Automatic Sensor and Light Source Positioning for Machine Vision

Seungku Yi, Robert M. Haralick and Linda G. Shapiro
Intelligent Systems Laboratory, FT-10
University of Washington
Seattle, WA 98195

Abstract

An optimization approach to automatic sensor and light source positioning for a machine vision task, where geometric measurement and/or object verification is important, is discussed. The goal of the vision task is assumed to be specified in terms of edge visibility. There are two types of edge visibility: (1) geometric edge visibility tells us how much of the given edge is not occluded, and (2) photometric visibility tells how much of the given edge has enough contrast to be detected in the image. A heuristic optimality criteria for the optimal sensor and light source position is defined in terms of these two edge visibilities. A preliminary experiment has been conducted to demonstrate the feasibility of the optimization approach. The result shows that the optimization problem we formulated can be solved by mathematical programming techniques.

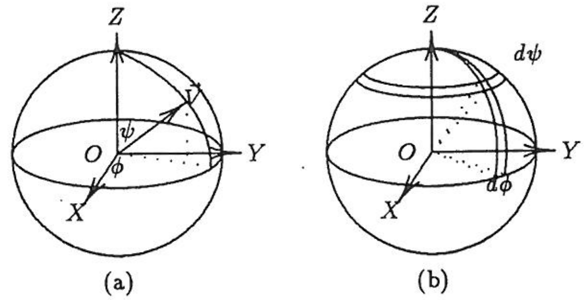

Figure 1: (a) The reference sphere is shown. The origin of the object coordinate system is placed at the center of the reference sphere. A point on the surface of the reference sphere is referenced by two angles: (ψ, ϕ). (b) The viewing space is approximated in such a way that the distance between any neighboring two points in the viewing space is approximately the same. In other words, $d\psi d\phi \sin\psi$ is approximately constant.

1 Introduction

A typical computer vision system can be decomposed functionally into three subsystems: the *image acquisition subsystem*, the *image processing subsystem*, and the *image understanding subsystem*. The image acquisition subsystem is responsible for providing pictures to the image processing subsystem. The image processing subsystem analyzes input pictures and generates lower-level information, such as edges and regions. The image understanding subsystem uses lower-level information produced by the image processing subsystem to generate higher-level information and produces an inference relative to a scene description or object mensuration. There has been much work done on image processing and image understanding, but there has been little work to automate the image acquisition subsystem.

Pentland [7] and Krotokov's [5] works are related to lens selection. Ikeuchi concentrated on view class classification rather than on camera and illumination control [4]. Shirai and Tsuji are two of the first researchers who took advantage of controlled illumination in extracting line drawings of 3-D objects [8]. Cowan and Kovesi studied automatic determination of sensor location[2]. VIO (Vision Illumination Object) developed by R. Niepold and S. Sakane [6] may be the first system that considered camera, illumination, and features simultaneously.

We have developed an illumination control system called ICE (Illumination Control Expert) that suggests an optimal sensor and light source position for a given environment and purpose [9]. Our approach to solving the problem, *for a given vision task, what is the location of the sensor and the light source in order to obtain the best image?*, is to formulate an optimization problem and take advantage of mathematical programming techniques.

2 Viewing Space

In ICE, the sensor is assumed to always point to an object reference point, and the sensor and the light sources are placed on the surface of a sphere with its center at the origin of the object coordinate system. We will call this sphere a reference sphere. Any point on the surface of the reference sphere can be referenced by two angles, one measured from the north pole and the other from the arbitrarily chosen reference line along the equator (see Figure 1 (a)). The viewing space is defined as the set of all points on the surface of the reference sphere. Every point on the surface is an element of the viewing space. However, the viewing space is a contiguous space and has an infinite number of elements in it. We approximate the contiguous viewing space by a discrete space in such a way that the distance between any neighboring two points in the viewing space is approximately the same. The discrete viewing space VS is defined by

$$\mathrm{VS} = \{(i,j) | 0 \le i \le 180, \quad 0 \le j \le \lfloor 360 \sin(\frac{\pi}{180} i) \rfloor\}$$

