A Novel Camera Parameters Auto-adjusting Method Based on Image Entropy

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Abstract. How to make vision system work robustly under dynamic light conditions is still a challenging research focus in robot vision community. In this paper, a novel camera parameters auto-adjusting method based on image entropy is proposed. Firstly image entropy is defined and its relationship with camera parameters is verified by experiments. Then how to optimize the camera parameters based on image entropy is proposed to make robot vision adaptive to the different light conditions. The algorithm is tested using the omnidirectional vision system in indoor RoboCup Middle Size League environment and outdoor RoboCup-like environment, and the results show that our method is effective and color constancy to some extent can be achieved.

1 Introduction

How to make vision system work robustly under dynamic light conditions is still a challenging research focus in computer vision/robot vision community [1]. There are mainly three approaches to achieve this goal. The first one is to process and transform the images to achieve some kind of constancy, such as color constancy by Retinex algorithm [2]. The second one is to analyze and understand the images robustly, such as designing adaptive or robust object recognition algorithms [3, 4]. These two approaches have attracted lots of researchers' interest, and lots of progresses have been achieved. The third one is always ignored by researchers, which is to output the images to describe the real scene as consistently as possible in different light conditions by auto-adjusting the camera parameters (in this paper, camera parameters are the image acquisition parameters, not the intrinsic or extrinsic parameters in camera calibration). In the digital still cameras and consumer video cameras, many parameters adjusting mechanisms have been developed to achieve good imaging results, such as auto exposure by changing the iris or the shutter time [5], auto white balance [6], and auto focus [7]. In some special multiple slope response cameras, the response curve can be adjusted to adapt the dynamic response range to different light conditions by automatic exposure control [8]. But these methods are always on the camera hardware level, and we can not do these things or make modification on most cameras used in robot vision system except some special hardware-support cameras.

The RoboCup Middle Size League (MSL) competition is a standard real-world test bed for robot vision and other related research subjects. It is still a color-coded environment, though some great changes have taken place in the latest competition rules,

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such as replacing the blue/yellow goals with white goal nets, no color flag post any more. The final goal of RoboCup is that robot soccer team defeats human champion, so robots will have to be able to play competition in highly dynamic light conditions even in outdoor environment. So designing robust vision system to recognize color-coded objects is a research focus in RoboCup community. Besides adaptive color segmentation methods [3], color online learning algorithms [9, 10], and object recognition methods independent on color information [11, 12], several researchers also have tried to apply the third approach to help achieving the robustness of vision sensors. Paper [13] defined the camera parameters adjustment as an optimization problem, and used the genetic meta-heuristic algorithm to solve it by minimizing the distance between the color values of some image areas and the theoretic values in color space. The theoretic color values were used as referenced values, so the effect from illumination could be eliminated, but the special image areas needed to be selected manually by users in the method. Paper [14] used a set of PID controllers to modify the camera parameters like gain, iris, and two white balance channels according to the changes of a white reference color always visible in the omnidirectional vision system. Paper [15] adjusted the shutter time by designing a PI controller to modify the reference green field color to be the desired color values.

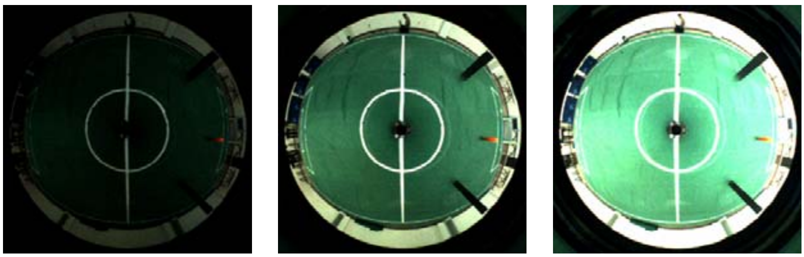
In this paper, we try to use the third approach to achieve the robustness and adaptability of camera's output under different light conditions. We also want to provide an objective method for vision/camera setup by this research, for the cameras are usually set manually according to user's subjective experiences when coming to a totally new working environment. We define the image entropy as the optimizing goal of camera parameters adjustment, and propose a novel camera parameters auto-adjusting technique based on image entropy. We use our omnidirectional vision systems [16] and the RoboCup MSL environment as the test bed for our algorithm.

