Adaptive Light Field Sampling and Sensor Fusion for Smart Lighting Control

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Abstract—For the development of flexible and adaptive control in smart lighting, it is important to have a systematic methodology for monitoring the generated light field and for fusion of the sensor information. This paper introduces a systematic approach to light field sampling using a distributed sensor network. This approach is based on the multiscale representation of the light field and adaptive selection of sample locations to maximize the information obtained from the field. Experimental results have shown that a systematic selection of sensor locations can significantly reduce the error in representation of the light field with corresponding improvement in the lighting control.

I. INTRODUCTION

Recent lighting design for both commercial and residential buildings has begun to shift from electric lighting to electronic smart lighting based on solid-state light sources such as light emitting diodes (LEDs). The goal of smart lighting is to provide high quality light to meet the occupant needs while balancing energy utilization. The criteria for lighting quality today are no longer just ‘visibility’, which aims to provide necessary illuminance in a workspace, but also includes other aspects of occupant satisfaction such as color preference, human productivity and health. These broad considerations of energy efficiency and lighting quality impose new constraints on the lighting design. Previous research [1], [11], [12], [15] has revealed various factors affecting the lighting conditions and indicated that an adaptive approach to lighting control can be very effective in improving the lighting quality. Since adaptive control requires real-time feedback of the actual lighting condition, obtaining an efficient and accurate estimate of lighting fields through real-time monitoring is critical in the implementation of smart lighting.

In recent years, real-time observation and monitoring of the physical environment has been facilitated by emerging sensor network technology [3], [8], [9], [10], [13], [14]. A spatially distributed network of compact and low cost sensor nodes can extract and estimate important features of the underlying phenomena from a set of point measurements in time and space. An example is the deployment of Autonomous Underwater Vehicles (AUVs) with embedded sensors to collaboratively observe and monitor oceanographic processes in order to understand the ocean’s health [4], [8], [16]. The understanding of environmental phenomena such as plankton layer structures [5] and harmful algal blooms [2] will be enhanced by three-dimensional monitoring and mapping. The research presented in this paper is based on the use of sensor network technology in the development of systematic methodologies for real-time light field monitoring in smart lighting applications. Light field sensing is based on a multi-scale modeling of the light field, and implemented adaptively by sequentially refining the field model. A sensor fusion algorithm is introduced to systematically select sensors, and incorporate the sensor information to generate a functional representation of the light field. Effective sampling and fusion of information is required to effectively meet performance goals of the lighting field while maintaining energy efficiency of the system.

This paper is organized as follows: In section II, a color-science-based specification of the light field is presented, and real-time light field monitoring is formulated as a sampling problem based on a distributed sensor network. In section III, an adaptive sampling algorithm is presented for systematic selection of sensor locations for light field monitoring. In section IV, the synthesis of adaptive light field sampling and lighting control is discussed, and a prototype lighting system with synthetic light field estimation is presented. In section V, experimental results from implementation of the prototype lighting system on a lighting testbed are presented and analyzed.

II. REAL-TIME LIGHT FIELD MONITORING

A. Light Field Specification

The light field is defined as a function describing the performance traveling in any direction through any point in space. In 3D space, the light field is a 7D function, parameterized by 3D position, 2D direction, and wavelength. In smart lighting design, a primary goal is to develop a full-spectrum lighting system to produce light with desired spectral properties (color) according to occupant needs. In order to meet this requirement, light field monitoring should take into consideration both the physical light spectrum and the human perception of the resulting colors. Therefore, it is important to appropriately...
specify the light field based on both color science and a human light response model.