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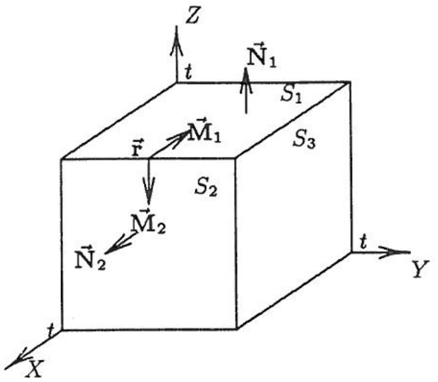

Figure 2: A cube whose edge length is t is shown. Three of its edges are aligned along the three coordinate axis.

where i, j are integers. There are

$$2\sum_{\psi=0}^{90}\lfloor 360\sin\psi\rfloor - 360 + 1$$

view points in VS. Details are given in [9].

3 Contrast

Contrast is very important since most of the intensity-based image processing algorithms use the contrast between regions or across regions as their criterion. Most of the region growing algorithms work with average intensity and most of the edge detection algorithms work with local gradient. In this section, we will discuss how to compute the contrast graph and the contrast distribution function along an edge of an object.

3.1 Contrast Graph

It is known that the image intensity I is proportional to the scene radiance. It is also known that the scene radiance depends on (1) the amount of light that falls on a surface, (2) the fraction of the incident light that is reflected, (3) the geometry of light reflection, *i.e.* the direction from which it is viewed as well as the direction from which it is illuminated.

Let $\mathbf{N}$ be the unit normal vector to a given surface at a certain surface point, and let $\mathbf{L}$ the unit vector in the direction of the light source from the given surface point. Then, the image intensity can be written as

$$I = \int d\omega \mathbf{N}\cdot\mathbf{L}(R_{\parallel}(\lambda)J^{i}_{\parallel}(\lambda) + R_{\perp}(\lambda)J^{i}_{\perp}(\lambda))d\lambda \qquad (1)$$

where λ is wavelength, and $R_{\parallel}$ and $R_{\perp}$ are the bi-directional reflectance functions for the parallelly polarized incident light and perpendicularly polarized incident light, respectively. A detailed derivation of equation 1 is in [9].

We will be using an object coordinate system with a reference point on the given 3-D object as its origin O. Let $\mathbf{l}$ and $\mathbf{v}$ be position vectors of the light and sensor, respectively, seen from O. As in Figure 2, let S_1 and S_2 be adjacent object surfaces. Let $\mathbf{r}$ be a point on the intersection curve, and $\mathbf{N}_j$ be the unit normal vector on surface S_j. Let $\mathbf{M}_j$ be the unit vector perpendicular to both $\mathbf{N}_j$ and $S_1 \cap S_2$ and on the surface S_j for $j = 1, 2$. Let $\mathbf{p}_j$ be a point on S_j located at a distance ζ_j away from $\mathbf{r}$ along $\mathbf{M}_j$. Explicitly,

$$\mathbf{p}_1 = \mathbf{r} + \zeta_1\mathbf{M}_1, \qquad \mathbf{p}_2 = \mathbf{r} + \zeta_2\mathbf{M}_2.$$

Assume that ζ_1 and ζ_2 are very small. The contrast at an edge point $\mathbf{r}$ is defined as the difference of the intensity of the reflected light between two small patches with centers at $\mathbf{p}_1$ and $\mathbf{p}_2$. Let the position vectors of the sensor and the light source at each $\mathbf{p}_j$ be $\mathbf{V}_j$ and $\mathbf{V}_j$, respectively. Let J^i be the incident light and J^r be the reflected light. Let R^1 and R^2 be the bi-directional reflectance functions of two surfaces. The contrast between the two small patches can be computed using equation 1.

$$|J^r_1 - J^r_2| = |\mathbf{N}_1\cdot\mathbf{L}_1(R^1_{\parallel}J^i_{\parallel} + R^1_{\perp}J^i_{\perp}) - \mathbf{N}_2\cdot\mathbf{L}_2(R^2_{\parallel}J^i_{\parallel} + R^2_{\perp}J^i_{\perp})|. \qquad (2)$$

The contrast graph $\mathcal{G}$ along a given edge can be obtained by evaluating equation 2 along the intersection curve $S_1 \cap S_2$. In practice, the contrast graph $\mathcal{G}$ is computed by evaluating the intensity differences only on a finite number of edge points.

