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A Spline Framework for ECG Analysis

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Abstract— **In this effort we introduce a spline framework for ECG waveform analysis, with initial application to the ECG delineation (segmentation) problem. The framework comprises knot initialization, spline interpolant, error metric, and knot location optimization to parametrically represent the waveform for analysis, classification, or compression. Choice of these constituents is driven by the application of the framework. For our initial application of ECG delineation, we use the framework to identify characteristic points corresponding to waveform onset and offset times, peak values, and junction points. These are represented mathematically as critical points and points of inflection, which serve as knot locations for linear or cubic Hermite interpolants in the framework. Preliminary tests on a limited but diverse set of morphologies from the European ST-T database indicate that the framework obtains knot locations corresponding to characteristic points, and the resultant interpolated waveform represents the original signal well with low mean squared error.**

I. INTRODUCTION

Analysis of electrocardiogram signals, whether performed by human expert or by machine, requires identifying key morphological features in the waveform that correspond to temporal sequences of depolarization and repolarization of the myocardium. Electrical activity in specific areas of cardiac tissue gives the ECG waveform its characteristic shape: the P wave corresponds to atrial depolarization, the QRS complex to ventricular depolarization, and the T wave to ventricular repolarization. Locating and quantifying these shapes, as well as obtaining other metrics derived from the waveform (such as QT interval, ST segment deviation, PR interval, etc.) provide a non-invasive view of cardiac function for analytic or diagnostic purposes.

Due to the importance of identifying the constituent shapes of the ECG waveform, the problem of delineating (or segmenting) the ECG waveform is well-established in the literature. Existing work includes use of wavelets [1]–[3], Hidden Markov Models [4], [5], templates [6], spectral analysis [7], mathematical morphology [8], empirical mode decomposition [9], and model-based methods [10], [11].

Splines have also been applied to ECG signal processing, but predominantly in the areas of waveform compression [12]–[14] and baseline wander elimination [15], [16]. There is very little literature exploring use of splines for detection and tracking of waveform features using knot locations, although this was a recognized need articulated in [17]. Unlike, for example, spline signal compression (where the interpolated waveform shape is the key factor), for ECG delineation spline knot locations are of paramount importance as they correspond to the waveform's characteristic points.

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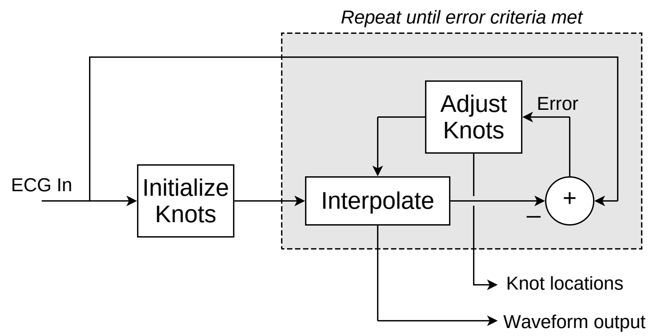


Fig. 1. Spline Framework for ECG Analysis

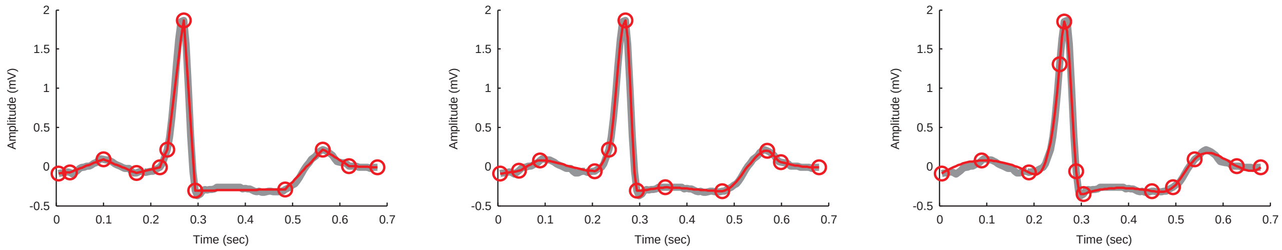
Mathematically, we define characteristic points as the critical points or points of inflection in the ECG waveform. With an appropriate interpolant, these points naturally serve as knots in a spline representation and define both temporal and morphological features of the waveform. Complexes of interest in the ECG waveform are demarcated or defined by the characteristic points: P, QRS, and T onset and offset times, J point, peak values, and various intervals of interest can all be defined or derived from characteristic points.

