Fast, Accurate, and Robust Segmentation of Long-Term Electrocardiograms Through Multi-Point Iterative Warping and Dynamic Template Generation

Paolo G Cachi, Andrew Heroy, Nate Ehat, Mark C Haigney, Soroosh Solhjoo

Military Cardiovascular Outcomes Research (MiCOR), Bethesda, MD, USA
F Edward Hébert School of Medicine, Bethesda, MD, USA

Abstract

Accurate beat-wise ECG segmentation is critical for extracting clinically relevant biomarkers such as QT and TpeakTend intervals. However, traditional methods often struggle with precision in the presence of morphological variability and signal drift. We present an Enhanced Two-Dimensional Warping (E2DW) framework that extends the original 2DW algorithm through two key innovations: dynamic template adaptation, which employs drift detection to continuously update beat templates in response to evolving morphology, and multi-point grid alignment, which generalizes the warping process via a vectorized multi-point optimization strategy. Evaluated on the QT Database and a full-night clinical sleep study, E2DW outperformed wavelet-based methods and the baseline 2DW in segmentation accuracy, robustness, and computational efficiency. These results demonstrate reliable beat-by-beat segmentation of long ECG recordings, underscoring E2DW's potential as a high-fidelity tool for both clinical and research applications.

1. Introduction

Accurate segmentation of the electrocardiogram (ECG) to identify fiducial points at the beat level is critical for clinical diagnostics and automated cardiovascular analysis. The resulting features, including heart rate variability and QT interval variability measures, support applications such as arrhythmia detection [1, 2], repolarization studies [3, 4], and drug safety evaluation [5]. However, their precision and accuracy are often compromised by segmentation errors, especially in recordings with high morphological variability or significant noise, hindering research that rely on accurate beat-to-beat ECG intervals and limiting the utility of automatic ECG analysis applications in clinical settings [6].

Among recent advances, two-dimensional warping (2DW) has emerged as a promising approach for high-accuracy ECG segmentation [7]. In 2DW, each beat is aligned to a pre-annotated template by permitting deformations along both the time and amplitude axes, yielding a flexible mapping of waveform morphology. Once alignment is achieved, fiducial points on the template are directly transferred to the processed beats. This dual-axis formulation enhances sensitivity to subtle morphological changes that are critical for biomarkers, such as the QT and TpeakTend intervals [8].

Despite its advantages, the practical deployment of 2DW for ECG segmentation faces two main challenges. First, the selection of a representative beat template in dynamic or ambulatory settings is not trivial. ECG beat morphology can change due to physiological, pathological, or sensor-related changes, hence a static template can quickly become obsolete (Fig. 1). Second, 2DW's computational cost scales poorly with the recording length and optimization complexity, making real-time implementation difficult without significant trade-offs in precision or speed.

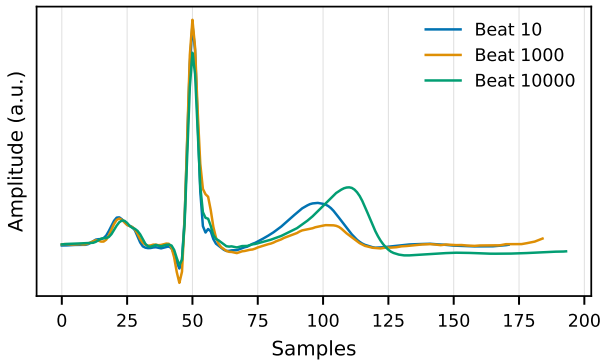

Figure 1. Representative ECG beats at different times showing morphology changes over the recording.

To address these limitations, we propose an Enhanced Two-Dimensional Warping (E2DW) framework that extends the original 2DW method with two key innovations: (1) adaptive template generation using concept drift detection, and (2) a vectorized multi-point optimization strategy for 2DW that improves alignment accuracy while reducing computation time. Together, these enhancements im-

prove segmentation precision and efficiency. We benchmark E2DW against wavelet-based and original 2DW algorithms, demonstrating superior performance.

