numerous types of physiological ailments such as myocardial infarction, mortality, autonomic responses, and hypoglycemia, (Javorka et al. 2002; Khandoker, Jelinek, and Palaniswami 2009). The measurement of HRV and HRC rely on calculating the time delay between heart beats; this term is clinically known as the R-R intervals. In order to calculate R-R intervals, it is critical to detect the QRS complexes within the ECG signal, which corresponds to the depolarization of the ventricles in the heart. Thus, predicting potential complications for a patient using HRV and HRC is dependent on accurate and precise detection of QRS complexes in the ECG signal.

Prior Work. Standard benchmarking methodologies utilized for QRS detection are cross-correlation and non-syntactic algorithms (T. Last and Owens 2004; Nugent et al. 1999). These approaches are well developed, easy to implement, and have been around for decades. Cross-Correlation examines how well the shape of the waveform coincides with a particular template (Thompkins 2000). The basic idea is that these approaches acquire a template and pass the template through the signal searching for a set threshold in the correlation coefficient in order to assume a match (Krasteva and Jekova 2007). Non-syntactic algorithms manipulate the signal to form peaks at the locations of the QRS complexes and attenuate the other waveforms in the signal. A threshold is set for the height of the peaks to determine which peaks indicate a QRS complex; however, when noise is introduced in the signal, this threshold fails to provide information on the quality or context of the prediction. These methods raise three interesting questions: 1) How can we determine the quality of the QRS complex prediction, 2) what can be done if the ECG lead or multiple leads are corrupted or inconsistent in their predictions, 3) can an algorithm address these questions using little or no prior knowledge?

Challenges. The current discussed QRS detection paradigms pose a challenging problem because the real-time data from the ICU faces corruption and a multitude of noise artifacts. These problematic conditions are attributed to missing data, physical activities, muscle artifacts, electromagnetic interference and baseline wandering (Ganeshapillai and Guttag 2012). This noise is typically combated by attempting to manually or dynamically choose which lead (source) has the best signal-to-noise ratio (SNR), but this practice still detects QRS complexes from only a single source of information (Krasteva and Jekova 2007; Kothalkar and Manjusha 2014; Pan and Tompkins 1985). In order for this work to be practical, real-time implementation of these models is necessary. Thus, the approach must account for ingesting data that is continually streaming regardless of the quality and reliability of the information.

Insights. There are a number of factors that can contribute to the corruption of an ECG lead. However, a majority of these QRS detection algorithms require a supervised approach to account for their parameters (thresholds, windowing lengths, filtering). Furthermore, these algorithms continue to analyze information from only a single lead for QRS detection. Dempster-Shafer (DS) Theory is an approach that allows us to quantify uncertainty and fuse data to then refine uncertainty from imperfect data from multiple sources (such as conflicting source information or sources reporting similar information) (Sentz and Ferson 2002). DS Theory offers combination rules that fuse multiple evidence sources into a single set of hypotheses. Fusing sources captures contextual considerations, such as conflicts between sources, corrupt information, uncertainty, source reliability, and accuracy (Sentz and Ferson 2002). Recent work has developed a method for quantifying uncertainty in a set of correlation coefficients using a DS framework (Napoli, Barnes, and Premaratne 2015). We propose building upon this cross-correlation method to address the three questions posed in the Prior Work section.

The proposed DS theory-based approach for template matching addresses the issues of multiple templates and ambiguity. Using this methodology, we are able to capture different levels of ambiguity that occur when sources report either the same or conflicting information. If one ECG lead indicates QRS detection while another lead conflicts with that prediction, the uncertainty in the model should increase. Likewise, if there is no conflict (both sources report similar findings), then the uncertainty should decrease. Therefore, we sought a DS approach with the ability to use all available ECG leads, appropriately deal with corruption, conflict, and uncertainty, and use little to no prior knowledge.

