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Ambient Lighting Controller Based on Reinforcement Learning Components of Multi-Agents

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Introduction

Inspired by investigations of thermal comfort, indoor air quality and adequate luminance by using the Predicted Mean Vote Index (PMV) [1–3], the human Ambient Lighting Affect Reward (*ALAR)* index is proposed for automatic quality control of lighting in the ambient assisted living environment [4, 5]. The *ALAR* based multi-agent ambient lighting controller is planned also to be used to improve energy savings. Specifically, it predicts the indoor RGB LED lighting conditions at a given time by measuring integrated *ALAR* index that defines ambient lighting affect to the human. Principles of development of the Ambient Lighting Affect Reward Based Multi-Agent Controller, the *ALARBMAC* are described in this paper. The *ALARBMAC* is planned to be applied in the process of development of Eco-social laboratory, the *ESLab* as a laboratory prototype of the Smart Eco-Social Apartment [4].

The *ALAR* based controller model

The developing process of the smart environment is based on automatic control which adopts environment by smart sensing of human physiological signals. The reinforcement learning is used to get optimal environment characteristics. The architecture of the reinforcement learning based ambient lighting controller (*RLBALC*) is shown in Fig. 1. Formally, the goal of the reinforcement learning based ambient lighting controller (*RLBALC*) is to find such environmental state characteristics that create an optimal RGB LED lighting for people affected by this environment.

The RLBALC consists of the following parts: the *Environment Evaluation System,* the *Radial Basis Neural Network,* and the *Learning Algorithm.* The *Environment Evaluation System* is used to evaluate the human comfort by sensing the affect of the following RGB LED lighting color and intensity parameters: the intensity of red (*Lr*), green (*Lg*) and blue (*Lb*) light.

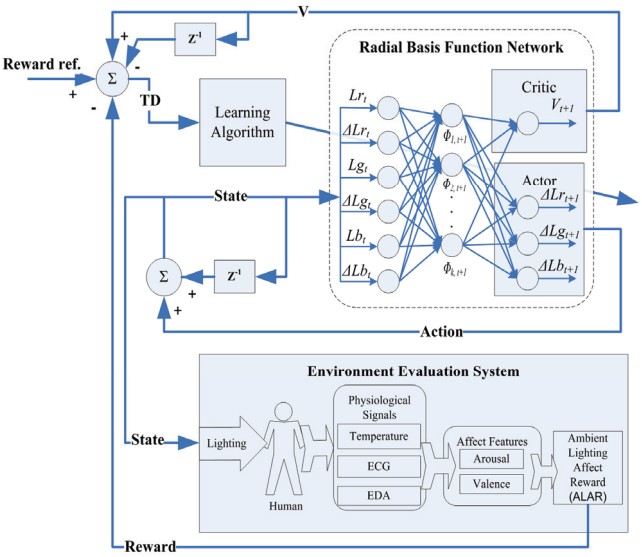


Fig. 1. Structural-functional schema of ambient lighting controller (*RLBALC*)

The human comfort is expressed as an Ambient Lighting Affect Reward, the *ALAR* index function

$$ALAR = f\{a(t,c,d), v(t,c,d)\},\ ALAR \in [-3,3], \quad (1)$$

where a and v are arousal and valence functions respectively dependent on human physiological parameters: t – temperature, c – *ECG*, electrocardiogram and d – *EDA*, electro-dermal activity. It is shown [4, 5], that (1) type function can be approximated by neural networks, fuzzy logic or other regression methods. In this case, we use fuzzy logic to approximate (1) by defining two fuzzy inference systems: the *Arousal-Valence System*, and the *Ambient Lighting Affect Reward (ALAR) System* as shown in Fig. 2.

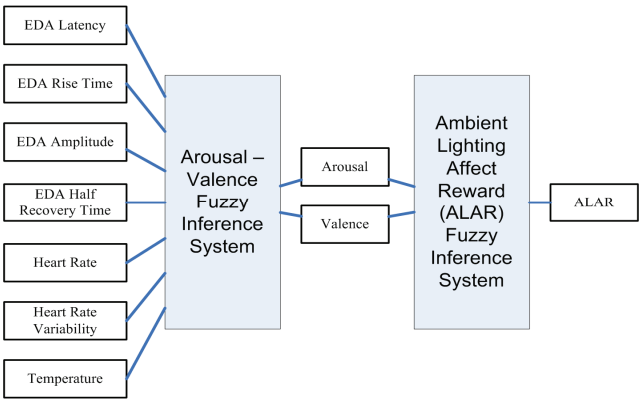


Fig. 2. Block diagram of the *Arousal-Valence* and the *Ambient Lighting Affect Reward (ALAR)* fuzzy inference system

