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Multi-Agent-Based Human Computer Interaction of E-Health Care System for People with Movement Disabilities

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Introduction

In creating of adaptive user-friendly e-health care service for people with movement disabilities, human's affect sensing is included in Human Computer Interaction (HCI), Human-Robot Interaction (HRI), and Computer Mediated Communication (CMC) [1, 2, and 3]. In recently [4, and 5] proposed system, the model of two adaptive moving wheelchair-type robots for remotely communicating with two wearable human's affect sensing bio-robots was used. To further development of this model, research results present the development of multi-agent-based human computer interaction model and its integration into the system of fuzzy neural control of speed of N wheelchair type robots to providing movement support for disabled individuals. An approach of filtering of skin conductance (SC) and electrocardiogram (ECG) signals using Nadaraya-Watson kernel regression smoothing in R tool for emotion recognition of disabled individuals is described and implemented in the system. The unsupervised clustering by self organizing maps (SOM) of data sample of physiological parameters extracted from SC and ECG signals noninvasively measured from disabled was proposed. It was implemented to reduce teacher noise as well as to increase of speed and accuracy of learning process of multi-layer preceptron (MLP), which was applied in the multi-agent-based human computer interaction model for online prediction of e-health care state of disabled individuals.

Computer mediated communication in the system

This paper gives some aspects of application of remote ECG and SC measurements used in providing multi-agent based e-health and e-social care assistance for people with movement disabilities [3, 5]. Fig. 1 presents a modified [5] model of N adaptive moving wheelchair-type robots for remotely communicating with N wearable human's affect sensing bio-robots. In this system, to capture towards e-social and e-health care context relevant episodes based on humans affect stages [2], the context aware sensors are incorporated into the design of the Human's Arousal Recognition Module's (HARM-x) for every disabled individual. The local Intelligent Decision Making Module's (IDMM-x) for every intelligent social care providing robot is used for multi-sensor data fusion before transmitting the data to the Remote Central Server (RCS) to minimize the TCP/IP (UDP) bandwidth usage.
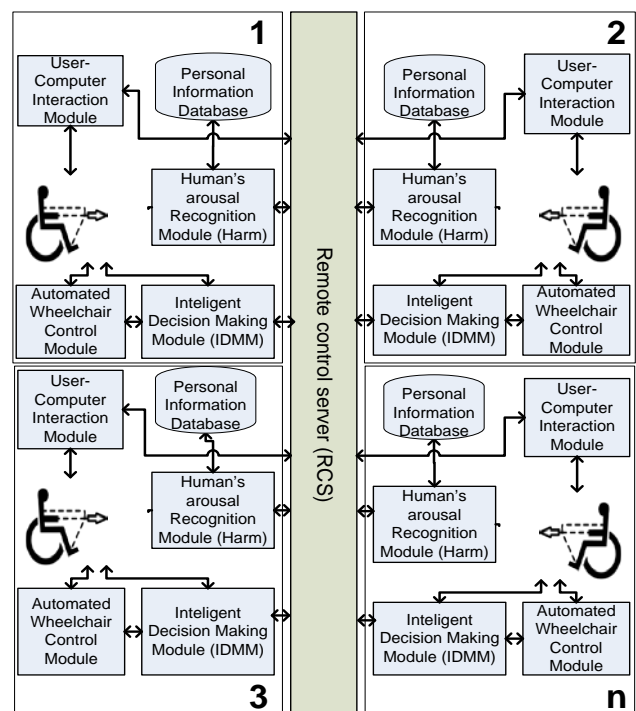

Fig. 1. The modified computer mediated communication model of the system by [5]