3.2 Contrast Distribution Function

A contrast graph tells us how contrast varies spatially along an edge but does not give the distribution of the contrast. Since most edge operators use threshold values, the contrast distribution is more important than the spatial variation. In order to compute the contrast distibution function $\mathcal{F}$, we need an explicit form which is easier to handle. The contrast graph is fitted with piece-wise continuous polynomials using a regression analysis technique [3]. From the fitted contrast graph, we can easily compute a distribution function $\mathcal{F}$ of contrast. The cumulative distribution function of a random variable C is defined by

$$\mathcal{F}(c) = \mathrm{Prob}(C \le c).$$

To compute the distribution function from the contrast graph, we define the length of a subset of real numbers.

Definition 1 *Let R be the set of real numbers. Let R' be a subset of R, which consists of n continuous line segments:*

$$R' = \{(a_i, b_i) | a_1 < b_1 < a_2 < b_2 < \ldots < a_n < b_n\}$$

The length of such a set R' is defined as the sum of the lengths of the n line segments in it.

$$\mathcal{L}(R') = \sum_{i=1}^{n}(b_i - a_i)$$

Suppose the polynomial that fits the given contrast graph is $y = g(x), a \le x \le b$ (see Figure 3). Let the solutions of $g(x) = c$ be $\alpha_1, \alpha_2, \ldots, \alpha_n$ in increasing order. Let $\alpha_0 = a$ and $\alpha_{n+1} = b$. Then the contrast distribution function $\mathcal{F}$ can be computed by

$$\mathcal{F}(c) = \frac{\mathcal{L}(\{(\alpha_i, \alpha_{i+1}) |\ g(x) \le c, \forall \alpha_i \le x \le \alpha_{i+1}\})}{b - a} \qquad (3)$$

We will call this distribution function a CDF(Contrast Distribution Function).

4 Edge Visibility

From a certain view point, any point on the object surface may be said to be visible or invisible depending on whether it is occluded or not. It is the case that an object point may not be visible even though it is not occluded by any other part of the object or the surroundings. This happens when the object point is in shadow and therfore no light is reflected from the object point. An object point is said to be in shadow if and only if it is visible from the sensor and it is not visible from the light source. It is also the case that the object point

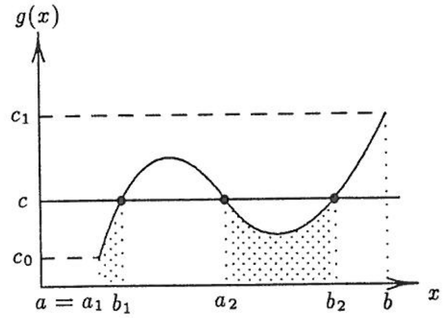

Figure 3: The value of the cumulative distribution function $\mathcal{F}$ of a random variable C at c is the probability of C being less than or equal to c. Since $g(x) \leq c$ where $a_1 \leq x \leq b_1$ and $a_2 \leq x \leq b_2$, $\mathcal{F}(c)$ is $\dfrac{(b_1 - a_1) + (b_2 - a_2)}{b - a}$.

may not appear in the image even though it is visible from both the sensor and the light source. This happens when the intensity of the reflected light from the object point which goes to the sensor is not strong enough. There are two types of visibility associated with an edge: one comes from the geometry and the other from the illumination. We will call the former γ-type visibility and the latter π-type visibility.

An edge is said to be *fully visible* if all of its points appear in the image, *fully invisible* if none of them appear in the image, *partially visible* if some of them appear in the image and others do not. For a given edge e, light source position $\mathbf{l}$ and sensor position $\mathbf{v}$, one may ask *how much of the edge will appear in the image.* This means how many of the edge pixels are not geometrically occluded or how many of the edge pixels have enough contrast to be detected by an edge operator.

