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Intelligent Lighting Control Providing Semi-Autonomous Assistance

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***Abstract*—Increasing resident's comfort and reducing energy costs have always been two primary objectives of intelligent lighting control systems. It is quite difficult to provide control satisfying the level of individual comfort, sufficient illumination and the energy reduction goals simultaneously. However, finding the balance between resident's preferred and recommended illumination for the current resident's activity may be beneficial. This paper addresses the problem of ensuring semi–autonomous assistance in controlling the intensity of light sources. The proposed decision making algorithm allows to provide gradual adaptation to the recommended illumination according the resident's activity. Resident's activity recognition is performed using one of the most popular models of deep learning, such as Convolutional Neural Networks (CNNs).**

***Index Terms*—Intelligent lighting control; image recognition; CNNs; resident's activity.**

I. INTRODUCTION

Lighting control problem is one of the most common tasks addressed in developing the intellectual control system. The relevance of this problem solution was firstly identified in the business sectors where the lighting cost makes up a considerable proportion in the total electricity consumption. The optimization of energy costs can be solved by lighting control system using various approaches [1], [2]. With the recent lighting control products, lighting energy consumption can be reduced up to 80%, depending on the current equipment. Using long life lamps, various sensors (e.g. daylight sensor), presence detectors, ballasts and lux controllers it's possible to obtain modern lighting solutions maximising energy savings [3]. A few examples of business solutions: it's possible to maintain the constant value of lux by taking advantage of natural daylight in the room; if there is no presence to turn off the light completely after a defined time delay; to maintain the light at the 100% when there is presence or to dim down after the defined delay time to particular level (50/25/10%); to adjust the maximum allowable light level to a lower recommended level and to set this level as the maximum output of the system, etc.

The systems that follow strict rules or certain constraints, as well as sensor systems cannot be called as intellectual ones. Such lighting systems are characterized by the ability to adapt in order to control light sources by optimizing energy consumption, which is a particularly important to commercial buildings. However, lighting control of residential houses has different priorities, first of all put those preferences on the personal control. In order to assess the need of intelligent lighting control systems and expectations of residents, the online survey was performed [4]. 288 respondents, whose average age is 37, have completed the questionnaire.

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Respondents have been asked to select only one from five available choices (Fig. 1). According to the answers concerning the question what type of intellectual lighting control system is the most attractive to them, 42% of the respondents have answered that lighting control system should be semi-autonomous, which allows to be controlled by the resident but also assists him by making certain lighting modification.

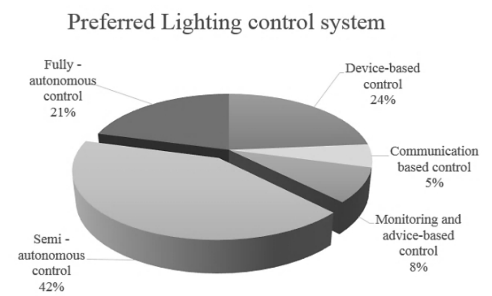

Fig. 1. Summary of respondents' answers to the preferred type of intelligent lighting control system of residential houses.

Fully- autonomous lighting control systems are useful for elderly or disabled people, because systems are able to adapt to their behaviour and needs [5]. However, fully autonomous system control doesn't allow to feel as real house owners. Such users expect more assistance from the system but not full control. Until the establishment of the system in the house, the residents usually perform full control of light sources, meaning that this is the natural process. Therefore, the intelligent lighting control should perform the regulation of light sources in user-friendly manner. This raises issues about how often the lighting regulation should be performed. Excessive system sensitivity to environmental changes can lead to very frequent changes of lighting, thus annoying the user and shortening the bulbs lifetime (e.g., switching on /off the fluorescent lamp). Thus, it's important to find solutions that meet some criteria of regulations.

