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AUTONOMOUS EMOTION RECOGNITION SYSTEM: APPROACHES FOR DATA MINING

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Abstract
The detection of emotion is becoming an increasingly important field for human-computer interaction as the advantages emotion recognition offer become more apparent and realisable. However there are still many issues (data filtering, parameter‘s extraction, data preprocessing, interpreting, adaptive control) in developing adaptive systems proeviding user-friendly e-health and e-social care for people with movement disabilities services based on physiological parameter’s recognition. Such systems include different intellectual components for control and monitoring of sensors by supporting multi-agent activities and, in accordance to the recognition of certain situations, integrate the possibilities to affect and control the devices of disable persons. So this paper presents principle of modelling of an autonomous emotion recognition system to creating of an intelligent e-health care environment. The model is based on remote research of human emotional states and remote bio robots intelligent control with ATmega8/16/32 microcontrollers. The proposed model uses skin conductance signal to recognize human emotional state i.e. the main process of this system is based on exploratory’s analog signal transformation to one of discreete emotional state (surprise, happy, calmness, sleepiness, sad, disgust, anger and fear). Using Firebird database to store physiological parameters makes proposed model more universal and extended in possibilities. There are described signal transformations, filtering, data recording methods using Atmel AVR microcontrollers, digital oscilloscope and R statistical environment. There are proposed self organizing maps (SOM) and multilayer perceptron (MLP) combinations for emotional state recognition and improved MLP training approach, which increases the learning rate and classification accuracy, in this paper as well.
KEYWORDS: human-computer interaction, e-social care, biorobot-based assistance, data mining, self organizing maps, multilayer perceptron..

Introduction

With the mass appeal of Internet-centered applications, it has become obvious that the digital computer is no longer viewed as a machine whose main purpose is to compute, but rather as a machine (with its attendant peripherals and networks) that provides new ways for human–computer interaction (HCI, henceforth) and for computer-mediated communication (CMC, henceforth) among users. Indeed, computers and robots are rapidly entering areas of our lives that typically involve socio-emotional content, such as telephone computerized receptionist, service robots in hospitals, homes, and offices, internet-based patient advising(where patients read textual information about their diseases), internet-based health chat lines (most often used for private mental health patient–clinician communications), and computer mediated patient monitoring and caring. Many similar applications are in the making (Lisetti et al., 2003).

Our research area is creating of adaptive user-friendly e-health care service for people with movement disabilities. Such system depends upon the possibility of extracting emotion without interrupting the user during HCI or CMC and using this information for patient monitoring and caring (Gricius et al. 2008; Bielskis et al. 2008; Drungilas et al., 2008) as appropriate emotional state could be a key indicator of the patient’s mental or physical health status (Lisetti et al. 2003)

The features of continuous physiological activity of disabled person are becoming accessible by use of intelligent bio-sensors coupled with computers. Such sensors provide information about the wearer's physical state or behaviour. They can gather data in a continuous way without having to interrupt the user and may include sensors for detecting of: Galvanic Skin Response (GSR) or Electro dermal Activity (EDA) based on measurements of Skin Conductance (SC), Blood Volume Pulse (BVP), Electrocardiogram (ECG), Respiration, Electromyogram (EMG), Body temperature (BT), and Facial Image Comparison (FIC). Galvanic Skin Response, the GSR, is a measure of the skin's conductance between two electrodes that apply a safe, imperceptibly tiny voltage across the skin of subject's fingers or toes. An individual's baseline skin conductance will vary for many reasons, including gender, diet, skin type and situation. When a subject is startled or experiences anxiety, there will be a fast increase in the skin conductance level, the SCL changing in a period of seconds due to increased activity in the sweat glands (unless the glands are saturated with sweat). After a startle, the SCL will decrease naturally due to reabsorption. Sweat gland activity increases the skin's capacity to conduct the current passing through it and changes in the skin conductance response, the SCR an indicator of the level of arousal in the sympathetic nervous system. A number of wearable systems have been proposed with integrated wireless transmission, GPS (Global Positioning System) sensor, and local processing. Commercial systems are also becoming available (Lisetti et al. 2003; Pentland 2004).