Color is a perceptual property from a spectral distribution of light, received by the human retina and processed by the brain. The human eye has three types of photoreceptors with different sensitivity peaks to perceive a color. Any color can be represented as a mixture of three primary colors in an additive color model. For a given color sample, the magnitudes of the three matching primaries is called the tristimulus value. A widely used color space to represent color is the RGB color space based on the RGB color model, which is an additive model with primary colors red, green and blue. Thus, any color in the RGB color space can be represented by three additive components. Given a light spectral distribution \( f(\lambda) \), with proper color matching functions \( \bar{r}(\lambda), \bar{g}(\lambda) \) and \( \bar{b}(\lambda) \), the corresponding tristimulus value can be derived by projection of the color on the RGB vector space:

\[
\begin{align*}
  f_R &= \int_0^\infty f(\lambda)\bar{r}(\lambda) \, d\lambda, \\
  f_G &= \int_0^\infty f(\lambda)\bar{g}(\lambda) \, d\lambda, \\
  f_B &= \int_0^\infty f(\lambda)\bar{b}(\lambda) \, d\lambda.
\end{align*}
\]

The matching functions in the above projection are not always positive along all wavelengths, therefore, there may be negative values which are not physically realizable. To avoid this problem, an XYZ color space was created by the International Commission on Illumination (CIE) based on measurements of human color perception. In the XYZ color space, each color is expressed by its tristimulus values denoted as \( X, Y, \) and \( Z \). Given the light spectral distribution \( f(\lambda) \), the corresponding tristimulus values are calculated as:

\[
\begin{align*}
  f_X &= \int_0^\infty f(\lambda)\bar{X}(\lambda) \, d\lambda, \\
  f_Y &= \int_0^\infty f(\lambda)\bar{Y}(\lambda) \, d\lambda, \\
  f_Z &= \int_0^\infty f(\lambda)\bar{Z}(\lambda) \, d\lambda,
\end{align*}
\]

where \( \lambda \) is the wavelength. \( \bar{X}(\lambda), \bar{Y}(\lambda) \) and \( \bar{Z}(\lambda) \), are the three CIE 1931 color matching functions defined as the spectral response curves for the detectors in the human eye.

With the linearity of projection, there exists a linear transformation between the RGB projection and the XYZ projection for the light spectrum \( f(\lambda) \):

\[
 f_{XYZ} = T f_{RGB},
\]

\[
 f_{XYZ} = \begin{bmatrix} f_X \\ f_Y \\ f_Z \end{bmatrix}, \quad f_{RGB} = \begin{bmatrix} f_R \\ f_G \\ f_B \end{bmatrix}.
\]

The XYZ color space is a device-independent color space. It mathematically represents the perceived light color and provides a basis for sensor fusion of spectral information as perceived by a human observer. However, in this color space, too much area is assigned for green and most of the color variations are allocated to a small area. So it is not perceptually uniform. That is, the change of the same amount in a color value may not produce the same perceived visual difference. For perceptual uniformity, the CIE \( L^*a^*b^* \) (CIELAB) color space (Fig. 1) was created to approximate human vision, where the \( L \) component denotes lightness and the \( a \) and \( b \) components represent chromaticity. This CIELAB color space is a three-dimensional space, and it is converted by a nonlinear transformation from CIE XYZ color space:

\[
\begin{align*}
  f_L &= 116g(f_Y/Y_n) - 16, \\
  f_a &= 500[\bar{g}(f_X/X_n) - \bar{g}(f_Y/Y_n)], \\
  f_b &= 200[\bar{g}(f_Y/Y_n) - \bar{g}(f_Z/Z_n)],
\end{align*}
\]

where \( f_L, f_a, f_b \) are the three coordinates of \( f(\lambda) \) in CIELAB space. \( X_n, Y_n, Z_n \) are the XYZ tristimulus values of the reference white point and function \( g(t) \) is defined as

\[
g(t) = \begin{cases} 
  t^2 & \text{if } t > \left(\frac{2}{3}\right)^3 \\
  \frac{1}{3}(\frac{2}{3})^2 t + \frac{4}{27} & \text{otherwise}.
\end{cases}
\]

![Fig. 1. 3D view of CIELAB color space](image)

As shown in Fig. 1, the CIELAB color space is organized in a cube form, and "colors" within the space are separated with a perceptually uniform color scale. The \( L, a \) and \( b \) axes are orthogonal to each other. The \( L \) axis runs from 0 to 100 while the \( a \) and \( b \) axes have no numerical limits. The perceptual difference of any two colors can be approximated by the Euclidean distance between their corresponding color points in this space. With the property of perceptual uniformity, the CIELAB color space is chosen for light field specification in smart lighting. In this case, the above light field with spectrum \( f(\lambda) \) can be represented by a three-dimensional vector in CIELAB space \( f_{Lab} = [f_L, f_a, f_b]^T \).