Fig. 2a shows concept model of physiological parameters recognition subsystem used in the arousal recognition modules *HARM-x* and the intelligent decision making modules *IDMM-x* for every user *x=1, 2, ..,* and *N* of Fig. 1. To recognizing of e-health aware state of every user *x*, a multi-layer preceptron (MLP) of Fig. 2b is used: with 5 neurons in an input layer to describing of parameters: the latency (*Lat*), the rise time (*RT*), the amplitude (*A*), the half recovery time (*hrt*) and heart rate variability (hrv) [5] derived from records of SC and ECG signals stored in every users *Personal Information Database* of Fig. 1; with 10 neurons, the $H_{11}, H_{12}, .., H_{110}$, of hidden layer 1; with 12 neurons, the $H_{21}, H_{22}, .., H_{212}$, of hidden layer 2; and with 8 neurons of output layer, the $S_1, S_2, ..., S_8$, to describing of the following human's emotional states: *Fear, Surprise, Anger, Happy, Disgust, Calmness, Sad, Sleepiness* [8]. Fig. 2c represents emotional state allocation on continuous arousal-valence space proposed by [8], predicted by using trained MLP of Fig. 2b.
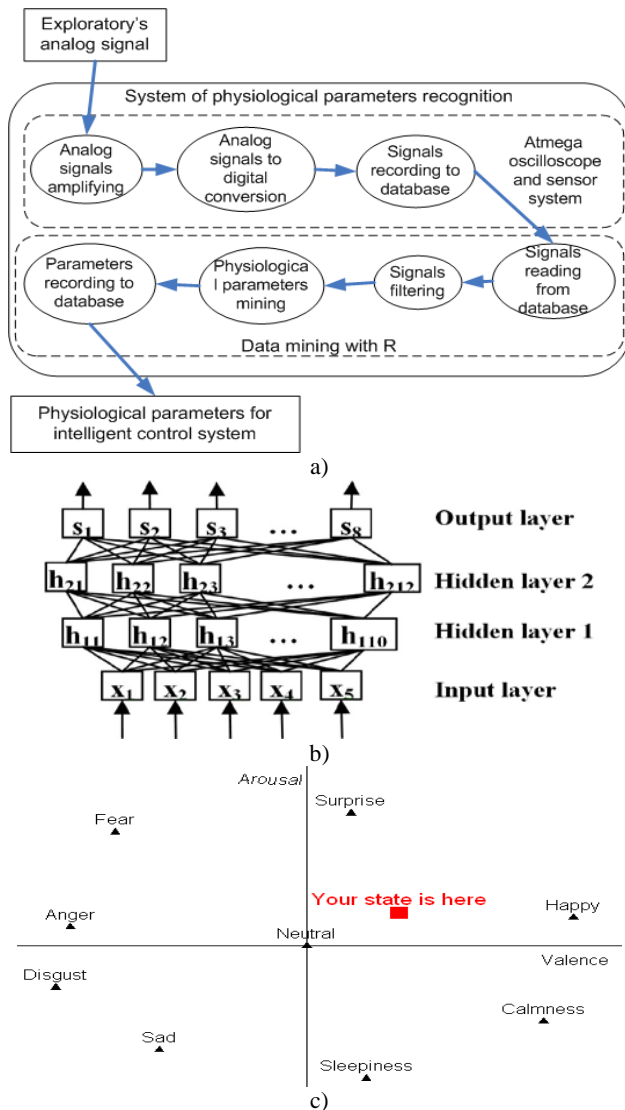

a)

b)

c)

Fig. 2. Elements of physiological parameters recognition subsystem: a – concept models, b – multi-layer preceptron (MLP) to recognizing e-health aware state of an individual, c – emotional state allocation on continuous arousal-valence space

Digital data filtering

Two methods were used for digitalized SC data filtering - Gaussian and kernel regression smoothing.

The Gaussian Smoothing is a type of blurring filter that uses a Gaussian distribution function. The Gaussian distribution in 1-D has the form

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}, \quad (1)$$

where *s* is the standard deviation of the distribution. It is also assumed that the distribution has a mean of zero.

