Elicitation and visualisation of uncertainty in electrograms for activation time maps

Silvia Liverani and Chris D. Cantwell

Abstract When treating atrial arrhythmias using catheter ablation it is standard practice to create local activation maps of a patient's atrium to guide treatment. Generating these maps involves recording hundreds of electrograms from the inside surface of the chamber and then using automated algorithms to identify deflections in the signal and choose the activation time for each recording point. The activation times are then visually represented on a 3D model of the chamber which is used to guide treatment. However, uncertainty in the selection of the activation time is not considered by the algorithm and may lead to poor quality data collection. To the best of our knowledge, this is the first attempt to quantify and communicate the uncertainty of each activation time.

Key words: eliciting uncertainty, expert judgement

1 Introduction

Atrial fibrillation is one of the leading causes of mortality and morbidity in the world and arises when the regular electrical activation wavefronts, which cause contraction of the tissue, become disorganised, leading to reduced cardiac throughput and increased risk of stroke. Treatment is often through intracardiac catheter ablation where radiofrequency energy is delivered to the myocardium to create electrically non-conductive lesions. During this procedure, the electrical activity of the atrium is often mapped to help guide clinicians in selecting the optimal sites for delivering

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treatment (see Figure 1). Bipolar electrograms (potential difference between two nearby electrodes) are recorded at a large number of points by a mapping catheter as it is moved throughout the chamber. Example electrograms from points on the map in Figure 1 are shown in Figure 2. As a wavefront passes an electrode, a *deflection* in the electrogram is registered. An automated algorithm identifies deflections to determine the local activation time (LAT). However, the complexity of myocardial architecture and the far-field effect of activation in other parts of the heart can cause spurious deflections in the signal resulting in incorrect activation times, which the clinician is not necessarily aware of until after data collection is complete.

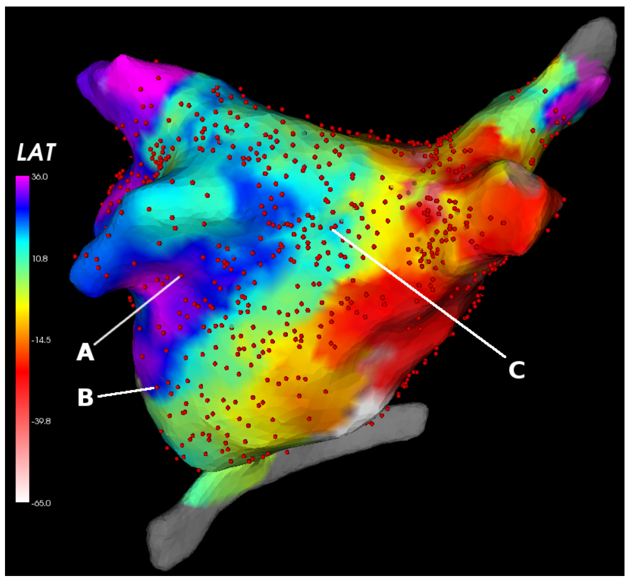

Fig. 1 Local activation map for a left atrium indicating times (in ms) relative to a reference signal. Red dots show locations of recordings. Elecrograms recorded at points A, B and C are shown in Figure 2.

There are three main sources of uncertainty in identifying the correct LAT for a given electrogram: measurement error due to electrical noise and electrode movement; errors due to the automated algorithm selecting the incorrect deflection; and the expert's uncertainty. The automated algorithm selects candidates for the LAT by measuring the widths and heights of deflections, as identified by local minima and maxima of the signal subject to prescribed window thresholds. This is a challenging task as noise is present in the measurements. We will not focus on this aspect of uncertainty, or measurement error, but it is important to be aware of them.

The main focus of this paper is the uncertainty that even the expert eye would encounter when asked to identify the activation time for a given electrogram. The expert, a cardiac electrophysiologist, will select one deflection as the LAT, but this is done with varying levels of uncertainty due mainly to the noise and number of