With this effort we are introducing a spline-based framework for ECG waveform analysis, with an initial application to the delineation problem. With appropriate knot initialization, choice of interpolant, and knot location optimization, the framework provides a parametric model enabling analysis, diagnosis, classification, compression, and tracking of features in the ECG waveform.

II. METHODOLOGY

Fig. 1 is a high-level depiction of the spline framework for ECG analysis. The algorithm initializes knot locations then optimizes them using error metrics calculated from the original waveform and interpolated representation. The framework allows choice of initialization algorithm, error measure, interpolant, and optimization algorithm to tailor the framework for applications with varying requirements.

Choice of interpolant is very important to ensure the goals of a given framework application are met. For waveform delineation, we need characteristic points placed at critical points and points of inflection as described above. Fig. 2 shows a sample ECG complex extracted from the European



(a) Linear interpolant, RMSE=44.4 μV (b) Cubic Hermite interpolant, RMSE=23.0 μV (c) Cubic spline interpolant, RMSE=43.0 μV

Fig. 2. Knots for several interpolants on a beat from EDB record e0406.

ST-T database (EDB) [18] record `e0406` superimposed with the results of three different interpolants. Each interpolant was run with 12 randomly-initialized knots and optimized using a genetic algorithm. The genetic algorithm was implemented by encoding a population of 25 chromosomes with random perturbations of the initial knot locations, then creating the next generation of offspring by applying single-point crossover and mutation in a constrained neighborhood around the knot locations. We used the mean squared error as the fitness function, and propagated the best offspring through 500 generations.

From Fig. 2 it is clear that with a sufficient number of knots the linear, cubic Hermite, and cubic spline interpolants represent the signal well. And while knot locations for the linear and cubic Hermite interpolants approximate waveform onsets, offsets, and peaks, differentiability constraints imposed by the cubic spline interpolant have forced them to vary from the desired characteristic points. This is evidenced in Fig. 2c, which shows knot locations no longer correspond to P and R wave onset and T wave peak.

A large number of knots will improve the spline representation of the waveform regardless of interpolant. However, too many knots increase computational effort required to implement the framework and make it difficult to determine correspondence of knots to characteristic points. The optimum number of knots to represent characteristic points is highly dependent on waveform morphology, so we require a dynamic, efficient method to make the initial assignments. For this purpose we used a recursive partitioning algorithm (RPA). RPA linearly interpolates between the endpoints of the signal segment and finds the waveform point farthest from the interpolated line. It then recursively applies itself to the new line segments generated by each existing endpoint and the point of maximum distance. The recursion terminates when the maximum difference between the interpolated and original waveforms is less than a waveform-dependent empirically-derived threshold selected to maintain key features.

Fig. 3 illustrates operation of the RPA at different stages. Fig. 3a follows the second partition. The next largest difference between the interpolated and original waveforms is the onset of the R wave, which is picked for the third partition in Fig. 3b. The final result is shown for a threshold value of 0.1 mV in Fig. 3c. Lowering the threshold further would have resulted in partitions at ≈ 0.3 and ≈ 0.5 seconds.

III. RESULTS

To validate applicability of the framework for characteristic point identification, we tested it on a larger number of samples from the EDB. We selected waveforms to illustrate a wide range of morphologies including fusion, ST segment deviation, T wave deviation and inversion, and premature ventricular contraction. We extracted pattern vectors from both available channels, including P and T waves around each fiducial marker obtained from the `atr` annotator for each record.

Recursive partitioning provided the initial knot locations which were optimized using the genetic algorithm described above, for both linear and cubic Hermite interpolants. Fig. 4 shows the results of framework applied to the selected beats for the cubic Hermite interpolant. Table I tabulates the number of knots (n_k) selected by the RPA and RMSE values between the original waveform and interpolated approximation for original (non-optimized) knots provided by RPA with linear interpolant (e_1), RPA knots optimized by genetic algorithm using a linear interpolant (e_2), and RPA knots optimized by genetic algorithm using a cubic Hermite interpolant (e_3). The final row indicates the mean and standard deviation of the RMSE values for each method.