By (1) equation one can calculate coefficients for any kernel width. These coefficients are used for digitalized signal filtering by this equation

$$y_i = \sum_{j=0}^{\frac{n-1}{2}} y_{i-j}G(-j) + \sum_{j=1}^{\frac{n-1}{2}} x_{i+j}G(j), \quad (2)$$

where $y_i - i^{th}$ processed *y* signal value, $x_i - i^{th}$ not processed *x* signal value, *n* – Gaussian kernel width (odd value).

Kernel Regression 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. The widely used Nadaraya-Watson estimator was proposed by Nadaraya and Watson and is of the form

$$\hat{m}(x) = \frac{\sum_{n=1}^{n} K_h(x - x_i) y_i}{\sum_{n=1}^{n} K_h(x - x_i)}, \quad (3)$$

where *K( )* is a function satisfying ∫*K (u)du = 1* , which we call the kernel, and *h* is a positive number, which is usually called the bandwidth or window width. All experiments reported in this work were written in *R*. Two filtering approaches of digital SC data have been used. The result of 7, 06 s Gaussian smoothing is shown in Fig. 3. It can be seen that little noise still remains.
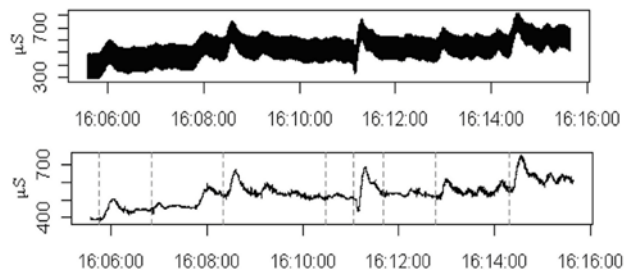

Fig. 3. SC signal filtering using Gaussian smoothing

For the SC data filtering by kernel smoothing, *R* tool's function *ksmooth()* was used, which implements the Nadaraya-Watson kernel regression estimation algorithm. Fig. 5 shows the case of this data smoothing (performed in

0.36 s), with *bandwidth*=9. It removes much better data noises and performs faster than Gaussian smoothing.
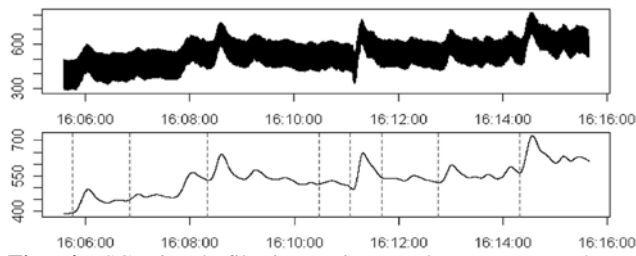

Fig. 4. SC signal filtering using Nadaraya-Watson kernel regression smoothing

Shown in Fig. 5, the ECG signals noninvasively measured from disabled was filtered by using agent „Smoother" of Fig. 7 input data (Fig. 5a.), and filtered by the agent output data (Fig. 5b).
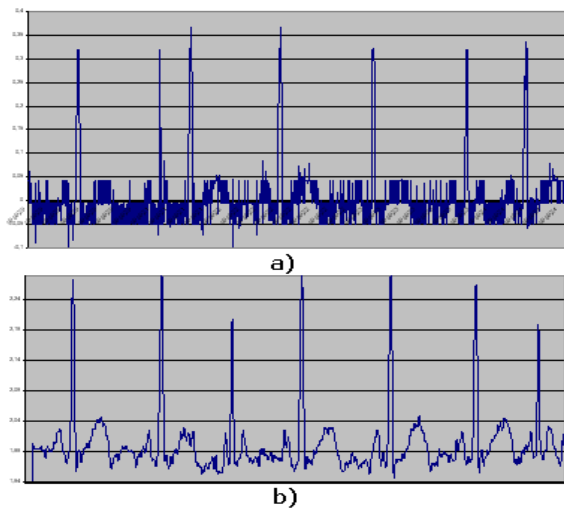

