Local Conduction Velocity Estimation during Wavefront Collisions and Reentrant Scenarios

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Abstract

Conduction velocity (CV) is an important electrophysiological biomarker for identifying slow-conducting cardiac regions related to pro-arrhythmic behavior. Measurement of CV is challenging during atypical or irregular activation patterns, such as those present during tachycardia and fibrillation because of the complexity of the underlying mechanics. We propose an approach for CV estimation designed for taking into account reentries and wavefront collisions. The algorithm is based on a set of constraints imposed on the velocity vector fields. The performance of the proposed algorithm was evaluated against the reference inverse spatial gradient algorithm by using an eikonal reentrant computational model over a left atria anatomy with different mesh resolutions and complexity of the propagation patterns. Our newly proposed CV mapping is able to identify anchoring zones and the collision of wavefronts without an overestimation of these regions. The performance of our proposed method does improve the reference inverse spatial gradient, with an increased percentage of nodes in which CV is estimated correctly (60.8 ± 7.1 % vs 78.1 ± 10.7 %).

1. Introduction

Conduction velocity (CV) is an electrophysiological measure which quantifies the velocity and direction of propagation of an action potential wavefront through excitable tissue. It can provide critical quantitative information about the structure, fiber orientation, and properties of the intrinsic substrate of the myocardium; all of which can aid in the elucidation of potential arrhythmogenic mechanisms [1].

At first glance, the method for calculating CV appears straightforward; detect the activation of a wavefront at various times and divide the distance travelled by the time interval. However, due to the complexity of the electrical activity during fibrillatory rhythms, in which trajectories and velocities can be chaotic, estimating conduction velocity is challenging. Most CV algorithms require the accurate annotation of local activation time (LAT) [2]. Moreover, during fibrillation, there are mainly two problems to cope with [3]. Firstly, during re-entrant patterns, the earliest activated area and the latest activated area are close to each other, resulting in an artificial propagation delay and wavefront orientation. Second, the existence of multiple simultaneous wavefronts colliding with each other produces in these regions a sink with no effective propagation where it is possible to overestimate the propagation delay. An example of both mechanisms can be seen in Figure 1.

In this work, a method based on the spatial gradient over surfaces was developed to estimate the propagation velocity, using constraints to account for the above situations in spatio-temporal distributions of multiple wavefronts, during rhythms of different complexity. The technique was tested in eikonal-diffusion computer simulations on a 3D mesh representing the atrial anatomy.
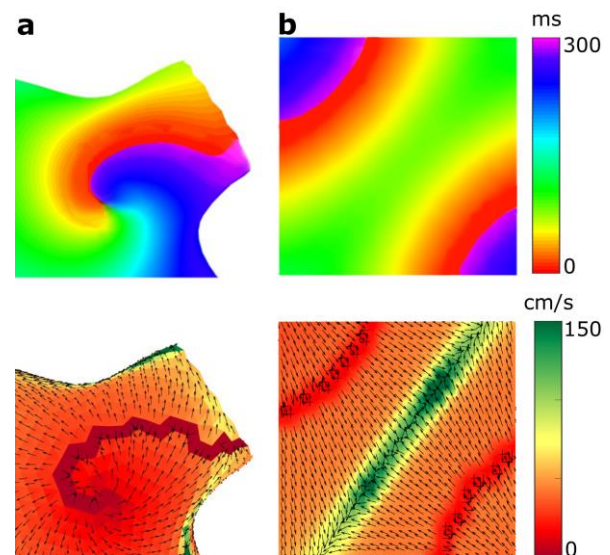

Figure 1. Example of LAT (top) and CV and estimated local propagation direction (bottom) distribution with complex patterns. (a) CV underestimation during a re-entrant pattern and (b) CV overestimation during wavefronts collision.

2.   Methods

2.1.   Conduction Velocity estimation

The objective of the proposed algorithm is to obtain the local CV belonging to effective propagations using the propagation direction vector field [4-5] on 3D meshes through the spatial gradient:

$$T(x,t) = \nabla LAT / \|\nabla LAT\| \qquad (1)$$

The 3D vector field T is composed of unit vectors that are normal to the wavefront propagation defined for the LAT map.