In this article, we focus on hardware and software design for physiological parameters recognition based on continuous SC measuring. We propose methods for automatic emotional state recognition using data filtering, self-organizing maps (SOM) and multilayer perceptron (MLP).

Emotion recognition and data mining system

The main concept of physiological parameters recognition is shown in Figure .1.

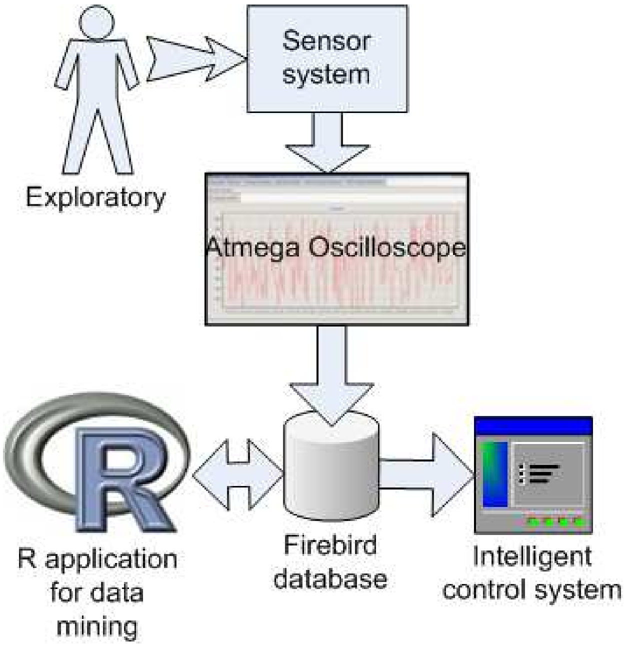

Figure 1. Hardware and software design for physiological parameters recognition

In this case, the sensor system contains skin conductance (SC) biometric sensor. The amplified signals are digitized and recorded to Firebird database by Atmega oscilloscope. R tool connected to Firebird database was used in order to extract useful information from collected data. R, as widely used for statistical software development and data analysis, is used for data filtering and physiological parameters mining. And all extracted information as a result is recorded to Firebird database, so that any intelligent control system connected to Firebird database could use this information. The connection between R tool and Firebird database is implemented by Open Database Connectivity (ODBC) interface. So the Firebird ODBC driver should be installed and configured. Besides in order to access ODBC database, RODBC package in R tool should be used. Package RODBC provides an interface to database sources supporting an ODBC interface. This is very widely available, and allows the same R code to access different database systems. RODBC runs on both Unix/Linux and Windows, and almost all database systems provide support for ODBC. Two groups of commands are provided. *odbc** commands implement relatively low level access to the odbc functions of similar name. *sql** commands are higher level constructs to read, save, copy and manipulate data between data frames and sql tables (R Development Core Team, 2008).

The concept model of the main processes in the system of physiological parameters recognition is shown in Figure 2.

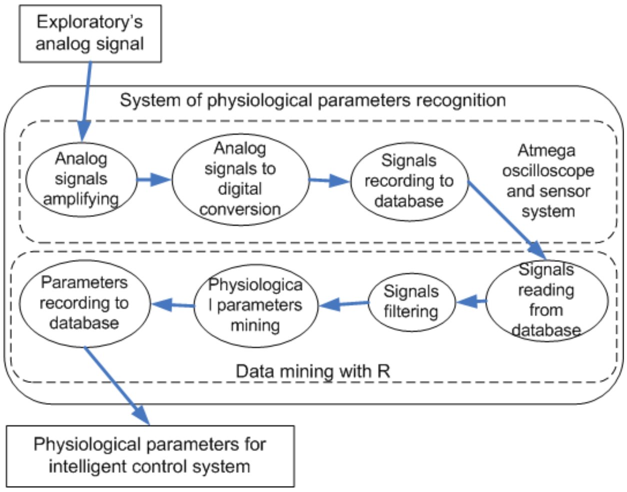

Figure 2. Concept model of physiological parameters recognition system

The main purpose of physiological parameters recognition system is to transform exploratory's analog signal into physiological parameters so that they could be used by any intelligent control system, to take patient monitoring and caring.

