Stochastic Algorithms for Adaptive Lighting Control using Psycho-Physiological Features

Ovidiu Grigore, Inge Gavat, Marius Cotescu, and Corina Grigore

Abstract— Light has a real important impact on our life, determining the circadian rhythm, the rhythm of our daily activity. Light is benefic for healthy people, but it can be also very helpful for treating disease or for enhancing the comfort and wellbeing. In the frame of our European project, *ALADIN*, light is intended to be a support for the elderly, in order to enhance their daily performance. The performance is appreciated by activity specific values of psycho-physiological features that can be modified by light. This paper will describe the signal processing techniques deployed for extracting useful features and the algorithms used for developing an adaptive light controller. Two algorithms were used to implement the light controller: Monte Carlo and Simulated Annealing. Experimental results obtained using the Simulated Annealing algorithm will be presented.

Keywords—adaptive lighting, bio-signal processing, stochastic methods.

I. INTRODUCTION

This paper is based on the work done inside the ALADIN project, which aims to extend our knowledge about the impact of lighting on the wellbeing and health of older people. Adaptive lighting can contribute considerably to sound sleep and a regular sleep-wake cycle, which are essential to preserve and enhance people's health and wellbeing. This will assist older adults in living at home autonomously for a longer time and contribute to their quality of life.

The project's aim is to develop an intelligent assistive system based on ambient lighting to support mental alertness and memory performance as well as relaxation in specific situations. The system is also expected to assist with regulating circadian rhythms. The system receives information about the impact of differences in the luminous environment on the subject's affective and cognitive state that is used by the lighting controller to automatically adapt the lighting parameters in order to achieve the subject's relaxation or activation.

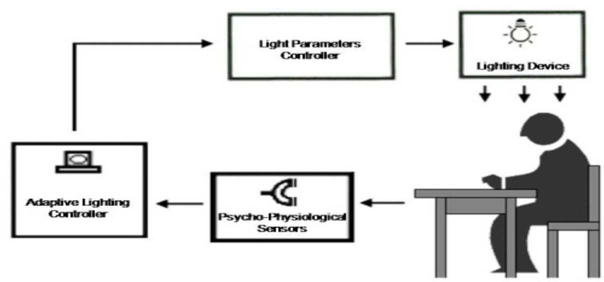

Figure 1. ALADIN system architecture

Our work consisted on one hand in determining in collaboration with our project partners which signals best reflect the subject's psycho-physiological state, and on the other, in choosing and implementing a suitable algorithm for the lighting controller.

In the following section we will show how we chose the appropriate signals and features, and also the signal processing techniques that we applied in order to obtain the required information.

The third section describes the process of selecting the best suited algorithm for the light controller and how we adapted and optimized this algorithm for our application.

The forth section shows the results obtained during system tests, while in the final section some conclusions are drawn.

II. SIGNAL PROCESSING AND FEATURE EXTRACTION

The subject's activation or relaxation state is reflected by several physiological parameters, amongst which the alpha brain waves, Electro-Dermal Activity (EDA) and Electrocardiogram (ECG) [1].

Because we want the system to be used by elderly persons in their households, it is of great importance that it offers a simple and non-intrusive interface. This means that the signals used have to be collected using simple and comfortable sensors. Based on these design criterions and a study of the published literature, we chose to use the EDA and ECG signals that are collected using electrodes placed on the subjects' skin and that can be wirelessly transmitted to the system. Further tests performed by our project partners at the

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O. Grigore is with the "Politehnica" University of Bucharest, Romania (phone: +404024897; fax: +404024957; e-mail: ogrigore@lpsv.pub.ro).

I. Gavat is with the "Politehnica" University of Bucharest, Romania (phone: +404024897; fax: +404024957; e-mail: igavat@lpsv.pub.ro).

M. Cotescu is with the "Politehnica" University of Bucharest, Romania (phone: +404024897; fax: +404024957; e-mail: mcotescu@lpsv.pub.ro).

C. Grigore is with the "Carol Davila" Medicine and Pharmacy University of Bucharest, Romania (phone: +404024897; fax: +404024957; e-mail: cgrigore@lpsv.pub.ro).

University of Budapest prove that the two signals provide sufficient information on the subjects' psycho-physiological state.

Our partners at the University of Budapest conducted a study to determine what features best describe the subjects' state. It consisted of recording the EDA and ECG signals while the members of a control group were asked to perform seven actions:

1. Lying down relaxed with eyes closed.
2. Lying down relaxed with eyes open.
3. Sitting relaxed with eyes open.
4. Sitting and watching a "calm" nature video.
5. Sitting and watching an "exciting" nature video.
6. Standing up from sitting and remain standing.
7. Performing NVT task as quickly and as accurately as possible.

A statistical study of the recordings showed that three features were correlated with the degree of relaxation or activation implied by the activities: Skin Conductance Response (SCR), Skin Conductance Level (SCL) from the EDA signal and Heart Rate (HR) from the ECG signal. It also showed that the SCR feature is the most important of the three, followed by the SCL and IBI features.

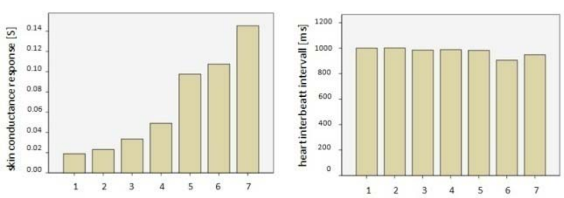


Fig. 2 SCR and IBI values for several activities

The SCL feature is defined by (1) as the mean values of the EDA signal over a moving window and represents the short term continuous component of the EDA signal. Figure 3 shows how the moving window is filled with values of the processed signal.

$$SCL(t_1) = \frac{1}{2k} \sum_{j=-K}^{K} EDA(t_1 + jT) \qquad (1)$$

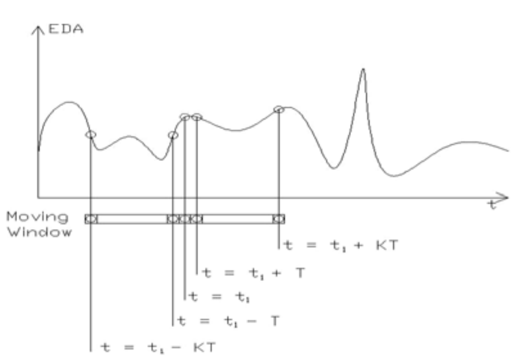


Fig. 3 Extracting SCL from the EDA signal.

