# A Comparison of Methods for Fiber Direction Estimation from Electrograms

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**Abstract**

*The estimation of conductivity parameters from Electrograms (EGMs) could provide valuable insights into the underlying electrophysiological mechanisms of cardiac arrhythmia. However, accurate estimation requires knowledge of the fiber orientation. Despite numerous proposed methods for determining the fiber direction from EGMs' derived activation and voltage maps, the most accurate approach remains uncertain. This study presents a performance evaluation of the different estimation techniques employing data generated from four distinct monodomain cardiac models mimicking the complex fiber distribution in Bachmann's bundle, the left atrium, and the left ventricle. The findings reveal that approaches based on ellipse-fitting to the projected components of local conduction velocity or slowness vectors, computed from an activation map, offer the highest accuracy. Nevertheless, the methods are susceptible to fiber direction heterogeneity across the myocardial wall.*

## 1. Introduction

The propagation of the action potential across the cardiac tissue enables the coordinated contraction of cardiomyocytes. These elongated cells are electrically coupled and mechanically adhered forming cardiac fibers. The orientation of the fibers plays a critical role in guiding the activation wavefronts, with faster conduction along the longitudinal fiber direction compared to the transverse direction. As a result, myocardial tissue exhibits anisotropic conduction properties [1].

Recording changes in transmembrane current provides valuable insights into cardiac activation propagation and aids in guiding heart arrhythmia treatment. By placing an electrode array on the epicardium or endocardium, electrograms (EGMs) are acquired, which can be translated into voltage or local activation time (LAT) maps for spatial visualization [2]. Voltage maps display the potential recorded by each electrode at a specific time, while LAT maps illustrate the activation time of underlying cells. Parameters such as conduction velocity (CV) vectors can be derived for enhanced map interpretation. Nonetheless, in pursuit of more robust parameters, efforts have been made to estimate local tissue conductivity from EGMs employing cardiac models [3, 4]. Due to conduction anisotropy, accurate parameter estimation requires prior fiber direction knowledge. Therefore, several approaches have been proposed to derive the fiber direction from EGMs, differing in the type of data employed and spatial resolution [5–10]. These methods have been validated under diverse yet overly simplified conditions, hampering the selection of a suitable approach for clinical and research applications.

Therefore, this paper aims to identify the most accurate and robust method for fiber direction estimation using epicardial EGMs by evaluating its performance in cardiac models.

## 2. Overview of methods

This study evaluates the performance of eight different methods for estimating the fiber direction, an overview of which is presented in Table 1. These methods vary in spatial resolution, with some providing a single fiber direction estimate for an entire electrode array (global) while others an estimate per electrode (local). For a consistent comparison, the local estimation approaches were adjusted to match the global resolution and all were implemented in MATLAB ver. R2020b. Brief descriptions of the methods are provided below, with more detailed information available in the corresponding references [5–10].

### 2.1. Potential maxima

The potential maxima (PM) method, proposed by Taccardi et al., employs a voltage map recorded 5 to 10 ms after epicardial stimulation [5]. The line joining the two positive potential maxima that appear on either side of the stimulation site aligns with the cardiac fibers in the epicardium area covered by the electrode array.

Table 1: Authors, approaches, resolutions and abbreviations of the fiber direction estimation methods [5–10].

| Author | Method approach | Resolution | Abbreviation |
|---|---|---|---|
| Taccardi et al. | Potential maxima | Global | PM |
| Muzikant et al. | Ellipse fitting to stimulus isopotential | Global | EIP |
| | Ellipse fitting to activation isochrone | Global | EIC |
| Linnenbank et al. | Average conduction velocity vector | Global | ACV |
| de Vries et al. | Ellipse fitting to conduction slowness vectors | Global | ECS |
| Houben et al.. | Ellipse fitting to conduction velocity vectors (PSF) | Local | ECVPSF |
| Roney et al. | Ellipse fitting to conduction velocity vectors (Geometric Model) | Local | ECVGM |
| | Linear transformation from elliptical to circular wavefront | Local | LTEC |

## 2.2. Isopotential or isochrone ellipse fitting

Muzikant et al. observed elliptical shapes in the 5 mV isopotential in a voltage map and 1.5 ms isochrone in a LAT map obtained after epicardial pacing, with the major axis following the fiber orientation [6]. This led to the development of two estimation methods: ellipse fitting to stimulus isopotential (EIP) and to activation isochrones (EIC). An ellipse is fitted to the data using the least squares (LS) errors technique described in [8, 11], and the rotation angle of the fitted ellipse corresponds to the fiber direction.

## 2.3. Average CV vector method

The average CV vector (ACV) method, proposed by Linnenbank et al., computes the CV vector for each electrode and groups them into ten bins according to their directions [7]. The direction of the bin with the highest average CV magnitude is considered the fiber direction. The Polynomial Surface Fitting (PSF) approach is used to derive the CV vectors, as detailed in [12], in which the LAT values of a 3-by-3 electrode subgrid are fitted to a quadratic surface using an LS algorithm. Subsequently, the CV vector at the central electrode is derived from the gradient of the fitted surface.

