Geometric Deep Learning

Содержание

1 Problem 8

1.1 Motivation

It is considered a time series classification problem. This task is solved using ODE-RNN model. The ODE-RNN architecture was decribed in [1].

1.2 Problem statement

Given a multivariate time series:

$$\mathfrak{D} = \{(x_i, y_i)\}, \quad i = \overline{1, n}, \quad x_i \in \mathbb{R}^m.$$

The problem of time series intervals classification is solved. We have to define if there is a P300 potential on the EEG interval.

Optimization task:

$$\hat{\theta} = \arg\max_{\theta} L(\theta, \mathbf{X}).$$

1.3 Problem solution

ODE-LSTM is based on standard LSTM architecture but the continuity of hidden state is added. Hidden state of LSTM is a pair $(\mathbf{c}_t, \mathbf{h}_t)$, where $\mathbf{c}_t$ is a long term memory state, $\mathbf{h}_t$ is a hiden state. The function $f_\theta(\mathbf{x}_{t+1}, (\mathbf{c}_t, \mathbf{h}_t), \mathbf{1}) \to (\mathbf{c}_{t+1}, \mathbf{h}_{t+1})$ that updates these states can be described using the following equations:

$$\begin{aligned}
\mathbf{z}_{t+1} &= \tanh(\mathbf{W}_z \mathbf{x}_{t+1} + \mathbf{R}_z \mathbf{h}_t + \mathbf{b}_z) \\
\mathbf{i}_{t+1} &= \sigma(\mathbf{W}_i \mathbf{x}_{t+1} + \mathbf{R}_i \mathbf{h}_t + \mathbf{b}_i) \\
\mathbf{f}_{t+1} &= \sigma(\mathbf{W}_f \mathbf{x}_{t+1} + \mathbf{R}_f \mathbf{h}_t + \mathbf{b}_f + \mathbf{1}) \\
\mathbf{o}_{t+1} &= \sigma(\mathbf{W}_o \mathbf{x}_{t+1} + \mathbf{R}_o \mathbf{h}_t + \mathbf{b}_o) \\
\mathbf{c}_{t+1} &= \mathbf{z}_{t+1} \odot \mathbf{i}_{t+1} + \mathbf{c}_t \odot \mathbf{f}_{t+1} \\
\mathbf{h}_{t+1} &= \tanh(\mathbf{c}_{t+1}) \odot \mathbf{o}_{t+1}
\end{aligned}$$

When shifting from LSTM to ODE-LSTM the above equations are changed as follows:

$$\begin{aligned}
(\mathbf{c}_i, \mathbf{h}'_i) &= \mathrm{LSTM}(\theta_l, (\mathbf{c}_i, \mathbf{h}_i), x_i) \\
\mathbf{h}_i &= \mathrm{ODESolve}(f_\theta, \mathbf{h}_{i-1}, \mathbf{h}'_i, t_i - t_{i-1}) \\
\mathbf{o}_i &= \mathbf{h}_i \mathbf{W}_{\text{output}} + b_{\text{output}}
\end{aligned}$$

The differential equation is solved numerically using fourth order Runge-Kutta methods.

1.4 Data

The data was collected on 60 healthy people. They were participating in a virtual reality game with a neural interface that is based on the classification of P300 potentials. It is considered a binary problem statement. In this dataset both the train and test samples are unbalanced. The class ratio is 1 to $(s-1)$, where s is a number of stimuli. The number of timestamps in the dataset is 56540.

1.5 Code analysis

Code for ODE-LSTM was taken from GitHub repository[1].

1.6 Experiment

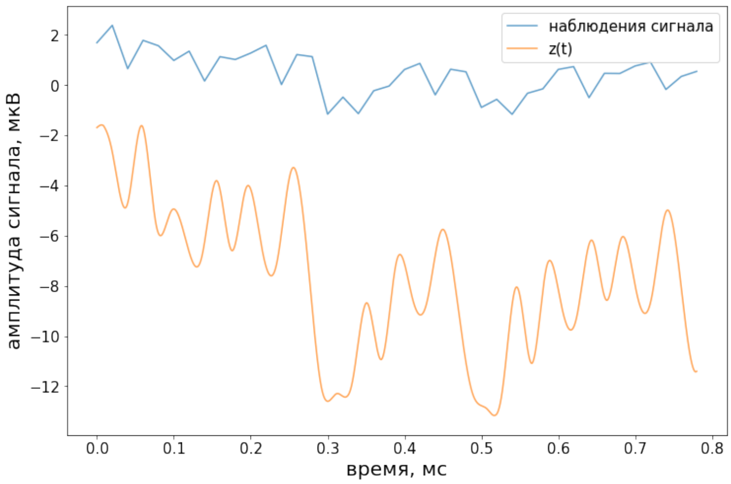

Рис. 1: Time series visualization

Fig. 1 plots P300 time series.
Fig. 2 plots the result of applying ODE-RNN.

[1]https://github.com/Alina-Samokhina/MasterThesis

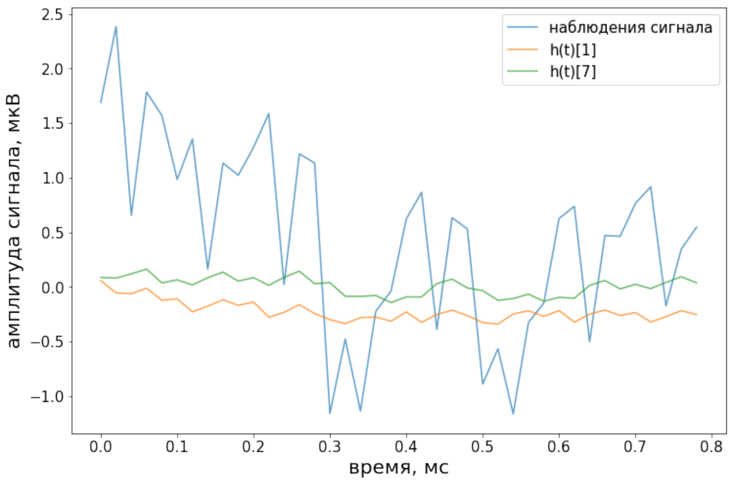

Рис. 2: Result after applying ODE-RNN

Список литературы

[1] Самохина Алина Максимовна. “Непрерывное представление времени в задачах декодирования сигналов”. В: (2021). URL: https://www.overleaf.com/project/6089144e08458454afed6b32.