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# Modeling of Human Physiological Parameters in an E-Laboratory by SOM Neural Networks

## A. A. Bielskis, V. Denisov, G. Kučinskas, O. Ramašauskas, N. Romas

*Department of Computer Science, Klaipėda University,*
*H. Manto st. 84, Klaipėda, Lithuania, e-mail: {bielskis, olegas, vitalij}@ik.ku.lt*

## Introduction

Ambient Intelligence (AmI) refers to the presence of a digital environment that is sensitive, adaptive, and responsive to the presence of people. AmI concepts can help in creating the intelligent e-advisors such that are able to generate some online advises to people about their current state of health in searching suitable for them e-possibilities. Such modern e-advising process may be based on an adaptive e-learning by doing remote experiments in a distributed environment of an e-laboratory [7]. These experiments can be organized for remote biological data sensing, acquisition and interpretation with the aim of increasing security and avoiding an overloading of working personal in an e-laboratory. Two unsupervised learning algorithms were recently applied to gain adaptively of an e-learning process: the Q-learning [2, 12] and the Self-Organizing Maps (SOM) [8, 9]. Methods of implementation of these algorithms in the curricula of Information technologies in the University of Klaipeda were described in [1–6, 11, 19].

An objective of this paper is to analyze and propose some methods of data classification having in mind a possibility to introduce adaptation properties of an e-learning process into a courseware of bioinformatics by using Self-Organizing Map (SOM) type neural networks. The paper explains principles of construction of Embedded Agents to collect ECG and EEG data for educational purposes. It describes the principles of applications of SOM neural networks for interpretation of both EEG data and data of medical databases. An original method of personal health status prediction is proposed. It is based on defining a level of influence of insertion of a new random input vector into the SOM network by using SOM Toolbox and Matlab environment.

## Bioinformatics Data Selections in an E-Laboratory

This Section explains principles of construction of Embedded Agents to collect ECG and EEG data for educational purposes within a distributed environment of an e-laboratory. We see a possibility measuring ECG (Electro-

cardiogram) and EEG (Electroencephalogram) signals of learners by using embedded agents in an e-laboratory. We use OpenEEG project [13, 14] to construct embedded agents for biological data collection within a virtual laboratory by [7]. The proposed concept in [7] is based on communication and control principles of embedded agents via integration of remote Internet Relay Chat (IRC) Protocol [7]. Seeking both to realize remote communications between embedded agents and to gain adaptive features of controllable bio-robots for their investigations of a changing e-laboratory environment, the multi-agent control system is proposed.
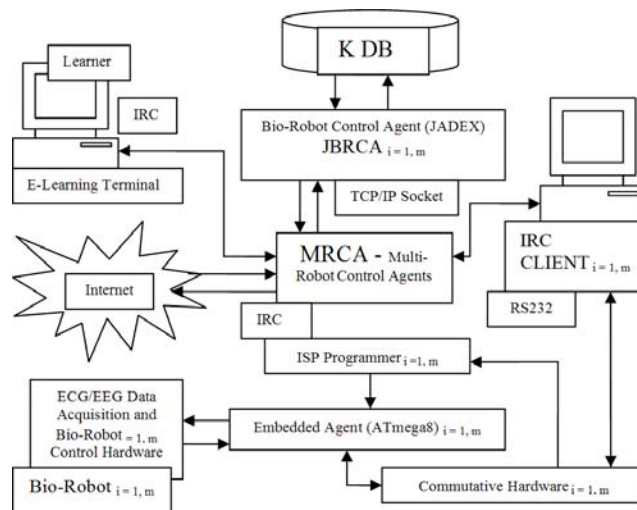