Smoothing method

Kernel regression smoothing was used to remove noise from recorded signals. Kernel smoothing, also named as kernel regression, offers a way of estimating the regression function without the specification of a parametric model. In kernel smoothing, the value of the estimate at a point Y can be calculated by a weighted average of this point and its neighbors. This weight function is often referred as a kernel. Usually, the kernel is a continuous, bounded and symmetric real function K that integrates to one (Zhang et al. 2007).

The widely used Nadaraya–Watson estimator was proposed by Nadaraya and Watson and is of the form

$$\hat{m}(x) = \frac{\sum_{i=1}^{n} K_h(x - x_i) y_i}{\sum_{i=1}^{n} K_h(x - x_i)} \quad (1)$$

Here, $K(\cdot)$ is a function satisfying $\int K(u)du = 1$, which we call the kernel, and h is a positive number, which is usually called the bandwidth or window width (Zhang et al., 2007). We see the larger the bandwidth – the smoother the result. Note that the kernels are scaled so that their quartiles (viewed as probability densities) are at +/- (0.25*bandwidth) (R Development Core Team, 2008).

For the SC data filtering R tool's function *ksmooth()* was used, which implements the Nadaraya-Watson kernel regression estimation (R Development Core Team, 2008). As we see in Figure 3, this data smoothing, with bandwidth=9, properly removes data noises and allows to do further data analisis.

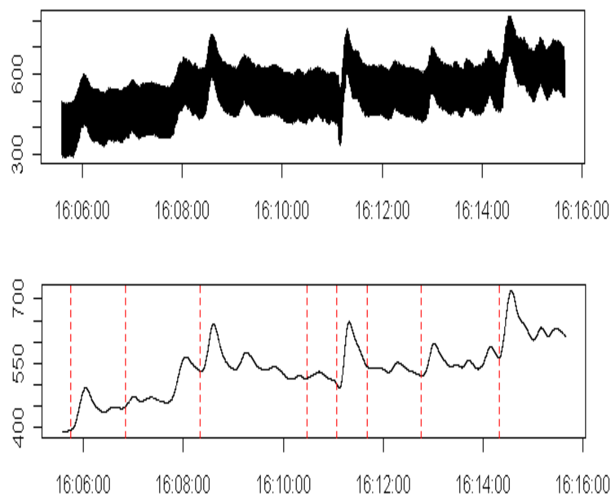

Figure 3. SC signal filtering using Nadaraya-Watson kernel regression smoothing

Data analysis

In Figure 4, we can see typical SC curve. From stimulus point (when emotional change ocures), four characteristics can be extracted from SC data: latency, rise time, amplitude and half recovery time (Figure4.).

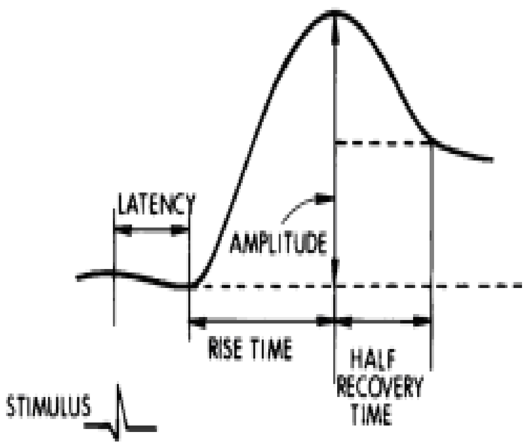

Figure 4. SC characteristics by Wang and McCreary (2006)

The purpose is to transform these four parameters into particular emotional state. In this case, we used eight discrete emotional states shown in Figure5. (Russell 1980)

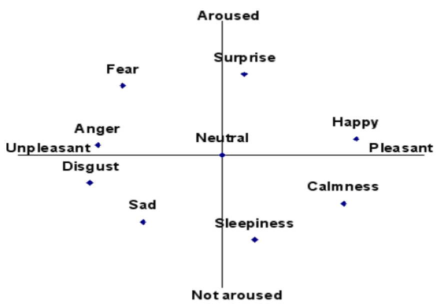

Figure 5. Emotional states by Russel (1980)

The clustering was done in order to make sure that the parameters classes of different states differs enough that could be used in prediction. As the errors could come from labeling the data points (teacher noise) classifying data into somewhat similar clusters can lead to noise reduction, and therefore, higher accuracy (Amin-Naseri and Soroush 2008; Alpaydin 2004).

