Nové metody a postupy v oblasti přístrojové techniky, automatického řízení a informatiky 2010
Ústav přístrojové a řídicí techniky ČVUT v Praze, Odbor přesné mechaniky a optiky
Technická 4, 166 07 Praha 6

TMD-DQNU PRO MONITOROVÁNÍ ECG

Time-Delay Dynamic Quadratic Neural Unit for Adaptive Monitoring of ECG

Martina Mironovova

Abstract

This paper is focused on adaptation of the novel dynamic neural model (Time-Delayed Dynamic Quadratic Neural Unit) and a novel application prospect to adaptive evaluation of bio-signals. The adaptation learning technique of the neuron will be derived and experimentally verified. The novel prospect of adaptive evaluation of ECG using the neural adaptive model and independent component analysis is discussed.

Keywords: neural model, time delay dynamic neural unit, real time recurrent learning, adaptive evaluation, physiological signals, independent component analysis,

1. INTRODUCTION

Diagnostic and prediction systems are nowadays used in various applications in different fields of study. Medicine, particularly the study of cardiovascular system, is not the exception. The paper is focused on adaptation of continuous time-delayed quadratic dynamic neural unit for the task of ECG prediction and thus for new extensions of the adaptive methodology for arrhythmia detection and classification. Quadratic Neural Unit (QNU) [1]-[3] is a nonconventional neural architecture that can be considered a special class of polynomial neural network or a special neural unit of higher order neural networks that are getting popular today in the field of artificial neural networks [13]-[16]. Continuous Time-Delayed Dynamic Quadratic Neural Unit (TmD-DQNU) [1]-[3] is a non-conventional dynamic single-neuron model. The model has a relatively simple mathematical structure and its approximation qualities of a nonlinear and dynamic behavior are superior to conventional models of neurons due to its quadratic aggregation structure and adaptable time delays.

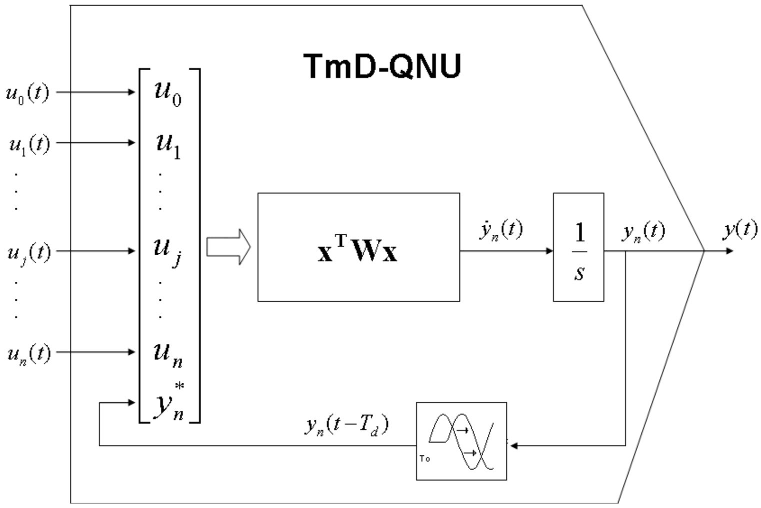

Figure 1: Schematics of continuous-time TmD-DQNU; a plausible understanding to the parallel between biological neurons and quadratic (higher order) nonlinearity was proposed in [1]-[3].

2. TMD-DQNU AND ITS ADAPTATION

A version of the neural model described above and shown in *Figure 1* can be described mathematically as follows. The neural output $y_n(t)$ can be calculated using dynamic equation according to the formula bellow:

$$y_n(t) = \int \left(\mathbf{x}(t)^{\mathrm{T}} \mathbf{W} \mathbf{x}(t) \right) dt$$
$$= \int \left(w_{00} + w_{01}u(t) + w_{02}y(t-T_d{}^2) + w_{11}u^2(t) + w_{12}u(t)y(t-T_d{}^2) + w_{22}y^2(t-T_d{}^2) \right) dt$$

(1.1)

Where column vector $\mathbf{x}(t) = \begin{bmatrix} 1 \\ u(t) \\ y(t-T_d) \end{bmatrix}$ represents inputs to the neuron and upper triangular matrix $\mathbf{W} = \begin{bmatrix} w_{00} & w_{01} & w_{02} \\ 0 & w_{11} & w_{12} \\ 0 & 0 & w_{22} \end{bmatrix}$ represents weights that have to be adapted.