**Fig. 1.** Intelligent embedded agents for biological data acquisition in an environment of a distributed e-laboratory

It is designed using both JADEX – Java type open source agent oriented ontology based software for an adaptive control and Delphi programming environment for realizing IRC communication between remote objects. Physical communications with remote objects are designed via TCP/IP sockets. An implementation of a remote adaptive bio-robot control within an e-laboratory is based on ATmega8 microcontrollers as embedded agents (Fig. 1). The embedded agents are supported by remotely communicable hardware implementing In System Programming (ISP) fea-

ture of each microcontroller. Every $Bio\text{-}Robot_{i=1,m}$ in an e-laboratory is controlled by its own JADEX-based bio-robot control agent $JBRCA_{i=1,m}$. Multi-robot control strategy by Multi-user is being permanently realized by adaptive multi-robot control agents, *the MRCA.*. Each $Bio\text{-}Robot_{i=1,m}$ is controlled directly by its $IRC\ Client_{i=1,m}$ via serial RS232 port using *HyperTerminal* software. Adaptive control strategy of $Bio\text{-}Robot_{i=1,m}$ can be implemented only having its online reprogramming capabilities by permanently using In System Programming (ISP) feature of each microcontroller. In the e-laboratory of Fig. 1, this is realized by arranging for each $Bio\text{-}Robot_{i=1,m}$ both the *Commutative Hardware*$_{i=1,m}$ and *ISP Programmer*$_{i=1,m}$. These additional elements allow communication with each remote ATmega8-based embedded agent either for its control or reprogramming purposes implementing adaptive properties of $Bio\text{-}Robot_{i=1,m}$. A learner – a multi-user type client is able to run e-laboratory experiments by an aid of *the MRCA* and IRC protocol. This is realized by using two type programming Delphi and Java based JADEX environments. This approach allows to realize software type communication between *MRCA* and *Bio-Robot Control Agent JBRCA*$_{i=1,m}$ via TCP/IP sockets. The $JBRCA_{i=1,m}$ also communicates with KDB – the dynamically changing knowledge base of an e-laboratory. We acknowledge the Computer Science Department at Colorado State University in our communications of their work "Classification of Electroencephalogram (EEG) Signals for Brain-Machine Interfaces" by [16] involving their EEG data recorded by Zak Keirn at Purdue University for his work on his Masters of Science thesis in the Electrical Engineering Department at Purdue. This data is available as a 23 MB, from **binary Matlab mat-file** [10, 18]. The data is a cell array of cell arrays. Each individual cell array is made up of a subject string, task string, trial string, and data array. Each data array is 7 rows by 2500 columns. The 7 rows correspond to channels $c3$, $c4$, $p3$, $p4$, $o1$, $o2$, and ECG of the 10-20 System (Fig. 2).
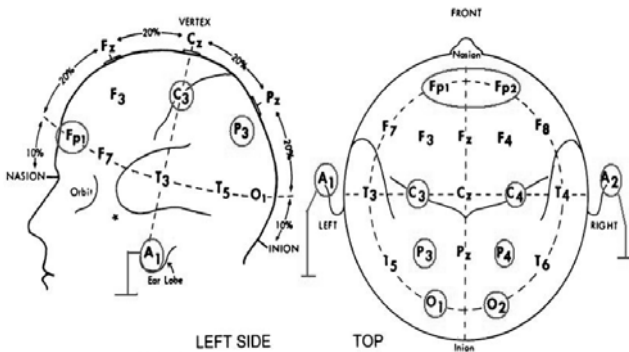


**Fig. 2.** International 10-20 System with marked positions $c3$, $c4$, $p3$, $p4$, $o1$, $o2$, and EEG of placement of electrodes for 7 channels [14, 15, 16]

There is a standardized EEG electrodes placement system called the 10-20 System [14, 15]. The 10-20 System is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. Each point on it indicates a possible electrode position. Each site has a letter (to identify the lobe) and a number or another letter to identify the hemisphere location. The letters F, T, C, P, and O stand for Frontal, Temporal, Central, Parietal