Contributions. This DS framework is then designed to be applied to quasi-periodic signals (such as ECG data (Ganeshapillai and Guttag 2012)) using a set of cross-correlated ECG templates as a form of evidence. The contributions of this work are:

1. We develop an uncertainty and 'probability' value at each point in time of the ECG signal to provide information on the quality of each QRS prediction.
2. We develop a template cross-correlation approach using DS theory to fuse ECG leads to overcome corruption.
3. We demonstrate that the only prior information used was a single set of templates for each ECG lead.

Background

In this section we introduce DS theory, cross-correlation, and the non-syntactic approach for QRS complex detection in ECG signals.

Cross-Correlation. The central idea of cross-correlation is to examine how well the shape of the waveform coincides with a particular template (Thompkins 2000). This correlation coefficient is assigned to the template for a particular point in time within the ECG signal, providing evidence of a match. A correlation coefficient of $\rho = 1$ demonstrates a perfect match between the template and the signal, a coefficient of $\rho = 0$ indicates no match, and when $\rho = -1$ the topology is the same but the two signals are out of phase or negatively correlated. A recently explored method reduces the original template into multiple components which searches for specific components within the ECG waveform (T. Last and Owens 2004).

Non-Syntactic. The Non-Syntactic approaches tend to have two stages, a pre-processing stage and a decision stage (T. Last and Owens 2004; Pan and Tompkins 1985). There are many designs for a non-syntactic approach; however, (Pan and Tompkins 1985) has one of the most accepted approaches for QRS detection. The pre-processing stage filters the signal to remove baseline wandering and increase the SNR. The signal is then differentiated to provide slope information of the QRS complex and rectified using a squaring function (Pan and Tompkins 1985). A moving window integration is applied to obtain features of the QRS and essentially defines how many peaks are produced from a QRS complex. Fiducial Marks are then placed on the rising edges to indicate the locations of the assumed QRS complex.

Dempster Shafer Theory. DS Theory is an evidence-based approach which develops support for hypotheses. Evidence is constructed using information from different events, and it can be gathered from sources such as experts, databases, or sensors, where a single piece of evidence may also support multiple hypotheses. DS theory, can be thought of as a generalization of probability theory (Dewasurendra, Bauer, and Premaratne 2007), where support for hypotheses can be considered a set of propositions. The set of propositions is mutually exclusive and exhaustive and is referred to as the *frame of discernment (FOD).* The FOD Ω is defined as a finite set (i.e., $\Omega = \{\theta_1, \ldots, \theta_n\}$), composed of n *singleton* propositions. The *basic probability assignment (BPA),* otherwise referred to as a *basic belief assignment* or *mass function* is a function $m : 2^\Omega \to [0, 1]$, where 2^Ω is the power set of Ω, such that $m(\emptyset) = 0; \quad \sum_{A_i \subseteq 2^\Omega} m(A_i) = 1$. While $m(A_i)$ measures the support that is directly assigned to proposition $A_i \subseteq \Omega$ *only,* the *belief* $Bl(A_i)$ represents the total support that can move into A_i from other proposition that contain A_i. So, $Bl(A_i) = \sum_{B \subseteq A_i} m(B)$. Belief is the minimum amount of support that is given for a specific proposition. For the singleton case, the DS mass of the singleton is equal to the belief. In order to develop a mass function, evidence is required. Evidence is typically defined subjectively by experts and data. When modeling evidence there are two main types of uncertainties, *aleatory uncertainty* and *epistemic uncertainty.* DS Theory reduces epistemic uncertainty, caused by lack of knowledge, through increased understanding (Dewasurendra, Bauer, and Premaratne 2007). Evidence that is fused dynamically updates the mass function to aid in the reduction of uncertainty and to redistribute mass to the propositions (Beliefs).