For the adaptation of weights and time-delay, gradient adaptation method, also called RTRL (Real Time Recurrent Learning) [8]–[10] was used. According to this method, updated weights in each step of learning are calculated according to the formula below:

$$w_{ij} = w_{ij} + \Delta w_{ij}, \qquad (2.1)$$

and the weight increments can be calculated as follows:

$$\Delta w_{ij} = \mu e(t) \frac{\partial y_n(t)}{\partial w_{ij}} = \mu e(t) \int \frac{\partial}{\partial w_{ij}} \left(\mathbf{x}^{\mathbf{T}} \mathbf{W} \mathbf{x} \right) dt = \mu e(t) \int \left(\frac{\partial \mathbf{x}^{\mathbf{T}}}{\partial w_{ij}} \mathbf{W} \mathbf{x} + \mathbf{x}^{\mathbf{T}} \frac{\partial \mathbf{W}}{\partial w_{ij}} \mathbf{x} + \mathbf{x}^{\mathbf{T}} \mathbf{W} \frac{\partial \mathbf{x}}{\partial w_{ij}} \right) dt$$

(2.2)

where

$$\frac{\partial \mathbf{x}(t)}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}} \begin{bmatrix} 1 \\ u(t) \\ y(t - T_d^{\,2}) \end{bmatrix} = \begin{bmatrix} \frac{\partial 1}{\partial w_{ij}} \\ \frac{\partial u(t)}{\partial w_{ij}} \\ \frac{\partial y(t - T_d^{\,2})}{\partial w_{ij}} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{\partial y(t - T_d^{\,2})}{\partial w_{ij}} \end{bmatrix}, \qquad \mathbf{x}^{\mathrm{T}} \frac{\partial \mathbf{W}}{\partial w_{ij}} \mathbf{x} = x_i x_j .$$

For example, the weight increment w_{00} can be derived as

$$\Delta w_{00} = \mu e(t) \frac{\partial y_n(t)}{\partial w_{00}} =$$

$$= \mu e(t) \int \left(1 + w_{02} \frac{\partial y_n(t - T_d^{\,2})}{\partial w_{00}} + w_{12} u(t) \frac{\partial y_n(t - T_d^{\,2})}{\partial w_{00}} + w_{22} 2 y_n(t - T_d) \frac{\partial y_n(t - T_d^{\,2})}{\partial w_{00}} \right) dt$$

(2.3)

The adaptation of the time-delay can be derived similarly as in the case of weights as

$$T_d = T_d + \Delta T_d \,, \qquad (2.9)$$

and the time-delay increment can be expressed as follows:

$$\Delta T_d = \mu e(t) \frac{\partial y_n(t)}{\partial T_d}$$
$$= \mu e(t) \int \left(w_{02} \frac{\partial y_n(t - T_d^{\,2})}{\partial T_d} + w_{12} u(t) \frac{\partial y_n(t - T_d^{\,2})}{\partial T_d} + w_{22} \cdot 2 \cdot y_n(t - T_d) \frac{\partial y_n(t - T_d^{\,2})}{\partial T_d} \right) dt. \qquad (2.10)$$

The formula for time-delay increment can be further expressed as shown in formula (2.11) below:

$$\Delta T_d = \mu e(t) \int \left(-w_{02} 2 T_d \dot{y}_n(t - T_d^{\,2}) - w_{12} 2 T_d u(t) \dot{y}_n(t - T_d^{\,2}) - w_{22} 4 T_d y_n(t - T_d^{\,2}) \dot{y}_n(t - T_d^{\,2}) \right) dt \,,$$

(2.11)

because the partial derivative $\frac{\partial y_n(t - T_d)}{\partial T_d} = -\dot{y}_n(t - T_d)$ can be also derived by Laplace domain, as it is obvious from the summary in *Table 2.1*.

Table 2.1: Derivation of time delay partial derivative in Laplace domain

Original	**Laplace**
$y_n(t - T_d)$	$Y_n(s) e^{-sT_d}$
$\dot{y}_n(t - T_d)$	$Y_n(s) e^{-sT_d} s$
$\frac{\partial y_n(t - T_d)}{\partial T_d}$	$\frac{\partial}{\partial T_d} \left(Y_n(s) e^{-sT_d} \right) = Y_n(s) e^{-sT_d} (-s) = -Y_n(s) e^{-sT_d} s$

3. PROBLEM FORMULATION AND SOLVING

Main purpose of the paper is to derive and experimentally verify the adaptation process of TmD-DQNU in order to sample-by-sample monitor changes of dynamics of bio-signals such as ECG. The supervised learning is based on adaptation of neural output signal $y_n(t)$ to real signal $y_{real}(t)$. Error $e(t) = y_{real}(t) - y_n(t)$ of these two signals is used for adaptation of neural weights in weight matrix $\boldsymbol{W}$ and adaptation of time delay T_d. The methodology based on adaptive ECG prediction will be tested on two types of input signals. In the first tested methodology it is assumed that a sine input is fed into the neuron and neural output will be compared with known signal. In the second methodology a time-delayed artificial ECG signal is used as an input of the neuron and neural output is compared to non-delayed artificial ECG signal. Last method works with real ECG signal, where time-delayed ECG signal is fed to the neuron and neural output value is compared with non-delayed ECG signal.