Definition 2 *The γ-index of an edge e is defined as the ratio of the unoccluded portion of the edge to the actual edge length when it is seen from* $\mathbf{v}$.

$$\gamma\text{-index}(e, \mathbf{v}) = 1 - \frac{\mathcal{L}_3(\textit{occluded portion of } e)}{\mathcal{L}_3(e)}$$

where $\mathcal{L}_3$ gives 3D length.

Definition 3 *The π-index of an edge e is defined as the ratio of the portion of edge whose contrast is greater than a given threshold value of an edge operator to the whole edge.*

$$\pi\text{-}index(e, \mathbf{v}, \mathbf{l}) = 1 - \mathcal{F}(e, \mathbf{v}, \mathbf{l}; c_t)$$

where $\mathcal{F}$ is the contrast distribution function along the edge e when it is seen from $\mathbf{v}$ *and illuminated from* $\mathbf{l}$, *and c_t is the threshold value of an edge operator.*

5 Feasible Region

The requirements for the vision task we consider are specified in terms of object edges. Let E be the set of all edges of the given object. A required edge list, denoted by REL, is a set of object edges that we want to have in the image. Suppose we have a vision task whose requirements are as follows:

1. $\{\text{REL}_1, ..., \text{REL}_n\}$ where $\text{REL}_i = \{e_{i_1}, ..., e_{i_{n_i}}\} \subseteq E, \forall i$. An edge e_{i_j} has weight w_{ij}. There must be at least one REL_i, all of whose edges appear in the image.
2. $\gamma \geq p_i$ for all edges in each REL_i, where p_i is the minimum γ-index required by REL_i.
3. $\pi \geq q_i$ for all edges in each REL_i, where q_i is the minimum π-index required by REL_i.
4. The minimum edge contrast is c_t.

Each edge in a REL has an associated weight w which represents the preference of that edge in that REL. Among the points in the viewing space, there are sets whose elements satisfy the above requirements. We will call these sets *feasible regions.*

Definition 4 *The γ-feasible region for an edge e is defined as a set*

$$\gamma\text{-F}(e; p) = \{\mathbf{v} \in \text{VS} | \gamma(e, \mathbf{v}) \geq p\}$$

where p is the minimum γ-index required by the vision task. For a required edge list REL_i, *the γ-feasible region is the intersection of the γ-feasible regions for all edges in it,*

$$\gamma\text{-FR}(\text{REL}_i) = \bigcap_{e \in \text{REL}_i} \gamma\text{-F}(e; p_i)$$

where p_i is the minimum required γ-index of REL_i.

Definition 5 *The π-feasible region for an edge e and a sensor position* $\mathbf{v}$ *is defined as a set*

$$\pi\text{-F}(e, \mathbf{v}; q) = \{\mathbf{l} \in \text{VS} | \pi(e, \mathbf{v}, \mathbf{l}) \geq q\}$$

where q is the minimum required π-index. For a required edge list REL_i, *the π-feasible region is the intersection of the π-feasible regions for all edges in it.*

$$\pi\text{-FR}(\text{REL}_i, \mathbf{v}) = \bigcap_{e \in \text{REL}_i} \pi\text{-F}(e, \mathbf{v}; q_i)$$

where q_i is the minimum required π-index of REL_i.

If $\gamma\text{-FR}(\text{REL}_i) = \phi$, then not all edges in REL_i can appear in the image. This means the edge requirement can not be met with one view point, and more than one picture from different view points are needed. If $\pi\text{-FR}(\text{REL}_i, \mathbf{v}) = \phi$, not all edges in REL_i can have enough contrast to be detected by an edge operator. This means the edge requirement cannot be met with one lighting setup, and more than one picture with different lighting setups are needed. The γ-feasible region can be directly computed from PREMIO [1], and π-feasible region can be directly computed from the CDF described in section 3.