2. Methods

2.1. Two-Dimensional Warping

Two-dimensional warping (2DW) is a signal alignment technique that has shown promise for ECG segmentation. In 2DW, the objective is to transfer expert-labeled fiducial points from a reference beat template to each beat in a continuous ECG recording [7]. A reference beat annotated with landmarks such as the QRS onset, R peak, and T wave peak is represented as the template $T(t)$, while each incoming beat serves as the target $X(t)$. The template is embedded on a two-dimensional grid $\mathcal{G}$, whose control points can be moved along both temporal and amplitude axes, allowing $\mathcal{G}$ to undergo smooth, nonrigid deformations that generate a warped version of the template, $T_w(t)$. The alignment problem is then formulated as the search for the optimal grid configuration $\{P^*_{i,j}\}$ that minimizes the misalignment between the warped template $T_w(t)$ and the target beat $X(t)$:

$$\{P^*_{i,j}\} = \arg\min_{\{P_{i,j}\}} C\left(\{P_{i,j}\}; T, X\right),$$

where $C(\cdot)$ is a cost function, typically chosen as the squared Euclidean distance,

$$C = \sum_{i=1}^{N} \left(T_w(t_i) - X(t_i)\right)^2,$$

with $\{t_i\}_{i=1}^N$ denoting the sampling points after temporal deformation. Once the optimal mapping is found, fiducial points from the template are projected onto the target beat. This enables a segmentation process that is flexible, morphology-aware, and robust to beat-to-beat variability. Efficient implementations typically employ dynamic programming over the deformable grid [7], with continuity and monotonicity constraints on the temporal component to preserve signal coherence.

Although 2DW achieves high accuracy, its reliance on a static template makes it vulnerable to morphological drift, and its computational cost limits real-time applicability.

2.2. Enhanced Two-Dimensional Warping

Enhanced Two-Dimensional Warping (E2DW) extends 2DW with dynamic template adaptation and multi-point grid alignment, allowing continuous tracking of morphological drift and simultaneous optimization of multiple control points. These innovations improve segmentation precision, robustness, and computational efficiency for long-term ECG analysis.

2.2.1. Dynamic Template Adaptation

A major challenge in ECG segmentation with 2DW is morphological drift, where the waveform shape gradually evolves due to physiological variations, pathological events, or measurement artifacts (Fig. 1). To address this, E2DW employs a dynamic template adaptation mechanism that updates the reference template whenever significant morphological drift is detected.

Initial Template Construction - The initial template is derived from the first M beats, aligned on their R-peaks. A preliminary template is obtained by averaging the normalized beats, after which cosine similarity is used to retain the top 50% most similar beats. These beats are reaveraged to form the final reference template $T(t)$, which is semi-automatically annotated at the points of interest based on consensus across multiple open-source [9] and a proprietary segmentation algorithm [10] and subsequently manually verified.

Drift Detection - Morphological drift is monitored by measuring the weighted cosine similarity S_n between each incoming beat $X_n(t)$ and the current template $T(t)$:

$$S_n = \frac{\sum_i w_i\, T_i\, X_{n,i}}{\sqrt{\sum_i w_i\, T_i^2} \cdot \sqrt{\sum_i w_i\, X_{n,i}^2}},$$

where w_i emphasizes diagnostically relevant regions of the beat waveform (e.g., Q onset, ST segment, T wave). Similarity scores are tracked in a rolling buffer and a new template is generated if (i) the proportion of beats whose similarity score is above a threshold falls below θ_{sim}, or (ii) a statistically significant shift is detected using an ADWIN-inspired test [11].

Template Update - When drift is confirmed, a new template is constructed from the most recent M beats. By default, it is annotated by aligning to the most similar previous template using 2DW. If the alignment error exceeds a defined threshold, the semi-automatic procedure described for the initial template construction is applied.

2.2.2. Multi-Point Grid Alignment

E2DW aligns the template to each beat by jointly adjusting multiple grid control points through a vectorized and parallelized search, rather than optimizing them individually as in 2DW. This coordinated adjustment captures complex local deformations in waveform morphology, improving alignment accuracy, robustness, and computational efficiency.

Problem Formulation - Let a grid cell $\mathcal{P}$ be defined by four control points $\{p_i\}_{i=1}^4$, spanning a normalized domain $(x, y) \in [0, 1] \times [0, 1]$. A template signal T is embedded in this domain by n samples with positions (x_k, y_k). When the control points are displaced to $\{p_i'\}$, the domain undergoes a geometric transformation mapping (x_k, y_k) to (x_k', y_k'). The warped signal T_w is obtained by interpolating T at the transformed coordinates, and the alignment problem is to find $\{p_i'\}$ that minimizes the dissimilarity between T_w and the target beat X.

Vectorized Implementation - The mappings from normalized to deformed coordinates are implemented as fully vectorized bilinear interpolations. Each candidate configuration $\{p_i'^{(k)}\}_{i=1}^4$ is applied in a batch over the fixed sampling grid $\{(x_j, y_j)\}_{j=1}^n$, producing warped signals $\{T_w^{(k)}\}_{k=1}^K$. This tensorized formulation enables high-throughput evaluation across large sets of candidate deformations and generalizes to grids of arbitrary resolution.