Fig. 5. The agent's "Smoother" input data (a), and the agent's output smoothed data (b)

Emotional state recognition

From stimulus point (when emotional change occurs), four characteristics can be extracted from SC data: latency, rise time, amplitude, half recovery time, and one parameter from ECG – heart rate variability. The purpose is to transform these five parameters into particular emotional state. In this case, the eight discrete emotional states are used: *Fear, Surprise, Anger, Happy, Disgust, Calmness, Sad, and Sleepiness.* The clustering was done in order to make sure that the parameters classes of different states differs enough that could be used in prediction and, 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. 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. The *SOM* here defines a mapping from the input data space R^5 onto a two-dimensional array of units. Each unit in the array is associated with a parametric reference vector weight of dimension five. Each input vector is compared with the reference vector weight w_j of each unit. The best match is calculated with the smallest Euclidean distance

$$d_j = \|x - w_j\| \qquad (4)$$

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

$$\Delta w_j = \alpha_n(t)h_j(g,t)(x_i - w_j(t)), \qquad (5)$$

where $\alpha(t)$ is the learning rate at time t and $h_n(g, t)$ is the neighborhood function from winner unit neuron g to neuron n at time t. The *kohonen R* package was used to provide simple-to-use functions such as *som*, *xyf*, *bdk*, and *supersom* to define the mapping of the objects in the training set to the units of the map.
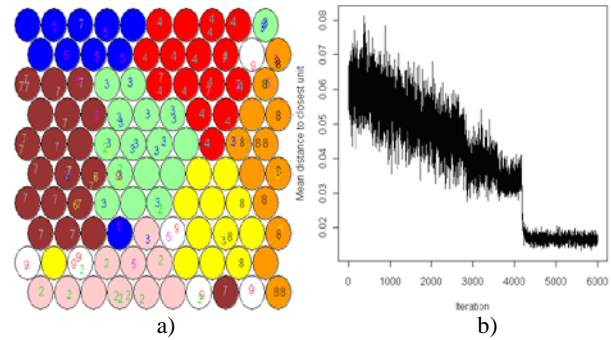

Fig. 6. Clustering SC parameters by SOM (a), and Training progress of SOM (b)

In Fig. 6a, we can see 10x10 *SOM* grids, where each unit contains R^5 weight vector that groups *SC and ECG* parameters by similarities. The numbers represent training data classes, and colors – different clusters after training. The *SOM*'s training progress is shown in Fig. 6b. 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. The cauterization accuracy can be calculated by:

$$A(h \mid X) = \frac{\sum_{t=1}^{N} h(x^t) = r^t}{N} \cdot 100\% , \qquad (6)$$

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 classified as r^t, and is equal to 0 otherwise. The clustering accuracy calculated by (4) is 79.55%. So the classes of parameters of different states are distinguishable enough to make emotional state recognition.

Prediction of discrete emotional states can be done by using multi-layer preceptor (*MLP*). As clustering data reduces noise, we will use classified data by *SOM* for *MLP* training. *MLP* was constructed by topology shown in Fig. 2c. It is feed forward neural network containing two

hidden layers. There are four neurons in input layer of *SC,* one of ECG parameters and 8 neurons in output layer representing predictable states. Adaptive gradient descend with momentum algorithm was used to train *MLP*. The weights are updated as:

$$w_{ij}^l(t) = w_{ij}^l(t-1) + \Delta w_{ij}^l(t), \tag{7}$$

$$\Delta w_{ij}^l(t) = -\gamma(t)\frac{\partial E_s(t)}{\partial w_{ij}^l(t-1)} + \lambda \Delta w_{ij}^l(t-1), \tag{8}$$

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 E_S is the criterion function.