The SCR feature is defined by (2) as the standard variation of the EDA signal's alternative component over the moving window. SCR shows the subject's current response to the active stimuli that he is currently, or had been recently exposed to.

$$SCR(t_1) = StDev(\,EDA(t_1) - SCL(t_1)) \qquad (2)$$

The HR feature is measured as the inverse of the time interval elapsed between two consecutive R waves – coresponding heart beats. It is more a measure of the physical effort, but it can also give away some information of the subject's psycho-physiological state.

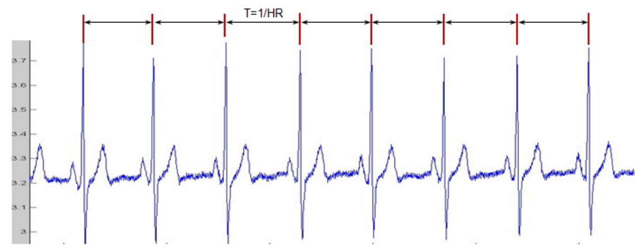


Fig.4 Extracting IBI from the ECG signal.

In order for the adaptive light system to function correctly, it needs to rely on a permanent flow of accurate data, which is insured by a strong signal processing module designed to eliminate any error. The module must handle two rather different signals: ECG and EDA, both with their particular problems [2]. In this section, we will present each of those problems and the manner we handled them.

A. ECG

The first signal we will discuss is the electrocardiogram (ECG), which is obtained by measuring the electrical activity of the heart. One of the most important is the R wave, from which information about the pulse and cardiac rhythm is extracted.

The feature that we extract from the ECG is Heart Rate, which is defined as the inverse of the time interval elapsed between two consecutive R waves, which can be seen in the ECG as a high frequency spike [3]. The fact that the R wave has high frequency components induces restraints on the sampling rate that should be high enough to follow the rapid variation of the wave. The sampling rate that we chose is 150 Hz.

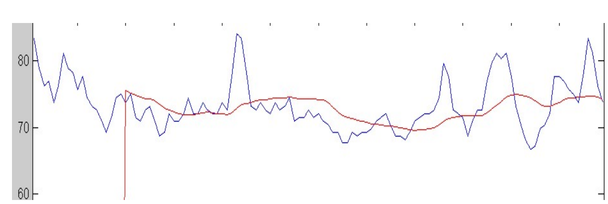


Fig. 5 Smoothing HR through integration

The R wave is located as a local maximum that had been preceded by a steep enough and high enough rising front.

Because of the additive high frequency noise and of the time resolution dictated by the sampling rate, the instantaneous HR extracted from ECG is rather noisy. Considering that it is not the instantaneous variation of the feature that we are interested in, but rather its long-term evolution, the HR feature is passed through an integration filter that smoothes it, see Figure 5.The integration buffer’s size determines how much of the variation is cut off.

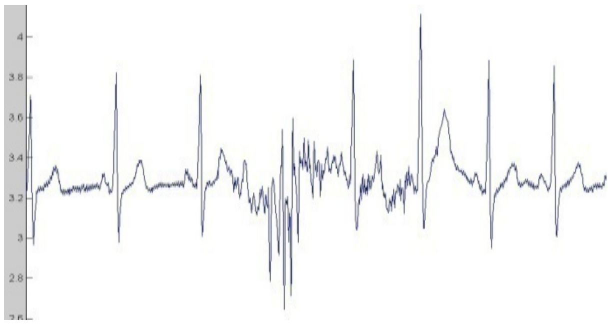


Fig. 6 Physical activity generated ECG artefact.

The ECG is meant to measure the activity of the heart, but it also picks up the signal from any other muscle in the body. This means that any movement of the subject induces artifacts in the ECG signal. An example of this situation is shown in Fig. 6.

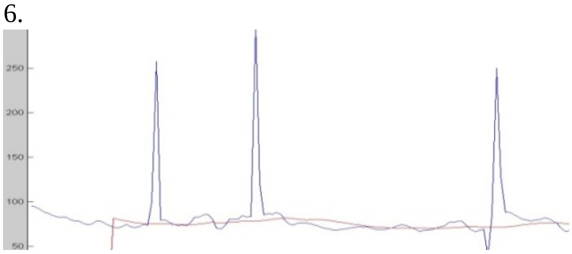


Fig. 7 Median filtered movement affected HR.

This high power, high frequency noise generates a spike in the HR signal (Figure 7). Because the system is meant to be used in the subjects’ home, these events are relatively likely to occur, so the system must be able to handle them without eliminating too many measurement cycles.

One way to avoid passing the afflicted data to the light controller is by eliminating the nonstandard measurement cycles based on a statistic criterion. This operation is done by the following algorithm:

1. Compute the mean value for the first cycle.
2. Let the dataset’s mean value be equal to that of the first cycle, and set the variance threshold.
3. Compute the current cycle’s variation from the mean value.
4. If the variation is higher than a given threshold, eliminate the cycle’s results.
5. Else, include new measurements into the valid dataset and re-evaluate the mean and variation for the new data set.
6. Repeat from Step 3.

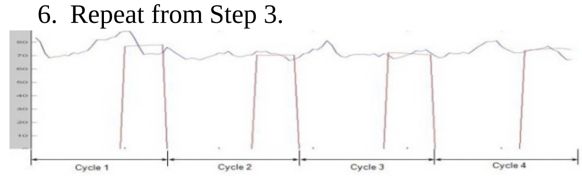


Fig. 8 HR measurement cycles.

B. EDA

Electro-Dermal Activity (EDA) is also referred to as skin conductivity or Skin Conductance (SC) and basically measures the electrical conductivity of the skin. The momentary fluctuations of EDA have been termed phasic responses – Skin Conductance Response (SCR), whereas the relatively stable EDA is referred to as the tonic level – Skin Conductance Level (SCL). Measures of EDA can be interpreted as mainly reflecting changes in sweating activity. This signal was found to be a good and sensitive indicator of psychological stress, as well as other stimuli, and helps to differentiate between conflict/no conflict situations.

