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Adaptive Image Filtering for Tracking Control of Robots

Di Cao[1], Yingmin Jia[1], Junping Du[2]

1. The Seventh Research Division, Beihang University(BUAA), Beijing 100191, P.R.China
2. Beijing Key Laboratory of Intelligent Telecommunications Software and Multimedia,
Beijing University of Posts and Telecommunications, Beijing 100876, P.R.China
(dic_2003@yahoo.com.cn, ymjia@buaa.edu.cn, junpingd@bupt.edu.cn)

Abstract: In this paper, a new adaptive image filtering scheme is first proposed based on color and pixel features, in which a compensation algorithm for the background difference of global illumination, and the H/S Model based adaptive image filtering algorithm are developed respectively. Then a tracking control strategy of robots is given, and the corresponding experimental results are provided to demonstrate the effectiveness of the proposed scheme.

Keywords: *Image Processing, Adaptive Filtering, Visual Tracking, Mobile Robots*

I. Introduction

Recently, the adaptive image filtering problem has attracted a great deal of attention in many fields such as robotics, signal processing, pattern recognition, control engineering, etc.. Image filtering is a set of techniques used to enhance or restore images, including image smoothing, sharpening, blurring, edge detection, mean removal and embossing. At present, some valuable adaptive filters have been proposed, whose fundamental issues includes temporal averaging [1] and median filtering. The Wiener filter is not adequate for removing speckle since it is designed mainly for additive noise suppression. To address the multiplicative nature of speckle noise, Jain developed an approach by which the multiplicative noise can be turned into additive noise by taking the logarithm of the image [2]. Kuan considered a multiplicative speckle model and designed a linear filter based on the minimum mean-square error criterion when the scene and the detected intensities are Gaussian distribution [3]. Sadjadi and Bannour proposed a two-dimensional Kalman filter, which is in a Markov field satisfying autoregressive model [4]. The Model-Based Diagnosis(MBD) technique [5] is essentially a Maximum Aposteriori Probability(MAP) filter, which was developed based on modeling textured areas.

In reality, there exist a variety of local image feature-dependent adaptive filtering strategies, including local image statistics filtering [6], adaptive neighborhood averaging which uses piecewise approximation of uniform regions [7], least-squares error filtering [8], gradient inverse-weighted filtering [9], multiple-model filtering, local shape-based template-matched adaptive filtering, and gradient-controlled anisotropic diffusive filtering [10-13]. Whitaker and Pizer [14] presented a multi-scale nonlinear diffusive filtering approach in which diffusion is controlled under a time varying scale parameter. Weickert [15] proposed an anisotropic, nonlinear diffusion process that uses both modulus as well as direction of gradients. De Grandi presented a wavelet multi-resolution representation to provide a unified framework for signal approximation, filtering and classification [16].

With this background, we investigate an adaptive image filtering based on color and pixel features, and apply it to the tracking control of mobile robots. To this end, we first present an algorithm to compensate the background difference for global illumination. Then, we propose the H/S Model and the adaptive image filtering algorithm.

II. Main Results

The task of adaptive image filtering is to recognize target in the image acquired by the camera. The general flowchart of the algorithm is shown in Fig. 1. There, we can see clearly that the input to the algorithm is raw image from the camera, and the output is tracking control strategy of robots. Adaptive image filtering consists of three core aspects, i.e., illumination compensation algorithm, adaptive image filtering algorithm based on H/S model and tracking control strategy of robots. These are described in detail below.

A. Illumination Compensation Algorithm

The algorithm is used to compensate the background difference for global illumination, which can be completed by five steps.

Step 1 Initialization: Monitor the change of attribute values of the reference points. Determine the initial thresholds of the image of environment. The initial thresholds are (H_0, S_0). Let $\triangle H = 0, \triangle S = 0$, where $\triangle H$ is the change in hue and $\triangle S$ is the change in saturation.

Step 2 Filtering: Perform 5×5 median filtering on the resulted image.

Step 3 Reference points P_i sampling: Obtain the values of reference points, and calculate hue mean value

μ_{REFH} and saturation mean value μ_{REFS} of reference points.

$$\mu_{REF} = [\mu_{REFH}, \mu_{REFS}] \tag{1}$$

Then, calculate the standard deviation σ_{REF}.

$$\sigma_{REF} = [\sigma_{REFH}, \sigma_{REFS}] \tag{2}$$

Step 4 Standard deviation analysis: if $\sigma_{REF} > \sigma_T$, then calculate $\triangle H$ and $\triangle S$:

$$[\triangle H, \triangle S] = \mu_{REF} - \mu'_{REF} \tag{3}$$

The thresholds are calculated as follows:

$$\begin{aligned} H_{TH} &= H_0 + \triangle H \\ S_{TH} &= S_0 + \triangle S \end{aligned} \tag{4}$$

The new thresholds (H_{TH}, S_{TH}) are used in the next operation.