Minimizing the E_S 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 as the

$$E_S(t) = \frac{1}{2}\sum_{i=1}^{S}\sum_{j=1}^{2}\left(y_j(t) - \hat{y}_j(t)\right)^2, \tag{9}$$

where S is the total number of training samples. The learning rate $\gamma(t)$ is usually initialized as a small positive value and it is able to be adjusted according to the following information presented to the network

$$\gamma(t) = \begin{cases} \gamma(t-1)\cdot a_1, 0 < a_1 < 1, E_S(t) \geq E_S(t-1); \\ \gamma(t-1)\cdot a_2, a_2 > 1, E_S(t) < E_S(t-1). \end{cases} \tag{10}$$

It has to be 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 E_S is either sufficiently low or zero.

After teacher's noise elimination and MLP training, 5-fold cross-validation, the classification into eight dimensional emotional space accuracy was calculated: $35.78 \pm 1.91\%$. For more flexible and accurate emotional state recognition representation shown in Fig. 2c, the arousal-valence continuous space [8] was used to allocate predictable emotional state which coordinates could be calculated as

$$\vec{a} = \sum_{i=1}^{n}\vec{b}_n \cdot S_n, \tag{11}$$

where S is the MPL output of nth neuron; $\vec{b}_n$ is the nth emotional state's vector in arousal-valence space, related with appropriate MLP's neuron.

Agent-Based Human computer interaction in the system

Human Computer Interaction (HCI) in the system is realized in providing of necessary e-health care support actions for *user1* to *userN* discovered in the *Personal Information Databases* of Fig. 1. To proposing of precisely controllable social care aware movement actions by robot *1, 2, ..,* and *N* for given user with movement disabilities, a real-time Off-Policy Agent Q-learning algorithm [7] was used

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max_{a'}Q(s',a') - Q(s,a)]. \tag{11}$$

It was implemented by using multi-agent based human computer interaction system of Fig. 7. The system was constructed by using *Java*–based *JACK* agent oriented environment to laying-down an optimal path of robot in assisting a disabled person for a given his/her arousal context aware situation.
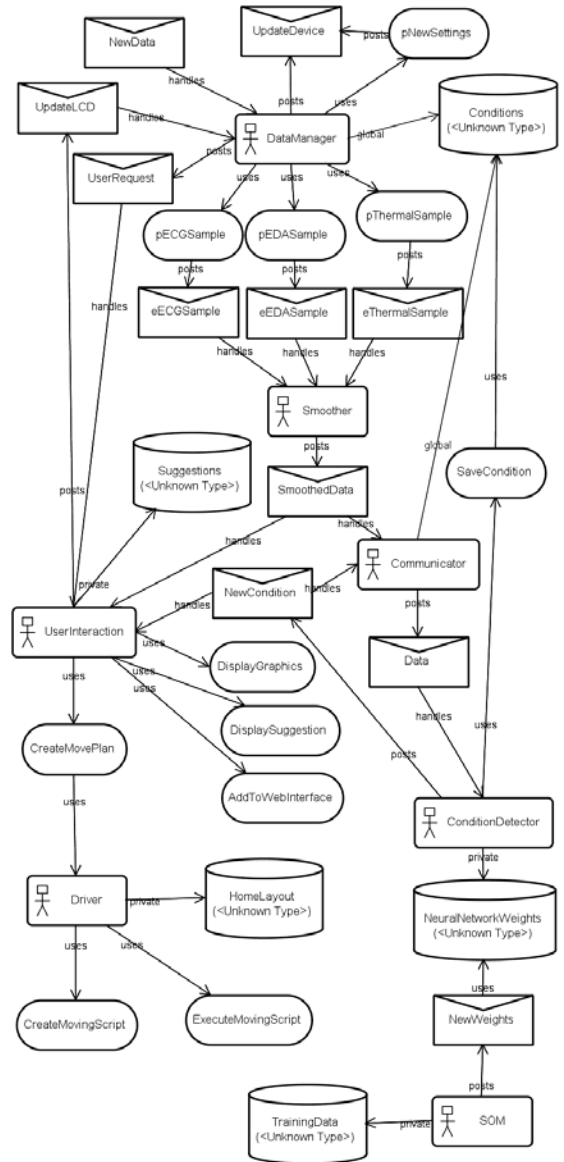