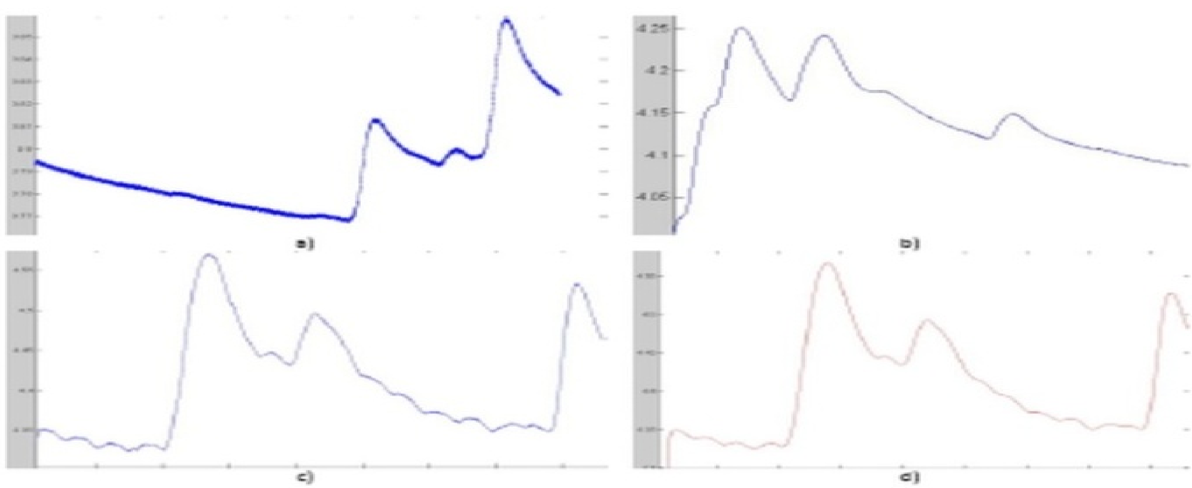


Fig. 9 EDA signals. a) 150 Hz Sampling Rate; b) 50 Hz Sampling Rate; c) Decimated EDA from 150 Hz Sampling Rate; d) Noise filtered decimated EDA.

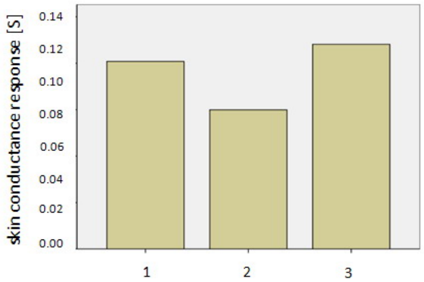


Fig. 10 SCR values while performing NVT under different illumination conditions: 1. "Normal" lighting; 2. "Relaxing" lighting; 3. "Strong" lighting.

Just like the ECG signal, EDA raises several problems for both the acquisition and processing modules. The first is choosing the sampling rate. If a sampling rate of 150 Hz is chosen, the same as for ECG, to ensure system uniformity, the signal picks up too much high frequency noise that is disturbing especially when extracting the SCR feature. A more appropriate value would be 50 Hz, but that would render two separate acquisition systems that would both be costly and would unnecessarily complicate the system. In order to overcome this problem, the EDA signal is re-sampled at 50 Hz by decimation procedure, thus suppressing part of the noise. A mean filter than eliminates the remaining noise.

Skin Conductance Level is the short term continuous component of the EDA signal. It is computed as the mean value of the samples in the processing frame (Eq. 2). In our measurements, the time window was 2 seconds long, but slightly shorter or longer windows are also applicable.

Being a conductance the Electro-Dermal Activity (EDA) is measured in micro-Siemens; the value of an average adult is between 10 – 20 micro-Siemens. According to our and BLL's experiments, elderly subjects' skin conductance is often very low.

Although there are many definitions in physiology used to describe the momentary state of this parameter, we finally – based on experience concerning our present purposes – settled on the following: SCR is, by definition, EDA's alternative component standard deviation. To obtain the EDA alternative component, the SCL (moving average) is subtracted from the raw EDA data. The SCR feature shows a good response to the light stimulus.

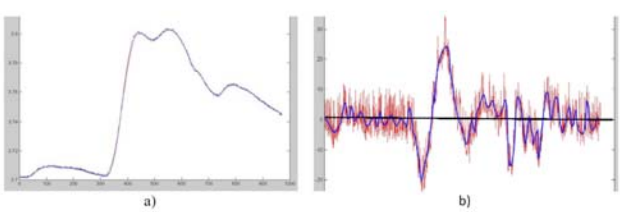


Fig. 11 The continuous (a) and alternative (b) components of EDA.

EDA's alternative component, shown in Fig. 11 b), is also low pass filtered before calculating its standard deviation and extracting SCR.

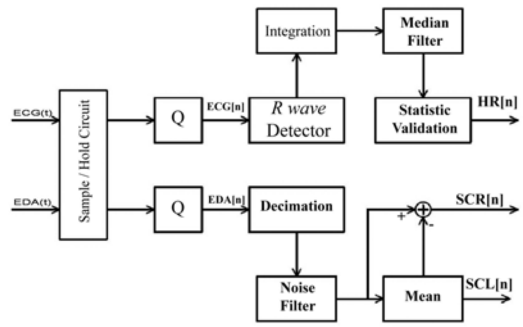


Fig. 12 Signal processing chain architecture

Fig. 12 shows the architecture of the system's signal processing and feature extraction module.

III. Light Controller Algorithms

Using the information of the subject's psycho-physiological state provided by the signal processing module, the light controller module has to adaptively optimize it by varying the lighting parameters so as to achieve the desired state [4]. One's state is described by the objective function *E*, defined as a linear combination of the three biological features:

$$E = 0.7 \cdot SCR + 0.2 \cdot SCL + 0.1 \cdot IBI \quad (3)$$

The task of the controller is to try finding the optimal $x \in D$ based on measurements of an objective function $E = E(x)$. Stochastic searching algorithms are among the simplest optimization methods and can be quite effective in solving different applications. Their relative simplicity is an appealing feature to both practitioners and theoreticians. These methods have a number of advantages relative to most other search methods. The advantages include relative ease of software implementation, the need to only obtain *E* measurements (versus gradients or other ancillary information), reasonable computational efficiency (especially for those direct search algorithms that make use of some local information in their search), and broad applicability to non-trivial energy functions and/or to search spaces that may be continuous, discrete, or some hybrid form. Some of these attributes were mentioned in [5]. A good recent survey of random search and related methods are presented in [6].

This section describes three stochastic search techniques: Blind Random Search, Local Random Search and Simulated Annealing. These three algorithms represent only a tiny fraction of available methods described in [7] and [8]. The two algorithms here are intended to convey the essential flavor of most available direct random search algorithms. With the exception of some discussion at the end of the subsection, the methods here assume perfect (noise-free) values of the objective function *E*.

