2nd International Conference on Advances in Signal Processing and Artificial Intelligence (ASPAI' 2020), 1-3 April 2020, Berlin, Germany

Poster Topic: Artificial Intelligence

Determination of psychotic behaviour using a network of chemical oscillators

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Summary Schizophrenia is the most common form of psychotic behaviour where patients experiences hallucination, dillusion or chaotic speech. Schizophrenia is difficult to detect and easily go undetected for years. Here we propose the idea of detecting schizophrenia by a network of interacting chemical oscillators. We optimized a classifier based on six interacting oscillator using genetic algorithm and obtained 82% accuracy of schizophrenia detection on a selected training dataset.

Keywords: Schizophrenia, EEG signal, chemical computing, oscillatory network, Oregonator model, genetic optimization

1. Introduction

The modern information processing has been dominated by semiconductor technology and the binary information coding in electric potentials. Semiconductor logic gates are reliable, fast and inexpensive. Moreover, they can be concatenated into large structures. As the result the bottom-up approach is used to make more complex information processing devices as a combination of the simple ones [1].

Living organisms use chemistry for information processing. Experiments with man-made chemical information procesing media shows that the maximum processing power can be achieved if different parts of the medium process information in parallel [2]. It can be expected that the top-down design strategy is more appropiate to reveal the computing power of a chemical medium than the bottom-up approach. The results presented below are continuation of the previous studies on top-down design of chemistry based clasifiers [3,4,5]. We consider a chemical system that works as a classifier of a selected dataset containing records in a form of (n+1) tuples, where the first n elements are predictors and the last one is a discrete data type. Our computing medium is supposed to return the correct data type if the predictor values are used as the input. Problems of such structure are common in medical applications [4], where one is supposed to determine if a patient is healthy or not (data type) on the basis of medical tests performed (the predictor values).

In our approach a computing medium made of interacting chemical oscillators is studied in-silico. The numerical model of a chemical oscillator is inspired by the two-variable Oregonator model [6,7] of the Belousov-Zhabotinsky(B-Z) reaction[8]. This reaction is probably the most studied chemical process where the nonlinear phenomena, like oscillations, excitability, wave propagation or chaotic behavior, are clearly manifested [9]. The interest in BZ-reaction as a medium for chemical information processing has been motivated by the fact that its properties are similar to that observed for the nerve system [2,10]. One can form channels in which propagation of concentration pulses is observed. These pulses interact (annihilate) one with another and can change their frequency on the junctions between channels [11]. The output information is usually coded in the presence of excitation (a high concentration of a selected reagent) at a given point of the medium and at the specific time.

For a specific choice of the catalyst BZ-reaction becomes photosensitive and it can be inhibited by illumination [12,13,14]. If a hight intensity illumination is applied to an oscillatory medium then excitations are rapidly damped and the system reaches a stable, steady state. On the other hand, the oscillatory behaviour re-appears immediately after the illumination is switched off [15]. The existence of such external inhibiting factor is very important for information processing applications because it allows to control the medium evolution by inhibiting its selected parts. Morover, we can input digital information into the computing medium by inhibiting specific reactions for times functionally related to the input value.

Our recent results suggest that reasonably accurate database classifiers can be constructed with a network of interacting chemical oscillators [3,4,5], like the one illustrated in Fig. 1(b). The output information is extracted from the network evolution, for example from the number of concentrartion maxima observed within a

fixed time interval. The network is made of two types of ocillators. There are input oscillators that are used to input predictor values. Oscillators assigned as inputs of predictor #l are inhibited for time related to this predictor value. There are also so called "normal oscillators", that are inhibited for a fixed time that is not related to the predictor value. These normal oscillators are supposed to moderate interactions in the medium and optimize them for a specific problem. In order to find a classifier for a given problem we need to specify the number of oscillators and their interactions. Also, such parameters as loactions of input and normal droplets, inhibition of normal droplets, method for inputing the predictor values or the type of interactions between droplets have to be optimized. To do it we can use the top-down strategy [3,4,5]: First we specify the function that should be performed by the considered system. Next, we search for possible factors that can modify the system evolution and increase its information processing ability. Finally we combine all these factors and apply them to achieve the optimum performance. We have found [3,4,5] that evolutionary optimization oriented on obtaining the best classifier for a representative training dataset of the problem can lead to the desired computing medium.