For clustering, SOM, unsupervised self-learning algorithm, was used, that discovers the natural association found in the data. SOM combines an input layer with a competitive layer where the units compete with one another for the opportunity to respond to the input data. The winner unit represents the category for the input pattern. Similarities among the data are mapped into closeness of relationship on the competitive layer (Talbi and Charef 2009).

The SOM here defines amapping from the input data space R^4 onto a two-dimensional array of units. Each unit in the array is associated with a parametric reference vector weight of dimension four.Figure 6.

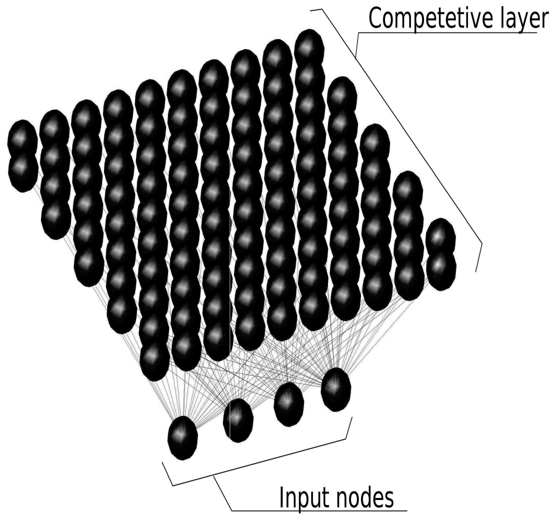

Figure 6. SOM's architecture to transform R4 input data space into a two-dimensional array of units

Each input vector is compared with the reference vector weight w_j of each unit. The best match, with the smallest Euclidean distance

$$d_j = \left\| x - w_j \right\| \quad (2)$$

is defined as response, and the input is mapped onto this location. Initially, all reference vector weights are assigned to small random values and they are updated as:

$$\Delta w_j = \alpha_n(t) h_j(g,t)(x_i - w_j(t)) \quad (3)$$

Where $\alpha(t)$ is the learning rate at time t and $h_n(g, t)$ is the neighbourhood function from winner unit neuron g to neuron n at time t. In general, neighbourhood function decreases monotonically as a function of the distance from neuron g to neuron n. This decreasing property has been reported to be a necessary condition for convergence.

Few packages are provided in R tool to implement SOM: kohonen, som, wccsom and other. In this case, kohonen R package was used as it aims to provide simple-to-use functions for self-organizing maps and the various extensions, with specific emphasis on visualisation. The basic functions are som, for the usual form of self-organizing maps; xyf, for supervised self-organizing maps, or X-Y fused maps, which are useful when additional information in the form of, e.g., a class variable is available for all objects; bdk, an alternative formulation called bi-directional Kohonen maps; and finally, from version 2.0.0 on, the generalisation of the xyf maps to more than two layers of information, in the function supersom. These functions can be used to define the mapping of the objects in the training set to the units of the map (Wehrens, Buydens 2007).

After the training phase, one can use several plotting functions for the visualisation; the package can show where objects are mapped, has several options for visualizing the codebook vectors of the map units, and provides means to assess the training progress. Summary functions exist for all SOM types. Furthermore, one can easily project new data into the trained map; this provides possibilities for property estimation (Wehrens, Buydens 2007).