The researchers often try to prove the significance of their results of developed intellectual control system by providing the accuracy in percent. Considering the lighting system, the small deviations are not critical because the resident does not notice them. According to the Ernest H. Weber law, less than 8% deviation from the current lighting is not significant for human's eyes [6]. Therefore, the more important task is to ensure the sufficient illumination for the resident. Energy consumption and control are important as well but the balance between comfort and cost optimization should be achieved. Existing lighting standards are based on activity zones and on the activity performed [7], [8]. Following those standards allows residents to get used to the lighting that is necessary and good to their health, however relying only to those standards is not the best solution because of the following reasons: Primarily, the lighting standards may be differentiated based on human's age or health [9]; then, the lighting requirements for certain zones of residential space may differ significantly based on the activities performed. It means that the identification of resident's activity is more important than his area of activity.

Due to the considerations given above, this paper proposes the lighting control system that assists in controlling the intensity of light sources by finding the balance between habits of resident (light intensity) and established standards based on activity performed. Resident's activity recognition has been performed through the image recognition employing one of the most popular models of deep learning, such as Convolutional Neural Networks (CNNs).

II. PROPOSED ALGORITHM

In this paper the intelligent lighting control system is developed which provides the unnoticeable lighting regulation according to the resident's preferences and regulation standards relevant to the activities being performed by the resident (Fig. 2).

The unnoticeable lighting regulation means that the changes in the control of light sources wouldn't be noticed by the resident. According to the Weber's Law, a just noticeable difference ΔI for light intensity is in a constant relationship with the intensity level I, $\Delta I/I$=constant, where constant = 0.08. This means that if the lighting is measured in $I = 500$ lux, the minimum change, which may be noticeable by the human, is ΔI, $\Delta I = I * 0.08 = 40$ lux. In the proposed regulation system, there are only three possible ways how the actuator can be modified: (1) Increase actuator value by value less than ΔI; (2) decrease actuator value by value less than ΔI; (3) turn off the actuator if the resident is absent. The question is when the settings of the actuator must be changed? Since the main purpose is to maintain the balance between the resident's predetermined lighting level and the recommended lightning norms, these two values should be compared. In the case that the present lighting doesn't fall into to the interval of recommended standard values, the regulation actions should be taken. However, using the recommended values for the specific areas of residential home is not always appropriate, since the performed activity very often doesn't match with the target activity in the occupied zone. Therefore, the identification of resident's activity must be performed.

Human activity recognition, a field that has garnered gained a lot of attention in recent years due to its high demand in various application domains. In the last decade CNN as one of the most widely used model of deep learning, has improved significantly their performance in many image recognition tasks and have shown a very high accuracy results in the image recognition tasks [10],[11]. Human activity recognition can achieve less than 10% error rate using CNNs [12], [13], however very often additional techniques such as wearable sensors [14], [15], accelerometer and gyroscope [16] are employing. In this paper, only residents images extracted from video stream have been used for human activity recognitions.

30 images per second are extracted and processed in the activity recognition block using the image classification approach. The estimated confusion matrices, as well as time moments of picture taken are stored in the database and used by the decision block.

The decisions related to the regulations of actuators are generated per constant time period Δt between decisions d_h and d_{h-1}, $h = \overline{1, n}$. Value of Δt may be evaluated experimentally, taking into account that too frequent regulations of the lighting are unnecessary since a frequent on-and-off action for a light bulb will wear it out sooner. Besides, the activities of the human usually are not changing very often. All information gathered during the time period Δt is used to evaluate the dominant activity (*DA*) selecting only one resident's activity from all activities.