In the following part, we will firstly present the definition of image entropy and verify that the image entropy is valid to represent the image quality for image processing and to indicate that whether the camera parameters are properly set by experiments in section 2, and then propose how to auto-adjust the camera parameters based on image entropy to adapt to the different illumination in section 3. The experiment results in indoor and outdoor environment and the discussions will be presented in section 4 and section 5 respectively. The conclusion will be given in section 6 finally.

2 Image Entropy and Its Relationship with Camera Parameters

The setting of camera parameters affects the quality of outputting images greatly. Taking the cameras of our omnidirectional vision system as the example, only exposure time and gain can be adjusted (auto white balance has been realized in the camera, so we don't consider white balance). Several images captured under different parameters are shown in figure 1. The quality of images in figure 1(a) and (c) are much worse than that in figure 1(b), because they are less-exposed and over-exposed respectively, and the image in figure 1(b) is well exposed. The two images in figure 1(a) and (c) can't represent the environments well, and we can say that the information content in these two images is less than that in figure 1(b). So both less-exposure and over-exposure will cause the loss of image information [17].

According to Shannon's information theory, the information content can be measured by entropy, and entropy increases with the information content. So we use image entropy to measure the image quality, and we also assume that the entropy of outputting images can indicate that whether the camera parameters are properly set. In the following part of this section, we will firstly present the definition of the image entropy, and then verify this assumption by analyzing the distribution of image entropy with different camera parameters.



(a) (b) (c)

Fig. 1. The images captured by our omnidirectional vision system with different exposure time. The gain is always 18. (a) The exposure time is 5ms. (b) The exposure time is 18ms. (c) The exposure time is 40ms.

2.1 The Definition of Image Entropy

We use Shannon's entropy to define the image entropy. So the image entropy can be expressed as follows:

$$Entropy = -\sum_{i=0}^{L-1} p_{Ri} \log p_{Ri} - \sum_{i=0}^{L-1} p_{Gi} \log p_{Gi} - \sum_{i=0}^{L-1} p_{Bi} \log p_{Bi} \quad (1)$$

Where $L = 256$ is the discrete level of RGB color channels, and p_{Ri}, p_{Gi}, p_{Bi} are the probability of color Ri, Gi, Bi existing in the image, and they can be replaced with frequency approximately and then calculated according to the histogram distribution of RGB color channels.

According to the definition in (1), $0 = Min(Entropy) \leq Entropy \leq Max(Entropy) = -3 * \sum_{i=0}^{256-1} \frac{1}{256} \log \frac{1}{256} = 16.6355$, and the entropy will increase monotonously with the degree of average distribution of color values.

2.2 Image Entropy's Relationship with Camera Parameters

We capture a series of panoramic images by using our omnidirectional vision system with different exposure time and gain in indoor environment and outdoor environment, and then calculate the image entropy according to equation (1) to see how image entropy varies with camera parameters. The indoor environment is a standard RoboCup MSL field with dimension of 18m*12m, but the illumination is not only determined by the artificial lights, but also influenced greatly by natural light through lots of windows. The outdoor environment includes two blue patches and several components of the indoor environment such as a piece of green carpet, two orange balls and black obstacles. All the experiments of this paper are performed in these two environments. Furthermore, because the illumination in two environments is totally different and the dynamic response range of our cameras is limited, so we use two omnidirectional vision systems (two robots) with different iris setting (the iris can be adjusted only manually) in the two environments.

In the experiment of indoor environment, the range of exposure time is from 5ms to 40ms and the range of gain is from 5 to 22. The experiment time of this section is evening, so the illumination is not affected by natural light. In the experiment of outdoor environment, the range of exposure time is from 1ms to 22ms and the range of gain is from 1 to 22. The weather is cloudy, and the experiment time is midday. The minimal adjusting step of the two parameters is 1ms and 1 respectively. We captured one image with each group of parameters. The image entropies changing with different camera parameters are shown in figure 2 and figure 3 in the two experiments.