B. Problem Formulation

This paper describes an approach to sampling and estimation of the generated light field using a distributed sensor network. The goal is to sample and recover features of any generated light field for feedback lighting control. To achieve this goal, one needs to consider two general problems in smart lighting design: where to optimally deploy the sensors (sampling) and how to recover the color distribution using the sensor samples (fusion).

While the smart lighting system aims to produce the right light, a desired light field is usually designed to satisfy the light field requirements in a specific lighting application. This desired light field should be the target of lighting control, and thus the generated light field will be a set of fields similar to the target one. In this case, it is reasonable to deploy sensors...
based on the target field to maximize the information obtained from the deployed sensor array.

Suppose there exists a target light field \( f_{\text{tar}} : \Omega \rightarrow \mathbb{R}^3 \), and \( f_{\text{Lab}} = [f_{\text{tar}}^L f_{\text{tar}}^a f_{\text{tar}}^b]^T \). For analysis, the space domain \( \Omega \) is discretized by a prescribed spatial resolution \( \Delta x \). For the target field \( f_{\text{Lab}} \), a discrete estimate \( \hat{f}_{\text{Lab}} := [\hat{f}_{\text{tar}}^L \hat{f}_{\text{tar}}^a \hat{f}_{\text{tar}}^b]^T \) with a spatial resolution \( \Delta x \) can be generated from a set of point samples \( \{f_{\text{Lab}}(x_i) ; X_s = \{x_i\}_{i=1}^N, x_i \in \Omega \} \). The estimation quality depends on the approximation model \( \hat{f} \) and the choice of samples \( X_s \). With the light field specified in CIELAB color space, a metric of the estimation quality can be defined as the Euclidean norm between the target field and the estimate:

\[
I(X_s) = \sum_{x \in \Omega} \| f_{\text{Lab}}(x) - \hat{f}_{\text{Lab}}(x, X_s, f(X_s)) \|_2. \tag{6}
\]

In light field sampling design, the goal is to select a best set of samples \( \{f_{\text{Lab}}(x_i), X_s \} \) with an appropriate model \( \hat{f} \) to minimize the estimation error \( I(X_s) \) of the target light field. The most commonly used sampling approach is uniform grid sampling [16], where the sampling points in each spatial direction are equally separated. Generally speaking, uniform sampling is often relatively easier to design and implement. However, it can be quite inefficient when applied in an environment with non-uniform features. Since the samples are uniformly distributed over the space, regions with features may be undersampled while regions lacking features are oversampled. Thus, efficient and effective sampling requires a sampling regime which can adaptively allocate different spatial resolutions appropriate to capture the variation of the process in different regions. The resultant sampling approach is adaptive sampling [6], [7], [9], [17]. In this paper, an adaptive sampling approach is developed to guide sensor deployment for target field sampling.

### III. Adaptive Sampling Design

#### A. Hierarchical Radial Basis Functions

In adaptive sampling, it is important to choose an appropriate field model to integrate initial samples into an estimation of the underlying function. In [9], Hombal et al. introduced a multi-scale surrogate model for sampling and estimation of the unknown underlying process based on localized radial basis functions. To be consistent with this general sampling regime for an unknown process, in this paper, we employ hierarchical radial basis functions (HRBF) to implement coarse-to-fine modeling of the underlying light field. The HRBF network [6], [14] may be viewed as a neural model for multi-scale approximation of a function through multi-layer decomposition of the approximation error space. Each layer of the model is approximated by a radial basis function (RBF) network with a different scale.