In this report we concentrate on design of a clasifier that is supposed to determine if a patient has schizophrenia or not. Schizophrenia is the most common form of psychotic behavior where patients experiences hallucination, delusion, chaotic speech. However, schizophrenia is difficult to detect and easily go undetected for years. We postulate that the detection of schizophrenia can be done by a network of interacting chemical oscillators that process information extracted from brain activity of a patient. There are two aspects of using the concepts of Artificial Intelligence in the presented study. First the network parameters are optimized using an evolutionary algorithm without a human involvement. Second, the resulting network can be seen as an example of Artificial Intelligence, that can predict if a patient is ill or not.

2. Results

We postulate that information necessary to detect schizophrenia can be extracted from the EEG signals recording brain activity [16]. Signals (the time dependent potential values) were recorded from electrodes placed in different parts of the scalp (see Fig. 1(a)). For the analysis we used signals received from F7 and F8 channels marked red in Fig.1(a). The signal dataset available on the web [17] containing signals recorded on 84 patients, out of which 45 were schizophrenic and 39 were healthy controls, was used as our training dataset.

The time dependent potentials were time averaged over 60 second interval and next standardized in the following way:

$$p_{7,m} = \frac{x^1_{7,m} - \mu_7}{\sigma_7} \qquad p_{8,m} = \frac{x^2_{8,m} - \mu_8}{\sigma_8}$$

Here the index m $(0<m<85)$ numbers patients in the considered database. The values $x_{7,m}$ and $x_{8,m}$ are the averaged potentials from F7 and F8 channels, μ_7 and μ_8 are the mean values of $x_{7,m}$and $x_{8,m}$averaged over all patients and σ_7 and σ_8 are the standard deviations of $x_{7,m}$ and $x_{8,m}$. A record of the considered training database has a form of 3-tuple: $(p_{7,m}, p_{8,m}, z)$ where the record type $z = 0$ for schizophrenic patients and $z = 1$ for healthy ones.

We assumed that a classifier that can distinguish between schizophrenic and healthy subject was formed of just 6 oscillators arranged in geometry shown in Fig 1 (b). The broken arrows illustrate interactions between the oscillators. Following the analogy with Belousov Zhabotinsky reaction as a computing medium we used the same two-variable Oregonator model [6,7] to simulate the time evolution of each oscillator:

$$\frac{\partial u}{\partial t} = \frac{1}{\varepsilon}\left(u - u^2 - (\mathrm{fv} + \varphi(t))\frac{u-q}{u+q}\right) \qquad 1(a)$$

$$\frac{\partial v}{\partial t} = u - v \qquad 1(b)$$

where: u and v denote concentrations of activator U and inhibitor V of Belousov-Zhabotinsky reaction respectively. In our simulations we used the following values of model parameters: $q=0.0002$, $\varepsilon=0.2$, $f=1.1$. The parameters of the Oregonator model were fixed and did not undergo optimization. In the Equation 1(a) the function $\varphi(t)$ represents time dependent illumination of the medium. We used illumination to control the time evolution of an oscillator and considered $\varphi(t)$ in the form:

$$\varphi_k(t) = 0.1 * (1.001 + \tanh(-10 * (t - t_{\mathrm{osc}}(k)))) \qquad (2)$$

where: $t_{osc}(k)$ is the time when illumination of oscillator #k was terminated. At the beginning the value of $\varphi_k(t=0)$ = 0.2 and the Oregonator model predicts a stable steady state corresponding to $u=0.0002$ and $v=0.0002$. For long times $\varphi_k(t)$ goes to 0.0001 what correspond to an oscillator with the period of approximately 10.8 time units. In an oscillator #k is a normal one than the value of $t_{osc}(k)$ is the same for all processed records of the training dataset. If the oscillator #j functions as the input of the predictor p_l $(l = 7 \text{ or } 8)$ than:

$$t_{\mathrm{osc}}(j) = t_{\mathrm{start}} + (t_{\mathrm{end}} - t_{\mathrm{start}}) * p_l \qquad (3)$$

The coupling between the oscillators #k and #j is described by additional reactions involving the activators U_k and U_j of these oscillators:

$U_k + A_j \rightarrow$ products

with the reaction rate α and:

$U_j + B_j \rightarrow U_k + C_k$

$U_k + B_k \rightarrow U_j + C_j$

with the reaction rate β.