The Radial Basis Neural Network is the main component of the *RLBALC* responsible for two roles - the policy structure, known as the *Actor*, used to select actions, and the estimated value function, known as the *Critic* that criticizes the actions made by the *Actor*. We use *Critic* as value function approximates for continuous learning tasks (like *RLBALC*), because discrete state representation of environment can be problematic. The continuous MDP can lose its Markov property if the state discretization is too coarse. As a consequence, there are states which are not distinguishable by the agent, but which have quite different effects on the agent's future. Using reinforcement learning for control tasks is a challenging problem, because we typically have continuous state and action spaces. For learning with continuous state and action space, a function approximation must be used. Linear function approximations are very popular in this problem area, because they can generalize better than discrete states and are also easy to learn at least when using local features [6, 7]. A feature state consists of N features, each having an activation factor in the interval [0, 1]. Linear approximations calculate their function value with

$$f(x) = \sum_{i=1}^{N} \phi_i(x) \cdot w_i\ , \quad (2)$$

where $\varphi(x)$ is the activation function and w_i is the weight of the feature i. Instead of keeping track of each unique state separately, we seek to find a function that approximates the state space with a small number of adjustable parameters.

Radial basis functions (RBFs) are the natural generalization of coarse coding to continuous-valued features. Rather than each feature being either *0* or *1*, it can be anything in the interval [0, 1], reflecting various degrees to which the feature is present. A typical RBF feature, i have a Gaussian (bell-shaped) response $\phi_s(i)$ dependent only on the distance between the state, s and prototypical or center state of the feature, c_i and relative to the feature's width σ_i

$$\phi_s(i) = \exp\left(-\frac{\|s - c_i\|^2}{2\sigma_i^2}\right). \quad (3)$$

The RBF network is a linear function approximation using RBFs for its features. The *Learning Algorithm* is used to adopt RBF network weights in order to fit *Actor* and *Critic* functions. The feature of the *Actor-Critic* learning is that the *Actor* learns the policy function and the *Critic* learns the value function using the *TD* method simultaneously [7]. The *TD* error $\delta_{TD}(t)$ is calculated by the temporal difference of the value function between successive states in the state transition as

$$\delta_{TD}(t) = r(t) + \gamma V(t+1) - V(t), \quad (4)$$

where $r(t)$ is the external reinforcement reward signal, $0 < \gamma < 1$ denotes the discount factor that is used to determine the proportion of the delay to the future rewards. The *TD* error indicates, in fact, the goodness of the actual action. Therefore, the weight vector θ of the policy function and the value function are updated as

$$\vec{\theta}_{t+1} = \vec{\theta}_t + \alpha \delta_t \vec{e}_t\ , \quad (5)$$

where α is the learning rate and the eligibility trace, e can be calculated by:

$$\begin{cases} \vec{e}_0 = 0, \\ \vec{e}_{t+1} = \gamma\lambda\vec{e}_{t-1} + \nabla_{\vec{\theta}_t} V(t). \end{cases} \quad (6)$$

As an example, by empirically defining fuzzy membership functions and fuzzy rules, we get the fuzzy system surface for recognition of the *ALAR* index versus arousal and valence (Fig. 3).

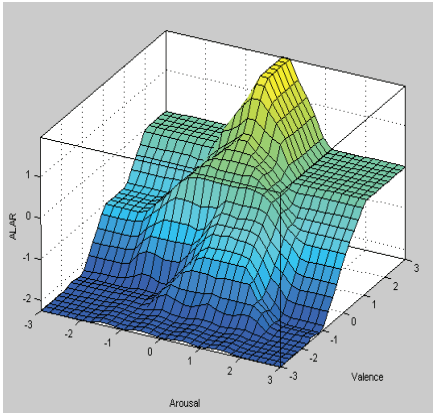


Fig. 3. Fuzzy system surface for recognition of the *ALAR* index versus arousal and valence

The ambient comfort affect reward based multi-agent controller

Ambient comfort measurement and environment control multi-agent system (*MAS*) of Fig. 4 monitors the environment and controls the devices in the *KUSLab* of Fig. 8 by returning the reward of ambient comfort.