Fig. 7. Multi-agent-based system: human-computer remote interaction block diagram

The proposed multi-agent system of Fig. 7 permanently performs the following actions:

"DataManager" agent is responsible for communication between hardware (ATMEGA oscilloscope [6]) and software. It takes data via RS232 protocol, determines the type of received data (ECG, EDA, temperature or and settings information) and performs appropriate actions. This agent is also responsible for the feedback to the hardware (LCD information transfer, ADC channels settings transfer, etc.). The agent communicates with the hardware via events:

- *NewData* - new data received from the technical equipment;
- *UpdateDevice* - sent new settings or information about technical equipment.

Upon receiving of new data, the agent identifies data and distinguishes new physiological parameters or device settings. On receiving the new physiological parameters, agent selects one of the plans *pECGSample, pEDASample* or *pThermalSample*, which will generate events *eECGSample, eEDASample,* and *eThermalSample* to the other agents. In a case on receiving new hardware parameters, it will execute the plan *pNewSettings* which will update the software settings, and report to the hardware information about the changes. Agent saves all received data to the database.

The agent also receives information from the agent "UserInteraction" of information, which should be displayed on the LCD display. Agent sends information to the hardware via event *UpdateDevice*.

"UserInteraction"– the agent is responsible for information conveying to the user and the users commands input. The agent has an internal database of *Suggestions* which holds the tips to the user, what user should do or what action should be taken by a change of emotional state. This agent also prints the ECG, SC, and temperature graphs on the screen, after receiving notice of the new emotional state shows it on the screen and, in the database "Suggestions", tries to find the appropriate advice to the user. User information is also sent to the agent "DataManager" to be printed in the LCD screen. Agent also adds all the data to the web server via plan *AddToWebInterface* which uses TCP/IP protocol for data transmission.

The agent takes the events with physiological data: *eECGSample, eEDASample, eThermalSample.* It smoothes them and displays on the screen. After receiving information about new human physiological state (event *NewCondition*), it decides whether to provide the user with any proposal. If it decides to provide, then the proposal is selected from the database *Suggestions* and displayed on the screen, and, via event *UpadeteLCD,* it is transmitted to the users LCD. It is also the agent that takes the user commands via event *UserRequest*, and, by the user desire, creates a dynamical agent "Driver" witch will have information about location to which the user wants to go. Agent "Driver" has an internal database *HomeLayout* which has schemes of the house layouts, and, according to the data, the agent creates a scenario by which the user is moved to the desired location. During the journey, where the way meets an obstacle or home layout has been changed, the agent updates the database *HomeLayout* data. After completing a journey, agent "Driver" retains the accumulated data.

"Som" and *"ConditionDetector"* agents are responsible for analyzing collected physiological data and emotional state detection. Agent "Som" has a private database *TraningData* in which a learning data is stored, and, using this data, it calculates the new weights for neural network. Agent "ConditionDetector" is realized by neural network, which, according to newly obtained physiological data and neural network weights in the database *NeuralNetworkWeights,* detects a new emotional state.

"Communicator" – the agent responsible for data storage, it gives information about the human physiological parameters, store them in the database and, when enough physiological data is collected, generates event *Date* which will activate agent "ConditionDetector" and new emotional state will be calculated with new data. The agent also takes information about new emotional state from the agent "Conddition Detector" and saves it in the database *Conditions*.

"Smoother" – the agent which is responsible for newly received data filtering and smoothing. It takes the events such as the *eECGSample, eEDASample, eThermalSample*, and in every case different filtering and smoothing method is used.