1) **Decomposition and HRBF Synthesis**: Given an underlying function \( f \), an \( M \)-level hierarchical decomposition can be expressed as:

\[
\begin{align*}
    e_1 &= \hat{f} - f = e_1 + e_2 & k = 1 \\
    e_2 &= e_2 + e_3 & k = 2 \\
    &\vdots & \vdots \\
    e_M &= e_M + e_{M+1} & k = M
\end{align*}
\]

where \( e_k \) is the approximation error in the \((k-1)^{th}\) layer and initially \( e_1 = \hat{f} \). \( \hat{e}_k \) is the approximation to the error \( e_k \) in the \( k^{th} \) layer and \( \hat{e}_k = e_k - e_{k+1} \). From this decomposition mechanism, an \( M \)-level approximation \( \hat{f}_M \) of the underlying function can be constructed as:

\[
\hat{f}_M = f - e_{M+1} = \sum_{k=1}^{M} \hat{e}_k. \tag{8}
\]

In any layer \( k \) in the above decomposition, the error \( e_k(x) \) at point \( x \) is approximated by an RBF network of \( N_k \) basis functions:

\[
\hat{e}_k(x) = \sum_{j=1}^{N_k} \omega_{k,j} \phi_{k,j}(x) = \Phi_k(x) w_k \tag{9}
\]

where \( \phi_{k,j}(x) \) denotes a basis function \( \phi(||x - c_{k,j}||; \sigma_k) \) centered at \( c_{k,j} \) with width \( \sigma_k \). \( \Phi_k(x) \) is the interpolation matrix and \( w_k \) is the vector of approximation parameters. Then \( \hat{f}_M \) can be represented by a multi-scale RBF approximation model:

\[
\hat{f}_M(x) = \sum_{k=1}^{M} \sum_{j=1}^{N_k} \omega_{k,j} \phi_{k,j}(x) = \sum_{k=1}^{M} \Phi_k(x) w_k = \Phi(x) W \tag{10}
\]

where \( W \) is the matrix of the approximation parameters and \( \Phi \) is the multi-scale interpolation matrix with structural parameters \( c \) and \( \sigma \).

2) **Structural and Approximation Parameters**: To determine the structural parameters in the HRBF model, a hierarchical analysis grid is constructed in the problem domain, where each layer is a dyadic partition of the previous layer and the intersections between partitions are considered as nodes. An analysis grid in a 1D domain \([a, b]\) is shown in Fig. 2. In the first layer, the partition starts with node number \( 3 \) and resolution \( \rho_1 = (b - a)/2 \). The nodes in subsequent layers will be generated as the child nodes of nodes in the previous layer [9]:

\[
C_{k+1}^{(j+1)} = \{ \begin{array}{ll}
    \{c_{k+1,j-1}, c_{k+1,j} \} & j = 1 \\
    \{c_{k+1,j-2}, c_{k+1,j-1}, c_{k+1,j} \} & 1 < j < 2^k + 1 \\
    \{c_{k+1,j-2}, c_{k+1,j-1} \} & j = 2^k + 1
\end{array} \}
\]

where nodes \( c_{k+1,j-2} \), \( c_{k+1,j-1} \) and \( c_{k+1,j} \) respectively represent the left, middle and right child of node \( c_{k,j} \). Their locations are calculated as:

\[
\begin{align*}
    c_{k+1,j-2} &= \frac{1}{2} (c_{k,j} + c_{k,j-1}) \\
    c_{k+1,j-1} &= c_{k,j} \\
    c_{k+1,j} &= \frac{1}{2} (c_{k,j+1} + c_{k,j}). \tag{12}
\end{align*}
\]

Given a problem domain, the structural parameters in the HRBF model can be uniquely defined by this analysis grid.
Thus in the above partition approach on each dimension of the domain. Fig. 3 shows the analysis grid in a 2D domain. For a problem domain \([a, b]^\lambda\) with dimension \(\lambda\), a \(\lambda\)-dimensional analysis grid can be constructed by applying the above partition approach on each dimension of the domain. Thus in the \(k^{th}\) layer, the total number of nodes is \(N_k = (2^k + 1)^\lambda\) and the corresponding resolution is \(\rho_k = (b - a)/2^k\). Fig. 3 shows the analysis grid in a 2D domain \([-4, 4]^2\).