and Occipital. (Note that there is no "central lobe", but this is just used for identification purposes.) Even numbers (2, 4, 6, and 8) refer to the right hemisphere and odd numbers (1, 3, 5, 7) refer to the left hemisphere. The z refers to an electrode placed on the midline. Also note that the smaller the number, the closer the position is to the midline. In our case, across columns are samples taken at 250 Hz for 10 seconds, for 2500 samples (Fig. 3–4). For example, the first cell array of Fig. 3 represents data of subject 1 who completed task 1 – The Baseline Task under the trial 1 for 10 seconds. This data may look like a plot in Fig. 4. Recordings were made by Zak Keirn at Purdue University with reference to electrically linked mastoids A1 and A2 of Fig. 2. EEG was recorded between the forehead above the left brow line and another on the left cheekbone.
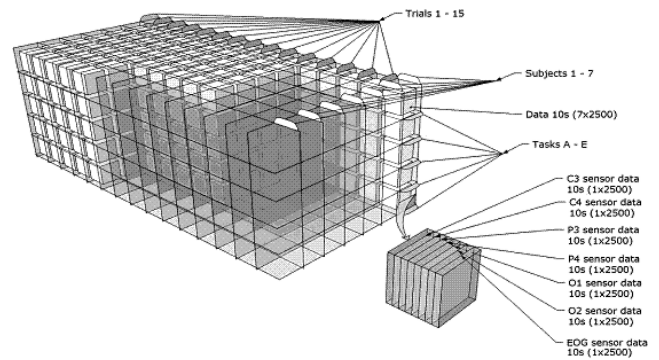


**Fig. 3.** 3D interpretation of data from binary Matlab mat-file

Recording was performed with a bank of Grass 7P511 amplifiers whose band pass analog filters were set at 0.1 to 100 Hz. Subjects 1 and 2 were employees of a university and were left-handed age 48 and right-handed age 39, respectively. Subjects 3 through 7 were right-handed college students between the age of 20 and 30 years old. All were mail subjects with the exception of Subject 5. Subjects performed five trials of each task in one day. They returned to do a second five trials on another day. Subjects 2 and 7 completed only one 5-trial session. Subject 5 completed three sessions. The mental tasks and their labels are described in Table 1. The recorded EEG Data from [15] was preprocessed by constructing separate arrays of different length vectors. The last attribute of each vector in every array was a label A through E interpreting a mental task performed by a subject in accordance with the Table 1. The arrays were constructed for vectors of $15^{th}$ order representing a sampling interval of 0.06 seconds through vectors of $1000^{th}$ order with sampling interval of 4 seconds in recorded data. The SOM networks for $226^{th}$ order vectors are given in Fig. 5. The method of label prescription for the SOM clusters is applied constructing right part of Fig. 5. It allows interpreting the clusters by giving them the names A, B, C, D, and E of the mental tasks described in Table 1. For data interpretation during a process of constructing a courseware in an e-laboratory, the results of visual indication of some mental states can be used. This indication of subject's mental states can be seen on the SOM's of Fig. 8. The right part SOM of Fig. 8 shows that the clusters representing the mental task B are located at the corners of the map. We can also see from the left part SOM of Fig. 5 that the mental task B (Math Task) is represented by higher values of EEG

signals of relative range 200 through 300. The central cluster mainly represents tasks A (Baseline Task of relaxation), D (Geometric Figure Rotation), and E (Visual Counting) having the lowest values of EEG signals of relative range 10 through 50. The outside part of this cluster more often represents the task C (Letter Task) among other tasks. This part of cluster displays values of EEG signals of relative range 100 through 150.
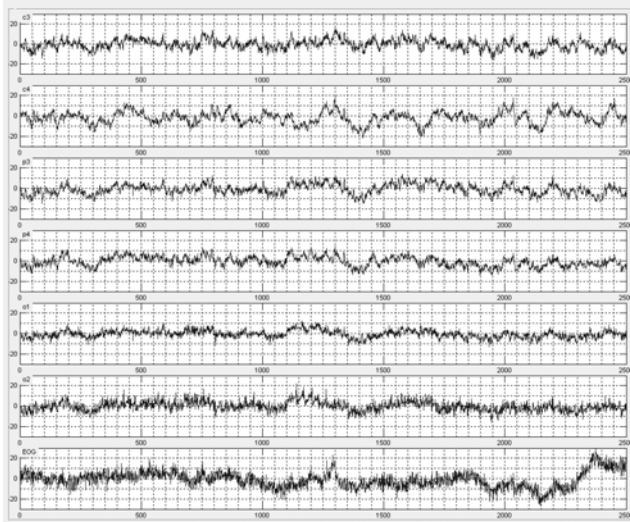