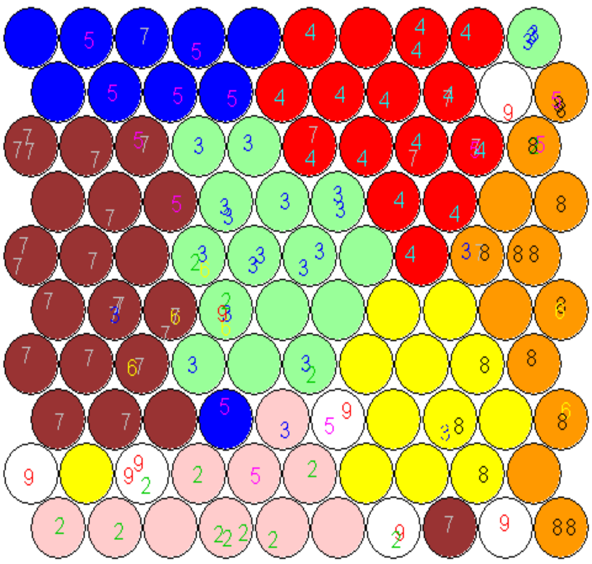

Figure 7. Clustering SC parameters using SOM

In Fig.7, we can see 10x10 SOM grids, where each unit contains R^4 weight vector that groups SC parameters by similarities. The numbers represent training data classes, and colours – different clusters after training.

The SOM's training progress is shown in Figure 8. As we know the SOM's units on competitive layer are arranged by similarities i.e. by distance, so the training is measured as mean distance to the closest unit on each iteration of training.

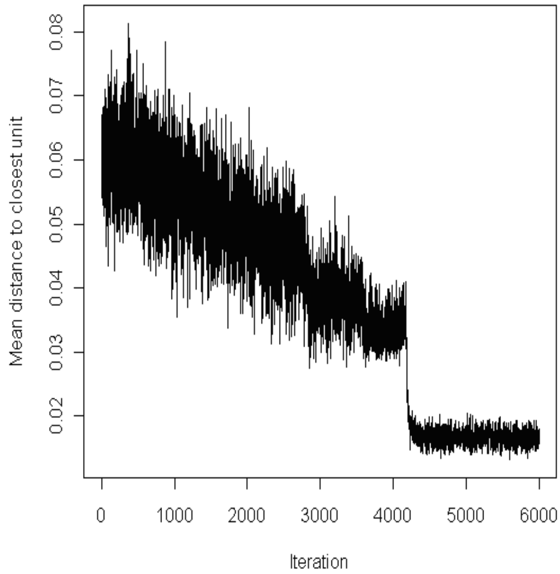

Figure 8. SOM's training progress

The classification accuracy can be calculated by:

$$A(h|X)=\frac{\sum_{t=1}^{N}\left[h(x^t)=r^t\right]}{N}\cdot 100\% \qquad (4)$$

Where h(x) is hypothesis of assigning x to appropriate class, r^t – experts indicated class, N – classification sample. $h(x^t)=r^t$ is equal to 1, when x^t is classiefied as r^t, and is equal to 0 othervise.

The clustering accuracy calculated by (4) is 75.00%. So the parameters classes of different states differs enough to make emotional state recognition. In order to know which factor is most important for emotional state classification we will make clustering with SOM by each factor and calculate clustering accuracy.

Clustering results we can see in Figure 9.

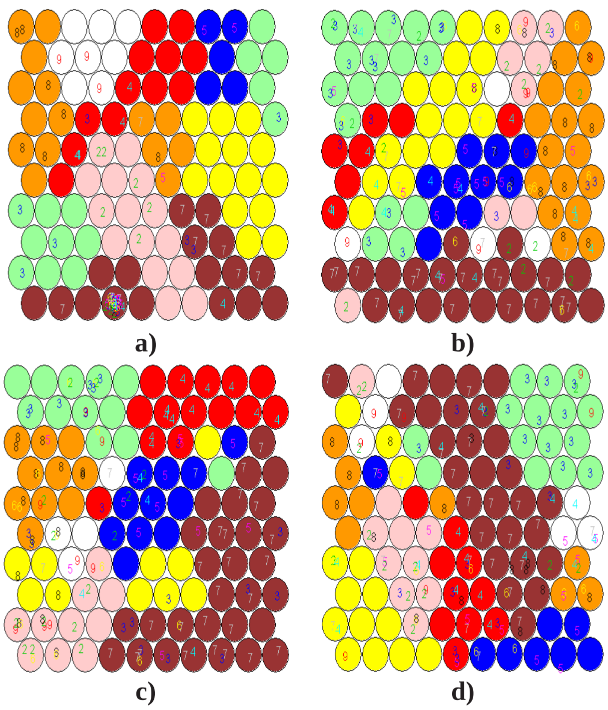

Figure 9. Clustering emotional states with SOM by SC parameters: a) latency, b) rise time, c) amplitude, and d) half recovery time