![Fig. 2. 1D analysis grid [9]](image)

![Fig. 3. 2D analysis grid](image)

In each layer of the grid, the location and density of nodes determine the center and scale of RBFs in the corresponding HRBF layer. Thus a node \(c_{k,j}\) in the \(k^{th}\) layer corresponds to a basis function \(\phi_{k,j}\) centered on this node and with scale \(\sigma_k = (b - a)/2^k\). This partition strategy can also be used in higher dimensions. For a problem domain \([a, b]^\lambda\) with dimension \(\lambda\), \(\lambda\)-dimensional analysis grid can be constructed by applying the above partition approach on each dimension of the domain. Thus in the \(k^{th}\) layer, the total number of nodes is \(N_k = (2^k + 1)^\lambda\) and the corresponding resolution is \(\rho_k = (b - a)/2^k\). Fig. 3 shows the analysis grid in a 2D domain \([-4, 4]^2\).

**B. Adaptive Sample Selection**

Based on the choice of the HRBF network as the approximation model, given a target light field, a multi-layer analysis grid is first constructed on the problem domain \(\Omega\). As shown in Fig. 2, such an analysis grid will discretize the target domain \(\Omega\) to a set of available sample points, which are equally separated with a prescribed spatial scale \(\Delta x\). Suppose we are interested in the target color on these \(m\) sample points, but have only \(n\) available sensors where \(n < m\). Then sampling and approximation of the target field should consider the optimal deployment of sensors on the sample points.

In HRBF modeling, each sampled point is associated with a set of localized radial basis functions centered on this point but with different scales. While a node on the analysis grid is selected for sampling, its corresponding basis function will be employed in the estimation of the underlying function. In this case, the sensor deployment problem is equivalent to a basis function selection problem. In this problem, there is a set of radial basis functions centered at \(m\) available sample points \(X = \{x_1, x_2, ..., x_m\}\) and we would like to select a subset of basis functions associated with \(n\) points for best approximation of the target light field \(f_{tar}^{Lab}\). However, for a non-trivial data set, it is N-P complete to select the optimal subset of centers of basis functions. Thus instead of globally selecting the optimal \(n\) samples, suboptimal selection methods must be considered.

A greedy algorithm may be used to sequentially select basis functions and corresponding samples. In this algorithm, at every iteration, only one basis function is selected and it, along with previously selected basis functions, can be introduced to best approximate the target field at this iteration. Let \(\Psi\) denote the set of available basis functions to be selected, and \(\Phi_s\) denote the vectors consisting of selected basis functions and initially \(\Phi_s = \emptyset\). In the first iteration, a basis function is selected from \(\Psi\) for the best approximation of the target field \(f_{tar}^{Lab}\). Specifically, for each basis function \(\phi^i\) in \(\Psi\), based on the measurements of the target field on its center \(x_i\), an interpolation function \(\hat{f}_i\) is constructed to approximate \(f_{tar}^{Lab}\):

\[
\hat{f}_i = w_i \phi^i = \frac{f_{tar}^{Lab}(x_i)}{\phi^i(x_i)} \phi^i = \begin{bmatrix} \frac{f_{tar}^{Lab}(x_i)}{\phi^i(x_i)} \phi^i \\ \frac{f_{tar}^{Lab}(x_i)}{\phi^i(x_i)} \phi^i \\ \end{bmatrix}
\]

Then the basis function \(\phi^*\) with minimum interpolation error is selected:

\[
\phi^* = \arg \min_{\phi^i \in \Psi} \sum_{x \in \Omega} ||f_{tar}^{Lab}(x) - \hat{f}_i(x)||^2.
\]

Once selected, \(\phi^*\) is removed from \(\Psi\) and added to \(\Phi_s\).

In each successive iteration, one basis function is selected from \(\Psi\) such that the interpolation function formed by it and previously selected basis functions in \(\Phi_s\) can best approximate the data \(f_{tar}^{Lab}\). For example, in the \(k^{th}\) iteration where \(1 < k < n\), let \(\Phi_s = \{\phi_1^*, \phi_2^*, ..., \phi_{k-1}^*\}\) be the vector consisting of previously selected basis functions and \(X_s\) be the set of their centers. For every basis function \(\phi^i\) with center \(c_i\) remaining
in $\Psi$, an interpolation function will be constructed using the previously selected basis $\Phi_s$ and $\phi^i$:

$$\hat{f}_k^i = W_i \left[ \begin{array}{c} \Phi_s \\ \phi^i \end{array} \right],$$

