Analysis of ECG Signal for Optimization of Input Data to the Dynamic Quadratic Neural Unit

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Abstract

The paper is focused on analysis of ECG signal in order to optimize the input parameters of dynamic quadratic neural unit using fast Fourier transform and Wavelet analysis. Optimization of input parameters of neural network allows an efficient adaptation of neural weights and time delay of the quadratic unit. By use of data obtained from the analysis, performance of the network is further observed.

Abstrakt

Práce se zabývá analýzou EKG signálu pro optimalizaci vstupních parametrů dynamického kvadratického neuronu pomocí rychlé fourierovy transformace a waveletové analýzy. Optimalizace vstupních parametrů neuronové sítě umožňují efektivní adaptaci neuronových vah a dopravního zpoždění kvadratického neuronu, jehož vlastnosti jsou dále analyzovány a výstup neuronové sítě je dale pozorován.

Keywords

Dynamic quadratic neural unit (DQNU), neural network, Fourier transform, Wavelet analysis, amplitude, frequency, optimization

Klíčová slova

Dynamický kvadratický neuron (DQNU), neuronová síť, Fourierova transformace, Waveletova analýza, amplituda, frekvence, optimalizace

1. Introduction

Study of bio signals, such as ECG, was proposed in [1] and [2] describes adaptation of Dynamic Quadratic Neural Unit (DQNU) with time delay [3] - a special case of Neural Network (NN). In the adaptation process, values of neural weights and time delay changes in each step of the adaptation process. Initial values of these parameters have influence on the speed of adaptation. DQNU can be briefly described by the following equation:

$$y_{n}(t) = \int_{-\infty}^{\infty} (\mathbf{x}(t)^{T} \mathbf{W} \mathbf{x}(t)) dt =$$

$$= \int_{-\infty}^{\infty} (w_{00} + w_{01} u(t) + w_{02} y(t - T_{d}) + w_{11} u^{2}(t) + w_{12} u(t) y(t - T_{d}) + w_{22} u^{2}(t - T_{d})) dt$$
(1)

In the equation (1) the vector $\mathbf{x}(t)$ represents inputs to the neuron and triangular matrix \mathbf{W} represents weights that have to be adapted:

$$\mathbf{x}(t) = \begin{bmatrix} 1 \\ u(t) \\ y(t - T_d) \end{bmatrix}$$

$$\mathbf{W} = \begin{bmatrix} w_{00} & w_{01} & w_{02} \\ 0 & w_{11} & w_{12} \\ 0 & 0 & w_{22} \end{bmatrix}$$
(2)

In order to reach the optimal input parameters for DQNU, such as initial values of neural weights and time delay, a genetic algorithm was used and results are described in [4], [5]. The neural network uses a combined sine signal as one of the inputs to DQNU and its characteristics have an impact on the performance of NN. Analysis of ECG signal that will be used for the NN for further study can help along with reaching optimal characteristics of sine signal fed into the NN. Fourier transform enables to analyze the signal and in case of ECG it is possible to reveal frequencies and amplitudes present in the signal. These characteristics can be then applied to a sine wave – one of the input signals to the NN.

2. Fast Fourier Transform

Fast Fourier Transform (FFT) represents and efficient algorithm for calculation of discrete Fourier transform and can be used in various applications from data filtering, digital signal processing and solving of partial differential equations.

A piecewise continuous function f(t) defined on interval $t \in (0; a)$ can be defined by a periodic extension with period a:

$$f(t) = \sum_{k=-\infty}^{\infty} c_k e^{i2\pi k \frac{t}{a}}$$
(3)

Function f(t) can be sampled at discrete time $t_j = j \frac{a}{N}$, j = 0, ..., N:

$$f_j = f(t_j) = \sum_{k=-\frac{N}{2}}^{\frac{N}{2}} c_k e^{i2\pi k j \frac{1}{N}}, j = 0, \dots, N$$
(4)

This extension has N + 1 values f_j and therefore N + 1 coefficients c_k can be calculated [6]. Because FFT can reflect only values of all frequencies present in the observed signal but do not give information where frequencies are positioned within the signal, Wavelet Transform (WT) can be used as an additional tool for location of these frequencies. Wavelet transform of a signal x(t) is a time-frequency decomposition that can be represented as a correlation of the signal x(t) with wavelets derived from the mother wavelet $\psi(t)$.

$$y(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) dt$$
(5)

The resulting function y(a, b) is described by two parameters – time shift *b* and dilatation *a* $(a, b \in R, a > 0)$ that determine a frequency spectra of a given wavelet [7], [8].