Methods

The overview of the methodology is to construct a template for each lead, capturing the inherent characteristics of the topology for an ECG lead. This template is partitioned to compartmentalize critical waveforms of the ECG signal (P-wave, T-Wave, QRS Complex). These partitioned components of the template are then cross-correlated with their associated lead producing correlation coefficients for each component over the time span of the signal. Using these correlation coefficients for each lead, we apply the DS Framework to the correlation coefficients to produce DS Masses. We then apply Dempster Combination Rule (DCR) to analyze conflict between leads and refine our detection by evaluating the belief and uncertainty of the propositions. The proposed template fusion algorithm and the non-syntactic model, otherwise known as the Pan Algorithm, described by (Pan and Tompkins 1985) are compared to evaluate performance under corrupted signal conditions.

Template Framework.

Creating a proper template framework is one of the cornerstones of this algorithm. First, the template must accurately develop and compartmentalize the waveforms of interest that comprise the ECG signal. Moreover, for unsupervised detection regarding the partitioning, it is crucial to know where the compartmentalized critical waveforms are located within the master template.

Master Template. We first construct a *master template* for each lead using a sample of the first 20 seconds of data. The template is developed by segmenting the raw ECG waveform over multiple iterations. In the time-domain, the ECG waveforms are optimally aligned using cross-correlation coefficients and the lag before averaging all of the time series together, a process similar to (Goldberger and Ng 2010; Kim, Noh, and Jeong 2013). This provides a stronger model by accentuating prevalent waveform features of the signal and filtering out the noise.

Compartmentalizing Template Components. A multi-component template method is developed around the master template for each lead. This method aids us in avoiding previous thresholding techniques in the detection process (Pan and Tompkins 1985), assessing conflict between competing components, and incorporating a DS framework using this conflict between competing coefficients (Napoli 2014). To incorporate this DS Theory into a multi-component template method, the compartmentalization within the master template needs to be formalized with meaningful evidence to satisfy the FOD framework. Therefore, we propose a windowing scheme that will capture a set of *critical events* to be $\mathbf{K} = \{\kappa_1, \ldots \kappa_D\}$, of the ECG signal, where we consider a single critical event in the set as κ_i. For our purposes, we defined these critical events as the P-Wave, T-Wave, and QRS Complex with a window length n. In addition, a fifty percent window overlap scheme is implemented to capture transitions from one criteria event, κ_i, to the next criteria event, κ_{i+1}. Thus, we form additional events called *transitional events*. The number of events, N, using a fifty percent windowing scheme is defined as

$$N = |\mathbf{ev}| = 2|K|. \tag{1}$$

Each event has fixed windowed length, n, segmenting the master template into $N/2$ critical events. Therefore we produce N events, ev_i, which are considered as a doubletons, due to the overlapping windows having intersections within the finite set, shown in Figure 1. Formulating this windowing framework will later enable us to apply DCR as a fusion method by treating the additional leads as evidence sources by accounting for these intersections, which will aid in refining our decision.

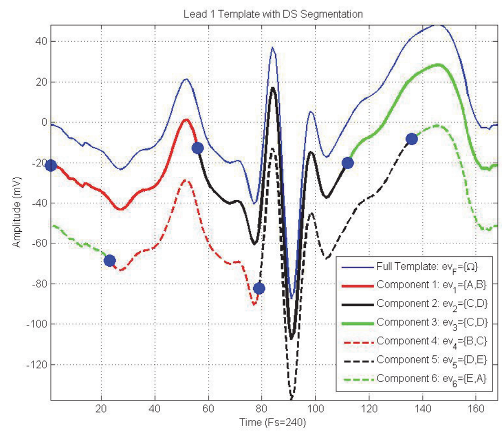


Figure 1: Compartmentalized Evidence Templates

Templates to DS Masses

Cross Correlation of Components. In the implementation of any template matching scheme, the evidence that is obtained informs us of how well a segmented component or event matches a specific time point within the signal. We quantify this evidence for each ECG lead by calculating a cross-correlation coefficient using Equation 2 for every time instance, t, in the signal. We quantify the strength of the match between the two signals with a correlation coefficient, which gauges the 'closeness' or similarity between two signals. This quantification can be expressed as:

$$\rho_{\mathbf{x},\mathbf{y}}(\tau) = \frac{\sum_{i=1}^{n}(x_i - \overline{\mathbf{x}})(y_{i+\tau} - \overline{\mathbf{y}})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{\mathbf{x}})^2 \sum_{j=1}^{n}(y_{j+\tau} - \overline{\mathbf{y}})^2}}, \tag{2}$$

where the correlation coefficient $\rho \in [-1, 1]$, $\overline{\mathbf{x}} = \frac{1}{n}\sum_{i=1}^{n} x_i$ and $\overline{\mathbf{y}} = \frac{1}{n}\sum_{j=1}^{n} y_j$ denote the 'sample' means of the real-valued time series data vectors $\mathbf{x} = [x_1, \ldots, x_n]^T$ and $\mathbf{y} = [y_1, \ldots, y_n]^T$, respectively.

Correlations to DS Framework. Evidence is formed around each indexed time point, where we produce a vector of normalized correlation coefficients, $\mathbf{V}$, for each ECG Lead. Within $\mathbf{V}$, we have N elements, where each element is a coefficient that represents the correlation of a specific event, ev_i, to the signal at time t. Therefore, each ECG lead can be considered a separate, independent source of evidence, producing a set of N correlation coefficients. The correlation coefficients are developed into a DS Frameworks by analyzing the conflict and penalizing the propositions that are weak within the set described in (Napoli, Barnes, and Premaratne 2015). This framework is appropriately suited for the singleton cases. However, due to the size of set

(n) and uniqueness of the QRS in the set, this framework should roughly capture the conflict appropriately. Applying the windowing scheme discussed above for a single lead, a vector of normalized correlation coefficients are generated, thus taking the form $\mathbf{V} = [V_1 \quad V_2 \quad \cdots \quad V_N]^T$, where $V_i \in [-1, 1]$ and $V_i,\ i = 1, \ldots, N$, denotes only the positive normalized correlation coefficient between a corresponding windowed event within the ECG signal and the i^{th} event in the template data set. We consider negative correlations events that have already passed in time because of the phase change in the signal. We follow (Napoli 2014)'s DS framework for correlation coefficients to capture the overall magnitude of each element in **V** by utilizing a weighting strategy as

$$\begin{aligned}\Delta\mathbf{W} &= \Delta\mathbf{V} \circ \mathbf{J}_{NN}\mathbf{D}_N \\ &= \begin{pmatrix} V_1\Delta V_{11} & V_2\Delta V_{21} & \cdots & V_N\Delta V_{N1} \\ V_1\Delta V_{12} & Ev_2\Delta V_{22} & \cdots & V_N\Delta V_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ V_1\Delta V_{1N} & V_2\Delta V_{2N} & \ldots & V_N\Delta V_{NN} \end{pmatrix}, \quad (3)\end{aligned}$$

where $\circ$ denotes the matrix Hadamard product, $\Delta V_{ij} = (V_i - V_j) \in [-1, +1], \forall i, j \in \overline{1, N}$. $\mathbf{J}_{NM}$ denotes the $N \times M$ matrix with each entry being 1 and $\mathbf{D}_N = diag\,[V_1,\, V_2 \cdots,\, V_N]$ denotes the diagonal matrix with the diagonal entries being $\{V_1,\, V_2,\, \cdots,\, V_N\}$. The columns of $\Delta\mathbf{W}$ compares the distance of an element V_i with all the elements in **V** and weights V_{ij} with V_i. This weighting of V_i could be thought of as an indication of the "strength" of the corresponding prototype being a match. Thus, the *column weight*, the summation of the column vectors, informs us how each element in **V** is different from the other elements and how strongly it matches a specific event. The *column weights*, C_i, are calculated as

$$\mathbf{C} = [C_1 \quad C_2 \quad \cdots \quad C_N]^T = (\mathbf{J}_{1N}\Delta\mathbf{W})^T, \qquad (4)$$

where $C_i \in [-(N-1)/4, (N-1)],\ \forall\ i \in \overline{1, N}$.