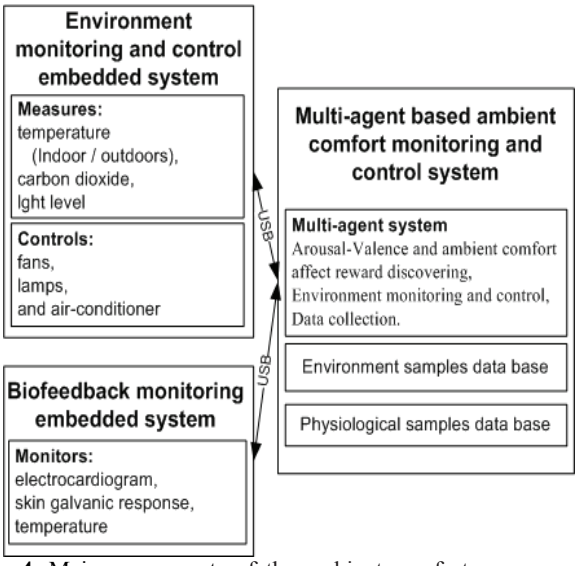


Fig. 4. Main components of the ambient comfort measurement and the environment control multi-agent system (*MAS*)

Whole smart ambient comfort control model was implemented by using multiple interacting intelligent agents. The multi-agent system (*MAS*) was constructed by using *JACK – Java*-based framework for multi-agent system development. The *MAS* model consists of the three main parts: 1) the environment monitoring and data collecting subsystem of Fig. 5; the Ambient Comfort Affect Reward (*ACAR*) index recognition subsystem of Fig. 6, and 3) the ambient comfort control subsystem of Fig. 7. The hardware part of the smart e. wellness meter, the *SeWM* (see Fig. 1), which is the part of the biofeedback monitoring agent, has been realized on ATmega32 microcontroller, and it has four environment sensing devices: two digital thermometers, the carbon dioxide sensor and the light level sensor. The microcontroller communicates with computer and the *MAS* via RS232-based PC interface.

When the new data has been received to the PC, the *MAS* generates appropriate event: *"IT_sample"* for the indoor temperature sample, *"OT_sample"* for outdoor temperature sample, *"CO2_sample"* for carbon dioxide sample and *"Light_sample"* for light sensor sample. Agents *"Thermo_measurer", "CO2_measurer"* and *"Light_measurer"* handle these events, analyse them, stores to the database named *"EnvironmentData",* and, if needed, generate an appropriate event for the environment monitoring agent.

ACAR recognition also contains of hardware and software parts. Hardware part is based on Atmega32 microcontroller, and it is used for sampling and processing simultaneously obtained skin galvanic response (*EDA*), electrocardiogram (*ECG*) and skin temperature signals.

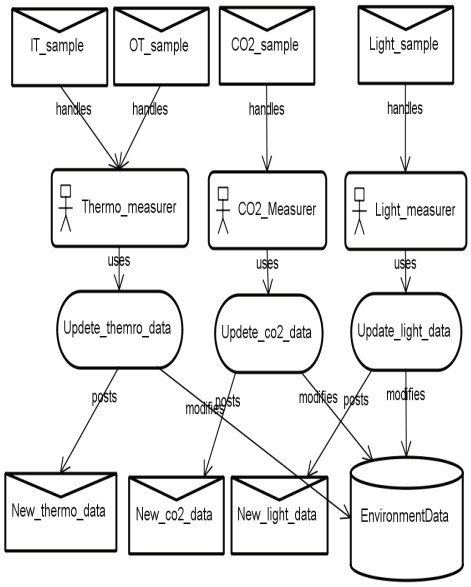


Fig. 5. The environment monitoring and data collecting agents

Human physiological signals sensing is based on using the high input impedance AD620 type instrumentation amplifier for amplification of *ECG* and *EDA* signals taken from electrodes placed on human's arms. Two ring type electrodes are placed on adjacent left hand fingers for acquisition of *EDA* signals, and one additional electrode is placed on human's right hand used to collect differential *ECG* signals in respect to the left hand placed electrode. The additional electrode is placed on the human's right leg or hand to compensating electrical noise from human body. Amplified as well as primarily filtered, the *ECG* and *EDA* signals are applied to the separate ADC converters on ATmega32 microcontroller. The human body temperatures are measured by DS18B20 digital thermometers and communicate with IC over the 1-Wire bus. The microcontroller filters the *ECG* signal using kernel regression smoothing, the *EDA* signal - using Gaussian smoothing and sends these samples to the PC via USB/RS232 based interface. When new data is collected, an appropriate event occurs in the *MAS* to be handled by *"AV_FIA"* (arousal valence fuzzy inference agent) agent of Fig. 6.