**Fig. 4.** Interpretation of data samples of 7 channels $c3$, $c4$, $p3$, $p4$, $o1$, $o2$, and EEG taken at 250 Hz for 10 seconds, for 7x2500 samples from binary Matlab mat-file
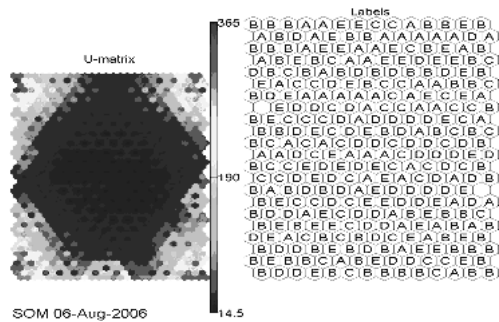


**Fig. 5.** SOM network of EEG data by using vector of an $226^{th}$ order (interval of 0.904 seconds)

**Table 1.** The Mental Tasks and their Labels

| Mental Tasks | A Label for a Task |
|---|---|
| **Baseline Task** – The subjects were asked to relax and think of nothing in particular | A |
| **Math Task** – The subjects were given nontrivial multiplication problems, such as 49 times 78, and were asked to solve them without visualizing or making any other physical movements | B |
| **Letter task** – The subjects were instructed to mentally compose a letter to a friend or relative without visualizing | C |
| **Geometric Figure Rotation** – The subjects were given 30 seconds to | D |

| | |
|---|---|
| study a drawing of a complex three dimensional block figure after which the drawing was removed and the subjects instructed to visualize the object being rotated about an axis | |
| **Visual Counting** – The subjects were asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number was written. The subjects were further instructed not to verbally read the numbers but to visualize them, and to pick up counting from the previous task rather then starting over each time | E |

**A proposed method of personal health status prediction**

The method is based on defining a level of influence of insertion of a new random input vector into the SOM network by using SOM Toolbox and Matlab environment. The method is realized using the following 12-stepped algorithm.

1. For a given Preprocessed Data of Selected Medical Database, the *PDofSMDB*, a number N (N=1000 was used) of selected size of $r*c$ nodes (there were used 9*7=63 nodes) of SOM's is to be trained by using a random initialization algorithm, the "randinit", and saved.

2. The best 3 SOM's having the minimum final quantization and topographical errors are selected from a number of N randomly initialized and trained SOM's.

3. For the *PDofSMDB,* one additional SOM is trained by using a linear initialization algorithm, the "lininit" and saved.

4. The selected 4 SOM's (see Fig. 6 as an example) are visually examined for their similarity of having the same number of nodes of each class to be predicted. If such SOM visually was not found go to the next step else reject an unproper SOM and go to the step 1.

5. The mutual correlation coefficients of each selected of 4 SOM's by using *corrcoef()* m-function are being calculated (see the upper part of Fig. 7 where the values of correlation coefficients versus a number of every node from 1 through 63 are plotted) by (1):

$$CC_m = \begin{cases} cc_{m1} = corrcoef \ (x_{11}, x_{21}); \\ .......... ..... \\ cc_{mi} = corrcoef \ (x_{ki}, x_{li}); \\ .......... ....... \\ cc_{m63} = corrcoef \ (x_{1\_63}, x_{2\_63}); \end{cases} \quad (1)$$

where $i$ – a number of SOM node from 1 to $r*c$=63; $x_{ki}$ – a vector of $i^{th}$ node of $k^{th}$ SOM (from 1 to 4); $x_{li}$ – a vector of $i^{th}$ node of $l^{th}$ SOM (from 1 to 4); $cc_{mi}$ – correlation coefficient of $i^{th}$ nodes of $k^{th}$ and $l^{th}$ SOM.