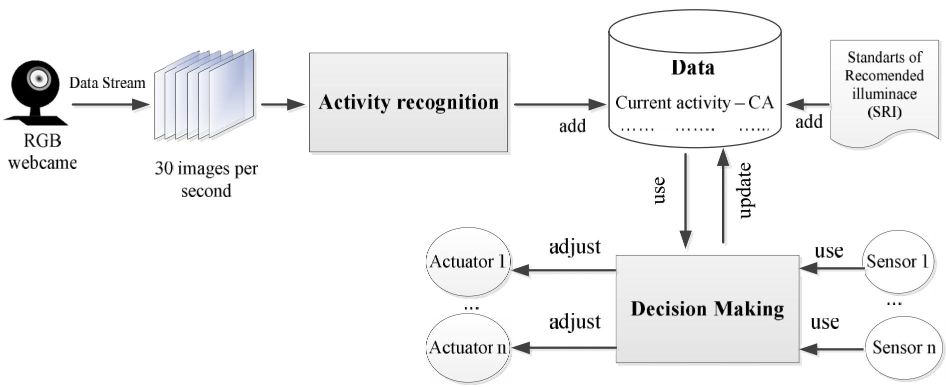

Fig. 2. The architecture of lightning control system.

Usually, the recent resident's behaviour is more important than the one in the past. In this case, value y_i of the particular activity i during the time period Δt is a weighted sum, where each value a^i (a^i – probability of i activity obtained from image confusion matrix at the activity recognition block) has a specific weight w_{t_j} assigned to it in each time moment t_j, $j = \overline{1,n}$, $n = img \times \Delta t$ ($img = 30$ – number of images per second, Δt – time value in seconds)

$$y_i = (a_{t_1}^i \times w_{t_1} + a_{t_2}^i \times w_{t_2} + ... + a_{t_n}^i \times w_{t_n}), \quad (1)$$

with $i \in \{Activities\,L\}$, where *ActivitiesL* is a set of possible activities and $|\,Activities\,L\,| = m$. The values of weights are increasing in time according to the exponential law, which means that $w_{t_{k-1}} < w_{t_k}$, $2 \le k \le n$. The sum of all weights should be equal to 1

$$\sum_{j=1}^{n} w_{t_j} = 1. \quad (2)$$

DA is estimated by computing the maximum value of y_i, $DA = \max(y_i)$. The current activity *CA* in the database is updated with a new string value as *CA=i*. The number of possible activities is defined in the activity recognition block, and it must be related to the list of activities in the SRI (Standards of Recommended Illuminance) document, because the final decision depends on two components: value of light sensor (VLS) and SRI for the *CA*.

The algorithm of actuators' adjustment is presented in Fig 3.

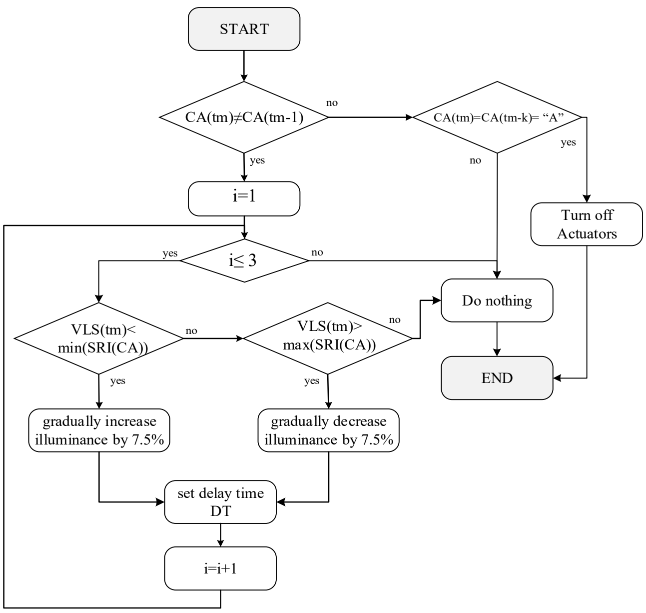

Fig. 3. Block scheme of the algorithm for actuators adjustments.

If VLS at the present time moment *tm* is lower than a minimum recommended value for this type of activity, it is increased by 7.5%. If VLS is higher than a maximum recommended value for this type of activity, it's decreased by 7.5%. Procedures of increasing or decreasing of VLS value can be repeated within three times including the delay time (DT) between regulations. If the current activity at the present time *tm* hasn't changed compared with the activity from the previous time moment (*tm-1*), the adjustments are not performed. The exceptions are made in the case when the resident is absent more than *k* units of time (e.g., 20 minutes).