A. *Blind Random Search*

The first method we discuss is "blind random search" that searches for solution in the entire states space *D*. This is the simplest random search method, where the current sampling for *x* does not take into account the previous samples. That is, this blind search approach does not adapt the current sampling strategy to information that has been garnered in the search process. The approach can be implemented in batch (non-recursive) form simply by laying down a number of points in *D* and taking the value of *x* yielding the lowest *E* value as our estimate of the optimum. The approach can be conveniently implemented in recursive form as we illustrate below.

The simplest setting for conducting the random sampling of new (candidate) values of *x* is when *D* is a hypercube and we are using uniformly generated values of *x*. The uniform distribution is continuous or discrete for the elements of *x* depending on the definitions for these elements. *In fact, the blind search form of the algorithm is unique among all general stochastic optimization algorithms in that it is the only one without any adjustable algorithm coefficients that need to be "tuned" to the problem at hand.* (Of course, a de facto tuning decision has been made by choosing the uniform distribution for sampling.)

For a domain *D* that is not a hypercube or for other sampling distributions, one may use transformations, rejection methods, or Markov chain Monte Carlo to generate the sample *x* values (see, [9]). For example, if *D* is an irregular shape, one can generate a sample on a hypercube superset containing *D* and then reject the sample point if it lies outside of *D*.

The steps for a recursive implementation of blind random search are given below. This method applies when *x* has continuous, discrete, or hybrid elements.

Step 0: (Initialization) Choose an initial value of *x*, say $\hat{x}_0 \in D$, either randomly or deterministically. (If random, usually a uniform distribution on *D* is used). Calculate $E(\hat{x}_0)$. Set *k=0.*

Step 1: Generate a new independent value $x_{new}(k+1) \in D$, according to the chosen probability distribution. If $E(x_{new}(k+1)) < E(\hat{x}_0)$, set $\hat{x}_{k+1} = x_{new}(k+1)$. Else, take $\hat{x}_{k+1} = \hat{x}_k$.

Step 2: Stop if the maximum number of *E* evaluations has been reached or the user is otherwise satisfied with the current estimate for *x* via appropriate stopping criteria; else, return to Step 1 with the new *k* set to the former *k+1.*

The above algorithm converges almost surely to x^* under very general conditions (see [10]). Of course, convergence alone is an incomplete indication of the performance of the algorithm. It is also of interest to examine the *rate* of convergence. The rate is intended to tell the analyst how close $\hat{x}_k$ is likely to be to x^* for a given cost of search. While blind random search is a reasonable algorithm when *x* is low dimensional, it can be shown that the method is generally a very slow algorithm for even moderately dimensioned *x* (see [10]). This is a direct consequence of the exponential increase in the size of the search space as *p* increases.

B. Local Random Search

This algorithm was first described in [11]. Note that the use of the term "local" here pertains to the sampling strategy and does not imply that the algorithm is only useful for local (versus global) optimization. As with blind search, the algorithm may be used for continuous or discrete problems.

Step 0: (Initialization) Pick an initial guess $\hat{x}_0 \in D$, either randomly or with prior information. Set *k=0.*

Step 1: Generate an independent random vector $d_k \in R^p$ and add it to the current *x* value, $\hat{x}_k$. Check if $\hat{x}_k + d_k \in D$. If $\hat{x}_k + d_k \notin D$, generate a new d_k and repeat or, alternatively, move $\hat{x}_k + d_k$ to the nearest valid point within *D*. Let $x_{new}(k+1)$ equal $\hat{x}_k + d_k \in D$ or the aforementioned nearest valid point in D.

Step 2: If $E(x_{new}(k+1)) < E(\hat{x}_0)$, set $\hat{x}_{k+1} = x_{new}(k+1)$; else, set $\hat{x}_{k+1} = \hat{x}_k$.

Step 3: Stop if the maximum number of *E* evaluations has been reached or the user is otherwise satisfied with the current estimate for *x* via appropriate stopping criteria; else, return to Step 1 with the new *k* set to the former *k+1.*

In [11], the (multivariate) normal distribution was used for generating d_k for continuous problems. However, the user is free to set the distribution of the deviation vector d_k. The distribution should have mean zero and each component should have a variation (e.g., standard deviation) consistent with the magnitudes of the corresponding *x* elements. This allows the algorithm to assign roughly equal weight to each of the components of *x* as it moves through the search space. Although not formally allowed in the convergence theory, it is often advantageous in practice if the variability in d_k is reduced as *k* increases. This allows one to focus the search more tightly as evidence is accrued on the location of the solution (as expressed by the location of our current estimate $\hat{x}_k$).

C. Simulated Annealing

Simulated annealing is a generalization of a Monte Carlo method for examining the equations of state and frozen states of n-body systems [12]. The concept is based on the manner in which liquids freeze or metals re-crystallize in the process of annealing. In an annealing process a melt, initially at high temperature and disordered, is slowly cooled so that the system at any time is approximately in thermodynamic equilibrium. As cooling proceeds, the system becomes more ordered and approaches a "frozen" ground state at *T=0*. Hence the process can be thought of as an adiabatic approach to the lowest energy state. If the initial temperature of the system is too low or cooling is done insufficiently slowly the system may become quenched forming defects or freezing out in meta-stable states (i.e. trapped in a local minimum energy state).

The original Metropolis scheme was that an initial state of a thermodynamic system was chosen at energy *E* and temperature T, holding T constant the initial configuration is perturbed and the change in energy dE is computed. If the change in energy is negative the new configuration is accepted. If the change in energy is positive it is accepted with a probability given by the Boltzmann distribution $\exp(-dE/T)$. This processes is then repeated sufficient times to give good sampling statistics for the current temperature, and then the temperature is decremented and the entire process repeated until a frozen state is achieved at $T=0$.

By analogy the generalization of this Monte Carlo approach to combinatorial problems is straight forward [13], [14]. The current state of the thermodynamic system is analogous to the current solution to the combinatorial problem, the energy equation for the thermodynamic system is analogous to at the objective function, and ground state is analogous to the global minimum. The major difficulty (art) in implementation of the algorithm is that there is no obvious analogy for the temperature T with respect to a free parameter in the combinatorial problem. Furthermore, avoidance of entrainment in local minima (quenching) is dependent on the "annealing schedule", the choice of initial temperature, how many iterations are performed at each temperature, and how much the temperature is decremented at each step as cooling proceeds.