The agent *"AV_FIA"* uses two plans, the "*GetEDAParams*" and the "*GetECGParams*" to analyze new samples and get standardized parameters (latency, rise time, amplitude, half recovery time for *EDA* and heart rate, heart rate variability for *ECG*) and then stores new data to database. The agent *"AV_FIA"* uses plan *"calculate_AV*" to calculate affect features: arousal and valence from physiological data. Then the agent *ACAR_FIA*, by communicating with the fuzzy inference system, gets the *ACAR* index parameter and generates event *"ACAR"* which will be handled by the *"AmbiantComfort"* agent (Fig. 7).

The whole MAS are shown in the Fig. 7. Agent "*Environment_monitor"* monitors environment, analyses new and collected environment data and if environment changes then event "*New_state*" occurs which is handled by two agents. Agent "*AmbiantComfort*"takes *ACAR* and new environment state and if needed, using plan

"*ModifyEnvironment*" generates event to the agent "*EnvironmentController*".

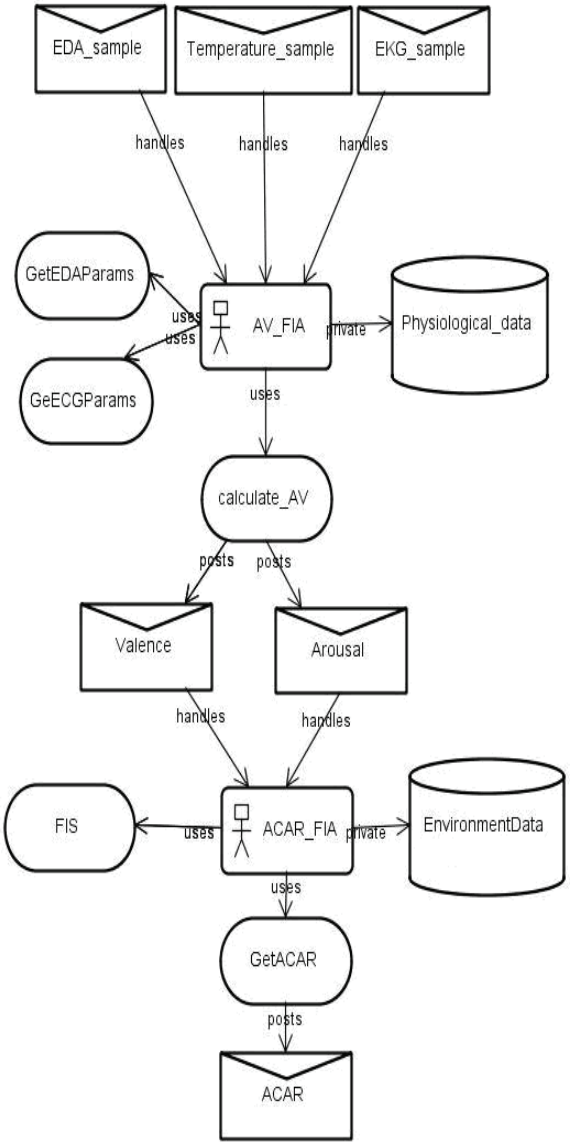


Fig. 6. The *ACAR* index recognition multi-agent subsystem

Vision of embedding of the multi-agent-based comfort control subsystem into the *ESLab*

Based on the idea of the development of the Smart Eco-Social Apartment [4], the block diagram of the Eco-social laboratory, the *ESLab* is proposed in Fig. 8. Fig. 8 depicts a block diagram of the *ESLab* with integrated wind generator, PV panels, solar collector, air -to –water-air-to-air heat pump, heating-ventilation –automatic controller HVAC as well as a smart energy meter, the *SEM* and the Ambient Comfort Affect Reward Meter, the *ACARM*.