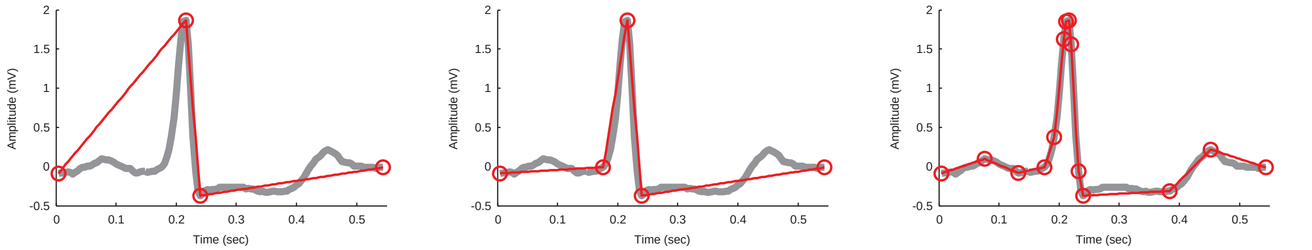
TABLE I

FRAMEWORK RESULTS ON TEST SET

Record	Lead	n_k	e_1 (μV)	e_2 (μV)	e_3 (μV)
`e0114`	MLIII	16	20.4	14.4	14.4
	V4	18	19.0	14.2	12.1
`e0116`	V4	11	57.2	44.1	42.2
	MLIII	9	30.8	21.7	22.4
`e0123`	V4	23	20.7	16.7	9.7
	MLIII	14	13.3	11.1	13.1
`e0161`	V4	22	17.0	12.8	7.9
	MLIII	15	18.5	11.7	9.0
`e0206`	V5	19	29.9	25.8	23.7
	MLI	14	23.7	16.7	14.6
`e0413`	V2	13	36.3	32.7	17.7
	V5	11	41.0	37.0	27.9
$\mu \pm \sigma$			27.3±12.6	21.6 ±11.0	17.9 ±9.9

IV. DISCUSSION

Results with a small but diverse set of beats indicate that the spline framework is a viable, complementary option to existing methods for parametric modeling of the ECG



(a) Second partition (b) Third partition (c) Final partition, 0.1 mV threshold

Fig. 3. Recursive Partitioning Algorithm applied to a beat from EDB record e0406. The thick gray line is the original waveform; the thinner red line is the interpolation, and the red circles indicate the initial knot locations.

waveform, and with appropriate choices (interpolant, knot initialization/optimization algorithm, error criteria) can identify waveform characteristic points.

Recursive partitioning provides a good initial estimate of knot locations corresponding to waveform characteristic points and dynamically selects an appropriate number of knots, but choice of threshold is very important: smaller values will be more sensitive and can pick undesired artifact as initial knot locations; larger values may miss required features. Fig. 4b illustrates a good compromise for a waveform with a large amount of line noise. Smaller threshold values for this example resulted in all sinusoidal peaks and valleys being selected; with proper threshold and MSE criterion, the interpolated result effectively reduces the line noise and characteristic points are reasonably represented by the knots.

For overall waveform reproduction fidelity, RMSE values for the cubic Hermite interpolant are generally superior to those from the optimized linear interpolant (although there are a few exceptions). Our experience with this interpolant is consistent with [14], in which Hermite basis functions are used to model the ECG signal. Subsequent work will evaluate knot locations corresponding to each interpolant.

V. SUMMARY

We have presented preliminary results of a spline-based framework for ECG analysis, with initial application to ECG waveform delineation. For this application the framework is structured (by choice of knot initialization algorithm, error criterion, interpolant, and knot optimization algorithm) to place knots at characteristic points which define waveform onset, offset, and peak values, as well as junctions corresponding to points of inflection.

The flexibility provided by the framework allows the practitioner to make tradeoffs between computational complexity, fidelity of signal reproduction, and physiological relevance of knot location, complementing existing parametric models of the ECG waveform.

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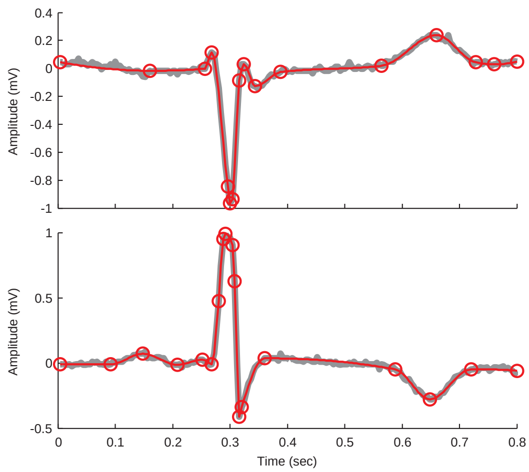

