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Identification of Action Potential waveforms

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Abstract— Waveform analysis of oscillatory signals is crucial in the study of electrical processes in biomedical engineering. FMM is a simple parametric model that provides accurate parameter estimators, which are physically interpretable. The FMM parameters potential is shown in this work by solving two classification problems regarding neurons' action potential curves in a simulated experiment.

I. INTRODUCTION

Features of oscillatory waveforms are related to physiological processes. This work analyzes Action Potential (AP) curves which measure the neuron's potential difference due to an external stimulus, and that exhibit oscillatory patterns. The electrode locations or the variety of cell types, among others, result in different waveforms, see Figure 1. Also, overlapping spikes configurations may arise when recording APs from many neurons simultaneously. As a result, three main AP types can be differentiated: monophasic, biphasic, and multiphasic, see Figure 1. Cell-type characterization and overlapping appearance are interesting challenges in Neuroscience. The adequacy of the FMM wave decomposition approach to analyze APs was demonstrated in [1].

This works proposes a simulated experiment where a random forest (RF) classifier is conducted to illustrate the FMM parameters' potential classifying neurons' AP curves regarding both type and waveform. An impressive accuracy is achieved in the solution of both problems.

II. METHODS

Next, FMM is described. Let assume that time points are in $[0, 2\pi)$. Let $\boldsymbol{\upsilon} = (A, \alpha, \beta, \omega)'$ be the parameters describing a single FMM signal, defined as the wave: $W(t, \boldsymbol{\upsilon}) = A\cos(\phi(t, \alpha, \beta, \omega))$, where A is the amplitude and $\phi(t, \alpha, \beta, \omega) = \beta + 2\arctan(\omega\tan(\frac{t-\alpha}{2}))$ is the wave phase. α is a location parameter, while β and ω are shape parameters. The $\mathrm{FMM_m}$ is defined as the additive m-component signal plus error model as follows.

Definition 1: $\mathrm{FMM_m}$ model. Let $t_1 < \cdots < t_n$,

$$X(t_i) = \mu(t_i, \boldsymbol{\theta}) + e(t_i) = M + \sum_{J=1}^{m} W(t_i, \boldsymbol{\upsilon_J}) + e(t_i), \text{ where}$$

$(e(t_1), ..., e(t_n))' \sim N_n(0, \sigma^2\boldsymbol{I})$; $\boldsymbol{\theta} = (M, \boldsymbol{\upsilon_1}, ..., \boldsymbol{\upsilon_m})$

- $M \in \Re$; $\boldsymbol{\upsilon_J} \in \Theta_J = \Re^+ \times [0, 2\pi) \times [0, 2\pi) \times [0, 1]$; $J = 1, ..., m$
- $\alpha_1 \leq \alpha_2 \leq .... \leq \alpha_m \leq \alpha_1$
- $A_1 = \max_{1 \leq J \leq m} A_J$

Waveforms are characterized by FMM parameters [1]. A measure of the variance proportion explained by $\mathrm{FMM_m}$, $R^2_m = 1 - \sum_{i=1}^{n}(\mu(t_i, \boldsymbol{\theta}) - X(t_i))^2 / \sum_{i=1}^{n}(X(t_i) - \overline{X})^2$, is used.

Concerning the classifiers, RF facilitates the interpretation and allows euclidean and circular parameters be analyzed together. Accuracy is estimated by a ten-fold cross-validation.

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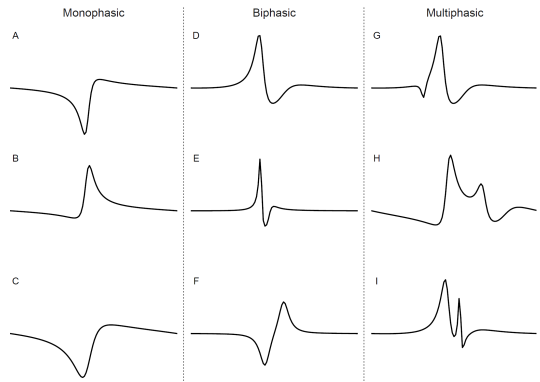

Fig. 1. Simulated AP waveforms

III. RESULTS

The simulated AP database is generated from the signals in Figure 1, described in [1], and $\sigma = 0.1$ is used. A total of 1000 simulated APs are uniformally distributed among the waveforms. The predicted $\mathrm{FMM_m}$, $m = 1, 2, 3$, signals and the corresponding parameters have been obtained.

The two classification problems at hand are much more different than may seem a priori. As noted in [1], the $\{R^2_m\}^3_{m=1}$ promise to be good predictors for the AP type problem as differences between the types are the number of relevant waves describing the signals. Adding the main FMM parameters to these predictors results in a smaller classification error rate, in this database. Still, we have discarded to do that in this problem, since we would face with a clear case of overfitting. It is because different waveforms are within the same AP type, which would be happening to a greater extent in real scenarios. However, main FMM parameters are crucial to differentiate groups in the AP waveform problem, where overfitting risk is very low. Table I shows the results when FMM models with 1, 2 and 3 waves are fitted achieving excellent results for FMM_3 in both problems.

TABLE I

Accuracy and predictors for classification problems.

	3 AP Types		9 AP Waveforms	
	Accuracy	Predictors	Accuracy	Predictors
$\mathrm{FMM_1}$	0.874	R^2_1	0.923	$\boldsymbol{\upsilon_1}$
$\mathrm{FMM_2}$	0.913	R^2_1, R^2_2	0.962	$\boldsymbol{\upsilon_1}, \boldsymbol{\upsilon_2}$
$\mathrm{FMM_3}$	0.977	R^2_1, R^2_2, R^2_3	0.999	$\boldsymbol{\upsilon_1}, \boldsymbol{\upsilon_2}, \boldsymbol{\upsilon_3}$

IV. DISCUSSION AND CONCLUSION

This work shows the good performance of FMM parameters to identify waveforms mainly contributing to cell-type classification and APs overlapping distinction.

References

[1] C. Rueda, A. Rodríguez-Collado, and Y. Larriba, "A novel wave decomposition for oscillatory signals," IEEE Trans. Signal Process., vol. 69, pp. 960–972, 2021.