A reduction of propositions is done by applying a constraint to the column weights vector, **C**. This determines the propositions that are assigned DS masses, known as a focal element. The criterion to determine the number of focal elements, P, is the number of elements whose C_i is positive. This determines the propositions that are assigned DS masses, known as a focal element. The criterion to determine the number of focal elements, P, is the number of elements whose C_i is positive. The mass measure vector $\mathbf{H} = [H_1,\, H_2 \cdots,\, H_N]$ is defined as $H_i = \frac{C_i + |C_i|}{2}$. Thus, $H_i \in [0, (N-1)],\ \forall\ i \in \overline{1, N}$. The mass measure vector's elements are calculated to DS masses by

$$m(A) = \begin{cases} 1 - \left(\frac{S}{(N-1)P}\right), & \text{for } A = \Theta; \\ \\ H_i\left(\frac{1-m(\Theta)}{S}\right), & \text{for } A = H_i, \end{cases} \qquad (5)$$

where $\Theta = \{V_1, V_2, \cdots, V_N\}$ and $S = \sum_{i=1}^{N} \mathbf{H}_i$ is the the FoD consisting of the propositions $H_i,\ i \in \overline{1, N}$.

Template Fusion. The fusion of evidence sources (ECG Leads) allows us to refine our supports and our uncertainty. Thus, as additional information (ECG sources) is provided, we can refine our epistemic uncertainty by quantifying conflict within a single source and the conflict between sources. This ability to handle conflict allow us to work with imperfect data in an effective and more intuitive manner (Lefevre, Vannorenberghe, and Colot 1999). The fusion method utilizes the *Dempster's Combination Rule (DCR)* (Black 1988):

$$m(A_i) = \frac{\displaystyle\sum_{A_p \cap A_q = A_i \neq \emptyset} m_1(A_p)\, m_2(A_q)}{1 - \displaystyle\sum_{A_p \cap A_q = \emptyset} m_1(A_p)\, m_2(A_q)}, \qquad (6)$$

where the evidence provided by the mass functions m_1 (ECG lead 1) and m_2 (ECG lead 2) are combined to get the fused mass function m, denoted as $m = m_1 \oplus m_2$.

Evaluation and Discussion

This section evaluates and validates the performance of the proposed fusion algorithm using the following three research questions:

RQ1 Does our template fusion framework provide and capture contextual meaning about the quality of the information and the QRS prediction?

RQ2 Does our framework appropriately handle corrupted and inconsistent leads?

RQ3 Does this template approach require a large amount of historic information for its decision or training processes?

The non-syntactic model described by (Pan and Tompkins 1985) and the proposed fusion model were evaluated using the annotations and data from the MIT-BIH Normal Sinus Rhythm Database (Goldberger et al. 2000). The traditional template methodology was not used in the comparison since the proposed methodology is built upon this traditional approach and therefore would be expected to produce similar, if not better, results.

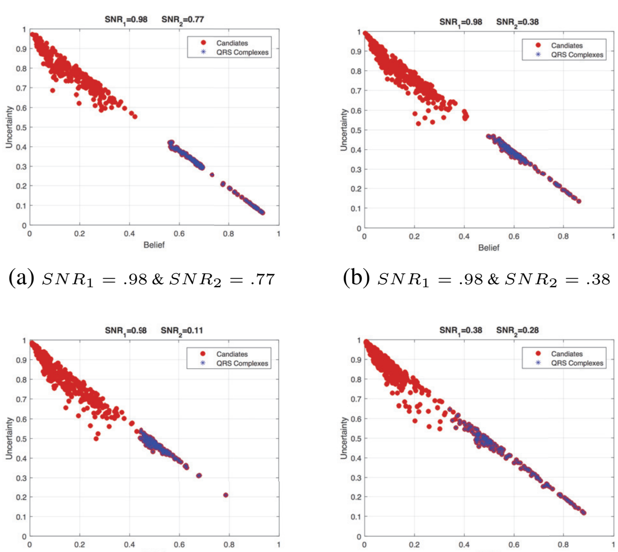
These signals are a two lead extended ECG recording from subjects with no significant arrhythmias that were taken at the Beth Israel Deaconess Medical Center, with annotated QRS complexes. Each original signal, X_s, from the Beth Israel Deaconess Medical Center was not initially filtered to enhance its SNR. Furthermore, Gaussian additive noise, N_g, was introduced by $X_c = X_s + N_g$, producing a further corrupted signal, X_c. The original signal, X_s, was bandpass filtered to produce a further degraded signal, X_E, and assess the SNR by $(E[X_E^2]/E[X_c^2])$ for quantifying the signal quality.