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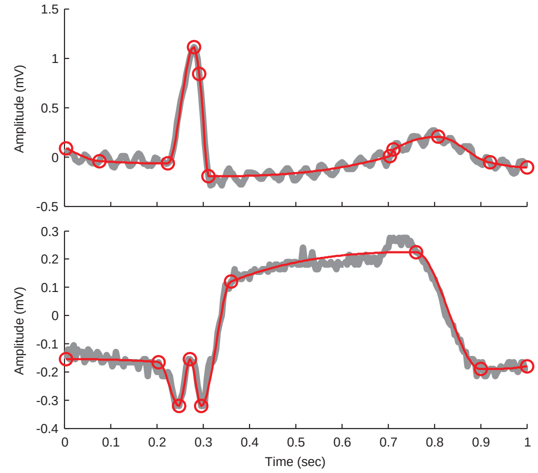

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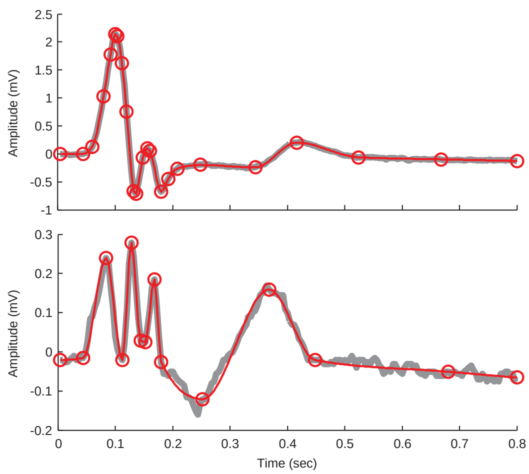

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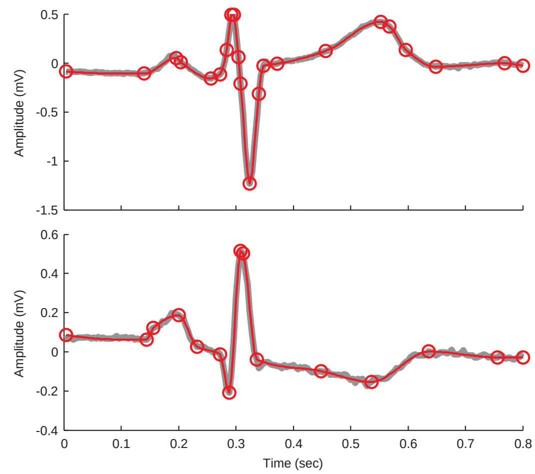

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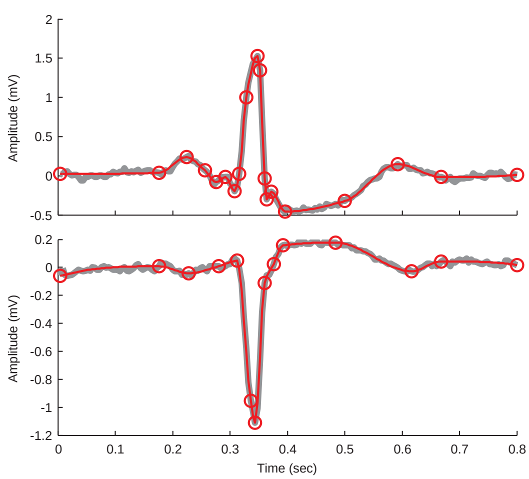

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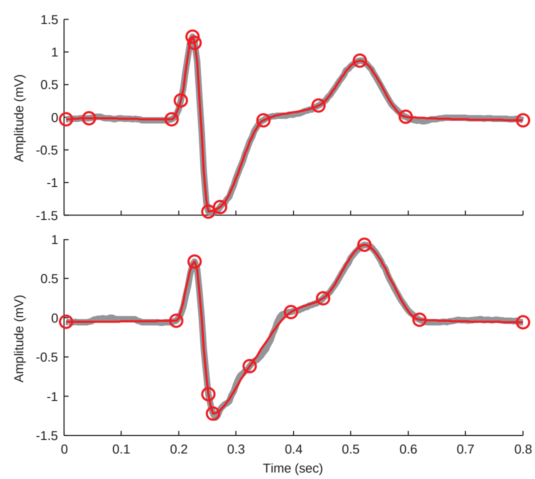

(f) e0413

Fig. 4. Framework results for beat delineation with cubic Hermite interpolant on selected beats from the European ST-T Database. The thick gray line is the original waveform; the thinner red line is the cubic Hermite interpolation, and the red circles indicate the optimized knot locations.