3.1. Model with known real signal

As it was described above, a periodical sine wave $u(t) = \sin(\omega t + \varphi)$ enters neuron and obtained neural output is compared to known signal that has a same structure as neuron has. This can be expressed schematically as is shown in Figure 2 below and known signal is represented by the following equation:

$$\dot{y}_{real}(t) = 0.1 + 0.1\sin(t) - 0.1y_{real}(t-1) + 0.1\sin^2(t) - 0.1\sin(t)y_n^2(t-1) - 0.1y_n^2(t-1) \quad (3.1.1)$$

With ascending time weights wij and time-delay T1 adapt according to equations described in chapter 2 and sine signal on the input of the neuron is transformed to the shape of a real signal.

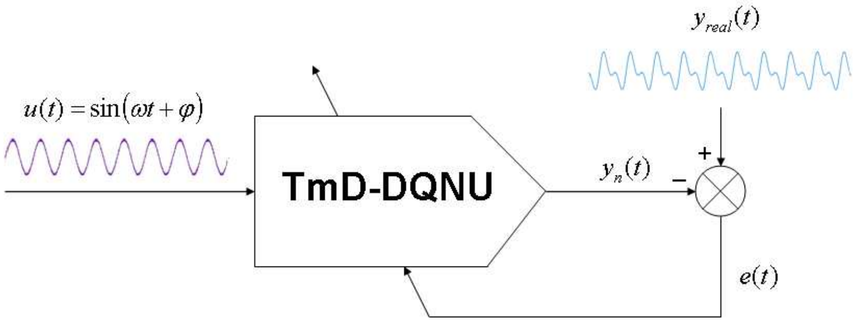

Figure 2: Schematics of continuous-time Time-Delay Quadratic Neural Unit fed by a sine input. The neural output $y_n(t)$ is compared to the real signal $y_{real}(t)$, error signal $e(t)$ is computed and weights and a time delay are adapted.

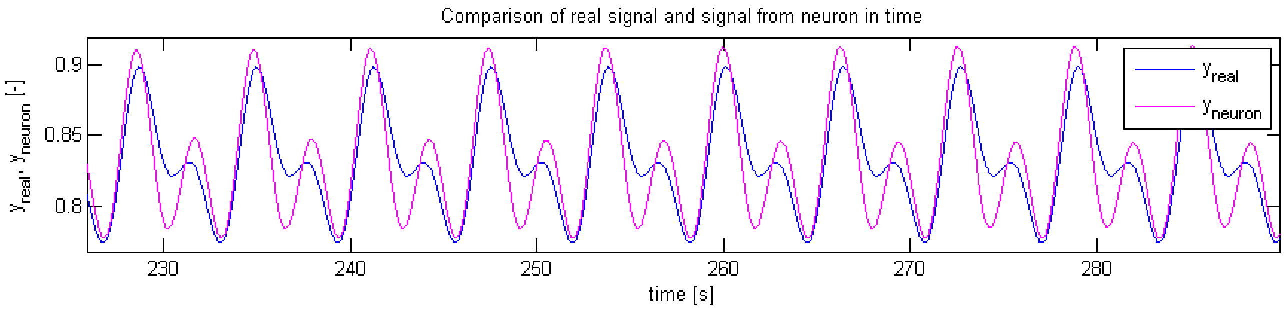

Figure 3: Comparison of neural output signal y_{neuron} and known signal y_{real}. Signal derived from the neuron synchronizes with known signal.