The performance was calculated using the number of false positives, F_P and false negatives, F_N. False positives occur when the method indicated that a QRS complex occurred but it actually did not. The number of false negatives is when a QRS complex was not detected when one actually did occur. The QRS failure rate is defined by,

$$\epsilon = \frac{F_P + F_N}{T_{QRS}} \qquad (7)$$

where T_{QRS} is the total number of QRS complexes in the signal (Pan and Tompkins 1985). Although, the precision and recall metric are typically used in analytics, this domain has used this metric for decades (Pan and Tompkins 1985). Since an hour of data would produce over a million samples, but only 4000 QRS complex. The goal is to strictly highlight the misses and detections of the QRS complex, rather than being over shadowed by total number of samples causing a small change in the performance metric. We discuss and present experimental results that address each of the research questions below. In each experiment, we address a research question demonstrating our findings associated with that specific question.

RQ1 — Capturing belief and uncertainty We address the question regarding capturing contextual meaning by running various experiments with different SNRs providing a graphical representation of belief vs uncertainty for QRS candidates. Figure 2 depicts the calculated belief and uncertainty for instances in the signal that indicated a possible 'candidate' of a QRS complex. A 'candidate', in red, is indicated by having the highest belief within the set after applying DCR for a particular time instance. The actual QRS complexes, in blue, are plotted over the candidates to demonstrate their belief and uncertainty relative to the other candidates. Note, if we took all the proposed candidates our error rate would be very high. However, we can note the linear separability of the two classes even when the SNR is below common standards (SNR less than 1), seen in Figure 2c. As the SNR degrades further, the class separation becomes more complex.



(a) $SNR_1 = .98$ & $SNR_2 = .77$ (b) $SNR_1 = .98$ & $SNR_2 = .38$

(c) $SNR_1 = .98$ & $SNR_2 = .11$ (d) $SNR_1 = .38$ & $SNR_2 = .28$

Figure 2: Uncertainty vs Belief

We can note the capturing of contextual meaning of the quality of the information by how the uncertainty graphically increases and belief decreases as SNR further degrades. Similar quantitative results can also be observed in Tables 1 and 2 discussed in research question two, where the average belief (Bel_μ) and uncertainty (Ω_μ) were listed.

RQ2— Robustness against noise Here we address whether our framework appropriately handles corrupted and inconsistent leads. Regardless of what pre-processing methods are utilized, imminent sporadic events of noise will always occur, which drastically affect the calculations for HRC and HRV and have downstream effects on predictive algorithms.The simulated noise that was added to these unfiltered signals was done to demonstrate the effectiveness of detection when these sporadic events occur and when pre-processing the signal fails to obtain adequate SNR. We also hypothesize that the proposed DS template algorithm is more effective than the benchmark non-syntactic methodology signal in corrupted situations. For simplicity, we took an arbitrary classification stance where, in order to classify a candidate as a QRS complex, it must have a $Bel > .4$ and $\Omega < .55$. However, it is recognized that optimizing these constraints on these given conditions would provide superior results for DS template method.