III. EXPERIMENTS

To implement the lighting control system, Arduino UNO microcontroller board with the two integrated components, Digital Light Sensor BH1750 and potentiometer B5K, has been used. The activity recognition block has been implemented using MatConvNet [17]. It's an open source implementation of CNNs in the MATLAB environment and can be easily extended to the new CNNs architectures. However, there exist specific software and hardware requirements for the deep learning models implementations, such as MATLAB 2016a (or later version), C\C++ compiler, the computer with CUDA – enabled NVIDIA GPU with compute capability 2.0 or above.

To evaluate the accuracy of CNNs, the scenario including home office zone (specifically desk area) with four possible illumination categories depending on the type of performed activity (Table I) has been created. Range of illuminance has been selected according to the IESNA recommendations based on the type of activity [18], [7]. Illuminance category A is included to identify the absence of resident.

TABLE I. RECOMMENDED ILLUMINANCE RANGE FOR THE DIFFERENT TYPES OF ACTIVITY.

Type of Activity	Illuminance Category	Range of Illuminance, (Lux)	Examples of activities
Absence of resident	A	0	Absence of resident
Working spaces where visual tasks are only occasionally performed	B	100 -150 -200	Activities near the table (e.g., talking with phone)
Performance of visual tasks of high contrast or large size	C	200 -300- 500	Simple tasks with computer
Performance of visual tasks of medium contrast or small size	D	500 -750- 1000	Writing tasks

In the experiments, the illuminance category A is assigned to the situation where a desk area and other objects are seen but the resident is absent. The illuminance category B relates to the situation where visual tasks can be performed only occasionally (e.g., walking near the table or talking on the phone). Any resident's work on the computer is assigned to the category C, and any type of writing/reading activity – to the category D. The experiments are performed during the dark period of the day using only artificial light sources (Fig. 4).

Various CNNs architectures, AlexNet [19], CaffeRef [20] and VGG [21] have been used in order to highlight the one with highest accuracy. Each of the architectures has 23 layers (deployment depends of the architecture) including input layer and output layer (Fig. 5). Each model has a different input size requirements (pixels). For the AlexNet picture size is 227×227×3, for VGG 224×224×3 and for CaffeRef 227×227×3. Three main types of layers are used to build CNNs architectures:

- *Convolutional layer* computes the output of neurons that are connected to local regions in the input;
- *ReLU layer* applies an element-wise activation function;

Pooling layer reduces the spatial size of the representation to reduce the amount of parameters and computation in the network.

All these layers are followed by fully connected layers leading into a Softmax – a final classifier. The created networks have been pretrained using the 617 images for each group of four (Table I).

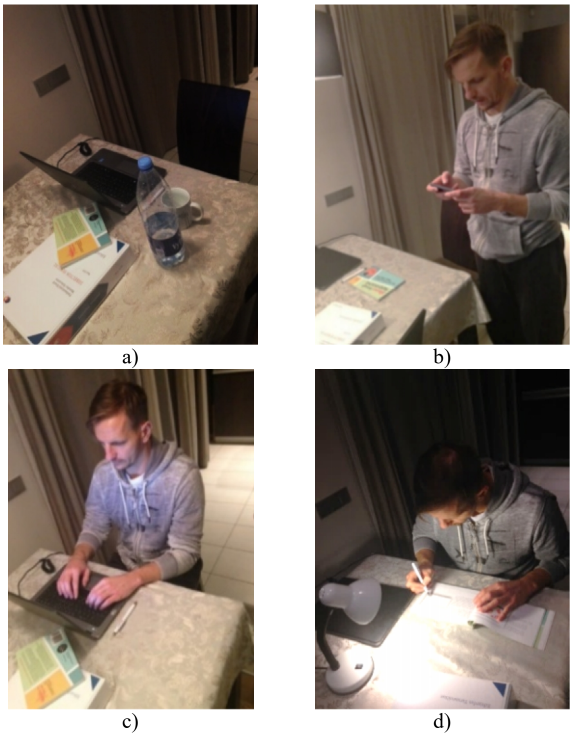

Fig. 4. Examples of different types of resident's activities: (a) absence of resident; (b) resident's activity near the table; (c) resident is working with computer; (d) resident is writing with a pen.