Effective propagations are defined as local propagations that do not include a source or sink at the measured location, or in other words, the LAT sequence in an area whose propagation direction vector field is smooth and shows almost no variation in the angles in adjacent vectors. Figure 2a shows an example of effective propagation in a triangulated portion mesh where each adjacent vector has a similar propagation direction. A collision between wavefronts produces large variations of the angle between adjacent vectors as is displayed in Figure 2b.
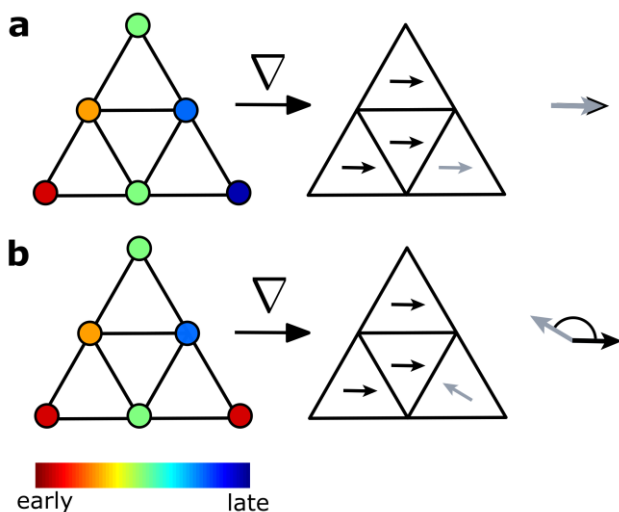

Figure 2. Example of LAT distributions and their propagation direction vector fields applying the spatial gradient. (a) Local effective propagation with no angle variation. (b) Collision shows a large angle variation between adjacent vectors.

To obtain which region has an effective propagation, the angle between adjacent faces on the 3D mesh was obtained. First, the direction vectors of the adjacent triangles of each face of the mesh were projected as:

$$v = n \times (u \times n) \qquad (2)$$

where v is the projected direction vector u of the 1-ring around the central face which has normal vector n. Then, the angles were obtained using the four-quadrant inverse tangent:

$$\theta = \text{atan}(\|u_c \times v\|, u_c \cdot v) \qquad (3)$$

where u_c is the central direction vector and v are the adjacent projected direction vectors. Since measured differences in propagation angle are dependent on the resolution and distance between vertices of the mesh, we imposed a threshold in degrees per millimeter of the face edge to make the threshold independent of the mesh resolution. A lower threshold of 10 degrees per mm was set.

Local CV estimation was calculated in the areas of effective propagation with the inverse spatial gradient:

$$CV = 1/\|\nabla LAT\| \qquad (4)$$

CV was estimated in areas of not effective propagation using an interpolation of Radial Basis Functions (RBFs) using the geodesical distances of the manifold instead of Euclidian distances. In order to compare this approach, the inverse spatial gradient (eq. 4) was also calculated directly in the entire geometry.

2.2.   Validation

To generate benchmark data to validate CV estimation, a dataset of LAT distributions was created by solving the eikonal-diffusion equation for the initiation of re-entrant cardiac propagations [6].

This approach allows determining activation times based on the tissue's conduction properties and can handle anatomical or functional reentries and wavefront collision. Such an approach also allows setting a CV distribution a priori, which means that the LAT distribution obtained must reflect these settings, providing a referenced CV.
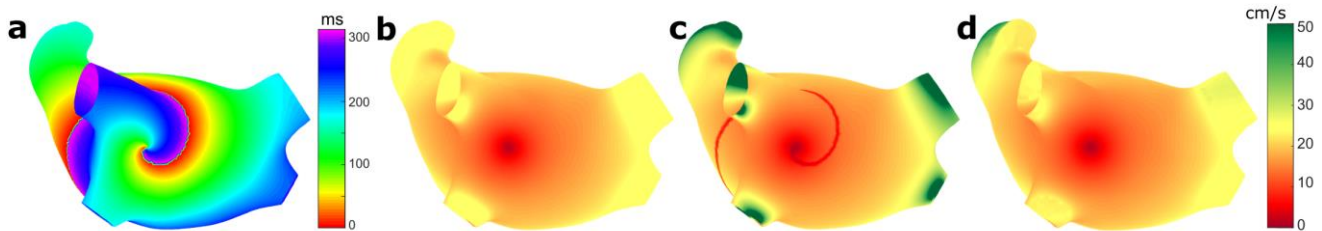
Figure 3. Performance of the CV estimation on a reentry simulation. (a) LAT distribution generated using eikonal-difussion equation (b) imposed CV map to create a reentry around low CV distribution in the eikonal-difussion approach. (c) CV estimation using the inverse spatial gradient directly. (d) Proposed CV estimation using effective propagation regions to interpolate the rest of areas.

Eight reentrant scenarios with 1 to 8 singularities were created setting a CV distribution a priori over on a 3D mesh representing left atrial anatomy. Solutions were obtained with a fine resolution mesh with regular triangles of 0.2 mm^2 area with 24863 vertices. RBF interpolation was used to project the data to 12 coarse meshes (0.4 – 44.3 mm^2, with 17071 – 180 vertices). The error between the imposed CV to eikonal-diffusion solutions and the CV estimation was computed as the percentage of nodes of the mesh that exceed 20% of the CV difference. The t-student test was used to evaluate the null hypothesis of differences between resolutions using CV estimation with the inverse spatial gradient and proposed estimation (inverse spatial gradient and interpolation), p-values < 0.05 were interpreted as significative.