The time evolution of the network is described by the following kinetic equation:

$$\frac{\partial u_j}{\partial t} = \frac{1}{\varepsilon}(u_j - u_j^2 - (\mathrm{fv}_j + \varphi(t))\frac{u_j - q}{u_j + q}) - (\alpha + \beta \sum_{k=1}^{6} s_{j,k}) + \beta(\sum_{k=1}^{6} s_{j,k} u_k) \quad 4(a)$$

$$\frac{\partial v_j}{\partial t} = u_j - v_j \quad 4(b)$$

where: u_j and v_j denote concentrations of activator and inhibitor in the oscillator #j. The last terms in Eq.4(a) represent the coupling between oscillators #j and #k. The values of symbols $s_{j,k}$ are equal to 1 if oscillators #j and #k interact and $s_{j,k} = 0$ if they do not.

In order to get information if a patient characterized by the predictors p_7 and p_8 is healthy or ill we simulated numerically Eqs.4(a,b) the network evolution within the time interval [0, t_{max}] using Cash-Karp R-K45 method [18] with $\Delta t = 10^{-3}$ time steps. We postulate that information about patient's health can be extracted from the number of activator maxima recorded on a selected oscillator of the network, during the time interval [0, t_{max}].

Following the idea of cancer classification described in[3] we optimized the system parameters to maximize the mutual information [19] between the number of oscillations received from the output droplet and the health of a patient represented by records of the training database. It can be expected that the value of mutual information increases with the classifier accuracy. An evolutionary algorithm covering all parameters of the network, i.e.:

– the time during which network evolution is studied t_{max} ($t_{max} < 100$ time units),

-- locations and illumination times (t_{osc} (i)) for all normal oscillators,

-- locations of input oscillators and times t_{end}, t_{start} in the Eq.(3),

-- the rate constants α,β describing interactions between oscillators,

was applied.

The quality (fitness) of a specific classifier was calculated as the mutual information between the list of types in the training database and the list of numbers of activator maxima observed on the output droplet [3]. As the output droplet we select the one for which the mutual information was the maximum one. The network optimization was performed using an evolutionary optimization algorithm presented in [5]. We considered 740 optimization generations over the population of 200 classifiers. The progress of optimization is illustrated in Fig. 2(a). When the optimization was terminated the mutual information between the list of types in the training database and the number of activator maxima observed on the output droplet was 0.416. The most fit network we obtained is illustrated in Fig. 2(c). The symbols In_1 and In_2 mark locations of inputs for predictors p_7 and p_8 respectively. The normal oscillators are represented by pie-charts. The ratio between the surface of the red area and the area of disk representing an oscillator represents the value of $t_{osc}(\#)/\ t_{max}$. The optimized network is characterized by: t_{max}= *79.5*, t_{start} = *72.1*, t_{end} =*4.9*, α = *0.46*, β = *0.65*, $t_{osc}(1)$ = *52.3*, $t_{osc}(5)$ = *52.3*.

Figure 2(b) illustrates the mutual information between the list of numbers of activator maxima observed on a specific oscillator and the list of types of the training database. As seen the highest values of mutual information are observed for oscillators that are also the inputs of predictor p_8. The maximum mutual information is for the oscillator #2. It can be expected the classifier accuracy increases with the mutual information, thus using the number of maxima of the activator for the oscillator #2 we should obtain the most accurate diagnosis. The number of cases corresponding to a given number of activator maxima observed on the oscillator #2 for healthy and schizophrenic patients is shown in Fig. 2(c). Using these results we can postulate the classification rule: if 1,3 or 4 maxima of activator are observed during the time evolution on the oscillator #2 then the patient is healthy. If the number of observed maxima is different then the patient is schizophrenic. This rule gives the accuracy of 82% in determination of schizophrenic patients in the considered database.