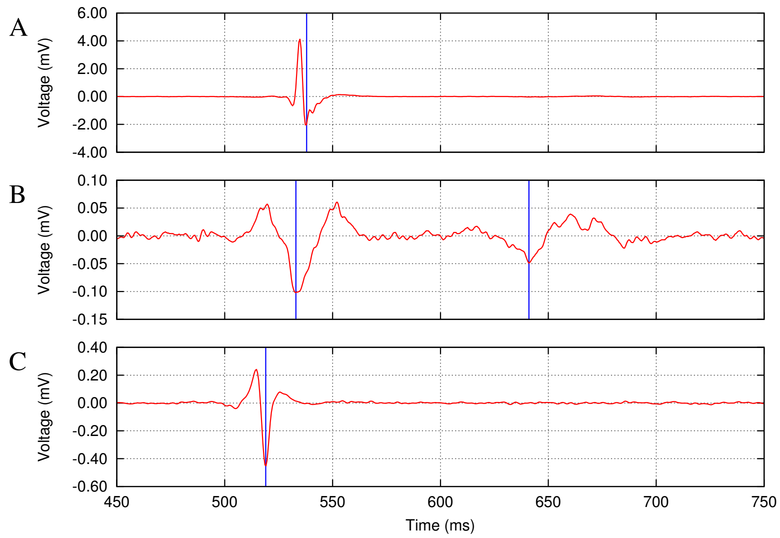

Fig. 2 Three example electrograms corresponding to A, B and C in Figure 1.

deflections present in the data. The automated algorithm is intended to replace the expert, and it should in most cases select the same activation time that the expert would choose. However, if the expert identifies a challenging electrogram for which she has high uncertainty, she would be able to request a new recording at that point. The automated algorithm enables real-time mapping of the atrium during the ablation procedure. However, at present it always makes a *best guess* at the LAT, which is potentially wrong, and medical staff are therefore losing vital information.

The aim of our work is to use the automated algorithm to identify parameters that affect the uncertainty of its output, and define an uncertainty measure (Garthwaite et al, 2005) that the electrophysiologist can use to make decisions such as to repeat recordings for certain parts of the chamber.

2 Expert judgements

We devised a measure of uncertainty as follows.

1. We discussed with the expert the features of electrograms that would prompt her to classify an electrogram with low or high uncertainty. These features are:
   - the presence of few or many deflections;
   - the presence of multiple deflections of similar amplitude and duration;
   - the presence of only low amplitude deflections;
   - no deflections identified.

2. We asked the expert to score between 0 and 1 her uncertainty regarding a number of simulated electrograms. Zero corresponds to certainty.
3. We devised an uncertainty measure.
4. We asked the expert to rate a number of electrograms as High or Low uncertanty.
5. We independently scored them according to our uncertainty measure.

We repeated steps 1-4 until the measure that we had devised was consistent with the expert cardiac electrophysiologist's opinion in classifying High and Low uncertainty electrograms. This iterative process resulted in the identification of the measure given in this paper. We show in Table 1 some examples of the score provided by our expert for simulated deflection data.

Table 1 Scores provided by the expert in response to electrograms which presented deflections defined by the amplitudes a_i (in mV) and lengths l_i (in ms).

Score	a_1	l_1	a_2	l_2	a_3	l_3	a_4	l_4
0	5.0	6.0						
0.1	5.0	6.0	0.5	18.0				
0.1	0.5	18.0	5.0	6.0				
0.1	0.5	6.0	5.0	6.0	0.5	6.0		
0.3	0.5	6.0	5.0	12.0				
0.6	5.0	6.0	5.0	12.0				
1	5.0	6.0	5.0	6.0				
1	5.0	6.0	5.0	6.0	5.0	6.0		

3 Eliciting the uncertainty

We have devised a measure of uncertainty u. We assume that the automated algorithm is capable of identifying all deflections present in the electrogram, subject to the constraints outlined previously, with the same reliability of an expert. The number of identified deflections is n. If $n = 1$ the algorithm has no choice but to select the single deflection present and $\hat{u} = 0$. For $n > 1$, we define the uncertainty as

$$\hat{u} = \frac{n}{\sum_{i=1}^{n} w_i \sqrt{(r_i - \bar{r})}}, \tag{1}$$

where

$$w_i = \frac{a_i}{\sum_{i=1}^{n} a_i}, \tag{2}$$

$r_i = a_i / \sqrt{l_i}$ and $\bar{r}$ is the mean of the r_i's. The measure of uncertainty u has the following properties:

1. The uncertainty u increases as the number of deflections n increases, implying that if many deflections are present in the electrogram, we will be more uncertain about our choice than if few are present.