Step 5 Update image: For each pixel on position(x,y) of the reference points, compute the change of attribute values.

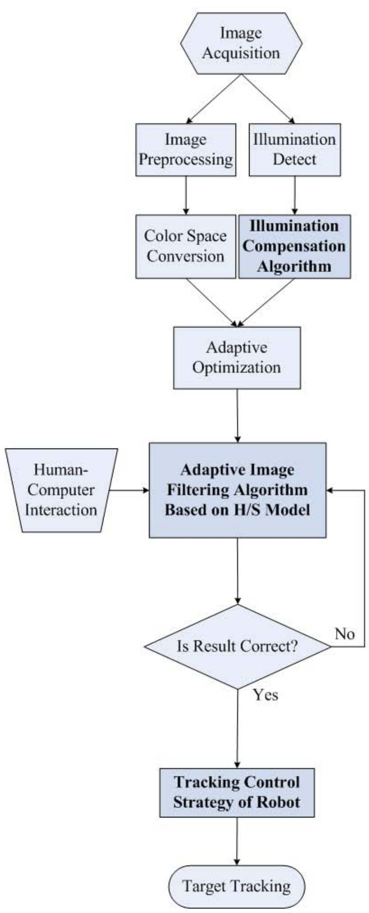

Fig.1. General Flow Chart of the Algorithm

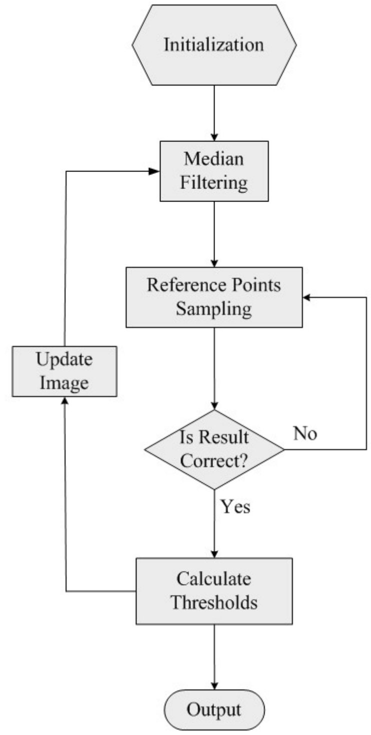

Fig.2. Illumination Compensation Method

B. Adaptive Image Filtering Algorithm Based on H/S Model

The algorithm is designed to set the thresholds of images adaptively. The thresholds will be calculated in HSI color spaces [17]. The calculation is important to subsequent operations. The next step is to select the target that is recognized during initialization of image. And the initial values of thresholds are determined by means of off-line learning. We propose the H/S Model based on which the adaptive image filtering algorithm is formulated as follows:

Step 1: For each pixel in the image:

$$D_i = [R_i, G_i, B_i] \tag{5}$$

Most color grading systems use HSI rather than RGB values to specify color preferences because it is based on human-distinguishable hues and a more intuitive representation than RGB. Due to the geometric discontinuity of color space it is difficult to set or adjust color grade boundaries using hue values alone. It can be overcome by including the intensity component from the HSI color space in the computations [18]. Therefore, we convert the input RGB image to the HSI color space.

$$\begin{aligned} H_i &= \{\theta_i \mid if B_i \le Gi \; ; \; 360 - \theta_i \mid if B_i > Gi\} \\ S_i &= 1 - \frac{3}{R_i + G_i + B_i} \min(R_i, G_i, B_i) \\ I_i &= \frac{1}{3}(R_i + G_i + B_i) \end{aligned} \tag{6}$$

where

$$\theta_i = \cos^{-1} \frac{(R_i - G_i) + (R_i + B_i)}{[(R_i - G_i)^2 + (R_i - B_i)(G_i - B_i)]^{\frac{1}{2}}} \tag{7}$$

And the value of $\min(R_i, G_i, B_i)$ denotes the minimum among of red, green and blue components of the image.