The clustering accuracies by latency, rise time, amplitude and half recovery time are 44.70%, 52.27%, 52.27% and 48.48% respectively. So the rise time and amplitude correlates with emotional states the most, and latency is least significant parameter for emotional state recognition. However all four SC parameters combined together give 22.73% higher accuracy (75.00%), than the best clusterization (52.27%) by separate SC parameters. In Fig.10. we can see the influence of SC parameters on each neuron so that the clustering of emotional states, as shown in Figure 7., could be made.

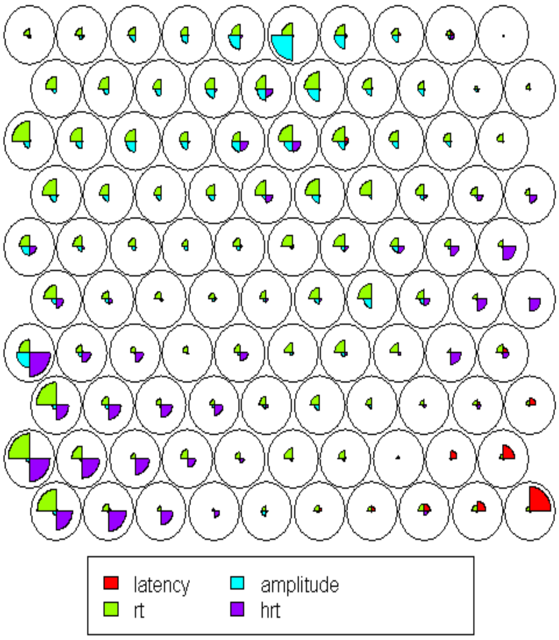

Figure 10. Influence of SC parameters on each neron of the SOM

As clustering data reduces noise, we will use classified data by SOM for MLP training. MLP was constructed by topology shown in Fig.11. It is feed forward neural network containing two hidden layers. There are four neurons in input layer for SC parameters and 8 neurons in output layer representing predictable states.

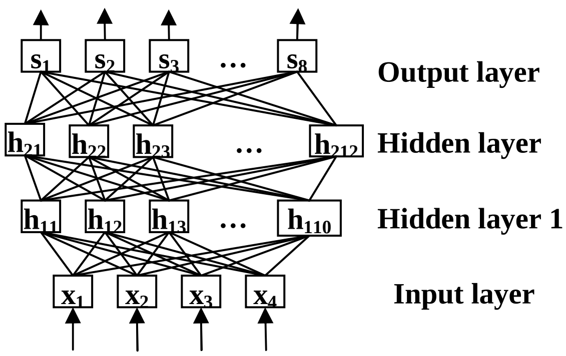

Figure 11. MLP topology

For experiment, two samples were used each containing training and testing data – 60% and 40% of all data sample respectively. First training sample was made from SOM's predicted data, second – from data not proceses by SOM.

Adaptative gradient descend with momentum algorithm was used to train MLP. The weights are updated as:

$$w_{ij}^{l}(t) = w_{ij}^{l}(t-1) + \Delta w_{ij}^{l}(t) \quad (5)$$

$$\Delta w_{ij}^{l}(t) = -\gamma(t)\frac{\partial E_s(t)}{\partial w_{ij}^{l}(t-1)} + \lambda \Delta w_{ij}^{l}(t-1) \quad (6)$$

Where $w_{ij}^{l}(t)$ is the weight from node i of lth layer to node j of (l + 1)th layer at time t, $\Delta w_{ij}^{l}(k)$ is the amount of change made to the connection, $\gamma(t)$ is the self-adjustable learning rate, λ is the momentum factor, $0 < \lambda < 1$, and ES is the criterion function. Minimizing the ES by adjusting the weights is the object of training neural network.