6 An Optimality Criterion

Now we turn to the question, *where should the sensor and light source be placed in order to obtain the best picture?* Our definition of a best picture is in terms of the edge visibility. For a given vision task, we want to see as many edges as possible in the image. For a given edge, we want to have as many of the edge pixels as possible in the image.

6.1 Optimal Sensor Position

In order to satisfy a vision task requirement, the sensor can be positioned at any point in a γ-feasible region; however, the bigger the γ-index is, the better. There arises a natural question *how much better is a larger γ-index than a smaller one?* Since every point in a γ-feasible region has γ-index greater than p, the degree of betterness should be measured within the interval $1 - p$. Suppose that $0 < p < \gamma_2 < \gamma_1 < 1$. Then γ_1 is better than γ_2 by

$$\frac{\gamma_1 - \gamma_2}{1 - p}.$$

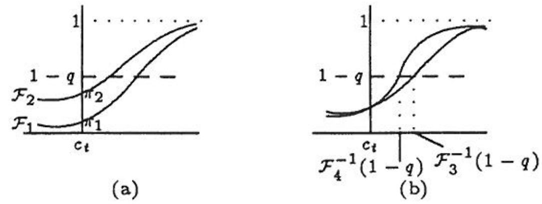

Figure 4: Optimality criterion on π-index is shown.

For any edge e and sensor position $\mathbf{v}$, define

$$\Gamma_1(e, \mathbf{v}; p) = \frac{\gamma(e, \mathbf{v}) - p}{1 - p}$$

Then, for a given edge e, the optimal sensor position is $\mathbf{v}^e \in \gamma\text{-F}(e; p)$ such that

$$\Gamma_1(e, \mathbf{v}; p) \leq \Gamma_1(e, \mathbf{v}^e; p), \forall \mathbf{v} \in \gamma\text{-F}(e; p). \quad (4)$$

We will call the above criterion the *edge-level γ-criterion*. For any required edge list REL_i and sensor position $\mathbf{v}$, define

$$\Gamma_2(\text{REL}_i, \mathbf{v}; p_i) = \sum_{e_j \in \text{REL}_i} w_{ij} \Gamma_1(e_j, \mathbf{v}; p_i)$$

where w_{ij} denotes the weight of edge e_j in REL_i. Then the best sensor position for the entire set of edges is $\mathbf{v}_i^c \in \gamma\text{-FR}(\text{REL}_i)$ such that

$$\Gamma_2(\text{REL}_i, \mathbf{v}; p_i) \leq \Gamma_2(\text{REL}_i, \mathbf{v}_i^c; p_i), \forall \mathbf{v} \in \gamma\text{-FR}(\text{REL}_i) \quad (5)$$

where w_j denotes the weight of each edge. The above is called the *combined-level γ-criterion*. Now suppose we have the corresponding optimal sensor positions for each required edge list in the vision task requirement, and let $\mathbf{v}_i^c$ be the optimal sensor position for REL_i. Let $\text{VC} = \{\mathbf{v}_1^c, \ldots, \mathbf{v}_n^c\}$. The best sensor position for the given vision task is $\mathbf{v}_k^c \in \text{VC}$ such that

$$\Gamma_2(\text{REL}_i, \mathbf{v}_i^c; p_i) \leq \Gamma_2(\text{REL}_i, \mathbf{v}_k^c; p_k), \forall \mathbf{v}_i^c \in \text{VC} \quad (6)$$

We call this the *task-level γ-criterion* and denote the task-level optimal sensor position as $\mathbf{v}^t$.