3. Experiments and Results

We evaluated E2DW on two datasets: the QT Database [12], to assess segmentation sensitivity, robustness, and computational efficiency, and ECG recordings from polysomnographic study of patients undergoing chronic methadone therapy [5], to demonstrate clinical applicability.

3.1. Evaluation on the QT Database

The QT Database contains 104 two-lead ECG recordings of about 15 minutes each, with expert annotations for at least 30 seconds per record [12]. We used 97 records with complete annotations and evaluated segmentation on a single lead, focusing on Q onset, T end, and QT interval detection.

Performance was measured by: (1) *sensitivity*, the percentage of beats with both Q onset and T end successfully segmented; (2) *robustness*, the standard deviation of absolute segmentation errors; and (3) *runtime efficiency*, measured as mean processing time per beat on an Apple M2 8-core processor.

E2DW was evaluated using four configurations of the multi-point grid alignment method, in which the optimization simultaneously displaced 1, 2, 3, or 4 grid points at a time. Performance was compared against the baseline 2DW [7] and two wavelet-based methods (CWT, DWT) [9]. Table 1 compares segmentation accuracy, and Table 2 compares runtimes among the tested methods.

Results show that wavelet methods had the lowest sensitivity and highest errors, while 2DW improved accuracy (86.1%) but was slower. E2DW achieved higher robustness, with the 1- and 2-point configurations providing real-time suitability (0.070 s/beat), and the 3-point configuration offering the best balance between accuracy and efficiency.

Table 1. Segmentation performance on the QT Database. Sensitivity (S, percentage of beats with both Q onset and T end successfully segmented) and standard deviation of absolute errors (Error) are reported.

Method	**S (%)**	**Error (ms)**		
		Q onset	T end	QT
CWT	68.62	37.70	205.63	206.58
DWT	77.80	16.36	38.88	39.55
2DW	86.12	4.56	11.61	11.74
E2DW (1-point)	86.09	4.53	9.20	9.17
E2DW (2-point)	86.19	4.62	9.61	9.73
E2DW (3-point)	86.24	2.42	10.79	10.19
E2DW (4-point)	86.00	2.58	10.60	10.02

Table 2. Runtime per beat on the QT Database.

Method	**Time (s)**		**Speed vs. 2DW**
	Mean	**SD**	
CWT	0.017	0.001	13.82
DWT	0.192	0.003	1.22
2DW	0.235	0.059	1.00
E2DW (1-point)	0.071	0.013	3.31
E2DW (2-point)	0.070	0.013	3.36
E2DW (3-point)	0.127	0.026	1.85
E2DW (4-point)	0.839	0.176	0.28

3.2. The Methadone Sleep Study

To demonstrate the clinical applicability of E2DW, we analyzed ten overnight single-lead ECG recordings from patients undergoing chronic methadone therapy [5]. ECG segments were processed using dynamic template adaptation and three-point grid alignment. The amplitude of each beat was normalized to unit norm before feature extraction. The derived metrics included conventional cardiac markers, including heart rate, SDNN (standard deviation of normal-to-normal beats, QTc (Bazett), QTVI (beat-to-beat QT variability index), and TpeakTend, as well as T-wave morphology descriptors, namely amplitude, asymmetry (TstartTpeak/TpeakTend), downslope, and area under the T-wave. Table 3 summarizes the extracted features.

The conventional measures are consistent with the previous report [5]. By adding the beat-to-beat morphological measurements across long overnight recordings, E2DW provides a multidimensional view of repolarization dynamics from single-lead ECGs.

These results demonstrate E2DW's ability to extract stable, high-fidelity ECG features from complex clinical data,

Table 3. Heart rate, QT, and T-wave metrics during sleep in methadone-treated patients (N=10).

Variable	Mean	SD
Heart rate (bpm)	64.71	8.13
SDNN (ms)	36.20	30.21
QTc (Bazett, ms)	432.73	23.28
QTVI	-0.307	0.74
TpeakTend (ms)	89.15	17.57
T-amplitude (a.u.)	0.020	0.018
T-asymmetry	1.34	0.34
T-downslope	1.03	0.62
T-area (a.u.)	11.28	6.11

establishing a strong methodological foundation for future studies of repolarization dynamics and arrhythmia risk in high-risk populations.