## 2.4. Ellipse fitting to conduction vectors

The fiber direction can also be estimated by fitting an ellipse through the LS errors technique to the projected components of the CV or conduction slowness (CS) vectors, derived from the gradient of the LAT maps and known as the reciprocals of the CV vectors. The ellipse's minor axis in the ellipse fitting to CS vectors (ECS) method, described by de Vries et al., indicates the fiber orientation [8]. Whereas in the ellipse fitting to CV vectors computed through PSF (ECVPSF) or with a geometric model (ECVGM) approaches, proposed by Houben et al. and Roney et al. respectively, the fiber direction is the major axis of the fitted ellipse [9, 10]. The ECVGM method employs a planar wavefront model to find the CV vectors.

## 2.5. Linear transformation from elliptical to circular wavefront

The linear transformation from elliptical to circular wavefront (LTEC) method, described by Roney et al., solves the geometrical model for a circular wavefront through a non-linear LS approach [9]. Nonetheless, given the elliptical nature of the activation wavefront, caused by conduction anisotropy, the coordinates of an elliptical wavefront are transformed to those of a circular wavefront. These two sets of coordinates are related through the rotation angle of the elliptical wavefront, specifying the fiber direction.

# 3. Performance evaluation framework

The accuracy of the fiber direction estimation methods was compared using simulation models replicating four cardiac wall structures. In the following section, the evaluation datasets and performance metrics are explained.

## 3.1. Datasets

Four datasets were generated using four distinct configurations of a Courtemanche-based monodomain model, each representing a fiber architecture found in the heart wall, using the implementation provided by [8, 13]. Despite variations in architectural features, all configurations had layers consisting of a $N_x$ x $N_y$ = 140 x 140 lattice with homogeneous conductivity and axially symmetric anisotropy. The following parameter values were held constant and chosen based on previously established models [3, 4]: longitudinal conductivity ($\sigma_l$ = 1.2 mS/cm), anisotropy ratio ($\alpha = \sigma_l/\sigma_t = 5$), extracellular conductivity ($\sigma_e$ = 1.1 mS/cm), capacitance ($C$ = 1 $\mu$F/cm$^2$), distance between cells in the x, y, and z direction ($\Delta x$, $\Delta y$, $\Delta z$ = 100 $\mu$m), stimulation current ($I_{st}$ = 40 pA/pF) and time ($\Delta t_{st}$ = 2 ms), and heartbeat duration ($\Delta t_{beat}$ = 1 s).

The first configuration comprised a single layer serving as the 2D reference. The remaining three configurations were simulated using a 1 mm thick tissue slab consisting of

ten layers ($N_z = 10$). The second configuration replicated the unimodal fiber direction distribution in Bachmann's bundle, achieved by assigning identical fiber orientations to the ten layers. The third configuration mimicked the bilayer structure characteristic of the left atrium, with one fiber direction in the five upper layers and the perpendicular direction in the five lower layers of the tissue slab [14]. The fourth model imitated the transmural fiber rotation in the ventricular wall, wherein the epicardial fibers are oriented perpendicular to the endocardial fibers [5].

The measuring setup was modeled as an 8 x 8 electrode array with a 2 mm interelectrode distance, placed 1 mm above the epicardium. The LAT was defined as the time when the transmembrane potential reached -40 mV, minimizing the impact of annotation errors on the method's performance. Each dataset included 36 simulated unipolar EGMs, and corresponding LAT maps, generated by varying epicardial fiber directions and pacing sites.

## 3.2. Performance measures

All methods output the fiber direction as the angle between the fiber and the x-axis. The accuracy of the methods was compared using the mean absolute error (MAE) of estimation, ranging from 0º to 90º due to the anisotropy symmetry, and was calculated as the average of the absolute differences between the estimated angle $\hat{\theta}_i$ and the true angle $\theta$ for the evaluation dataset of size $k$ = 36,

$$MAE = \frac{1}{k}\sum_{i=1}^{k}|\hat{\theta}_i - \theta|. \quad (1)$$

The variability of the methods was assessed with the maximum and minimum non-outlier absolute errors. An outlier was defined as an error value that is more than three scaled median absolute deviations from the median error.

## 4. Results and Discussion

Owing to conduction anisotropy, the epicardial wavefront takes on an elliptical shape as observed in the simulated LAT maps in Fig. 1. When fiber orientation is consistent across layers the wavefront mirrors the epicardial fiber direction. Differently, in the bilayer and transmural fiber rotation configuration, the wavefront undergoes a counterclockwise rotation following the fiber direction of deeper layers due to intramural activation propagation. Additionally, an initial local wavefront acceleration, manifested as a dimple-like inflection in the wavefront profile, is visible in the transmural fiber rotation configuration recordings. This transverse acceleration and inflection have been observed in canine ventricles [5]. The simulated LAT maps highlight how fiber direction heterogeneity across layers affects epicardial activation, potentially impacting the fiber direction estimation methods. Therefore, the tissue models utilized in this study provide a more authentic portrayal of the wavefront propagation compared to the frequently employed 2D or unimodal configurations. However, future studies should consider factors such as the imbrication angle, larger ventricular wall thickness, and heterogeneous conductivity properties and fiber direction within and between each layer for even more clinically applicable results [5].