Conclusions

This paper presents further development of recently proposed by author's model of intelligent e-health care system for people with movement disabilities. The research results present the development of multi-agent-based human computer interaction model and its integration into the system of fuzzy neural control of speed of two wheelchair type robots to providing movement support for disabled individuals. An approach of filtering of skin conductance (SC) and electrocardiogram (ECG) signals using Nadaraya-Watson kernel regression smoothing in R tool for emotion recognition of disabled individuals is described and implemented in the system. The unsupervised clustering by self organizing maps (SOM) of data sample of physiological parameters extracted from SC and ECG signals noninvasively measured from disabled was proposed. It was implemented to reduce teacher noise as well as to increase of speed and accuracy of learning process of multi-layer preceptron (MLP), which was applied in the multi-agent-based human computer interaction model for online prediction of e-health care state of disabled individuals.

An approach is discussed on integration into the model of an intelligent e-health care environment by modelling of an adaptive multi-agent-based e-health and e-social care system for people with movement disabilities. Human's Arousal Recognition Module is modified for online recognition of human's ECG and SC signals by using embedded Atmega32 type microcontrollers. Multi-agent based online motion control of *N* wheelchair-type robots is implemented by integration of real-time adaptive Fuzzy Neural Network Control algorithm into ATmega32 microcontroller. Human Computer Interaction in the system realized in providing of necessary e-health care

support actions for users with some movement disabilities by using *Java*–based *JACK* agent oriented environment. To proposing of precisely controllable social care aware movement actions by social-care robots in the system for given user with movement disabilities, an *Off-Policy Agent Q-learning* algorithm has been implemented in real time. The dynamic multi-agent system is proposed to permanently realizing e-social care support actions for disabled by: gathering data such as current position of robot and user's state information from intelligent robots; finding decisions for given situation; sending signals to performing appropriate actions of the objects in the system.

References

1. **Drungilas D., Bielskis A. A., Denisov V., Dzemydienė D.** Data Mining Approaches for Intelligent E-Social Care Decision Support System. – In: Rutkowski L., Scherer R., Tadeusiewicz R., Zadeh L. A., Zurada J. M. (eds.) Artificial Intelligence and Soft Computing, Part I, LNAI, Vol. 6113, Springer, Berlin Heidelberg 2010, pp. 605-612.
2. **Villon O., Lisett Ch.** A User–Modeling Approach to Build User's Psycho–Physiological Maps of Emotions using Bio–Sensors // Proc. of IEEE Roman. – 2006. – P. 269–276.
3. **Bielskis A. A., Dzemydienė D., Denisovas V., Andziulis A., Drungilas D**. An approach of multi–agent control of bio–robots using intelligent recognition diagnosis of persons with moving disabilities // Technological and economic development of economy. – Vilnius: Technika, 2009. – Vol. 15. – No. 3. – P. 377–394.
4. **Andziulis A., Bielskis A. A., Denisovas V., Ramašauskas O., Bielskienė J., Bielskis P., Guseinovienė E**. An Approach of Creating of an Intelligent Mobile Tutoring Eco–social Laboratory for Assisted Recreation // Electronics and Electrical Engineering. – Kaunas: Technologija, 2009. – No. 3(91). – P. 61–66.
5. **Bielskis A. A., Denisovas V., Drungilas D., Gricius G., Ramašauskas O**. Modeliing of Intelligent Multi–Agent based E–health Care System for People with Movement Disabilities // Electronics and Electrical Engineering. – Kaunas: Technologija, 2008. – No. 6(86). – P. 37–42.
6. **Gricius G., Bielskis A. A.** Development of "ATmega Oscilografas" as a Device for Autonomous Emotion Recognition System // Journal of Management. – 2009. – Vol. 1. – No. 14. – P. 89–106.
7. **Watkins C. J.** Learning from Delayed Rewards. PhD thesis. – England, Cambridge: Cambridge University, 1989. – P. 26–49.
8. **Russell J. A**. A circumflex model of affect // Journal of Personality and Social Psychology. – 1980. – Vol. 39. – No. 6. – P. 1161–1178.