Table 1: Corruption: MIT Data Set 16265 ($T_{QRS} = 253$)

Corruption		Pan Algo.		D.S. Fusion Algo.		
SNR_1	SNR_2	ϵ_{S_1}	ϵ_{S_2}	Bel_μ	Ω_μ	$\epsilon_{F_{12}}$
.96	.74	0	1.18	.66	.32	1.18
.47	.66	129.6	1.18	.64	.34	0
.29	.29	146.2	62.8	.58	.40	24.5
.13	.11	203.2	221.3	.52	.46	80.2

The simulation in Table 1 and the simulation in Table 2 were done for a small segment of the time series, associated with Data Sets 16125 and 16272, respectively. Equation 7 was applied providing the performance for the fusion algorithm ($\epsilon_{F_{12}}$) and the non-syntactic algorithm for each ECG lead (ϵ_{S_1} and ϵ_{S_2}). The two QRS algorithms have comparable performance at the higher SNR cases; however, the non-syntactic algorithms' performance deteriorates as corruption of the signal occurs. More interestingly, the proposed DS template algorithm is able to handle inconsistent leads. This can be seen when the performance of the non-syntactic algorithm deteriorates on a single lead or on both leads, and the marginal error for the DS template method is substantially smaller than the marginal errors for the non-syntactic algorithms.

Table 2: Corruption: MIT Data Set 16272 ($T_{QRS} = 164$)

Corruption		Pan Algo.		D.S. Fusion Algo.		
SNR_1	SNR_2	ϵ_{S_1}	ϵ_{S_2}	Bel_μ	Ω_μ	$\epsilon_{F_{12}}$
.70	.78	1.83	31.7	.76	.23	1.83
.64	.44	1.83	39.0	.74	.25	1.23
.52	.39	3.65	47.0	.70	.29	1.22
.40	.32	58.5	145.7	.66	.32	5.49

The experiment was then extended for approximately one hour's worth of data, providing a more accurate measure of performance, Table 3. We can note that for this specific example of the fusion algorithm performance, $\epsilon_{F_{12}}$, it outperformed the non-syntactic algorithm in both leads, S_1 and S_2. Obviously, S_2 had a higher QRS failure detection percentage of 54.5%, since the SNR for that particular signal was much lower. However, it is worth noting that we were able to obtain an improved detection using the degraded signal from S_2. This ultimately cuts our error by half.

Table 3: Method Comparison: MIT Data Set 16265

M	SNR	T_{QRS}	F_P	F_N	$\#\epsilon$	ϵ
F_{12}	$.82/.31$	4647	25	51	76	1.6%
S_1	.82	4647	128	19	147	3.2%
S_2	.31	4647	1680	857	2537	54.5%

RQ3 — Little Prior Knowledge The proposed approach requires very little to no information, where no training is required. The amount of information required is equivalent for the traditional template algorithm for a single ECG lead. which is important for the use of algorithms in clinical setting. Algorithms that are reliant on large data sets for clinical research can contain hidden biases that might restrict the algorithm's accuracy and application on heterogeneous data sources. Hence, this design was built around the idea of template matching. However, more data with respects to the number of ECG leads would further refine the support of the DS framework for further enhanced performance.

Conclusion

Future work will focus on optimization methods for defining the proper constraints for the belief and uncertainty values to enhance classification, and on producing a better framework to handle the doubleton case. We have demonstrated strong potential for further improvement, which could include utilizing more ECG leads as evidence sources, parallelizing the process (Napoli et al. 2016), and detection of other cardiac waveforms using this template paradigm.

The proposed DS fusion multiple template approach over multiple leads has demonstrated strong evidence for being a superior detection methodology when signals are corrupted with noise. This work demonstrates that using little to no prior knowledge, contextualized QRS detection provides powerful evidence to support a decision. Unlike the non-syntactic and conventional cross-correlation methods, where an arbitrary threshold is set and requires adjusting, this contextual meaning provides information on how corrupt the signals are by quantifying the uncertainty that is associated with the present conflict between competing templates. More importantly, unreliable information from corrupted signals still provides value to the detection process and are leveraged by addressing the conflicting information sources across additional leads.

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