4. Conclusions

We presented the Enhanced Two-Dimensional Warping framework, which extends the original 2DW method with dynamic template adaptation and multi-point grid alignment. Evaluations on the QT Database and a clinical sleep study demonstrated that E2DW improves segmentation accuracy, robustness, and computational efficiency compared to wavelet-based approaches and the baseline 2DW algorithm. The multi-point grid alignment enhanced the localization of Q-onset and T-end fiducial points, with the three-point configuration providing the best trade-off between accuracy and efficiency. Dynamic template adaptation further enabled reliable long-term tracking by mitigating morphological drift, supporting accurate QT and T-wave analysis across extended ECG recordings.

Author Contributions

P.G.C. conceptualized the project, developed the algorithm, and wrote the manuscript; A.H. assisted with automated ECG segmentation; M.C.H. provided clinical insights on ECG interpretation; S.S. conceptualized the project, developed the algorithm, wrote the manuscript, and supervised the project.

References

[1] Bollepalli SC, Sevakula RK, Au-Yeung WM, Kassab MB, Merchant FM, Bazoukis G, Boyer R, Isselbacher EM, Armoundas AA. Real-time arrhythmia detection using hybrid convolutional neural networks. Journal of the American Heart Association 2021;10(23):e023222.

[2] Haigney MC, Zareba W, Nasir JM, McNitt S, McAdams D, Gentlesk PJ, Goldstein RE, Moss AJ. Gender differences and risk of ventricular tachycardia or ventricular fibrillation. Heart Rhythm February 2009;6(2):180–186.

[3] Tse G, Gong M, Wong WT, Georgopoulos S, Letsas KP, Vassiliou VS, Chan YS, Yan BP, Wong SH, Wu WK, Ciobanu A, Li G, Shenthar J, Saguner AM, Ali-Hasan-Al-Saegh S, Bhardwaj A, Sawant AC, Whittaker P, Xia Y, Yan GX, Liu T. The t_{peak}–t_{end} interval as an electrocardiographic risk marker of arrhythmic and mortality outcomes: A systematic review and meta-analysis. Heart Rhythm Aug 2017; 14(8):1131–1137. ISSN 1547-5271.

[4] Monitillo F, Leone M, Rizzo C, Passantino A, Iacoviello M. Ventricular repolarization measures for arrhythmic risk stratification. World J Cardiol January 2016;8(1):57–73.

[5] Solhjoo S, Punjabi NM, Ivanescu AE, Crainiceanu C, Gaynanova I, Wicken C, Buckenmaier III C, Haigney MC. Methadone destabilizes cardiac repolarization during sleep. Clinical Pharmacology Therapeutics 2021;110(4):1066–1074.

[6] Faust O, Hagiwara Y, Hong TJ, Lih OS, Acharya UR. Deep learning for healthcare applications based on physiological signals: A review. Computer Methods and Programs in Biomedicine 2018;161:1–13. ISSN 0169-2607.

[7] Schmidt M, Baumert M, Malberg H, Zaunseder S. Iterative two-dimensional signal warping—towards a generalized approach for adaption of one-dimensional signals. Biomedical Signal Processing and Control 2018;43:311–319. ISSN 1746-8094.

[8] Chua KC, Rusinaru C, Reinier K, Uy-Evanado A, Chugh H, Gunson K, Jui J, Chugh SS. Tpeak-to-tend interval corrected for heart rate: A more precise measure of increased sudden death risk? Heart Rhythm 2016;13(11):2181–2185. ISSN 1547-5271.

[9] Makowski D, Pham T, Lau ZJ, Brammer JC, Lespinasse F, Pham H, Schölzel C, Chen SHA. NeuroKit2: A python toolbox for neurophysiological signal processing. Behavior Research Methods feb 2021;53(4):1689–1696.

[10] Heroy A, Arnold T, Ehat N, Haigney M, Solhjoo S, Cachi P. RAD_ECG: Robust Agile Detector for traversal of noisy ECGs, 2021. URL `https://github.com/METIS-MICOR/rad_ecg`.

[11] Bifet A, Gavaldà R. Learning from time-changing data with adaptive windowing. In Proceedings of the Seventh SIAM International Conference on Data Mining, April 26-28, 2007, Minneapolis, Minnesota, USA. SIAM, 2007; 443–448.

[12] Laguna P, Mark R, Goldberg A, Moody G. A database for evaluation of algorithms for measurement of qt and other waveform intervals in the ecg. In Computers in Cardiology 1997. 1997; 673–676.

Address for correspondence:

Paolo G. Cachi, paolo.cachi-delgado.ctr@usuhs.edu
Soroosh Solhjoo, soroosh@jhu.edu