Despite its name, *simulated annealing* has nothing to do either with simulation or annealing. Simulated annealing is a problem solving technique based loosely on the way in which a metal is annealed in order to increase its strength. When a heated metal is cooled very slowly, it freezes into a regular (minimum-energy) crystalline structure.

A simulated annealing algorithm searches for the optimum solution to a given problem in an analogous way. Specifically, it moves about randomly in the solution space looking for a solution that minimizes the value of some objective function. Because it is generated randomly, a given move may cause the objective function to increase, to decrease or to remain unchanged.

A simulated annealing algorithm always accepts moves that *decrease* the value of the objective function. Moves that *increase* the value of the objective function are accepted with probability

$$p = e^{-\frac{dE}{T}} \qquad (4)$$

where dE is the change in the value of the objective function E and T is a control parameter called the *temperature* i.e., a random number generator that generates numbers distributed uniformly on the interval (0, 1) is sampled, and if the sample is less than p, the move is accepted.

By analogy with the physical process, the temperature T is initially high. Therefore, the probability of accepting a move that increases the objective function is initially high. The temperature is gradually decreased as the search progresses, i.e. the system is *cooled* slowly. In the end, the probability of accepting a move that increases the objective function becomes vanishingly small. In general, the temperature is lowered in accordance with an *annealing schedule*.

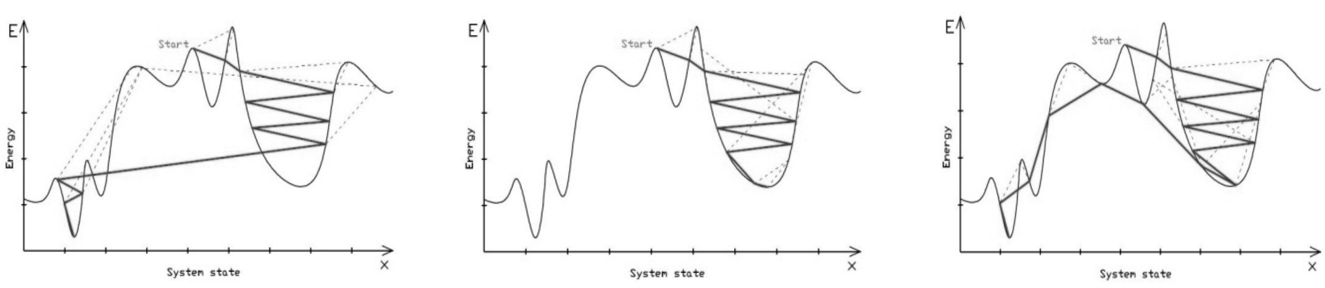
The most commonly used annealing schedule is the *exponential cooling*. Exponential cooling begins at some initial temperature T_0, and decreases the temperature in steps according to $T_{k+1}=\alpha\ T_k$ where $0<\alpha<1$ [15]. Typically, a fixed number of moves must be accepted at each temperature before proceeding to the next. The algorithm terminates either when the temperature reaches some final value T_f, or when some other stopping criterion has been met.

The choice of suitable values for α, T_0 and T_f is highly problem-dependent. However, empirical evidence suggests that a good value for α is 0.95 and that T_0 should be chosen so that the initial acceptance probability is 0.8. The search is terminated typically after some fixed, total number of solutions has been considered.

Finally, there is the question of selecting the initial solution from which to begin the search. A possible solution is to generate it randomly. However, sometimes the initial solution can be generated by some other means such as with a greedy algorithm.

D. Choosing the algorithm

In Figure 13 we compare the paths that the three previously presented algorithms would take through the domain D as they



a) b) c)

Figur 13. Different paths took by the optimum search algorithms on a given system: a) Global Search; b) Local Search; c) Simulated Annealing

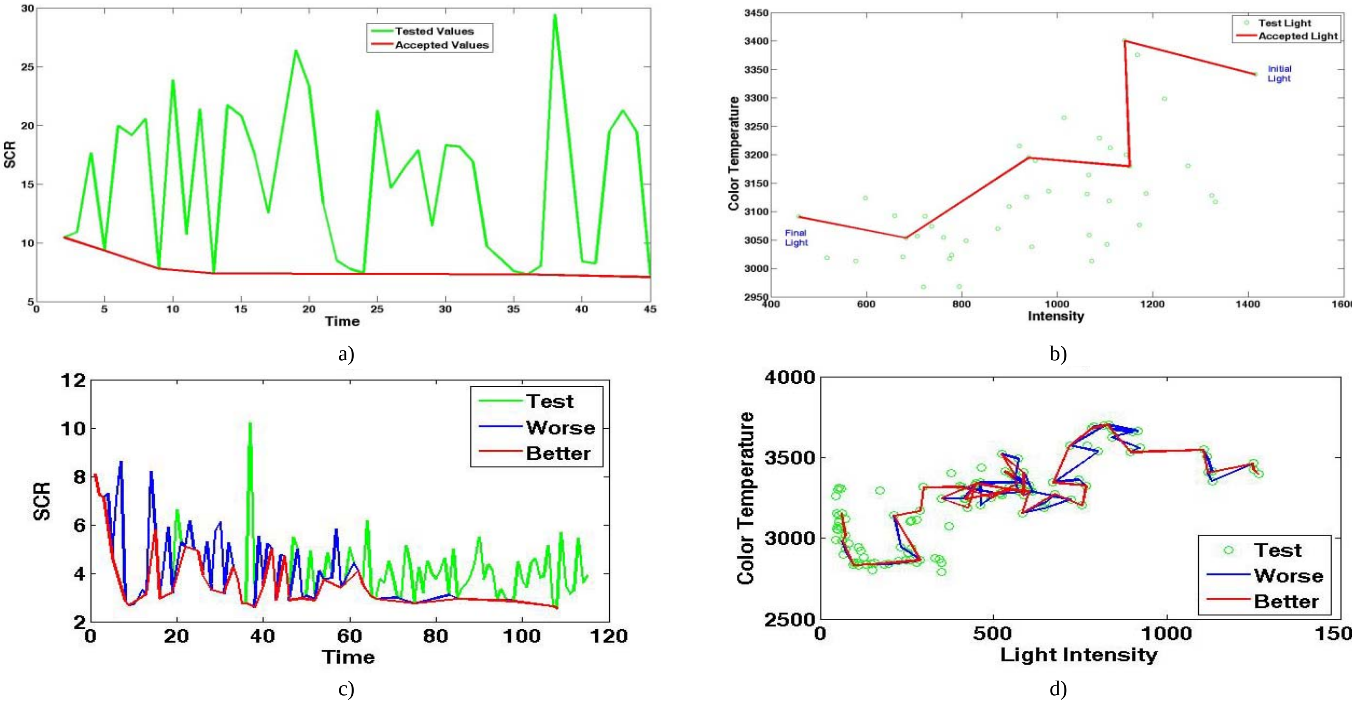


Figure 14. SCR and Lighting Parameters evolution during relaxation tests using Local Random Search (a, b) and Simulated Annealing (c, d)