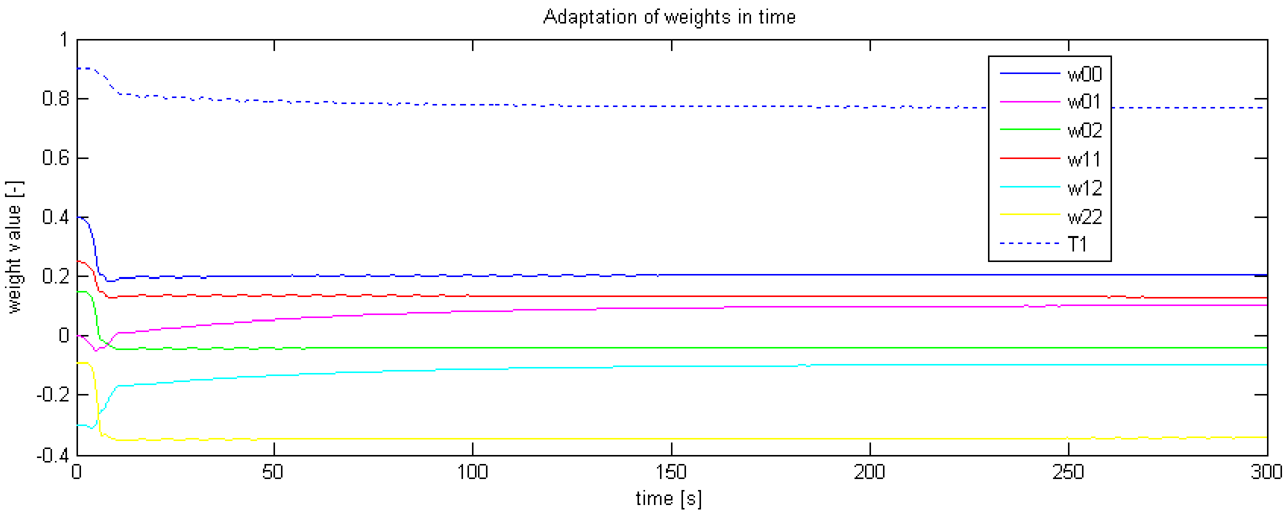

Figure 4: Adaptation of weights and the time delay; all parameters settled on some certain values and do not change in time while changes of known real signal are not present.

Described methodology is simulated and tested in MATLAB Simulink software for time of 300 sec. The neural output compared to the real signal is shown in *Figure 3*. Even if both signals do not match perfectly, it is obvious that neural output synchronized with desired signal, thus the neuron is capable of adaptation to the signal. *Figure 4* displays a progress of adaptation of weights and the time delay; all parameters settled on certain values and do not change rapidly.

3.2. Model with artificial ECG

The second methodology described previously is sketched in schematics shown in *Figure 5*. It represents the artificially created ECG time-delayed signal as input into the neuron. This signal is delayed by a variable time delay, thus this set-up allows a prediction of the current state of ECG to occur.

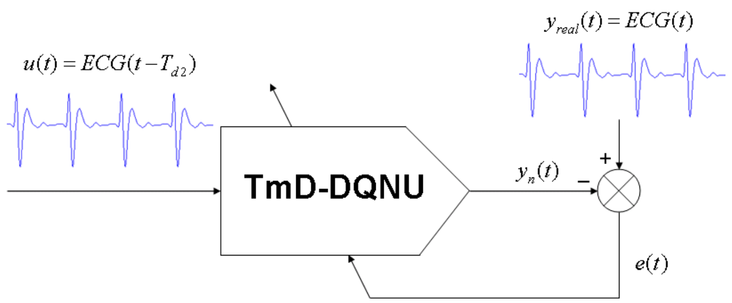

Figure 5: Schematics of a continuous-time Time-Delay Quadratic Neural Unit fed by time-delayed ECG signal input. The neural output is compared to the real ECG signal, error signal is computed and weights and the time delay are adapted. Time-delay of input ECG signal causes a prediction of a current stage of ECG bio-signal.

Neural output value is compared to artificial ECG signal and both behaviors are displayed in *Figure 6*. As in the methodology shown above, neuron is also able to adapt and synchronize to the artificial ECG signal, while all weights and time delays of ECG signal and neural output settle on certain values, as is displayed in *Figure 7*.

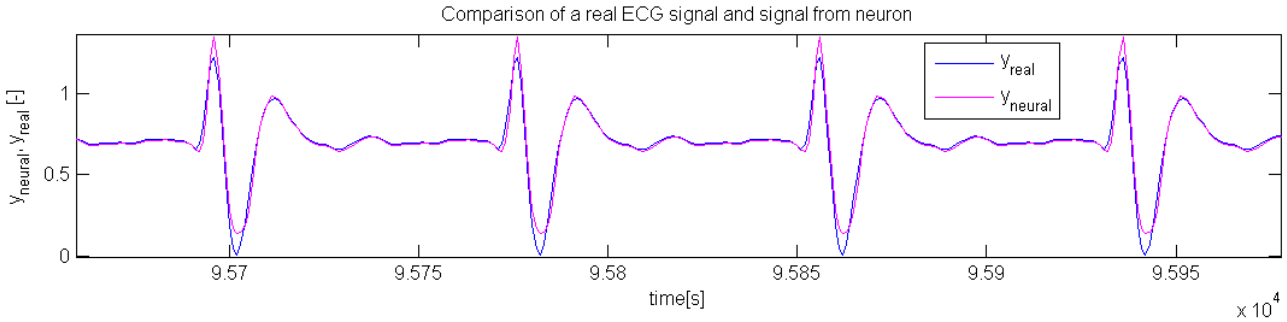

Figure 6: Comparison of neural output signal and artificially created ECG signal. Both signals are concurrent.