3. Results

CV distributions were estimated in each scenario. In Figure 3, an example is depicted using the methodology in the case of one reentry. LAT distribution was generated using an imposed CV map in the eikonal-difussion approach as shown in Figure 3a-b. In Figure 3c, the result of applying the inverse spatial gradient directly on the distribution of LATs is shown. It can be observed that the inverse spatial gradient estimation results in an artificial propagation delay in the site of the reentrant propagation wavefront, with velocities lower than 5cm/s because the head and the tail of the propagation vector are close to each other. On the other hand, at the pulmonary vein area, there are colliding wavefronts since propagation arrives from different directions. At these propagation sinks where there is no effective propagation, the CV is overestimated by, with velocities above 150 cm/s at some nodes. In the proposed methodology (Figure 3d), both areas are interpolated using the CV estimation of effective propagation regions, reducing these estimation errors.

Figure 4 shows the progression of the error made with respect the validation dataset grouping the different complexity scenarios according to the resolution of the mesh.
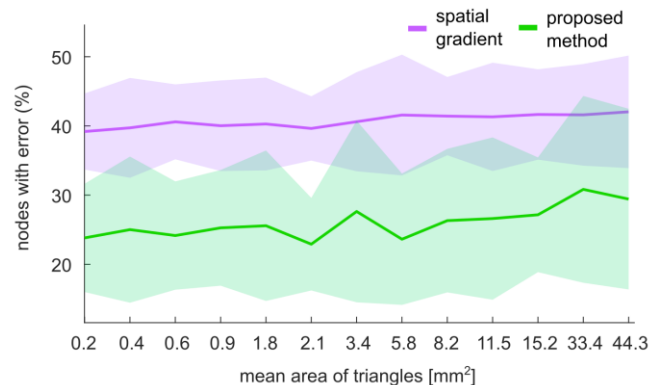

Figure 4. Progression of the percentage of error made with respect to the validation dataset grouping the different complexity scenarios according to the resolution of the mesh.

In the case of the mesh with more resolution, the percentage of nodes with error using the inverse spatial gradient directly was 36.1 ± 6.6 %, this error increased to 42.3 ± 7.4 % with the coarse geometry with less resolution. In the proposed methodology, the percentage of nodes with error was 15.3 ± 7.3 %, this error increased to 28.8 ± 14.1 % respectively. The percentage of vertices with error was reduced by 14.7 ± 3.6 % on average across all resolutions.

At a resolution of 3.4 mm^2 (3345 vertices) the differences between the two methodologies were not significant according to the t-test, although the error rate was always lower with the proposed methodology.

4. Discussion

A novel methodology to estimate conduction velocity

during irregular cardiac activation patterns has been proposed and tested its applicability in different scenarios. The concept of CV estimation just in regions of effective propagation considering the difference of angles of the propagation direction vector field has been introduced.

A challenge in estimating CV distributions is that it is currently very difficult to compare between methods due to a lack of gold standards. There is a clear need for reference data to evaluate algorithms, with special relevance in the case of fibrillation scenarios. Simulation computations where LAT is known everywhere is probably the easiest solution, but in a more complex scenario classical CV estimation methodologies [2] may have problems with multiple wavefronts and collisions between them. Therefore, the best approach seemed to use an eikonal-diffusion solution for reentries [6] that would find the closest solution for an imposed CV distribution.

On the other hand, another difficulty apart from the estimation of CV, is typically a lack of precision in defining the activation times. Determining the activation sequence in an arrhythmic process or fitting data always require that the obtained results be interpreted cautiously [2].

Future studies to be included in these analyses would be to test the effect of estimation in more complex realistic scenarios where pathological substrate exists, such as conduction anisotropy and the existence of regions of fibrosis. A strategy capable of reconstructing coherent maps and interpreting CV within the current mapping scenario is a promising tool for comprehending arrhythmic mechanisms and assisting in the accurate diagnosis and treatment of arrhythmias. These new concepts presented here should be considered and incorporated into further research.

5. Conclusions

We present a novel algorithm to quantify CVs that has been designed to carefully account for scenarios present during arrhythmias, such as reentrant activity or wavefront collision. This algorithm outperforms the classical inverse gradient approach by imposing restrictions on the inhomogeneity of the detected activation directions and allows for a lower error in the estimation of CVs in the setting of complex activation patterns.

Acknowledgements

Conflict of interests

AMC, MSG and IHR are co-founders and shareholders of Corify Care SL.

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