search for the minimum energy. The global search algorithm, shown in Figure 13 a), finds the system's optimum, but it regularly has jumps of up 80% of the search domain's extend that are very unpleasant in the case of adaptive lighting, as it induces rapid radical changes of both color and intensity of the light that wouldn't be able to relax, nor activate the subject, as they would rather annoy him. The local search algorithm eliminates this unpleasant effect of high variation in the lighting parameters, but it has high chances to get trapped in a local optimum, as it can be seen in Figure 13 b). The simulated annealing algorithm, shown in Figure 13 c) solves both of the previous problems, as its jumps are also local, but by allowing certain jumps to higher valued system states correlated with *T*, it can avoid local minimums if the color temperature parameter is high enough to permit the system to overcome or tunnel the energy barriers next to the local minimum.

We have implemented two light controllers using the Local Random Search and the Simulated Annealing algorithms and tested them in the laboratory in order to determine which one is the best suited for the current application. The preliminary tests were conducted on one volunteer and consisted of him being exposed to the lighting environment controlled by each of the implemented algorithms.

Figure 14 shows the SCR feature and lighting parameter variation during relaxation tests using the two implemented algorithms. The tests confirmed the theoretical analysis, showing that the Simulated Annealing algorithm was able to avoid local minima entrapment and converge to a better global solution.

E. Adapting and optimizing the algorithm

In Figure 15 we show some examples of acceptance rate's evolution during two tests. The first shows a system with a very high initial temperature and low *α*, while the second shows the desired behavior using optimal parameters. The first graphic shows the acceptance function's evolution with the optimal cooling parameters, and the second shows it for a very high temperature and a low α. In the first case, the acceptance function decreases slowly and almost linear,

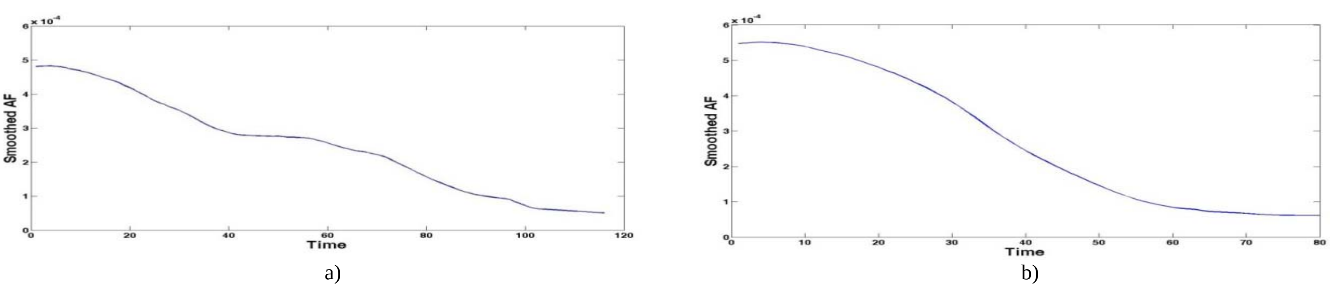


Figure 15. The evolutions of the acceptance function during tests using different cooling parameters. a) T_0 = 8, α = 0.9467; b) T_0 = 60, α = 0.90

allowing the system to avoid entrapment in local minimums and ensuring a steady path towards the optimum. The second set of cooling parameters generates a very poor and unwanted evolution. In this case, the acceptance function is very high for a long time in the beginning, and then it rapidly decreases to a low. This means that the algorithm is free to accept any move in the search space at the beginning for a rather long time, and then, suddenly, it becomes a Local Search Algorithm at a time when the solution may be very far from the optimum. This behavior both lengthens the path to the optimum and increases the chances of local minima entrapment. A more detailed description of the optimization process can be found in [16].

IV. Results

In this section, we will analyze the experimental results obtained during the tests performed in our facilities at the ¨Politehnica" University of Bucharest and in the field tests performed by our partners. The testing facility is a dark room whose only source of light is provided by the Adaptive Lighting System. The Lighting System is composed of ten independent lighting devices – five with a Color Temperature of 2700K and five with 4000K, controlled by the Adaptive Lighting Control System. By individually varying the intensity of each channel, the Color Temperature and Intensity of the ambient and local lighting can be changed. The simplified formula for computing the ambient Intensity and Color Temperature is:

$$I = \sum_{k=1}^{5} I_{wk} + I_{ck} \tag{5}$$

$$CT = \frac{1}{I}\sum_{k=1}^{5} I_{wk} \cdot CT_w + I_{ck} \cdot CT_c \tag{6}$$

A test consists of exposing elderly persons (aged above 65 years old) to the light generated by the system, and adapting the light in such a manner that the subject would relax. The measured used to determine the subject's degree of relaxation is the objective function *E* described in the previous section.

There are two questions that need answering. The first is whether a "relaxing" set of lighting parameters exists. The second is whether the system really determines a change in the subject's psycho-physiological state, measured by the features extracted, and if it does, how big is the change, and how stable is the result.

We have also studied the system's behavior for three different analysis window sizes and configurations: 20 and 40 seconds-long window starting just after applying the light stimulus and a 20 second window starting 20 seconds after applying the light stimulus. The results are presented in Table 1 and Figures 16.

The tests were conducted on two volunteers, and were each approximately 1 hour long for the 20 seconds analysis window, providing sufficient time for the system to *cool* and converge to an optimal solution. The tests performed using the 40 second and the delayed 20 second windows were two hours long. Each person performed 10 tests, yielding about 3600 measurements.