Progress of time-delays is shown in *Figure 8* and from the behaviors it is obvious that delay T_1 of ECG input settles to value close to zero, but delay T_2 of neural output fluctuates more frequently and needs more epochs to run in order to settle on some certain value.

For the complete image of model behavior a progress of error is also shown, as can be seen in *Figure 9*. The error between desired ECG value and output from the neuron decreases while time grows.

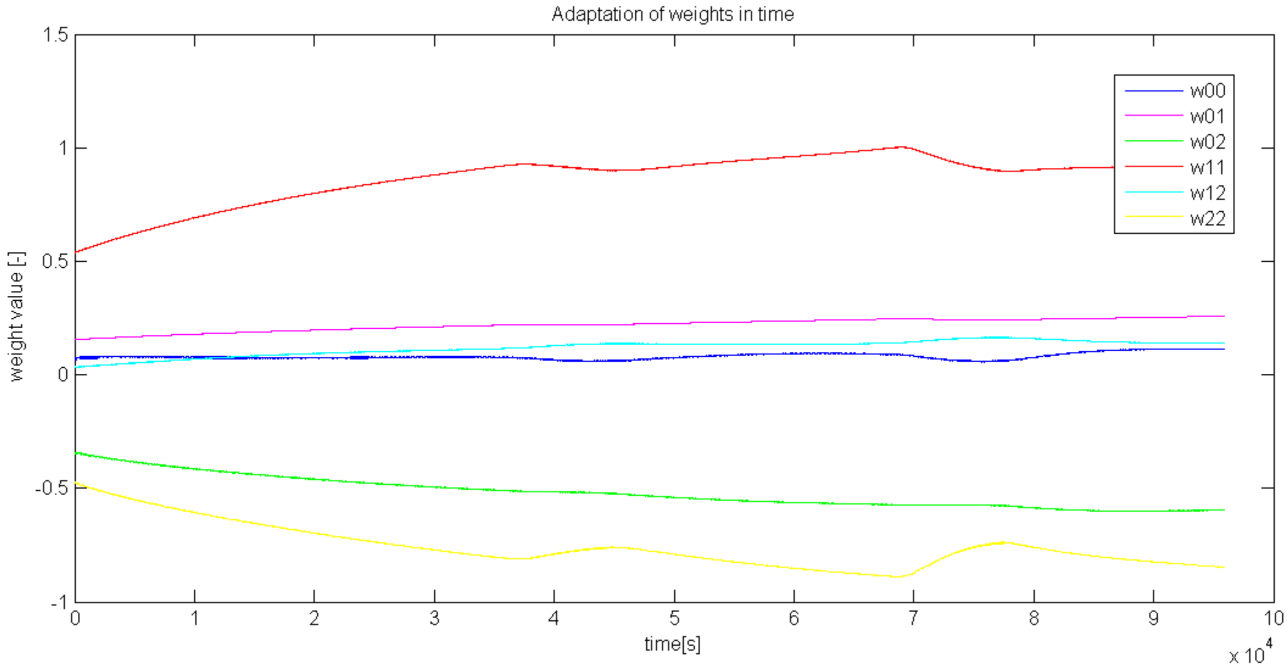

Figure 7: Adaptation of weights while a time-delayed artificial ECG signal is used as an input value to the neuron.

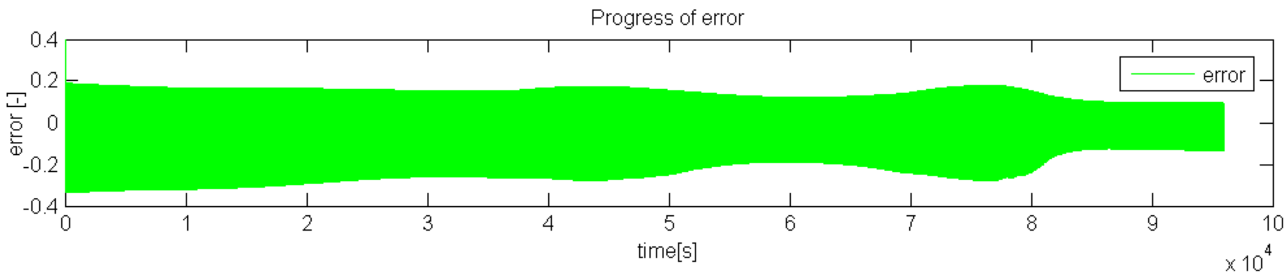

Figure 9: Progress of error signal between neural output value and measured ECG signal during adaptation to ECG. The error decreases with increasing time.