IV. EXPERIMENTAL RESULTS

The estimation of accuracy of the residents' activity recognition using different CNNs architectures is presented below (Table IITable IV). The obtained results show that the use of any of the three architectures provides very similar recognition estimates, but the average accuracy of AlexNet is the best one and approaches to 92.4%. According to the values of confusion matrix, the activities from illuminance category A is the most easily identified, while the recognition of activities from C category (work on the computer) is the most complicated.

TABLE II. CONFUSION MATRIX OF AlexNet ARCHITECTURE.

AlexNet		Target class				Total
Average accuracy: 92.4%		A	B	C	D	
Output class	A	97.8%	1.1%	1.1%	0%	100%
	B	1.6%	89.7%	6.5%	2.2%	100%
	C	2.7%	6.0%	89.2%	2.1%	100%
	D	0.5%	1.6%	4.9%	93.0%	100%

TABLE III. CONFUSION MATRIX OF CaffeRef ARCHITECTURE.

CaffeRef		Target class				Total
Average accuracy: 91.1%		A	B	C	D	
Output class	A	94.6%	2.1%	1.1%	2.2%	100%
	B	0%	90.3%	8.6%	1.1%	100%
	C	1.6%	7.1%	87.0%	4.3%	100%
	D	0%	1.6%	6.0%	92.4%	100%

TABLE IV. CONFUSION MATRIX OF VGG ARCHITECTURE.

VGG		Target class				Total
Average accuracy: 91.4%		A	B	C	D	
Output class	A	95.7%	1.1%	2.7%	0.5%	100%
	B	0.5%	92.5%	4.3%	2.7%	100%
	C	3.3%	8.1%	84.3%	4.3%	100%
	D	0.5%	2.2%	4.3%	93.0%	100%

In this paper, the experiment was carried out to analyse the changes of illumination for distinct types of activity assigned to particular illuminance category (Table). Ten movies of 4 hours duration (experimental scenarios) were recorded for each category. The influence of predetermined value of Δt on the number of illumination changes during 4 hours is depicted in Fig. 6. Figure does not include the activities from A category because the value of Δt does not affect the number of changes recorded by the lighting control system in chosen scenarios.

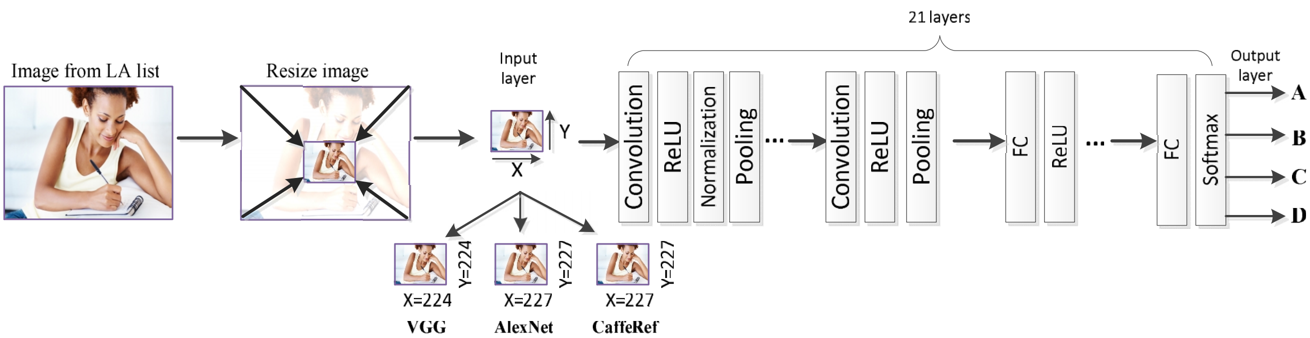

Fig. 5. The general structure of CNNs for three different architectures: AlexNet, VGG and CaffeRef.

