Energy and Buildings 68 (2014) 242–253

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Modeling and control of color tunable lighting systems

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ARTICLE INFO

Article history:
Received 8 April 2013
Received in revised form 15 July 2013
Accepted 20 August 2013

Keywords:
Smart lighting
Feedback control
Energy efficiency
Intelligent buildings

ABSTRACT

Electric lighting has not substantially changed in over 100 years. From incandescent bulbs to fluorescent tubes, the efficiency remains low and control mostly involves on/off or dimming. The new wave of solid state lighting offers the possibility of sensor-based intensity regulation, color control, and energy efficiency, under varying needs and environmental conditions. This paper formulates the lighting control problem as an optimization problem balancing color fidelity, human perception and comfort, light field uniformity, and energy efficiency. The optimization problem is solved based on the light propagation model, which is adaptively updated with color sensor feedback to account for changing ambient lighting conditions, such as daylighting. We demonstrate the proposed approach in a smart space testbed under a variety of use conditions. The testbed is instrumented with 12 color tunable lights and 12 light sensors, as well as simulated daylight. The results show substantial improvement in terms of energy usage and delivering good light field quality in the presence of varying lighting conditions. Experimental results corroborate the efficacy of the proposed algorithms.

1. Introduction

Lighting is a major source of energy consumption in the U.S., using an estimated amount of more than 850 billion KWh annually in commercial sector, 16% of total electricity consumption of the country in this sector [1]. For the residential sector, this number is more than 550 billion KWh, 9% of the total electricity consumption of the country in this sector [1]. With the increasing importance of energy to economy and national security, solid state lighting (SSL) (i.e., light emitting diodes (LEDs) technology) is heralded as an important part of the solution as it offers energy efficiency and longevity. Indeed, the projected penetration of SSL into the lighting market would reduce energy usage by a whopping 49% [2]. SSL also possesses other attractive attributes including spectral tunability and fast response, which enables its use as a programmable device. These unique advantages of SSL open up a new dimension of lighting, called *smart lighting*, where lighting together with sensors creates an intelligent networked control system to achieve new levels of functionality, efficiency, and performance.

With the surging interest in SSL, there has been a rapidly growing body of related literature. Most of these efforts concentrate on novel material design, device packaging, and manufacturing. More recently, system-level research has been increasing due to the emphasis on overall systems-wide energy saving. Smart lighting control is typically posed as an optimization problem adjusting the individual light intensity to minimize energy consumption subject to task requirements, varying ambient lighting conditions (e.g., daylighting), and occupant locations. Most of this work regulates the intensity of white light to satisfy user needs while minimizing energy usage. The lighting specification is established based on the occupant locations and natural light distribution, which are measured by sensor networks consisting of light sensors and occupancy sensors or from measured usage data [3–8].

The system description used for lighting control is typically the light transport model [9], which relates light intensity of LEDs (of specified spectra) to the color (RGB) output at locations of interest. This model is static (i.e., no dynamics) and is used to determine light input to minimize some optimization objective, which would depend on occupancy, energy consumption, and account for the ambient light condition. Various optimization algorithms have been used for solving the optimal lighting problem, including linear programming [3,10], genetic algorithms [11,12], global search algorithms [13], and artificial neural networks [8]. Color tunable lights consisting of separately controlled multi-color LEDs have also been used to improve the photometric characteristics

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http://dx.doi.org/10.1016/j.enbuild.2013.08.036

[14,4,13,15–17] and achieve desirable color temperature [18,19]. However, several key challenges remain in realizing the promise of smart lighting systems, including reliable and adaptive light field estimation, assessment and interpretation of user requirements, and self-commissioning light fixtures.

As shown in the graphical abstract, the goal of this paper is to present a system-theoretic approach to smart lighting control of color-tunable lights under varying ambient lighting and room usage conditions, while balancing occupant comfort and energy consumption. We draw on color science to establish the basis for modeling, identification, and optimization of smart lighting systems. To address the issue of changing room conditions, occupancy, and ambient light levels, we propose an adaptive control approach. The efficacy of our approach is demonstrated on an experimental testbed consisting of multiple color tunable light fixtures, simulated daylighting, and color sensors.

Section 2 presents the mathematical definitions and concepts used in the formulation of lighting systems modeling and control problem. Section 3 poses the model identification, lighting control and adaptation problems as optimization problems. This section also suggests analytical solutions to these problems and discusses the convergence properties of the solutions. In Section 4, the experimental results obtained from implementing these control algorithms on an actual testbed are presented. Finally, Section 5 discusses the conclusions and future work while the appendix proves one of the statements made in Section 3.

2. Problem formulation

The light field at a point in space is characterized by the plenoptic function, $\phi(r, \theta, \lambda)$, which is the radiance along the ray given by the location of the point, $r \in \mathbb{R}^3$, and solid angle of the incoming light direction, $\theta \in S^2$, for the wavelength, $\lambda \in \Lambda$ where Λ is the visible light range [390, 750] nm [20].