A. A. Bielskis, V. Denisovas, D. Drungilas, G. Gricius, D. Dzemydienė. Multi-Agent-Based Human Computer Interaction of E-Health Care System for People with Movement Disabilities // Electronics and Electrical Engineering. – Kaunas: Technologija, 2010. – No. 7(103). – P. 77–82.

This paper presents further development of intelligent e-health care system for people with movement disabilities. The research results present the development of multi-agent-based human computer interaction model and its integration into the system of fuzzy neural control of speed of two wheelchair type robots to providing movement support for disabled individuals. An approach of filtering of skin conductance (SC) and electrocardiogram (ECG) signals using Nadaraya-Watson kernel regression smoothing in R tool for emotion recognition of disabled individuals is described and implemented in the system. The unsupervised clustering by self organizing maps (SOM) of data sample of physiological parameters extracted from SC and ECG signals noninvasively measured from disabled was proposed. It was implemented to reduce teacher noise as well as to increase of speed and accuracy of learning process of multi-layer preceptron (MLP), which was applied in the multi-agent-based human computer interaction model for online prediction of e-health care state of disabled individuals. Keywords- multiple agent e-health care, bio-robots, human computer interaction, skin conductance, electrocardiogram, fuzzy logic, neural networks. Ill. 7, bibl. 8 (in English; abstracts in English, Russian and Lithuanian).

А. А. Бельскис, В. Денисовас, Д. Друнгилас, Г. Грицюс, Д. Дземидене. Моделирование многоагентной оболочки человеческо-компьютерного общения системы э-здоровья для людей с недугом по подвижности // Электроника и электротехника. – Каунас: Технология, 2010. – № 7(103). – С. 77–82.

Предложена модель многоагентной системы по предоставлению э-услуг для людей с недугом по подвижности. Разработанная модель (HARM) базируется на автоматическом опознавании человеческих эмоций с применением SC и ECG датчиков и ATmega32 микроконтроллеров, адаптивных, статистических инструментов и искусственной нейронной сети. Человеческо-компьютерное общение в системе реализовано через действующую на *Java–based JACK* оболочке многоагентную систему, которая собирает данные о деятельности системы, принимает решения в заданных ситуациях, ведет управление объектами по предоставлению адекватной в данной ситуации социальной помощи для людей с недугом по подвижности. Ил. 7, библ. 8 (на английском языке; рефераты на английском, русском и литовском яз.).

A. A. Bielskis, V. Denisovas, D. Drungilas, G. Gricius, D. Dzemydienė. Intelektualios daugelio agentų e.sveikatos paslaugų sistemos judėjimo negalią turintiems asmenims sąsajos modeliavimas // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2010. – Nr. 7(103). – P. 77–82.

Pasiūlytas intelektualios agentinės sistemos modelis e.sveikatos ir e.socialinės rūpybos paslaugoms teikti judėjimo negalią turintiems žmonėms. Modelis (HARM) paremtas nutolusiuoju žmogaus emocijų tyrimu per SC ir ECG jutiklius bei ATmega32 valdiklius dirbtinių neuronų adaptyviame tinkle taikant miglotuosius algoritmus ir statistinius metodus. Žmogaus ir kompiuterio bendravimas sistemoje vyksta per sukurtąją *JACK* (programavimo kalbos Java dialektas) pagrindu veikiančią daugelio agentų sistemą, renkančią duomenis apie sistemos veiklą, priimančią sprendimus esamoje situacijoje, valdančią objektus pagal situaciją teikiant e.sveikatos rūpybos paslaugas į sistemą įsijungusiems neįgaliesiems. Il. 7, bibl. 8 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).