The *ESLab* can be dislocated on the last floor of the building of any high education institution, and it may occupy 3 - 4 rooms for arranging of sustainable laboratory and office as well as some place on the roof to deploy an outdoor unit of air -to -water -air-to-air heat pumps, solar panel units, PV panel units, and small wind generator units. The renewable energy, the *Ewg* from wind generator as well as the *Epv* from photovoltaic panels is planned to be monitored and economically distributed by the smart energy meter, the *SEM*. The *SEM* has to adaptively control all available at that moment *Ewg* and *Epv* energy flow for feeding the heat pump and electrical heater of hydro unit. By using signals from the heating-ventilation-automation controller, the *HVAC*, the *SEM* should manage the climate control by adding energy from conventional sources such as central heating system of the building if there is not enough heating power from alternating energy sources at that moment. The hardware implementation of the smart ambient comfort control system in the *ESLab* is shown in Fig. 9.

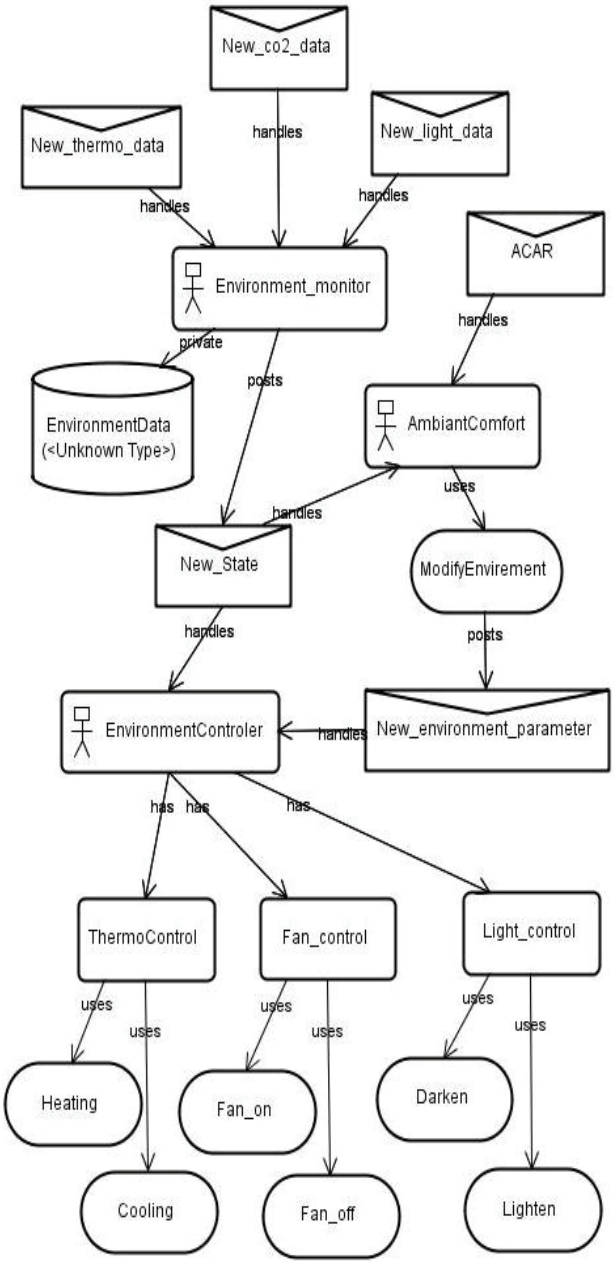


Fig. 7. Multi-agent-based comfort control subsystem

The Fig. 9 represents two embedded systems: a) the environment monitoring and control agent-based system and b) the biofeedback monitoring agent- based system. The environment monitoring and control agent consists of:

1) The central module of Fig. 9a-1which has the Atmega32 microcontroller connected to the computer via USB/RS232 interface to controlling devices and sending data to the multi-agent system implemented in the connected computer;

2) The environment monitoring and control module of Fig. 9a-4 which has the several sensors such as temperature, light level, carbon dioxide and has ability to control connected devices such as fan, lamps, and air-conditioner;

3) The information module (Fig. 9a-3) containing the LCD which displays an information about the system status as well as the keypad for manual system control.