2.1. Analyzed Signal

Studied ECG signal can be analyzed by FFT in Maple software using adjacent libraries. Calculation is fast and straightforward and using graphical tools, values of amplitude and frequency in the given signal can be observed. For practical use of the NN, two signals undertook the analysis – artificially generated ECG signal (Fig. 1) and real ECG signal (Fig. 2).



Fig. 1. Artificially generated ECG signal – each QRS complex (stroke) is identical



Fig. 2. Real ECG signal

For analysis of ECG signal different wavelet shapes can be used. In this analysis, rectangular shaped wavelet function was used (Fig. 3).



Fig. 3. Wavelet transform shape: blue - mother wavelet, green - scaled and shifted wavelet

2.2. Results of FFT

Fast Fourier transform and Wavelet analysis applied to both signals derived results that are summarized in Table 1.

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		Artificial ECG	Real ECG	
	Amplitude [-]	0.125	0.135	
	Frequency [rad/sample]	10	10	

Table 1. – Results for artificially generated ECG signal and signal of real ECG

Artificial ECG signal and real ECG signal have almost identical values of signal characteristics. These values will be used in DQNU for the sine wave as additional input signal to NN. Spectra to both signals displayed in Fig. 4 show that more non-zero amplitudes are present in the signal. Spectra are symmetrical and only values from the first half are considered. Most significant frequencies lay around 10 rad/sample for both signals.

Three-dimensional plot from wavelet analysis is displayed in Fig. 5 and shows not only frequency values, but position of frequencies in the signal.



Fig. 4. Graphical representation of amplitudes and frequencies in artificial ECG signal (left) and real ECG signal (right)



Fig. 5. Three-dimensional representation of results from wavelet analysis – positions of frequencies in the signal are also displayed – artificial ECG signal (left) and real ECG signal (right)

3. Performance of NN

In order to obtain an idea how the signal from neural network would change according to different parameters of sine wave as an input to the DQNU, several different parameters were set to compare the performance of the network.

For artificially generated ECG signal, constant amplitude of 0.125 was applied and four different frequency values were set for the sine wave: 0.1, 1, 10, 100 rad/sample. Performance for each case can be observed on adjacent Fig. 6.



Fig. 6. Performance of DQNU based on different values of frequency of the input sine signal to the neural network (pink: artificial ECG, blue: neural output)

Similarly, for a constant value of frequency (10 rad/sample), different values of amplitude were set for the sine signal. Performance of the network can be seen in Fig. 7.



Fig. 7. Performance of DQNU based on different values of amplitude of the input sine signal to the neural network (pink: artificial ECG, blue: neural output)

From Fig. 6. and 7. it is visible that both amplitude and frequency that were extracted from Fourier transform analysis of artificial and real ECG signal are somehow limiting values for the network performance. If lower values for the frequency than 10 rad/sample are selected, neural network is not able to follow the signal and the performance is not good. The same can be observed for amplitude, but in the opposite way. Greater the value of amplitude than 0.1 is, bigger oscillations of neural output are achieved. Very same phenomenon occur for real ECG signal and plots will not be displayed in the paper. From tests described above, following initial conditions for both artificial and real ECG were applied:

- Amplitude: 0.1 [-]
- Frequency: 100 rad/sample

The performance of the network for both cases can be seen in Fig. 8. Neural network does not match the ECG signal perfectly in amplitude, however, a periodicity of the DQNU can be observed. For the further research, the ability of the network to determine changes in ECG signal will be observed.



Fig. 8. Performance of DQNU (pink: artificial ECG, blue: neural output); artificial ECG signal (top), real ECG signal (bottom)

4. Summary

From analysis it is possible to obtain main characteristics of ECG signal – amplitude and frequency. These values can be used in sine wave of the input signal to the neural network and each value can influence the behavior of adaptation process in the network. Selection of amplitude and frequency is very crucial in obtaining good adaptation process of DQNU. With optimal initial conditions, DQNU can converge faster and good approximation of the network can be observed.

Further analysis will be based on testing the network with different ECG signals and ECG signals with arrhythmias and its ability to recognize between different signals and classify the disorder in ECG record of the heart.

List of Symbols

neural output	(-)
real signal	(-)
artificial signal	(-)
frequency	(-)
amplitude	(-)
general function	(-)
mother wavelet	(-)
wavelet shifts	(-)
Fourier coefficients	(-)
number of samples	(-)
ij-th weight of neural network	(-)
input signal to neural network	(-)
time delay of the signal	(-)
neural inputs	(-)
neural weights	(-)
	neural output real signal artificial signal frequency amplitude general function mother wavelet wavelet shifts Fourier coefficients number of samples ij-th weight of neural network input signal to neural network time delay of the signal neural inputs neural weights

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