The criterion function E_S usually consists of a fundamental part and an extended part. The fundamental part is defined as a differentiable function of relevant node outputs and parameters at appropriate time instants. The extended part is a function of derivatives of node output that is related to evaluation of criterion function. Therefore, the part is related to some notions that cannot be represented by the fundamental criterion, such as, smoothness, robustness, and stability. Here, the fundamental part is only considered.

$$E_S(t) = \frac{1}{2}\sum_{i=1}^{S}\sum_{j=1}^{2}\left(y_j(t) - \hat{y}_j(t)\right)^2 \quad (7)$$

Where S is the total number of training samples.

The learning rate $\gamma(t)$ is usually initialized a small positive value and is able to be adjusted according to the information presented to the network.

$$\gamma(t) = \begin{cases} \gamma(t-1)\cdot a_1, 0 < a_1 < 1, E_S(t) \geq E_S(t-1) \\ \gamma(t-1)\cdot a_2, a_2 > 1, E_S(t) < E_S(t-1) \end{cases} \quad (8)$$

It is noted that the weights only are substituted by the new weights when E_S decreases. This measure can assure the convergence of the neural network model.

Repeat the training process until ES is either sufficiently low or zero (Han and Wang 2009).

Few packages are provided in R tool to implement feedforward neural networks: AMORE, nnet, neural and other. In this case the AMORE (A MORE flexible neural network package) package was used as it provides the user with an unusual neural network simulator: a highly flexible environment that should allow the user to get direct access to the network parameters, providing more control over the learning details and allowing the user to customize the available functions in order to suit their needs. The package is capable of training a multilayer feedforward network according to both the adaptive and the batch versions of the gradient descent with momentum backpropagation algorithm. Thanks to the structure adopted, expanding the number of available error criteria is as difficult as programming the corresponding R costs functions (Wehrens, Buydens 2007).

MLP training progress using AMORE package is shown in Fig.12 for the first and the second training samples – bold and thin lines respectively. As we see, training is much faster for first trainings sample. So it was useful to preprocess MLP's training sample with SOM, as MLP easier finds the patern.

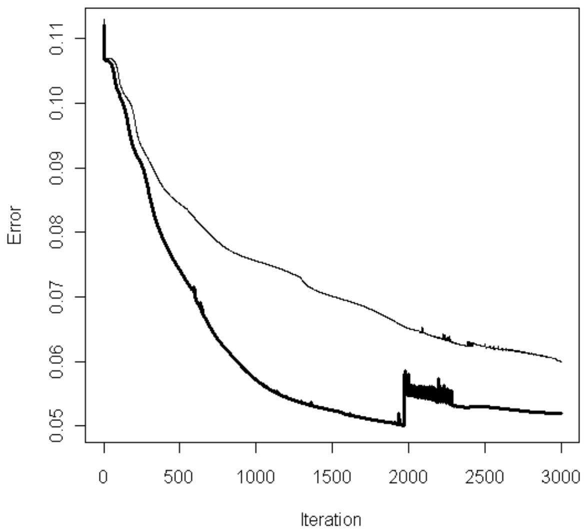

Fig.12. MLP training errors for different training samples

Another good point of training sample preprocession with SOM is that MLP classification accuracy increases 2.27% from 47.73% to 50.00%

Conclusion

In this paper, an approach of modelling of physiological parameters recognition system to creating of an intelligent e-health care environment is described. The process of physiological parameters recognition is based on measurements of very small physiological signals taken from electrodes noninvasively attached on human body. The amplified SC signal is used in the model for physiological parameters recognition and emotional state clustering. An approach of SC signals filtering using Nadaraya-Watson kernel regression smoothing in R tool is discribed. The data sample of physiological parameters extracted from SC signals was preprocessed by SOM using supervised clustering in order to reduce teacher noise that leads to higher accuracy. It was showed that using data sample preprocessed with SOM, in MLP training the learning process is much faster than using not preprocessed data sample. Besides the preprocession increases classification using MLP accuracy 2.27%