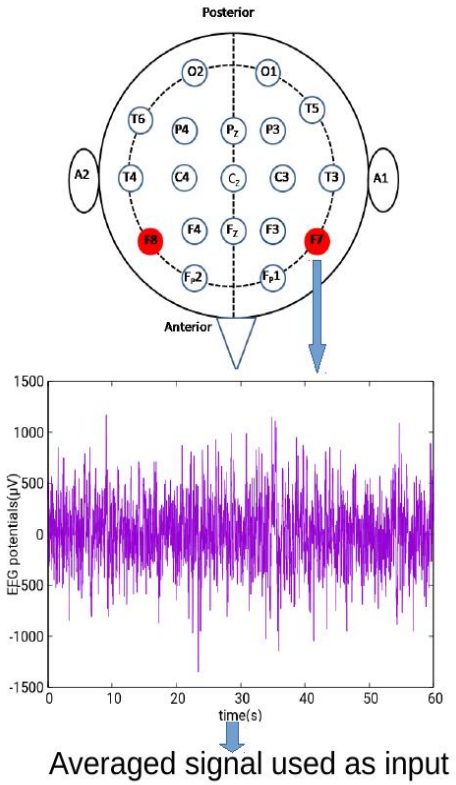
3. Conclusions and Discussions

In the presented study we assumed that schizophrenia can be detected by an Artificial Intelligence program that analyses EEG signals recorded from electrodes located on a patient scalp. Using a limited dataset we demonstrated that a interacting system of chemical oscillators can be trained to perform as a classifier and it has a potential to distinguish a schizophrenic patient. We considered a network of 6 coupled oscillators and optimize it to diagnoze correctly 82% of cases in the considered dataset. We tested a number of combinations of two signals and, within the available data, the highest

accuracy was obtained for F7 and F8 channels (cf. Fig. 1(a)). We think the result is promising and encourage future research in this field. Having access to much larger databases we could generalize the presented results. A larger network would allow to combine information from a large number of channels which should increase the diagnosis accuracy.

4. Figures

(a)



(b)

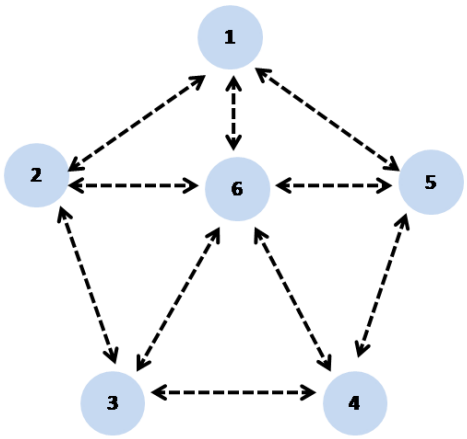
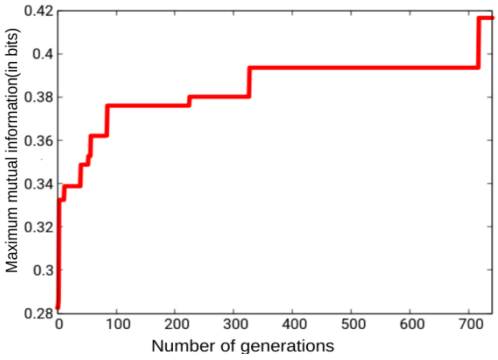
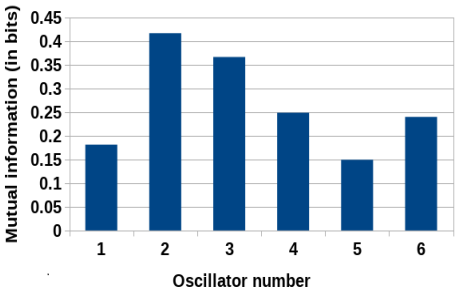


Fig 1(a) *The location of electrodes and EEG signals used as inputs .(b) The schematic representation of the network of oscillators used to determine a schizophrenic patient.*

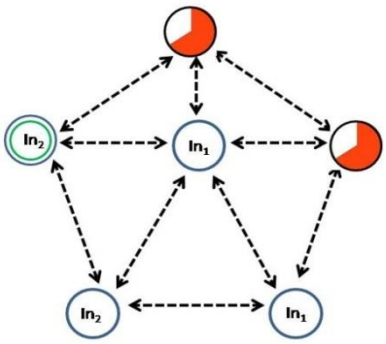
(a)



(b)



(c)



(d)

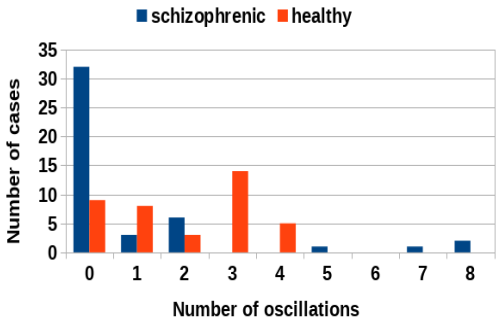


Fig 2: *The optimization of a schizophrenia classifier. (a) The maximum mutual information between the list of record types and the list of numbers of activator maxima as a function of the evolutionary step. (b) The mutual information between the list of record types and the list of numbers of activator maxima measured for different oscillators of the optimized network. The oscillator #2 gave the maximum mutual information and it was selected as the output one. (c)The structure of optimized schizophrenia classifier. In_1 and In_2 represent inputs for p_7 and p_8. The green ringed droplet represents the output droplet. (d) The numbers of cases in the considered training database for which a given number of activator maxima is observed on the oscillator #2.*

Acknowledgements

This publication is part of a project that has received funding from the European Union's Horizon 2020 (H2020-EU.1.3.4.) research and innovation program under the Marie Skłodowska-Curie Actions (MSCA-COFUND ID 711859) and from the Polish Ministry of Science and Higher Education for the implementation of an international co-financed project.