3.3. Model with real ECG

Last tested model used real ECG [12] signal that included arrhythmias. Firstly, neuron learned on part of the ECG signal without arrhythmias and when weights and time-delays of the neuron adapted, a full ECG signal including parts with arrhythmias was fed into the neuron. *Figure 10* shows the schematic sketch of the setup of the model.

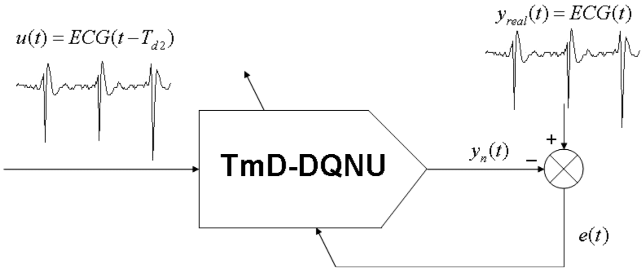

Figure 10: Schematics of a continuous-time TmD-DQNU fed by time-delayed real ECG signal. The neural output is compared to the non-delayed real ECG signal.

The real ECG signal with arrhythmias can be seen in *Figure 11.* The very beginning displays typical sine rhythm and this part served for adaptation process of the neuron. Further a spontaneous VT arrhythmia occurs and is followed by intentional stroke from defibrillator. This stroke starts the VT arrhythmia that is stopped by a second stroke by defibrillator. After this stroke a normal sine rhythm follows.

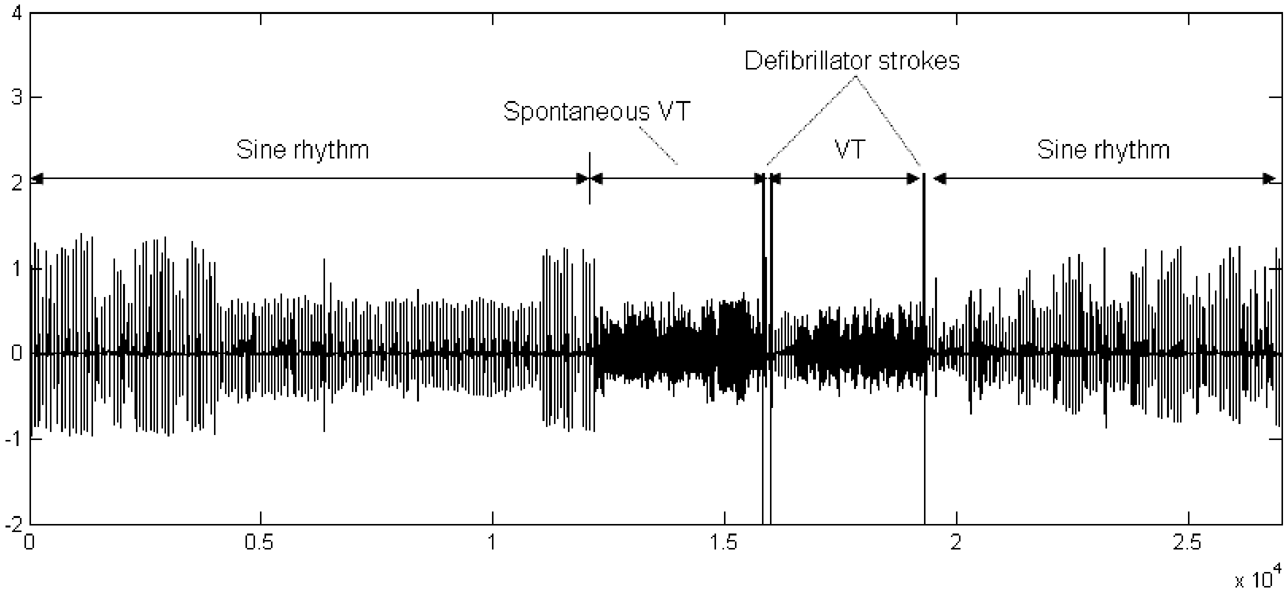

Figure 11: Real ECG record [12] with spontaneous ventricular tachycardia and defibrillator strokes.