6. For each of 4 trained SOM's, a declination of each node (63, in this case of Fig. 6) from the user's vector **sUser** (the vector which class is to be predicted) has to be calculated (the middle part of Fig. 7 where the declination values of each node from the user's vector **sUser** versus a

79

number of every node from 1 through 63 are plotted) by (2):

$$\Delta = \begin{cases} \Delta_1 = \begin{cases} \delta_{1\_1} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{11j}\right|/\max(X_j)/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \delta_{1\_i} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{1ij}\right|/\max(X_j)/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \delta_{1\_63} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{1\_63\,j}\right|/\max(X_j)/v\right), \end{cases} \\[6pt] \cdots\cdots \\[4pt] \Delta_p = \begin{cases} \delta_{p\_1} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{p1j}\right|/\max(X_j)/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \delta_{p\_i} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{pij}\right|/\max(X_j)/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \delta_{p\_63} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{p63\,j}\right|/\max(X_j)/v\right), \end{cases} \\[6pt] \cdots\cdots \\[4pt] \Delta_4 = \begin{cases} \delta_{4\_1} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{4\_1j}\right|/\max(X_j)/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \delta_{4\_i} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{4\_ij}\right|/\max(X_j)/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \delta_{4\_63} = \sum_{j=1}^{v}\left(\left|x_{0j}-x_{4\_63\,j}\right|/\max(X_j)/v\right), \end{cases} \end{cases} \qquad (2)$$

where $x_{0j}$ – $j^{th}$ member of user's data; $x_{pij}$ – $j^{th}$ member of $i^{th}$ node of $p^{th}$ SOM; $\delta_{p\_i}$ – distance of itch node of path SOM from user's data; $\Delta_p$ – matrix of the distance of $p^{th}$ SOM from user's data. $v$ – order of vectors.

7. The mutual distances, *Delta*, between the same nodes of all of 4 trained SOM's have to be calculated (the lower part of Fig. 7 where the values of mutual distances between the same nodes of SOM's, *Delta*, versus a number of every node from 1 through 63 are plotted) by (3):

$$\Psi = \begin{cases} \Psi_{12} = \begin{cases} \psi_{12\_1} = \sum_{j=1}^{v}\left(\left|x_{11j}-x_{21j}\right|/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \psi_{12\_i} = \sum_{j=1}^{v}\left(\left|x_{1ij}-x_{2ij}\right|/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \psi_{12\_63} = \sum_{j=1}^{v}\left(\left|x_{1\_63\,j}-x_{2\_63\,j}\right|/v\right), \end{cases} \\[6pt] \cdots\cdots \\[4pt] \Psi_{kl} = \begin{cases} \psi_{kl\_1} = \sum_{j=1}^{v}\left(\left|x_{k1j}-x_{l1j}\right|/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \psi_{kl\_i} = \sum_{j=1}^{v}\left(\left|x_{kij}-x_{lij}\right|/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \psi_{kl\_63} = \sum_{j=1}^{v}\left(\left|x_{k63\,j}-x_{l63\,j}\right|/v\right), \end{cases} \\[6pt] \cdots\cdots \\[4pt] \Psi_{34} = \begin{cases} \psi_{34\_1} = \sum_{j=1}^{v}\left(\left|x_{3\_1j}-x_{4\_1j}\right|/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \psi_{34\_i} = \sum_{j=1}^{v}\left(\left|x_{3\_ij}-x_{4\_ij}\right|/v\right), \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ \psi_{34\_63} = \sum_{j=1}^{v}\left(\left|x_{3\_63\,j}-x_{4\_63\,j}\right|/v\right), \end{cases} \end{cases} \qquad (3)$$

where $\Psi_{kl}$ – a matrix of difference between $k$ and $l$ SOM's; $\Psi_{kl\_i}$ – a difference of $i^{th}$ nodes of $k$ and $l$ SOM's; $x_{kij}$ – a $j^{th}$ number of $i^{th}$ node of $k^{th}$ SOM; $x_{lij}$ – a $j^{th}$ number of $i^{th}$ node of $l^{th}$ SOM.