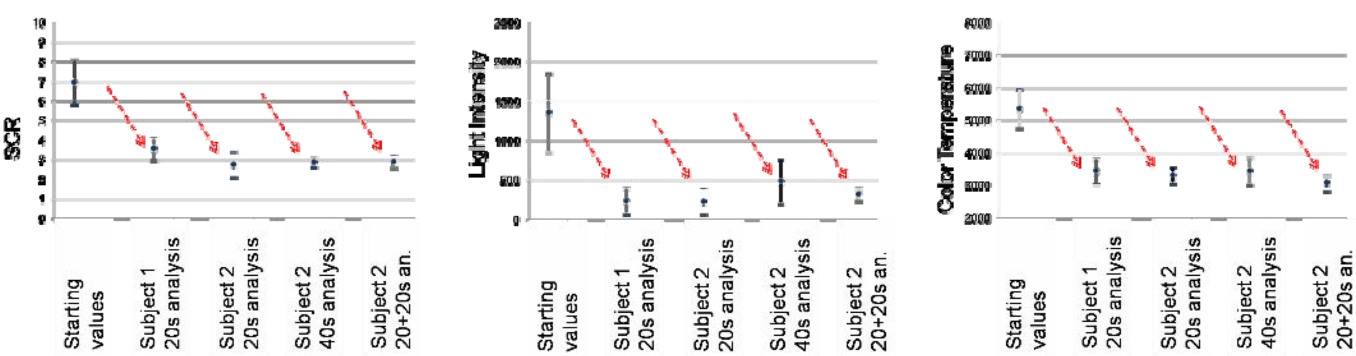
Table 1

	Final SCR		Final Intensity		Final Color Temperature	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Starting values	6.9	0.9	1350	500	3500	600
S1, 20s	3.52	0.56	232	163	3207	327
S2, 20s	2.74	0.66	227	158	3406	354
S1, 40s	2.85	0.25	480	280	3440	414
S1, 20+20s	2.87	0.31	317	84	3067	242

In Table 1 we show the results of the statistical studies performed on the data gathered from the two subjects. The values of SCR, Intensity and Color Temperature corresponding for each test's last accepted move were stored and their mean and dispersion were computed.

Both subjects show a low value of the SCR feature at the end of the test. Concerning the Lighting Parameters, the data indicates that the system stabilizes around a Color Temperature of 3400 K and an Intensity of 230 – about 10% of the system's maximum Intensity.

Because SCR is the most important feature in determining the psycho-physiological state of the subject, we will base our studies of the experimental results on it. The first thing that we would like to know is what the relationship between SCR and the lighting parameters is. In order to answer this question, a map of the SCR feature over the lighting parameters space has been built. The map was created by interpolating a set off



a) *b)* *c)*

Figure 16. SCR (a), Light Intensity (b) and Color Temperature (c) values evolution for different analysis windows.

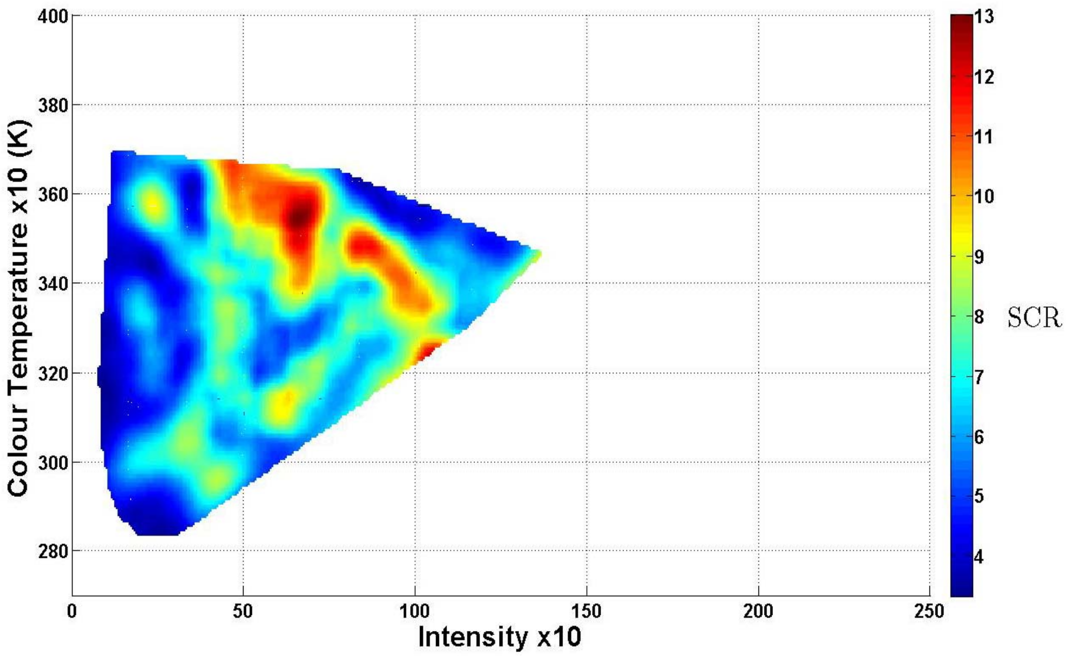


Figure 17. Map of the SCR values over the lighting space.

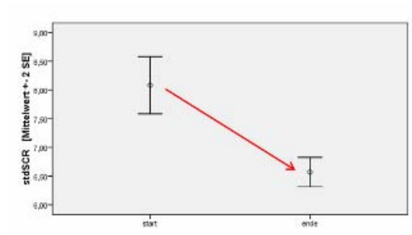
about 900 points, given by measurements done during the tests. As Figure 17 shows, the SCR values are decreasing with the light's intensity. In the middle of the SCR map, there is a local minimum zone that may entrap the algorithm, so the use of an appropriate cooling schedule becomes even more evident. By the time it reaches the low region, the system should still be able to accept large enough unfavorable moves to overcome the barrier, but it should not accept those large enough to stray it away from the global optimum.

The fact that for both subjects, the means and dispersions of the lighting parameters have close values confirms our presumption that there is a region in the lighting space that induces a relaxed psycho-physiological state. On the other side, concerning our second question, the data shows that, for both subjects, the system induces a significant drop in the SCR feature and that its final value is low and constant.

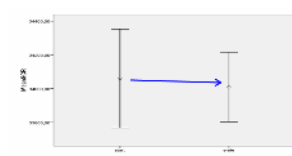
The different analysis windows that were used did not produce a significant change in the final results, so the 20 second window was chose for the final implementation as it needs less to converge to an acceptable and stable solution.