6.2 Optimal Light Source Position

We will now describe how the optimal light source position is determined. Let c_t be the minimum edge contrast, and consider the two CDF's shown in Figure 4(a). Both satisfy the π-visibility requirement since $\mathcal{F}_1(c_t) \leq 1-q$ and $\mathcal{F}_2(c_t) \leq 1-q$. Of these two CDF's, CDF_1 is better than CDF_2 by

$$\frac{\mathcal{F}_2(c_t) - \mathcal{F}_1(c_t)}{1 - q}. \quad (7)$$

Figure 4(b) shows two CDF's whose $\mathcal{F}(c_t)$ are the same. In this case CDF_3 is better than CDF_4 because CDF_3 is less steep than CDF_4, and therefore CDF_3 is less sensitive to the choice of the threshold value c_t. CDF_3 is better than CDF_4 by

$$\frac{\mathcal{F}_3{}^{-1}(1-q) - \mathcal{F}_4{}^{-1}(1-q)}{1 - q}. \quad (8)$$

Combining equations 7 and 8, the optimal light source position for a given edge e and sensor position $\mathbf{v}^t$ is $\mathbf{l}^e \in \pi\text{-F}(e, \mathbf{v}^t; q)$ such that

$$\Pi_1(e, \mathbf{v}^t, \mathbf{l}; q) \leq \Pi_1(e, \mathbf{v}^t, \mathbf{l}^e; q), \forall \mathbf{l} \in \pi\text{-F}(e, \mathbf{v}^t; q), \quad (9)$$

where

$$\Pi_1(e, \mathbf{v}^t, \mathbf{l}; q) = \left(\frac{\pi(e, \mathbf{v}^t, \mathbf{l}) - q}{1 - q}\right)\left(\frac{\mathcal{F}^{-1}(1-q) - c_t}{1 - c_t}\right).$$

The above is called the *edge-level π-criterion*. Let

$$\Pi_2(\text{REL}_i, \mathbf{v}^t, \mathbf{l}; q_i) = \sum_{e_j \in \text{REL}_i} w_{ij} \Pi_1(e_j, \mathbf{v}^t, \mathbf{l}; q_i)$$

where w_{ij} denotes the weight of edge e_j in REL_i. Then the best light source position for the entire set of edges is $\mathbf{l}_i^c \in \pi\text{-FR}(\text{REL}_i, \mathbf{v}^t)$ such that

$$\Pi_2(\text{REL}_i, \mathbf{v}^t, \mathbf{l}; q_i) \leq \Pi_2(\text{REL}_i, \mathbf{v}^t, \mathbf{l}_i^c; q_i) \quad \forall \mathbf{l} \in \pi\text{-FR}(\text{REL}_i, \mathbf{v}^t).$$

This is called the *combined-level π-criterion*. Now suppose we have the corresponding optimal light source positions for each required edge list in the vision task requirement, and let $\mathbf{l}_i^c$ be the optimal sensor position for REL_i. Let $\text{LC} = \{\mathbf{l}_1^c, \ldots, \mathbf{l}_n^c\}$. The best light source position for the given vision task is $\mathbf{l}_k^c \in \text{LC}$ such that

$$\Pi_2(\text{REL}_i, \mathbf{v}^t, \mathbf{l}_i^c; q_i) \leq \Pi_2(\text{REL}_i, \mathbf{v}^t, \mathbf{l}_k^c; q_k), \forall \mathbf{l}_i^c \in \text{LC} \quad (10)$$

We call this the *task-level π-criterion* and denote the task-level optimal light source position as $\mathbf{l}^t$.

7 Experiment

We assume that all surfaces of an object have the same photometric properties and thus they have the same bi-directional reflectance function. We also assume that the incident light is totally unpolarized and use the Torrance-Sparrow model which is given by

$$sR_s + dR_d$$

where R_s is for the specular reflection, and R_d is for the diffusion. R_s can be written as

$$\frac{FDG}{\pi(\mathbf{N} \cdot \mathbf{L})(\mathbf{N} \cdot \mathbf{V})}$$

where F is the Fresnel reflectance coefficient, D is a surface roughness distribution function, and G is the geometric attenuation factor. Note that the Torrance-Sparrow model is a special case of the model given in equation 1. In this experiment, the Fresnel term F is not considered for simplicity reason. The surface roughness distribution D is assumed to be Gaussian and is given by $D = \exp(-(\beta/m)^2)$ where m is some constant.