8. A visual inspection of results of steps 5 through 7 allows eliminating such a SOM which plots are the most different from others and the next better matching one has to be selected (in case of Fig. 7, all 4 SOM's supposed as having satisfactory matching).
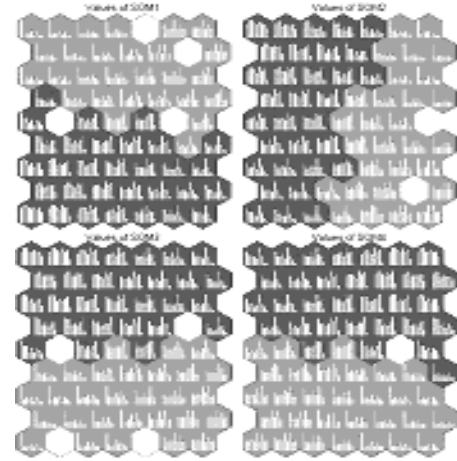


**Fig**. 6. Vizualization example of properly selected 4 SOM's of the step 4 of this algorithm for the *PDofSMDB* of the *Breast_Cancer_Data( )* [18]
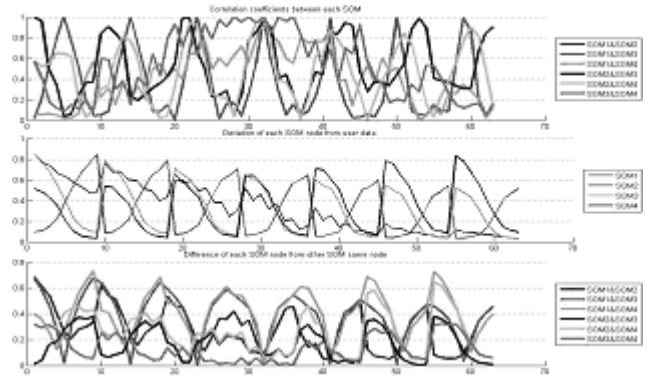


**Fig**. 7. An interpretation of the results of steps 5 through 7 for a visual inspection of this algorithm by using the *Breast_Cancer_Data( )* [18]

9. For each node of every of 4 trained SOM's, a probability of matching with the user's vector **sUser** (the vector which class is to be predicted) has to be calculated (see upper part of each quarter of Fig. 8 where a probability of activation level of each node after insertion of user's vector **sUser** versus a number of every node from 1 through 63 is plotted) by a code fragment:

```
for i1 = 1:rows1;
    af = 0;
for k1 =1:cols1;
  if (M(i1,k1)+W(k1) >= sUser(k1))
      && (M(i1,k1)-W(k1) <= sUser(k1));
af1 = exp(0.93)/sqrt(2*pi)*power(exp(1)-
    power(M2(i1,k1)-
    sUser(k1),2)/1.1);
  if af1 > 1;
    af1 = 1;
  end;
    af = af + af1 * 1/12;
end;
if af > 0;
  if sMap.labels{i1,1} == 'S';
```

```
    sLiga2(i1) = af;
    j1 = j1 + 1;
  elseif sMap.labels{i1,1} == 'N';
    sNeserga2(i1) = af;
    j2 = j2 + 1;
  else;
    sNezino2(i1) = af;
    j3 = j3 + 1;
  end;
 end;
end.
```

10. For each of 4 trained SOM's, a number of activated nodes for every class to be predicted (malignant, benign, not known) has to be calculated (see lower left part of each quarter of Fig. 8 where a number of activated nodes for every class to be predicted (malignant, benign, not known) after insertion of user's vector **sUser** is expressed).