In the learning process neuron adapted on a sine rhythm similarly as in case of the artificial ECG signal above. After the whole record of ECG was applied as an input into the neuron and for the comparison at the output, weights experienced change in the adaptation process in the moment when spontaneous VT arrhythmia occurred as can be seen in detail on *Figure 12.* Due to rapid changes in adaptation of weights the presence of arrhythmia can be observed and detected.

Because *Figure 12* shows that some weights are more sensitive to arrhythmia and some weights less, a possible application of the Independent Component Analysis (ICA) [9] will be discussed in further work. With ICA only weights with significant influence can be filtered out and on these bases the differences from standard ECG can be observed.

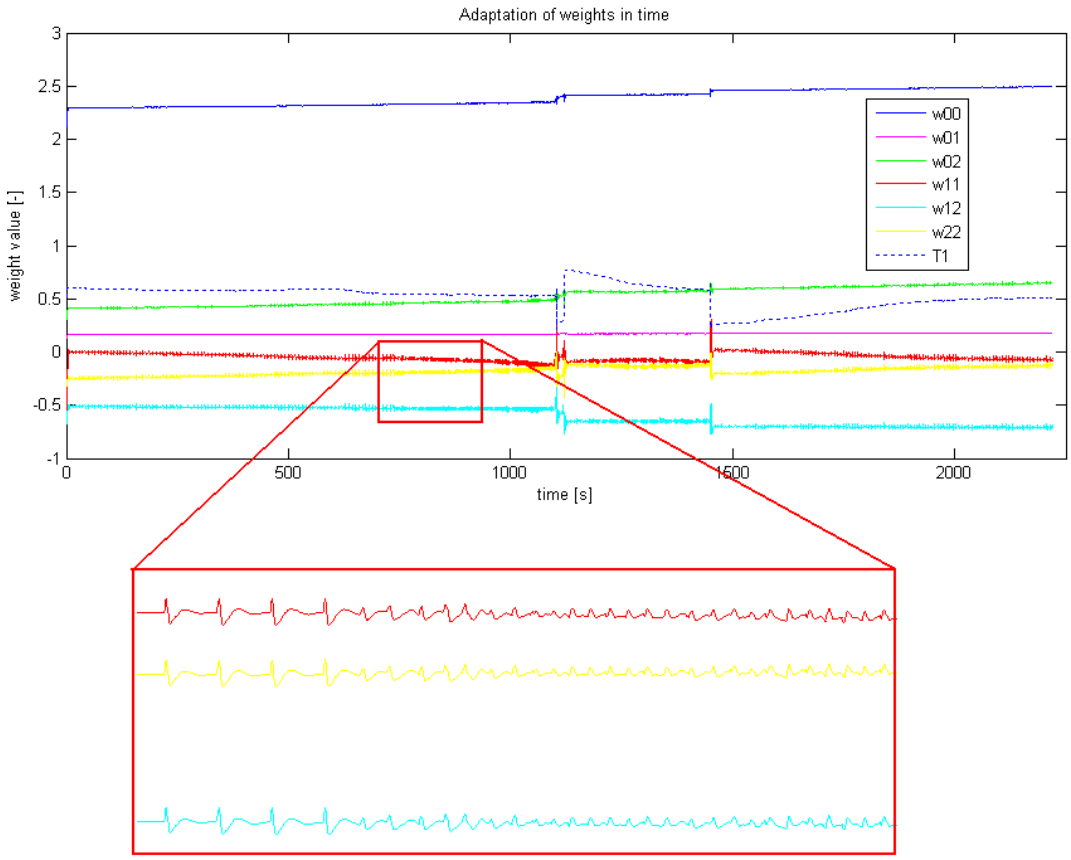

Figure 12: Adaptation of weights and time-delays during run of neuron with ECG record that includes arrhythmias. Huge peaks can be observed in places, where defibrillator strokes were applied. At the beginning of spontaneous arrhythmia it is possible to note changes in adaptation of weights.

RESEARCH PROSPECTIVE

Paper shows derived adaptation of Time-Delayed Quadratic Neural Unit. Future work that concurs on the adaptation is investigation of adaptive evaluation of ECG signal by continuous-time TmD-QNU. Obtained weights from the adaptation process can be observed and further processed using Independent Component Analysis (ICA) [10] and [11]. Because particular weights differ according to the importance and influence on output signal, only weights with significant influence on the signal are considered With ICA analysis, the new adaptive methodology of monitoring and evaluation of complex dynamic may be significantly improved and importantly extended.