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AUTONOMINĖ EMOCIJŲ ATPAŽINIMO SISITEMA: DUOMENŲ GAVYBOS METODAI

Santrauka

Šių dienų požiūris į kompiuterį vis labiau siejamas su žmogaus ir kompiuterių sąveika (HCI), kuri kompiuterį leidžia traktuoti ne tik kaip skaičiavimo mašiną, bet ir kaip pagalbininką pritaikytą vartotojo poreikiams, e-paslaugų teikėją. Iš tiesų, kompiuteriai ir robotai vis sparčiau skverbiasi į mūsų gyvenimus įsitraukdami į tokias veiklas kaip komunikavimas, robotizuotų sistemų paslaugų teikimas ligoninėse, namuose, biuruose, e-sveikatos paslaugos.

Intelektualių sistemų kūrimas e-sveikatos, socialinės e-rūpybos srityse yra viena sudėtingiausių ir svarbiausių problemų šiuo metu. Šios sistemos apima įvairius intelektualius komponentus tokius kaip valdymą, stebėjimą, diagnozavimą, kurių pagrindu sistemos geba rinkti žmogaus fiziologinius parametrus, juos apdoroti ir interpretuoti pasitelkiant įvairiausius duomenų gavybos metodus, ir, remiantis gautais rezultatais, valdyti neįgalaus asmens prietaisus, t.y. teikti socialinės e-rūpybos paslaugas.

Mūsų tyrimo objektas yra adaptyvių su vartotojui draugiška aplinka e-sveikatos paslaugų kūrimas judėjimo negalią turintiems žmonėms. Tokio tipo sistemos remiasi galimybe, leidžiančia žmogaus – kompiuterio sąveikos (HCI) metu fiksuoti žmogaus fiziologinius signalus bei, pritaikius duomenų gavybos metodus, grąžinti atsakomąjį veiksmą (duoti patarimą, valdyti prietaisą).

Darbe yra pasiūlytas autonominės žmogaus emocijų atpažinimo sistemos modelis kuriant intelektualią socuialinės e-rūpybos pa slaugų aplinką. Modelis yra paremtas nutolusiuoju žmogaus emocijų tyrimu ir nutolusiųjų biorobotų adaptyviuoju valdymu per ATmega8/16/32 valdiklius. Modelyje yra naudojami žmogaus elektrinio odos aktyvumo (SC) matavimo duomenys, kurie yra pagrindiniai fiziologiniai parametrai vertinant žmogaus emocinę būseną.

Fiziologinių parametrų tyrimais grindžiamų socialines e-paslaugas teikiančių sistemų kūrimas vis dar susiduria su parametrų išgavimo, duomenų apdorojimo, interpretavimo bei intelektualaus valdymo problemomis. Todėl darbe aprašomi SC duomenis charakterizuojančių signalų transformavimo, filtravimo ir duomenų kaupimo metodai bei, algoritmai, panaudojant Atmel AVR tipo mikrovaldiklius, skaitmeninį oscilografą bei R statistinį paketą. Darbe apžvelgiamos R priemonės (filtravimas, savaime susitvarkantys žemėlapiai, daugiasluoksnis perceptronas), kuriomis buvo atliekamas duomenų apdorojimas bei interpretavimas. Pasiūlytas fiziologinių parametrų atpažinimo sistemos modelis pasižymi universalumu, kadangi apdoroti rezultatai kaupiemi Firebir duomenų bazėje ,kuria gali naudotis betkuri, palaikanti suderinamumą su šia duomenų baze, intelektuali valdymo sistema.

Darbe pateikiamos savaime susitvarkančių žemėlapių ir daugiasluoksnio perceptrono panaudojimo galimybės kuriant žmogaus emocijų atpažinimo sistemas. Buvo parodyta, jog taikant savaime susitvarkančius žemėlapius, kaip daugiasluoksnio perceptrono mokymo imties apdorojimo metodą, galima paspartinti daugiasluoksnio perceptrono mokymąsi bei padidinti klasifikavimo tikslumą.

PAGRINDINIAI ŽODŽIAI: žmogaus ir kompiuterio bendravimas, socialinė e-rūpyba, biorobotų paslaugos, save organizuojantys tinklai, daugiasluoksnis perceptronas.

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