11. For each of 4 trained SOM's, an average value of probability of activated class of nodes is calculated (see lower middle part of each quarter of Fig. 8 where an average value of probability of activated class of nodes after insertion of user's vector **sUser** is expressed) as follows:

```
a1 = sum(sLiga1)/j1;
a2 = sum(sNeserga1)/j2;
a3 = sum(sNezino1)/j3.
```

12. For each of 4 trained SOM's, the final class prediction results are to be calculated (see lower right part of each quarter of Fig. 8 where the probabilities of final class prediction results after insertion of user's vector **sUser** are expressed) in lower middle part of each quarter of Fig. 8 where an average value of probability of activated class of nodes after insertion of user's vector **sUser** is expressed) as follows:

```
a1 = sum(sLiga1) /
(sum(sLiga1)+sum(sNeserga1) +sum(sNezino1));
a2 = sum(sNeserga1) /
(sum(sLiga1)+sum(sNeserga1) +sum(sNezino1));
a3 = sum(sNezino1) /
(sum(sLiga1)+sum(sNeserga1) +sum(sNezino1)).
```

**Results and Discussion**

The investigations of SOM results of Fig. 5 allow concluding that SOM type algorithm can be used interpreting some mental tasks representing EEG data. It allows recognizing the uniformed mental tasks which were many times performed by different subjects. Analysis of SOM's in Fig. 6 – 9 allows concluding that SOM type visualizations give's us useful knowledge about heart and breast cancer diseases. There exists a property of classification of given hearth disease data to be discovered by analysis of SOM visualization results in Fig. 6. A proposed method of personal health status prediction from SOM clusters by using the *Breast_Cancer_Data()* performs prediction with 86% accuracy (see Fig. 8). The same algorithm applied to *Heart_Cleveland_Data()* gave us results in Fig. 9. The accuracy of prediction is as follows: for the class *sick* – 31%, for the class *not sick* - 28% and for the class *not know* – 41%. This accuracy is not sufficient because results of training of SOM by using *Heart_Cleveland_Data()* were obtained having 64% of final quantization error.
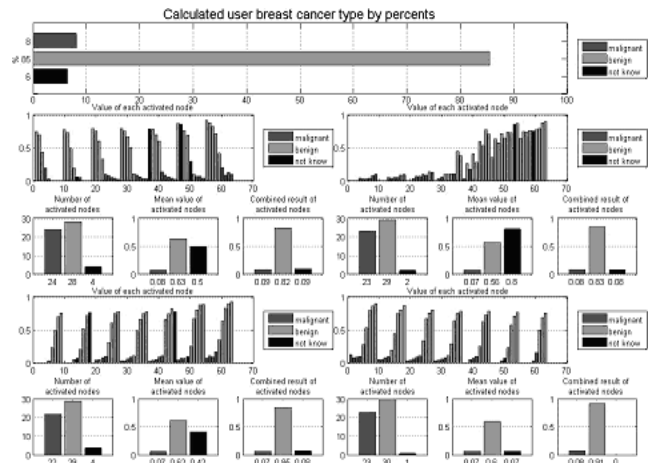


**Fig. 8.** The results of personal health status prediction after insertion of user's vector **sUser** into the network of 4 trained SOM's by using the *PDofSMDB* of the *Breast_Cancer_Data( )* [18]
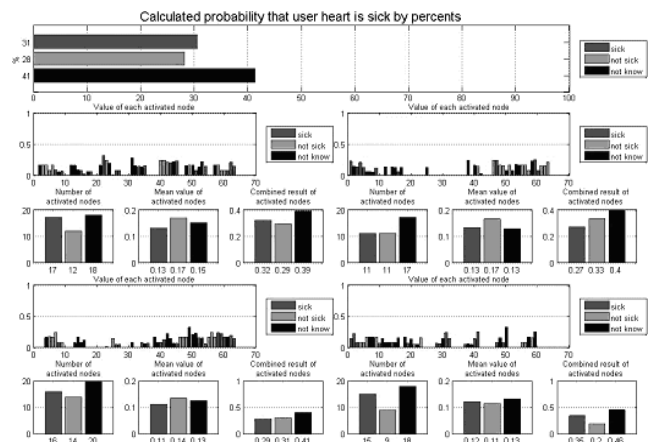


**Fig. 9.** The results of personal health status prediction after insertion of user's vector **sUser** into the same (Fig. 8) network by using the *PDofSMDB* of the *Heart_Cleveland_Data( )* [17, 18]

**Conclusions**

SOM based algorithms are successfully applied creating an original method of personal health status prediction. It is based on defining a level of influence of insertion of a new random input vector, the user's vector, into the SOM network by using SOM Toolbox and Matlab environment. Methods of recognizing of unified mental tasks performed by different experimentations using SOM-based EEG data interpretation algorithm are proposed and results are given illustrating a possibility to measure such mental tasks as nontrivial mathematical calculations. By using bioinformatics data interpreted by SOM algorithm, a courseware of bioinformatics may be permanently updated in an e-tutoring system.