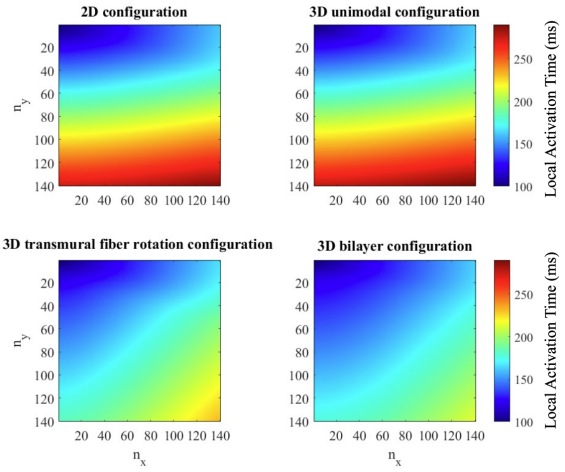


Figure 1: Comparison of the epicardial LAT maps generated by four cardiac model configurations with $\theta_{epi}$ = 0º.

The MAE and maximum and minimum non-outlier error of each method standardized to compute a single fiber direction estimate from one 8 x 8 LAT or voltage map are shown in Fig. 2.

When using 2D and unimodal configuration data, methods employing ellipse fitting to CS or CV vectors, ECS, ECVPSF and ECVGM, have the lowest MAE values. Nonetheless, their accuracy diminishes with bilayer and transmural fiber rotation data. This suggests that the approaches might estimate the degree of wavefront rotation observed on epicardial recordings. Although the EIC method shows high accuracy, it is accompanied by considerable variability. An elliptical-shaped isochrone can be found anywhere from 2 to 20 ms after stimulation. Thus, isochrone selection requires a visual examination of the maps, which is inefficient for processing large volumes of data or real-time applications. Potential-based methods, EIP and PM, consistently demonstrated high MAE values across all configurations, indicating the unpredictable nature. These approaches rely on features that appear in voltage maps at specific time points. Automatic snapshot time selection is prone to errors, making them unsuitable for clinical applications. ACV and LTEC methods also exhibited suboptimal performance. ACV's estimation error increases with smaller map sizes due to bin emptying, requiring a minimum map size of 14 x 14 [7]. The LTEC method

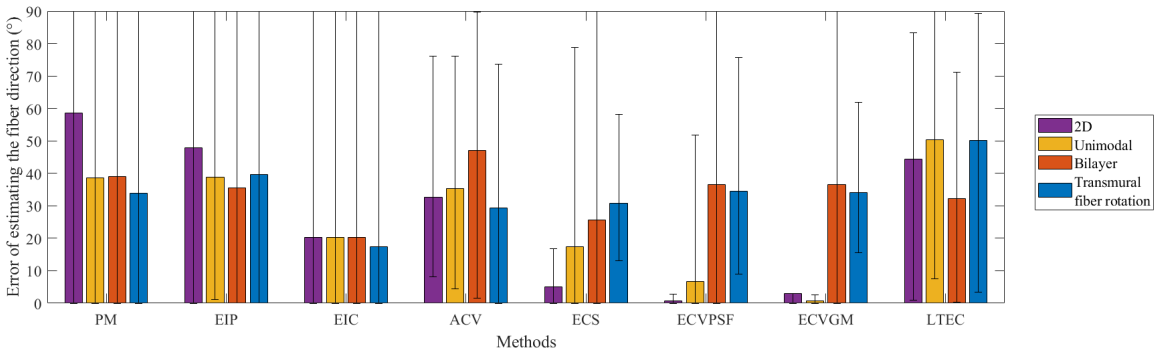


Figure 2: Comparison of mean absolute error, along with the maximum and minimum non-outlier errors, in fiber direction estimation methods.

is affected by ambiguously defined constraints and initial parameter approximations. Additionally, as it is based on fitting data to an elliptical wavefront model its applicability is limited to scenarios where a purely elliptical-shaped wavefront is present.

The ECS, ECVPSF and ECVGM methods' accuracy could improve by increasing the map size through interpolation techniques, employing multiple maps recorded after pacing at different sites, mitigating the impact of wavefront direction on the outcomes [8], or using endocardial recordings or intramural pacing, accounting for the intramural signal propagation. Additional analysis of these aspects is presented in [15].

## 5. Conclusion

The heterogeneity of fiber direction across the heart wall affects epicardial wavefront propagation, thereby impacting the performance of the fiber direction estimation methods. Approaches based on ellipse fitting to CS or CV vectors are the most promising ones [8–10], as they do not rely solely on the elliptical shape of the wavefront. Future research should focus on incorporating intramural signal propagation considerations for enhanced estimation.

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