References

[1] Feynman, Richard, Hey, Tony and Allen, Robin. Feynman Lectures on Computation. CRC Press, Boulder, Colorado, USA, 2000.

[2] Gorecki J., Gizynski K., Guzowski J., Gorecka J. N.,Garstecki P., Gruenert G. and Dittrich P.; Chemical computing with reaction–diffusion processes , Philosophical Transactions of the Royal Society A:Mathematical, Physical and Engineering Sciences,Vol. 373, Issue 2046, 2015, doi.org/10.1098/rsta.2014.0219,

[3] Gizynski, Konrad and Gruenert, Gerd and Dittrich, Peter and Gorecki, Jerzy, Evolutionary design of classifiers made of droplets containing a nonlinear chemical medium. MIT Evolutionary Computation Vol. 25, No. 4, 2017. pp 643–671.

[4] Gizynski, Konrad and Gorecki, Jerzy, Cancer classification with a network of chemical oscillators. Physical Chemistry Chemical Physics, Vol. 19, Issue 42, 2017 pp. 28808–28819.

[5] Gizynski, Konrad & Górecki, Jerzy. A Chemical System that Recognizes the Shape of a Sphere. Computational Methods in Science and Technology. Vol. 22, Issue 4, 2016, pp. 167-177.

[6] Field R.J., Noyes R.M., Oscillations in chemical systems. IV. Limit cycle behavior in a model of a real chemical reaction, The journal of Chemical Physics ,Vol. 60, Issue 5, 1974, pp. 1877-1884.

[7] Kuze, Masakazu and Horisaka, Mari and Suematsu, Nobuhiko J. and Amemiya, Takashi and Steinbock, Oliver and Nakata, Satoshi, Chemical Wave Propagation in the Belousov–Zhabotinsky Reaction Controlled by Electrical Potential,The Journal of Physical Chemistry A, Vol.123, No. 23, 2019. pp. 4853-4857.

[8] Epstein I.R., Pojman J.A., An introduction to nonlinear chemical dynamics: oscillations, waves,patterns, and chaos.; Oxford University Press: New York, NY, USA, 1998.

[9] Adamatzky A., De Lacy Costello B., Asai T.,Reaction–diffusion computers. , Elsevier: New York,NY,USA, 2005.

[10] Haken ,Hermann. Brain dynamics: synchronization and activity patterns in pulse-coupled neural nets with delays and noise; Springer, Berlin, Germany, 2002.

[11] Sielewiesiuk Jakub, Gorecki Jerzy, Logical functions of a cross junction of excitable chemical media, The Journal of Physical Chemistry A, Vol. 105, No. 35, 2001, pp. 8189-8195.

[12] Kuhnert L. A new optical photochemical memory device in a light-sensitive chemical active medium, Nature, Vol. 319, 1986, pp. 393–394.

[13] Kuhnert L., Agladze K.I., Krinsky V.I. Image processing using light-sensitive chemical waves. Nature Vol. 337, 1989, pp. 244–247.

[14] Rambidi N.G., Maximychev A.V. Towards a biomolecular computer. Information processing capabilities of biomolecular nonlinear dynamic media. BioSystems, Vol 41, Issue 3, 1997, pp. 195–211.

[15] Gizynski K., Gorecki J., Chemical memory with states coded in light controlled oscillations of interacting Belousov–Zhabotinsky droplets. Physical Chemistry Chemical Physics Vol. 19, Issue 9, 2017, pp. 6519–6531.

[16] Byeon, J.G., Kaplan, A.Y., Timashev, S.F. , Vstovskii,G.V. and Park,B.W. Variability of the EEG autocorrelation structure in adolescents with schizophrenia spectrum disorders. Human Phsysiology, Vol. 33, Issue 1, 2007, pp. 122-124.

[17] http://brain.bio.msu.ru/eeg_schizophrenia.htm

[18] William H. Press, Saul A. Teukolsky, William T. Vetterling, and Brian P.Flannery. Numerical recipes in C (2nd ed.): the art of scientific computing. Cambridge University Press, USA, 1992.

[19] Cover T. M., Thomas J. A., Elements of Information Theory, Wiley-Interscience, New York, 2006.