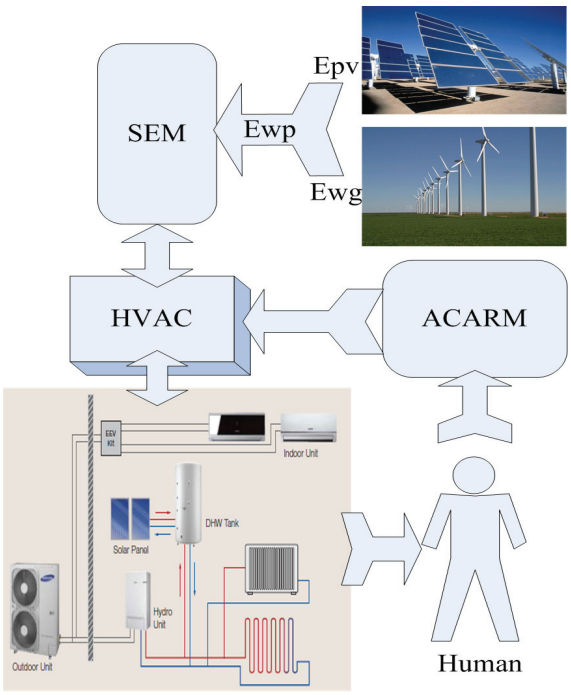
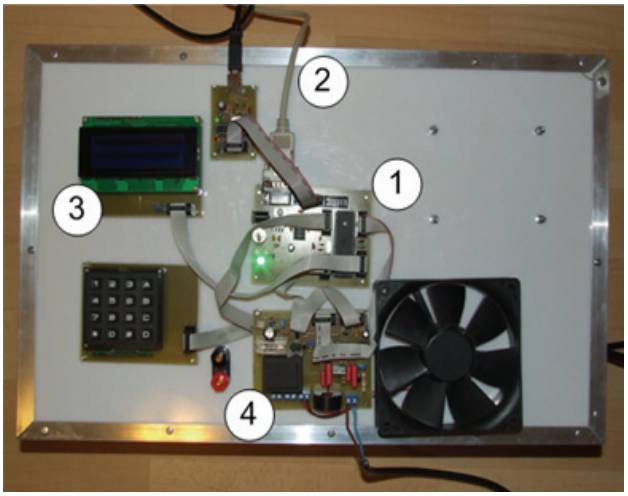
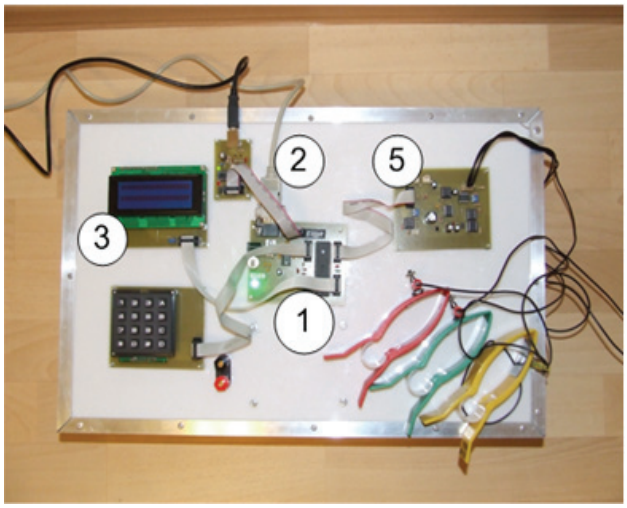


Fig. 8. Block diagram of Eko-social laboratory, the *ESLab*

The biofeedback monitoring agent of Fig. 9b has the same central and information modules similar to the environment monitoring and control agent, only the software of the microcontroller is different, and it has one physiological signal sampling module of Fig. 9b-5. This agent takes *ECG*, *EDA* and temperature samples.



a)



b)

Fig. 9. Hardware implementation of embedded agents: a) The environment monitoring and control embedded agent; b) The biofeedback monitoring embedded agent

The *ACARM,* described in this paper is developed by authors of this paper and tested in electronic laboratory by students during their laboratory works in the department. The measured data helped to predict some aspects of wellness of the students during their laboratory work and exams used to improve the software of the *ACARM.*

Conclusions

1) A vision is introduced of sustainable eco-social laboratory, the *ESLab* to be used to speed up the process of development of the Smart Eco-Social Apartment recently proposed by authors of this paper [4]. The multi- agent model of the ambient comfort measurement and environment control system is proposed and recommended to be used for further development of the *ESLab* in this paper.