In the following paragraphs, the evolution of the selected psycho-physiological features in the field tests performed by our partners will be discussed. The tests were conducted in four different locations: two in Austria, at Dornbirn and Aldrans, one in Germany at Bad Tolz, and one in Italy in Bolzano. In each location the Adaptive Lighting System was given to 4 senior citizens and they were asked to use it daily. Figure 18 shows the means and standard deviation of the features at the beginning and end of each test.

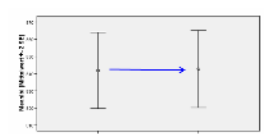
The results show that the SCR feature varies the most during tests and that it is the most useful in determining the subject's state. The SCL feature decreases slightly and has a smaller variation at the end of the tests, while IBI is more or less constant along the entire test.



a)



b)



c)

Figure 18. Evolution of SCR (a), SCL (b) and IBI (c) features during field tests

V. Conclusion

We have designed and developed an Adaptive Lighting System for elderly people psycho-physiological state improvement. In doing this, a first step was to analyze the biomedical signals that better describe their state and also the psycho-physiological feature extraction procedures were analyzed.

Two Adaptive Lighting Controllers were implemented using the Local Random Search and Simulated Annealing optimization algorithms and compared them, choosing the second due to its robustness to local minimum entrapment. During the development phase, we have tested the system in order to optimize the algorithm's parameters, thus insuring its proper functioning and convergence.

After optimizing the Simulated Annealing algorithm, we have performed a study of the light's impact on the humans' psycho-physiological state. The study was performed on two subjects and was aimed at determining whether there is a certain set of lighting parameters that would induce a state of relaxation and if the analysis window size is important.

After a statistical analysis of the data gathered during tests, we can say that the system functioned well and that a dimmer and warmer light induces a state of relaxation. We have also built a map of the SCR's feature values over the lighting space, and determined that the 20 seconds analysis window is optimum.

In the future we will continue our study and extend it to the activated psycho-physiological state. Also we intend to develop new algorithms for the Adaptive Lighting Controller.

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Ovidiu Grigore has got his Engineer's Degree in electronics at the "Politehnica" University of Bucharest, Romania in 1991 and his Ph. D. in electronics at the "Politehnica" University of Bucharest, Romania in 1997.
Since 2005 he is a Full Professor at the "Politehnica" University of Bucharest. Between 2000 and 2005 he is an Associate Professor at the "Politehnica" University of Bucharest. Between 2000 and 2005 he worked as a Post-Doctoral Researcher for INESC Porto in Portugal and Ulrecht University in Netherlands Between 1997 and 2000 he is a Lecturer at the "Politehnica" University of Bucharest. He is the author of numerous articles and books, amongst which: Ov. Grigore, A. Puga, "*Object Localization Procedure for Intratumoral Microvessel Density Estimation*", Recent Advances in Smulations, Computational Methods and Soft Computing, Ed. WSES Press, 2002, pp. 22-26 and *Polygonal Approximations. Algorithms and Implementations* (Bucharest, Romania, Ed. MatrixRom, 2003). His research interests are Pattern Recognition, Medical Image Processing, Biomedical Data and Signal Processing, Neural Networks, Genetic Algorithms and Evolution Strategies, Shape Approximation Algorithms, Fuzzy Systems, Neuro and Fuzzy Controller Design for Dynamic and Nonlinear Systems.

Inge Gavat, professor, received the M.S. and Ph.D. degrees in Electronics and Telecommunications from the University "Politehnica" of Bucharest UPB, Romania, in 1963 and 1998. She is currently a Professor at the Department of Applied Electronics and Information Engineering, Faculty for Electronics and Telecommunications, UPB and also at the German Branch of the Faculty of Engineering in Foreign Languages, UPB. She is teaching courses in Information and Estimation Theory, in Communication Theory and in Signal Processing and Artificial Intelligence for Man – Machine Communication. She is often a visiting professor at the Technical University – Darmstadt, Germany, at the University of Rouen, France. She is involved in advanced research projects and programs in pattern recognition with the Romanian Academy of Sciences, with the Military Technical Academy, with the Romanian Space Agency, with the Ministry for Education and Research. She is also involved in bilateral international cooperation with the Technical University of Munich, Germany, University of Maribor, Slovenia, the Rutgers University, N.J., USA. She is developing algorithms for pattern recognition with Markov models, neural networks and fuzzy systems. She worked for recognition applications, with emphasis on man-machine dialog and multimedia applications. Her interest is in stochastic processes conveying information, model-based sequence recognition and understanding, basics of man-machine communication, information managing and retrieval in extended databases. Recently she is involved in several projects in the frame of FP6 Programme concerning new technologies to support sustainable humanitarian crisis management using remote sensing imagery and also enhancement of elderlys dayly activities based on lighting technics controlled by inteligent or optimal algorithms She is coordinator of several ongoing national research and development projects in collaboration with Romanian Space Agency, regarding data mining for floods and other anomaly detection. She is leading projects in inteligent processing of speech and biological signals.. She published over 100 papers regarding speech recognition and understanding, speech enhancement, synthesis and coding, inteligent processing of various types of signals, application of information theory in the field of data mining and semantic interpretation.

Marius Cotescu got his Engineer's Degree in electronics at the "Politehnica" University of Bucharest in 2008, Department of Artificial Intelligence.
Since 2008 he is a Junior Researcher and Ph. D. student at the "Politehnica" University of Bucharest. He is the co-author of several articles, amongst which Ovidiu Grigore, Inge Gavat, Corina Grigore, and Marius Cotescu. "Stochastic Methods Used in Adaptive Lighting Control." *IMETI.* Orlando, 2008. His research interests are Biomedical Data and Signal Processing, Neural Networks, Genetic Algorithms and Evolution Strategies, Fuzzy Systems, Speech Processing.

Corina Grigore has got her MD's Degree at the "Iuliu Hatieganu" University of Medicine and Pharmacy, Cluj-Napoca, Romania.
Since 2006 she is PhD student in Internal Medicine, at the "Carol Davila" University of Medicine and Pharmacy, Bucharest, Romania and since 2005 is resident doctor in Emergency Medicine at Coltea Clinical Hospital, Bucharest. She is the co-author of several articles, amongst which Ovidiu Grigore, Inge Gavat, Corina Grigore, and Marius Cotescu, "Stochastic Methods Used in Adaptive Lighting Control." IMETI. Orlando, 2008. Her research interests are: Cardiology, Physiology, Cellular and Molecular Medicine, Genetics, Immunology, Biochemistry