(15)

where $W_i$ is a weighting vector which is chosen to satisfy the interpolation constraints on $c_i$ and previously selected centers in $X_s$:

$$\hat{f}_k^i(c_i) = f^i_{Lab}(c_i),$$

$$\hat{f}_k^i(X_s) = f^i_{Lab}(X_s).$$

(16)

Since these interpolation functions are used to approximate $f^i_{Lab}$, the basis function $\phi^*_k$ is selected corresponding to the minimum approximation error:

$$\phi^*_k = \arg \min_{\phi^{i} \in \Psi} \sum_{x \in \Omega} ||f^i_{Lab}(x) - \hat{f}_k^i(x)||_2.$$  

(17)

Once $\phi^*_k$ is selected, it is removed from $\Psi$ and added into $\Phi_s$ to update these sets. This greedy selection procedure is repeated until the number of centers of the selected radial basis functions is equal to $n$.

C. Recovery of the Generated Light Field

The previous section provides an iterative approach to selection of a set of samples based on the target light field. Sensors can then be deployed on the selected sample locations to sample and recover the generated light field. Suppose the location of these sensors are $X_s = \{x_i\}_{i=1}^n, x_i \in \Omega$ and the corresponding radial basis functions are in vector $\Phi_s = [\phi^*_1, \phi^*_2, \ldots, \phi^*_n]^T$ where $n \leq n'$. For any newly generated light field $f_{Lab}$, the estimation $\hat{f}_{Lab}$ can be derived as an HRBF interpolation based on the measurements of $f_{Lab}$ on $X_s$:

$$\hat{f}_{Lab} = W \Phi_s = \left[ \begin{array}{ccc} W_L & | & \Phi_s \end{array} \right],$$

(18)

where the interpolation weights are determined by the sensor measurements $f_{Lab}(X_s)$ such that:

$$\left[ \begin{array}{c} W_L \\ W_a \\ W_b \end{array} \right] \Phi_s(X_s) = f_{Lab}(X_s) = \left[ \begin{array}{c} f_L(X_s) \\ f_a(X_s) \\ f_b(X_s) \end{array} \right].$$

(19)

Through the interpolation, a multi-scale functional approximation $\hat{f}_{Lab}$ of the light field is generated and provides an effective basis for lighting control.

IV. A Prototype Lighting System

In this section, we will describe a prototype lighting system incorporating the proposed sampling methodology and adaptive lighting control. For full spectrum lighting, the lighting system consists of multispectral LED modules as light sources, and a set of color sensors are used for light field sampling and estimation.

A. System Model

Effective feedback control in a lighting system requires knowledge of the light propagation under given conditions. For an LED lighting system, Afshari et al. [1] introduced a linear light transport model to map the system input to the generated light field on sensors:

$$\hat{f}_{RGB} = Gu_{RGB} + w,$$

(20)

where $f_{RGB} \in \mathbb{R}^{m \times 1}$ is the generated light field represented in RGB color space on a set of spatial points, and $u_{RGB} \in \mathbb{R}^{m \times 1}$ is the RGB LED input. $G$ is an $m \times n$ matrix called the Light Transport Matrix (LTM) and $w \in \mathbb{R}^{m \times 1}$ denotes light disturbances in the system. The LTM $G$ depends on the room configuration and can be identified using a least square approach. Specifically, for a set of random lighting input $U_{RGB} = [u_{1RGB}, u_{2RGB}, \ldots, u_{nRGB}]^T$, the corresponding color outputs are measured as $F_{RGB} = [f_{RGB}, f_{RGB}^2, \ldots, f_{RGB}^n]^T$, and the LMT $G$ can be derived as:

$$G = U_{RGB}^T F_{RGB},$$

(21)

where $U_{RGB}^T$ is the pseudo inverse of $U_{RGB}$ and $U_{RGB}^T = (U_{RGB}^T U_{RGB})^{-1} U_{RGB}^T$.