2) The human Ambient Lighting Affect Reward index, the *ALAR* index is proposed at the first time used for development of the Reinforcement Learning Based Ambient Comfort Controller, the *RLBACC* for the *ESLab.*

3) The proposed *ALAR* index is described as a function that depends on the human physiological parameters: the temperature, the *ECG*- electrocardiogram and the *EDA*- electro-dermal activity. The fuzzy logic is used to approximate the *ALAR* index function by defining two fuzzy inference systems: the *Arousal-Valence System*, and the *Ambient Lighting Affect Reward (ALAR) System.*

4) The goal of the *RLBACC* controller is to find such environmental state characteristics that create an optimal comfort for people affected by this environment. The Radial Basis Neural Network is used as the main component of the *RLBACC* controller to performing of two roles of the *Actor* and the *Critic*.

5) The policy structure, known as the *Actor*, is used to select actions, and the estimated value function, known as the *Critic,* is applied to criticize the actions made by the *Actor*. The *Critic* was used as a value function approximation of the continuous learning tasks of the *RLBACC* controller.

Acknowledgments

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The paper presents a vision of sustainable eco-social laboratory, the *ESLab* which might be used to speed up the process of development of the recently proposed by authors of the Smart Eco-Social Apartment. It is presented the multi-agent model of the ambient comfort measurement and environment control system to be used for the development of the *ESLab*. The human Ambient Lighting Affect Reward index, the *ALAR* index is proposed at the first time used for development of the Reinforcement Learning Based Ambient Comfort Controller, the *RLBACC* for the *ESLab*. The *ALAR* index is dependent on human physiological parameters: the temperature, the *ECG*- electrocardiogram and the *EDA*-electro-dermal activity. The fuzzy logic is used to approximate the *ALAR* index function by defining two fuzzy inference systems: the *Arousal-Valence System*, and the *Ambient Lighting Affect Reward (ALAR) System.* The goal of the *RLBACC* is to find such the environmental state characteristics that create an optimal comfort for people affected by this environment. The Radial Basis Neural Network is used as the main component of the *RLBACC* to performing of two roles - the policy structure, known as the *Actor*, used to select actions, and the estimated value function, known as the *Critic* that criticizes the actions made by the *Actor*. The *Critic* in this paper was used as a value function approximation of the continuous learning tasks of the *RLBACC*. Ill. 9, bibl. 7 (in English; abstracts in English and Lithuanian).

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Pristatoma universitetinio tipo darniosios laboratorijos ESLab vizija, kuri plėtoja neseniai autorių pasiūlyto išmaniojo ekosocialaus būsto įgyvendinimo idėją. Pateikiamas aplinkos komforto matavimo ir aplinkos kontrolės sistemos valdiklio modelis, kuris bus panaudotas ESLab plėtotei. Straipsnyje pasiūlytas žmogaus aplinkos apšvietimo efekto paskatos AAAP (ALAR) indeksas pritaikytas kuriant paskatos mokytis pagrįstąjį aplinkos komforto valdiklį ESLab laboratorijai. AAAP (ALAR) indeksas priklauso nuo žmogaus fiziologinių parametrų: temperatūros, ECG (elektrokardiogramos) ir EDA (elektrinio odos aktyvumo). Neraiškioji logika yra panaudota AAAP (ALAR) indekso funkcijai aproksimuoti, taikant dvi neraiškias išvedimo sistemas: susijaudinimo ir malonumo sistemą ir žmogų supančios AAAP (ALAR) sistemą. Sukurtojo paskatos mokytis grindžiamo aplinkos apšvietimo valdiklio PMGAAV (RLBACC) tikslas yra skatinti tokias aplinkos valdymo savybes, kurios kuria optimalų patogumą šios aplinkos paveiktiems žmonėms. Valdiklio modelis pagrįstas radialinių bazių neuroninių tinklų taikymu, realizuojant aktoriaus strategijos struktūrą tinkamiems veiksmams išrinkti ir apskaičiuojant vertės funkciją, kuri yra žinoma kaip kritikas, kuris kritikuoja aktoriaus padarytus veiksmus. Kritikas šiame straipsnyje buvo panaudotas kaip tolydžiojo PMGAAV (RLBACC) mokymosi užduočių įverčio funkcijos aproksimacija. Il. 9, bibl. 7 (anglų kalba; santraukos anglų ir lietuvių k.).