7.1 Vision Task Requirements

The given object is a cube with side length t. Three of its sides are aligned along the three axes of the object coordinate system as shown in Figure 2. The requirements are

1. $\text{REL} = \{\{S_1 \cap S_2, S_1 \cap S_3\}, \{S_1 \cap S_2, S_2 \cap S_3\}\}$,
2. $p_1 = p_2 = 0.7$, $q_1 = q_2 = 0.8$,
3. $c_t = 0.05$.

A point $\mathbf{r}$ on the edge $S_1 \cap S_2$ has coordinates $\mathbf{r} = (t, y, t)^T$ with $0 \leq y \leq t$.

7.2 Optimality Criterion Computation

The optimality criterion for the edge $S_1 \cap S_2$ is computed as follows. The contrast graph along the edge is computed by changing $\mathbf{r}$. We chose 100 values of $\mathbf{r}$ varying y from 0.0 to 1.0 in steps of 0.01.

Figure 5: The edge-level π-criterion Π_1 for all possible light source positions for the edge $S_1 \cap S_2$ of the cube is shown. One can see the global maximum at the top-left area.

For each edge e in REL and a fixed sensor position $\mathbf{v}^t$, π-feasible region π-F$(e, \mathbf{v}^t; q)$, is computed. For each edge e in REL and a fixed sensor position $\mathbf{v}^t$, the edge-level π-criterion $\Pi_1(e, \mathbf{v}^t, \mathrm{l}; q)$ is evaluated for all possible light source positions in the π-feasible region of e. The following parameters are used in this experiment.

- the fraction of specular reflectance $s = 0.8$ and the fraction of diffuse reflectance $d = 0.2$
- diffuse constant $R_d = 0.5$
- surface roughness $m = 0.15$
- $\zeta_1 = \zeta_2 = 0.01$
- cube side length $t = 1.0$
- radius of the reference sphere = 3.0
- sensor position is fixed at $(45, 45)$

7.3 Result and Discussion

The optimization technique was implemented on a SUN-3/280 using the C programming language. The edge-level π-criterion Π_1 for the edge $S_1 \cap S_2$ of the cube is computed for all possible light source positions in the π-feasible region and shown in Figure 5. Each pixel in the picture corresponds to an element of the viewing space VS. The rows and columns denote the polar and azimuth angle, respectively. The top-left corner corresponds to $(0, 0)$, and the bottom-left corner corresponds to $(180, 0)$. The right-most corner corresponds to $(90, 359)$. The viewing space VS is shown as a triangular shape because the number of elements in each row increases as the polar angle gets bigger until 90°, and it decreases afterwards. The π-feasible region is the dark area in the picture. The darker a pixel is, the bigger Π_1 is at that position. One can easily notice the global maximum at the top-left area. A 3-D plot of the picture in Figure 5 is shown in Figure 6, and it shows the global maximum more clearly.

8 Conclusion

An optimization approach to the automatic sensor and light source positioning was discussed. The contrast was defined as the intensity difference between two small patches on the object surface in 3-D. The contrast was evaluated along the given edge, and the contrast distribution was computed using the regression method. A heuristic optimal criterion for both sensor and light source position was presented. An experiment was conducted to see if the optimization approach is feasible. We computed the edge-level optimization criterion and noticed that there was one and only one global maximum in the entire viewing space. We can claim that the optimization problem we formulated is a convex problem in

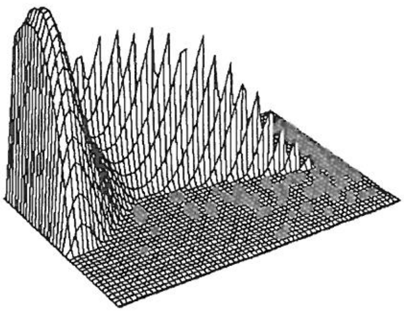

Figure 6: A 3-D plot clearly shows that there is one and only one global maximum in the edge-level π-criterion for the edge $S_1 \cap S_2$ of the cube.

the edge-level, at least in our examples, and therefore it can be solved by mathematical programming techniques. The complete experiments and results are presented in [9].

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