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**A. A. Bielskis, V. Denisov, G. Kučinskas, O. Ramašauskas, N. Romas. Modeling of Human Physiological Parameters in an E-Laboratory by SOM Neural Networks // Electronics and Electrical Engineering. – Kaunas: Technologija, 2007. – No. 3(75) – P. 77–82.**

An approach of interpreting some bioinformatics data using Self-Organizing Map (SOM) type neural networks is described. The ways are proposed constructing intelligent program tools of embedded agents to collect ECG and EEG data for academic usage in a virtual e-laboratory. A SOM-based diagnostic algorithm is proposed interpreting data from Medical databases donated by University of California Machine Learning Page hosts, etc. By applying SOM for EEG data of Colorado State University, methods recognizing some unified mental tasks performed by different subjects are proposed. It is also shown that knowledge discovered by SOM data interpretation can be involved in a process of e-tutoring of students and learners of bioinformatics. Keywords: Ambient Intelligence, Embedded Agents, Machine Learning, Self-Organizing Maps. Ill. 9, bibl. 19 (in English; summaries in English, Russian and Lithuanian).

**А. А. Белскис, В. Денисов, Г. Кучинскас, О. Рамашаускас, Н. Ромас. Моделирование физиологических параметров человека в е-лаборатории SOM нейронными сетями // Электроника и электротехника. – Каунас: Технология, 2007. – № 3(75). – С. 77–82.**

В работе описан частный случай интерпретации биоинформатических данных при применении нейронных сетей самоорганизующегося (SOM) типа. Предложено направление конструирования таких интеллектуальных программ, в которые внедренные агенты собирают ЭКГ и ЭЭГ данные для академического использования в виртуальной э-лаборатории. Для диагностики предложен SOM алгоритм, интерпретирующий базы медицинских данных, любезно предоставленных Калифорнийским и др. университетами США. Представлены методы исследования ЭЭГ некоторых задач умственного действия различных субъектов, полученые на основе данных от Колорадского ГУ. Показано, каким образом знания, полученные при интерпретации данных SOM-ами, могут включаться в процесс е-обучения студентов и слушателей по биоинформатике. Ил. 9, библ. 19 (на английском яз., рефераты на английском, русском и литовском яз.).

**A. A. Bielskis, V. Denisovas, G. Kučinskas, O. Ramašauskas, N. Romas. Žmogaus fiziologinių parametrų modeliavimas e-laboratorijoje SOM neuroniniais tinklais // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2007. – Nr. 3(75). – P. 77–82.**

Darbe aprašytas mėginimas interpretuoti dalį bioinformatikos duomenų, naudojantis savaiminio planavimo tipo neuroniniais tinklais. Pasiūlyti būdai konstruoti tokioms intelektualioms programoms, į kurias įterpti agentai surinktų EKG ir EEG duomenis akademiniam naudojimui virtualioje e-laboratorijoje. Pateiktas savaiminiu planavimu pagrįstas diagnostikos algoritmas interpretavimui medicininių duomenų bazėms, kuriomis nemokamai leido naudotis Kalifornijos ir kt. JAV universitetai, mašinų mokymo puslapių savininkai. Pritaikius savaiminio planavimo tinklą EEG duomenims iš Kolorado valstybinio universiteto, pasiūlyti metodai, kaip suvokti kai kurias skirtingų subjektų atliekamas protinės veiklos užduotis. Parodyta, kaip žinios, atskleistos interpretuojant duomenų savaiminį planavimą, gali būti įtrauktos į studentų ir klausytojų e. mokymo procesą. Il. 9, bibl. 19 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).