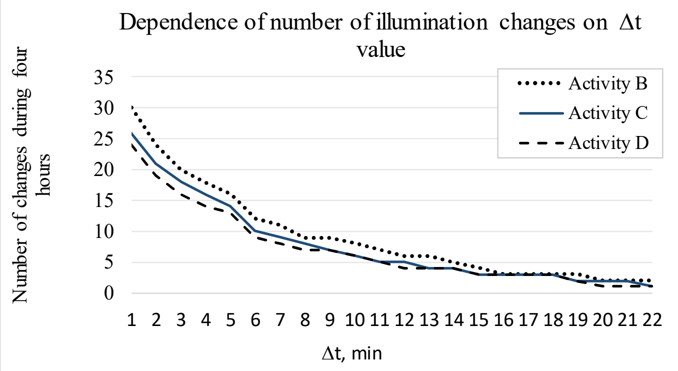

Fig. 6. The number of recorded activity changes during four hours with parameters DT= 10 s., Δt ∈[1-22] min.

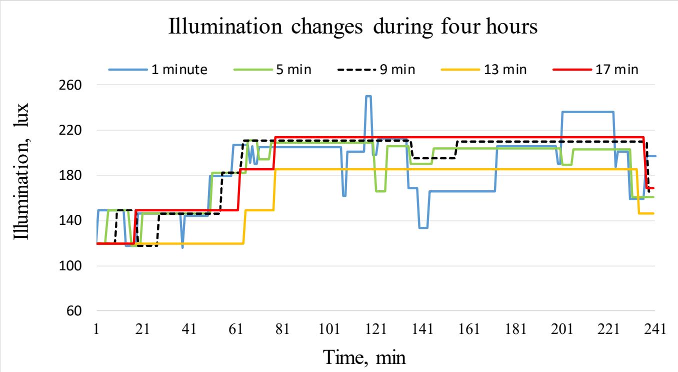

Fig. 7. Illumination changes during activity (working with computer) assigned to category C.

In the scenarios of experiment, the recorded changes in each of activities had the influence on decision of lighting intensity control; furthermore, the decision depends on the duration of those changes, as well as on Δt. If the time period between decisions is set to one minute, Δt=60s, the number of recorded changes in activities may approach 30 in four hours. The higher values of Δt allows to decrease the activity recognition error in final decision and to filter short deviations from the regular activity (e.g., short conversation on the phone, writing of particular notes, making a cup of tea.). For example, Fig. 7 depicts the influence of Δt on the number of recorded illumination changes while the resident performs the activities from illumination category C. The initial lighting intensity is set to 120 lux by the resident, but it should be from the interval [200–500] lux according to the regulation recommendations. The illumination intensity gradually approaches to minimal recommended value but the transitional regulations appear for decisions performed every 1-5 minutes caused by short-term changes in resident's activities.

V. CONCLUSIONS

This paper proposes the semi-autonomous lighting control system which allows to provide lighting control decisions keeping the balance between the lighting preferred by the resident and the recommended by the standards. The proposed decision making algorithm enables to ensure gradual adaptation to the recommended illumination based on the resident's activity. The application of CNNs allows to reason the efficiency of deep learning approach for the recognition of resident's activity obtaining 92.4% accuracy when the AlexNet architecture is used to classify residents' activities performed into four lighting categories. The experimental study has shown that frequent recording of changes in resident's activity is not appropriate since the algorithm becomes too sensitive to small changes in activities leading to the continual regulation of lighting system. The interval Δt of more than 7 minutes between decision making periods is recommended. Further studies need to be carried out in order to determine the efficiency of using the fixed value of Δt or different values of Δt based on resident's activity currently performed by introducing more activities that involve the performing tasks of low contrast or activities that require minimal lighting.

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