Step 2: Calculate color histogram of image and use it as its color feature. Then we divide image data into blocks and calculate the mean value (H_{Ki}, S_{Ki}) of each block that can be described by the normalized method [19] on both hue and saturation.

$$\begin{aligned} \triangledown Q &= (\triangledown Q_x, \triangledown Q_y) \\ \triangledown Q_x &= \| \partial_x H_{Ki}, \partial_x S_{Ki} \| \\ \triangledown Q_y &= \| \partial_y H_{Ki}, \partial_y S_{Ki} \| \end{aligned} \tag{8}$$

Note that

$$\begin{aligned} V_k &= [V_{kx}, V_{ky}], U_k = [U_{kx}, U_{ky}] \\ V_{kx} &= \partial_x H_{Ki} / \partial x \\ V_{ky} &= \partial_y H_{Ki} / \partial y \\ U_{kx} &= \partial_x S_{Ki} / \partial x \\ U_{ky} &= \partial_y S_{Ki} / \partial y \end{aligned} \tag{9}$$

Step 3: Establishing the H/S Model:

$$F_i = \Sigma_{j=1}^{n} \lambda_j P_j (n = 1, 2, 3, 4) \tag{10}$$

where

$$P_j = \begin{cases} V_k & j = 1 \\ U_k & j = 2 \\ H_{ki} & j = 3 \\ S_{ki} & j = 4 \end{cases}$$

λ_j is a weighted value, according to the contributions of the values of P_j. And F_i is confidence coefficient

$$\gamma_i = \begin{cases} 0 & F_i = [0, \alpha_1) \\ \varphi F_i & F_i = [\alpha_1, \alpha_2] \\ 1 & F_i = (\alpha_2, 1] \end{cases} \tag{11}$$

The value of γ_i denotes the output result of filtering.

C. Tracking Control Strategy of Robots

After adaptive image filtering, the moving object can be recognized in image. The motion vector of the object is calculated in image coordinate system. The coordinates of the moving object can be obtained by means of calculating the center vector G_c on image plane[20].

$$\Gamma_i = G_c K_i \tag{12}$$

where, Γ_i represents the position of object in the image coordinate system. K_i is the coefficient matrix of the image.

We can calculate the coordinates of the moving object relative to image.

$$\Gamma_R = M_i^r \Gamma_i N_R \tag{13}$$

$$N_R = G_i N_R^i \tag{14}$$

where, M_i^r is the coordinate conversion matrix. Γ_R represents position and angle parameters of the moving object relative to the mobile robot. Further, we can calculate the motion vector of the mobile robot.

III. Experiments and Results

The system architecture includes a camera, which is fixed up on the top of a lab mobile robot. The video frames are 320×240 pixels in size, and were recorded at 25 frames per second. The host computer was a PC/104 embedded industry controll computer, with an 850MHz Pentium processor and 512MB of 266MHz RAM. The entire tracking system was implemented using C++ under Microsoft Windows XP, with no platform specific optimizations.

In the experiment, the mobile robot begins to track the object, when the object starts to move. As shown in Figure 3, the horizontal and vertical axes in the figure stand for time and the error of robot tracking respectively. It shows that the error of robot tracking decreases along with time. We believe that the robot and the target move synchronously when the tracking error is less than 5 pixels.

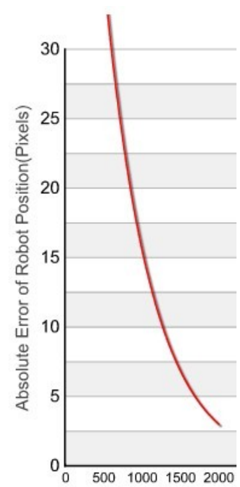

Fig.3. Robot Tracking Process

Fig.4 shows absolute error of robot position changing with time. The horizontal and vertical axes in the figure stand for time and absolute error of robot position respectively. It is known that the error of robot position can be constrained below 15 pixels.

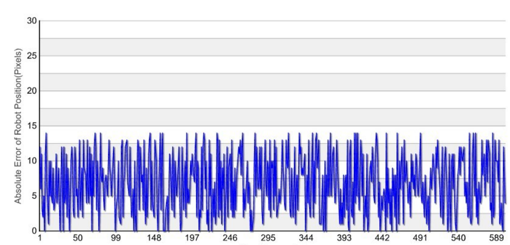

Fig.4. Absolute Error of Robot Position

IV. Conclusions

In this paper, we have proposed an adaptive image filtering approach based on color and pixel features, and applied it to solve the problem of tracking control of mobile robots. Experimental results show that the proposed approach is robust with high recognition rate and can find a wide application. Although discussion is done only within the indoor environment, and it is also possible to be used for outdoor environment, which is currently under consideration.

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