B. Feedback Control

Once an approximation to the generated lighting field is constructed, it can be used in feedback mode for adaptive lighting control. The objective of the control is to minimize the perceptual difference between the estimated and target light field. This can be formulated as an optimization problem:

$$\min_u J(u)$$

$$s.t. \quad \hat{f}_{RGB} = Gu + w$$

$$\hat{f}_{Lab} = h(f_{RGB})$$

$$\hat{f}_{Lab} = W(X_s, f_{Lab}(X_s))\Phi_s$$

where

$$J(u) = \sum_{x \in \Omega} ||f_{Lab}^i(x) - \hat{f}_{Lab}^i(x)||^2_2$$

and $h(\cdot)$ is a nonlinear mapping from the RGB color space to the CIELAB space. With this formulation, a gradient-based control method is developed to iteratively obtain the optimal LED input for the target light field. The control input at the $i$th time-step is calculated as:

$$u_{i+1} = u_i + \epsilon \left[ \begin{array}{c} \nabla_u (L_{tar} - L(u)) \\ \nabla_u (a_{tar} - a(u)) \\ \nabla_u (b_{tar} - b(u)) \end{array} \right] \left[ \begin{array}{c} (L_{tar} - \hat{L}) \\ (a_{tar} - \hat{a}) \\ (b_{tar} - \hat{b}) \end{array} \right],$$

(23)

where $\epsilon$ is a tunable step size and $\nabla_u (\cdot)$ is the gradient with respect to $u$.

V. EXPERIMENTAL RESULTS

The prototype lighting system described here has been tested and evaluated on the smart space lighting control testbed at the Smart Lighting Engineering Research Center (Fig. 4). This testbed is a room with full power, communications and computational access at all points, and a supporting software
architecture to facilitate implementation of distributed lighting and sensor systems. It consists of 12 Renaissance multispectral LED modules (Acuity Brands), which are accessible through wireless communications and offer real-time control of spectral characteristics. In addition, 10 Colorbug wireless RGB color sensors (Ocean Optics) are used in the testbed to monitor the generated light field for closed-loop lighting control. In our laboratory experiments, the light field is observed on a 2D horizontal plane at 81.28 cm high in the smart space. Figs. 5(a)-5(c) show one such target light field specified in the CIELAB color space as $f_{\text{tar}}^{\text{Lab}} = [L_{\text{tar}} a_{\text{tar}} b_{\text{tar}}]^T$. Fig. 5(d) shows the sample distribution generated by adaptive sampling corresponding to this target field.

Similarly, the light field estimation error $e_{\text{est}}$ is a measure of the perceptual difference between the generated and estimated light fields:

$$e_{\text{est}} := \|f_{\text{Lab}} - \hat{f}_{\text{Lab}}\|_2.$$
TABLE I
MEAN CONTROL ERRORS FOR DIFFERENT TARGET LIGHT FIELDS

<table>
<thead>
<tr>
<th>Target Field 1</th>
<th>Target Field 2</th>
<th>Target Field 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lighting System with Adaptive Sampling</td>
<td>5.90</td>
<td>5.82</td>
</tr>
<tr>
<td>Lighting System with Uniform Sampling</td>
<td>28.03</td>
<td>18.11</td>
</tr>
</tbody>
</table>

the region of interest due to the lack of sensors and resultant insufficient feedback to the generated light field. The mean control error on the problem domain is 4 times higher than that in the system with adaptive sampling.

A series of similar experiments have been implemented to test the performance of the adaptive sampling and feedback control systems in the smart space. Different target light fields are selected in these experiments, and the corresponding mean control errors of the two lighting systems are shown in Table I. In these experiments, the lighting system with adaptive light field sampling could consistently reduce the control error by more than 65% relative to that with uniform sampling.

VI. CONCLUSION AND FUTURE WORK

In this paper an adaptive sampling approach was introduced for systematic selection of sensors to sample the generated light field and fusion of sensor information to support feedback control of lighting. In this approach, a functional representation of the field is generated and provides an effective basis for sensor fusion and lighting control. Experimental results have shown that this systematic selection of sensor sample locations could significantly reduce the error in representation of the light field with corresponding improvement in lighting control.

For more accurate estimation of the generated light field, future work will consider light field sampling subject to dynamic disturbances such as user activities and natural light. Further experiments will be run to test and analyze the performance of the algorithm subject to different disturbances. On the other hand, with the incorporation of robotic technologies to the sensor network, real-time reallocation of sensor locations may be used to adaptively sample the dynamic light field.
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