2. The uncertainty is inversely proportional to the amplitude of the deflections. The length only affects the uncertainty through the ratio of amplitude and length.
3. The amplitude is a stronger indicator of uncertainty. Each deflection's influence in the uncertainty measure is weighted w_i which represents the proportion of overall amplitude in the given electrogram.
4. The high amplitude deflections influence the weighted mean at the denominator (and hence u) with equal weights, regardless of their lengths.

4 Example

We have applied our algorithm to real data collected during catheter ablation procedures and have compared the results to expert analysis of the data. Fifty-eight electrograms were scored across four patients and the expert was asked to independently score them as High or Low uncertainty. The results are shown in Figure 3, by patient and by expert score. With the exception of Patient 1, the score correctly classifies the electrogram uncertainty in line with the expert judgement. In Figure 4 we show an example of an uncertainty map drawn using our uncertainty measure, which, in this case, identifies a region of high uncertainty.

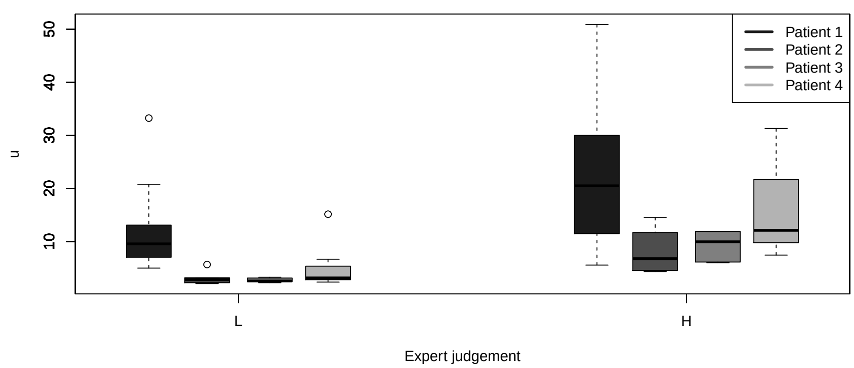

Fig. 3 Boxplots of the uncertainty measure by patient and by corresponding expert judgement. L is for Low uncertainty and H is for High uncertainty.

5 Discussion

To the best of our knowledge, this is the first attempt to elicit the uncertainty in the context of LAT determination. The automated mechanism should enable rapid real-time feedback of electrogram recording quality to medical staff during the data

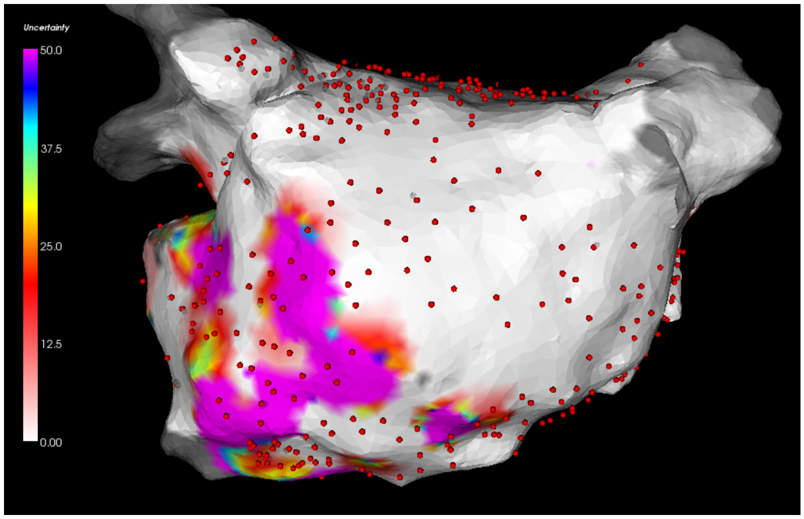

Fig. 4 Uncertainty map as it would be provided to the cardiologist to inform her of the confidence level of the measurements that she is basing the surgery on.

collection process and allow them to collect additional recordings in regions of high uncertainty. Although the measure correctly separates those electrograms with high and low uncertainty as judged by the expert, the separation is patient-specific. We aim to further extend this uncertainty measure by identifying a method to normalise the measure as well as augment it with additional properties of deflection morphology, signal-to-noise ratio of the electrogram, and relationship of identified deflections to those in other nearby electrograms considered to have low uncertainty.

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References

Garthwaite PH, Kadane JB, O'Hagan A (2005) Statistical methods for eliciting probability distributions. Journal of the American Statistical Association 100(470):680–701