ACKNOWLEDGMENT

This work was supported by the Grant Agency of the Czech Technical University in Prague, grant No. SGS10/252/OHK2/3T/12.

REFERENCES:

[1] Bukovsky, I., Bila., J.: “Foundation and Classification of Nonconventional Neural Units and Paradigm of Nonsynaptic Neural Interaction”, chapter in *Discoveries and Breakthroughs in*

Cognitive Informatics and Natural Intelligence in *Advances in Cognitive Informatics and Natural Intelligence* book series, ed. Y. Wang, Information Science Reference (IGI Global), Hershey PA, USA, Dec. 2009

[2] Bukovsky, I., Hou, Z-G., Bila, J., Gupta, M., M.: "Foundation of Nonconventional Neural Units and their Classification", *International Journal of Cognitive Informatics and Natural Intelligence* (IJCiNi), October-December 2008, IGI Global, Hershey PA, USA, pp.29-43, ISSN 1557-3958.

[3] Bukovsky, I.: *Modeling of Complex Dynamical systems by Nonconventional Artificial Neural Architectures and Adaptive Approach to Evaluation of Chaotic Time Series*, Ph.D. Thesis, Faculty of Mechanical Engineering, Czech Technical University in Prague (in English, defended September 7, 2007, supervisor Bila, J., supervisor-specialist Gupta, M., online at http://www.fs.cvut.cz/~bukovsky/ivo.htm).

[4] Bukovsky, I., Bila, J.: „Adaptive Evaluation of Complex Time Series using Nonconventional Neural Units", *ICCI 2008, The 7th IEEE International Conference on COGNITIVE INFORMATICS*, California, USA, 2008, ISBN 9781424425389.J.

[5] R. J. Williams and D. Zipser, "A learning algorithm for continually running fully recurrent neural networks," *Neural Computation*, vol. 1, pp. 270–280, 1989.

[6] Bukovsky, I., Homma, N.: "Dynamic Backpropagation" (in Czech), Automatizace, Vol. 52, No. 10, Prague, Czech Republic, Oct 2009, p.586-590, ISSN 0005-125X.

[7] Bukovsky, I., Homma, N.: "Dynamic Backpropagation and Prediction" (in Czech), Automatizace, Prague, Czech Republic, ISSN 0005-125X, 01-02 2010.

[8] Zitek, P. – Vyhlidal, T.: Low Order Time Delay Approximation of Conventional Linear Model. In: 4th *MATHMOD* Vienna Proc., Vienna 2003, p. 197-204

[9] Hyvärinen,A., Oja, E.: Independent component analysis: algorithms and applications Neural Networks,Volume 13, Issues 4-5, June 2000, Pages 411-430

[10] Potter, M.; Kinsner, W.; Competing ICA techniques in biomedical signal analysis, Canadian Conference on Electrical and Computer Engineering, 2001. vol.2, 2001 , Page(s): 987 - 992 vol.2

[11] Gadhok, N.; Kinsner, W.; Robust independent component analysis for cognitive informatics, Fourth IEEE Conference on Cognitive Informatics, 2005. (ICCI 2005). 2005 , Page(s): 86 - 92

[12] Sugai, T.K.; Yoshizawa, M.; Abe, M.; Shimizu, K.; Inagaki, M.; Sugimachi, M.; Sunagawa, K.; "Preliminary study on the detection of cardiac arrhythmias based on multiple simultaneous electrograms", *Engineering in Medicine and Biology Society, EMBC 2009*, Annual International Conference of the IEEE, 2009 , Page(s): 2498 – 2501

[13] E. Kosmatopoulos, M. Polycarpou, M. Christodoulou, and P. Ioannou, "High-Order Neural Network Structures for Identification of Dynamical Systems", *IEEE Trans. on Neural Networks*, vol. 6, no. 2, pp. 422-431, March 1995.

[14] N. Y. Nikolaev and H. Iba, *Adaptive Learning of Polynomial Networks: Genetic Programming, Backpropagation and Bayesian Methods*, Series: Genetic and Evolutionary Computation, Springer, New York, XIV, 316 p. , ISBN: 0-387-31239-0, 2006.

[15] *Artificial Higher Order Neural Networks for Economics and Business*, ed. by Ming Zhang, Christopher Newport Univ., USA, IGI-Global, ISBN: 978-1-59904-897-0, 2008.

[16] *Artificial Higher Order Neural Networks for Computer Science and Engineering: Trends for Emerging Applications*, ed. by Ming Zhang, Christopher Newport University, USA, Information Science Reference, ISBN: 978-1-59904-897-0, 2010.