Consider a space with n light fixtures each containing multiple adjustable intensity channels (p channels) represented as a vector $u_i \in \mathbb{R}^p$, $i = 1, \ldots, n$. Hence, there are pn control variables. Assume each control variable $u_i(j)$ is normalized to [0, 1].

Each light fixture generates a light-field distribution throughout the space. Let the unit (plenoptic) light field generated by fixture i be $S_i(r, \theta, \lambda) \in \mathbb{R}^p$ with the spectral dependence for each channel given by the spectral characteristics of the corresponding LED. Denote the ambient (uncontrolled) light field as $\psi(r, \theta, \lambda)$. Then the total light field is the linear combination of the two, based on the intensity levels of each fixture:

$$\phi(r, \theta, \lambda) = \sum_{i=1}^{n} S_i(r, \theta, \lambda)^T u_i + \psi(r, \theta, \lambda). \tag{1}$$

Assume there are m locations of interest for the light output. Because human color perception is based on three color-sensitive (red-green-blue, or RGB) photoreceptors (cones), we will consider $y_j \in \mathbb{R}^3$, consisting of the RGB measurements, $j = 1, \ldots, m$. The composite output vector is therefore a vector with $3m$ elements. Let light field weighting function for each sensor be $C_j(r, \theta, \lambda) \in \mathbb{R}^3$. The output at each location is therefore given by

$$y_j = \langle C_j, \phi \rangle + v_j \tag{2}$$

where $\langle \cdot, \cdot \rangle$ denotes integration over the spatial, angular, and spectral ranges of the light sensor, and v_j is the sensor noise. For a point light sensor at r_j, the r dependence in C_j is just $\delta(r - r_j)$. The θ dependence corresponds to the angular sensitivity, typically governed by the sensor optics. The spectral dependence is based on the spectral characteristics of the RGB sensor channels.

Substituting the light field (1) into the sensor equation (2), we get

$$y = Pu + w + v \tag{3}$$

where $y \in \mathbb{R}^{3m}$ is the output light measurement vector, $u \in \mathbb{R}^{pn}$ the input light intensity control vector, $P \in \mathbb{R}^{3m \times pn}$ is the *light transport matrix* with the (j, i)th $3 \times p$ submatrix given by $\langle C_j, S_i^T \rangle$, $w \in \mathbb{R}^{3m}$ is the ambient light with $w_j = \langle C_j, \psi \rangle$, and $v \in \mathbb{R}^{3m}$ the measurement noise vector.

We pose the lighting control problem as the adjustment of u to balance between the desired y, determined by occupants' needs and comfort, and the power consumption by the lights. First, input/output data is used to identify the light transport matrix. A cost function consisting of a weighted sum of power consumption and lighting quality is then constructed. A gradient projection method that aims to minimize this cost is then employed to update u based on the feedback of the output measurement y. In the presence of unknown external light disturbances and changing light transport properties in the room, we apply adaptive algorithms to improve the robustness of the control scheme. The desired lighting y_d depends on the location of occupants and spatial uniformity requirement. A key issue is the determination of an appropriate quality metric for color tunable lighting, for which human visual perception and comfort must be considered.

For spatial uniformity, we draw from existing literature in formation control [21] by considering the lights as an undirected graph. Each light is connected to its neighboring lights by links (neighbors may be defined as all lights within certain distance). We arbitrarily assign an orientation to the graph by designating one of the two nodes of a link to be the positive end. Denote by $\mathcal{L}_i^+$ ($\mathcal{L}_i^-$) the set of links for which node i is the positive (negative) end. Let the total number of links be ℓ. Then the incidence matrix $D \in \mathbb{R}^{n \times \ell}$ of the graph is defined by

$$d_{ik} = \begin{cases} +1 & \text{if } k \in \mathcal{L}_i^+ \\ -1 & \text{if } k \in \mathcal{L}_i^- \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

We shall use this graph as the basis for addressing light uniformity.

3. Optimal lighting control

3.1. Model identification

Measured input–output data may be used to identify the (static) light transport matrix, P. The typical approach [22] is a linear least squares fit to input–output data. Let $U = [u_1\, u_2 \ldots u_N]$ be a sequence of light inputs and $Y = [y_1\, y_2 \ldots y_N]$ be the corresponding measured outputs. In the absence of disturbance light, the least squares estimate of P is simply $\hat{P} = YU^+$ where U^+ is the Moore–Penrose pseudo-inverse of U. If the noise characteristics vary between sensors, a weighting matrix may be included in the least squares problem. Usual caution for least squares identification should always be exercised to ensure U is of full row rank and well conditioned (typical approach is to use randomly generated u).

However, the output consists of RGB measurements and it is well known that the Euclidean norm in the RGB space does not reflect the color sensitivity of human perception [23]. To mimic human perceptual uniformity, a common choice is the *Lab* color representation as defined in [24] (see Appendix A) which is a nonlinear transformation of the RGB space. We therefore pose