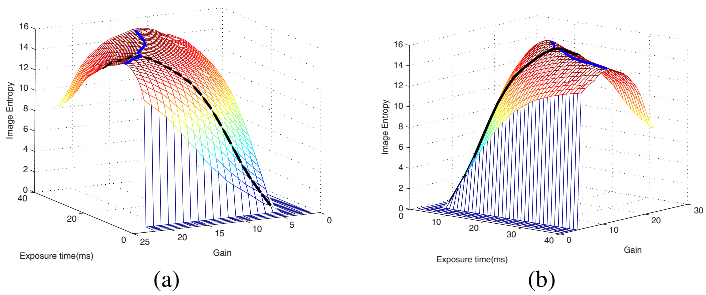


Fig. 2. The image entropies changing with different exposure time and gain in indoor environment. (a) and (b) are the same result viewed from two different view angles.

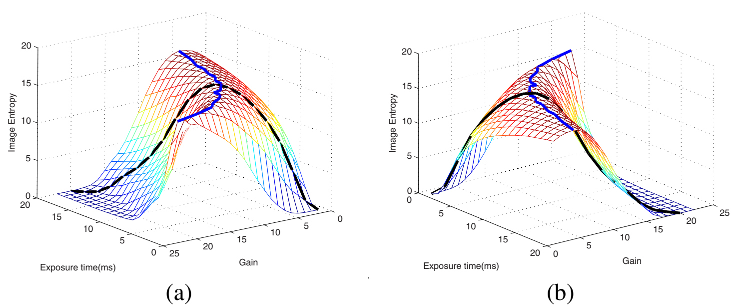


Fig. 3. The image entropies changing with different exposure time and gain in outdoor environment. (a) and (b) are the same result viewed from two different view angles.

From figure 2 and 3, we can find that the manner in which the image entropy varies with camera parameters is the same in the two experiments, and there is ridge curve (the blue curve in figure 2 and 3). Along the ridge curve, the image entropies are almost the same in each experiment, and there is not obvious maximal value. So which image entropy along the ridge curve indicates the best image, or whether all the images related to the image entropy along the ridge curve are good?

For the images are used to processed and analyzed to realize object recognition, self-localization or other robot vision task, we test the quality of images by using the same color calibration result learned from one image [18] corresponding to a certain entropy on the ridge curve to segment the images corresponding to all the entropies along the ridge curve and detect the white line points using the algorithm proposed in paper [4]. The typical images along the ridge curve and the processing results in the two experiments are demonstrated in figure 4 and figure 5.

As shown in the two figures, the images can be well segmented by the same color calibration result in each experiment, and object recognition can be realized successfully for soccer robots. The same processing results are achieved in all the other images related to the image entropy along the ridge curve. So all these images are good for robot vision, and there is some kind of color constancy in these images, though they are captured under different camera parameters. It also means that all the setting of exposure times and gains corresponding to the image entropy along the ridge curve are acceptable for robot vision. So the assumption is verified that the image entropy can indicate that whether the camera parameters are properly set.

3 Camera Parameters Auto-adjusting Based on Image Entropy

According to the experiments and analysis in last section, image entropy can indicate the image quality for robot vision and that whether the camera parameters are properly set, so camera parameters adjustment can be defined as an optimization problem, and image entropy can be used as optimizing goal. But as is shown in figure 2 and 3, the image entropies along the blue ridge curve are almost the same, and it is not easy to search the global optimal solution. Furthermore, camera parameters themselves will affect the performance of vision systems. For example, the real-time ability will decrease as exposure time increases, and the image noise will increase as gain increases. So exposure time and gain themselves have to be taken into account in this optimization problem. But it is difficult to measure the degree of these parameters' effect, so it is almost impossible to add some indicative or constraint function to image entropy directly for the optimization problem.

Considering that the images related to the image entropies along the ridge curve are all good for robot vision, we turn the two-dimension optimization problem to be one-dimension one by defining some searching path. For RoboCup MSL competition is a highly dynamic and color-coded environment, the exposure time and gain should not be too high for soccer robots. So we define the searching path as exposure time=gain (just equal in number value, fo`r the unit of exposure time is ms, and there is no unit for gain) to search the maximal image entropy in this path, and the camera parameters corresponding to the maximal image entropy are best for robot vision in current environment and current light condition. The searching path is shown as the black curve in figure 2 and 3 respectively in indoor environment and outdoor environment. The distributions of image entropy along the path in the two environments are demonstrated in figure 6.

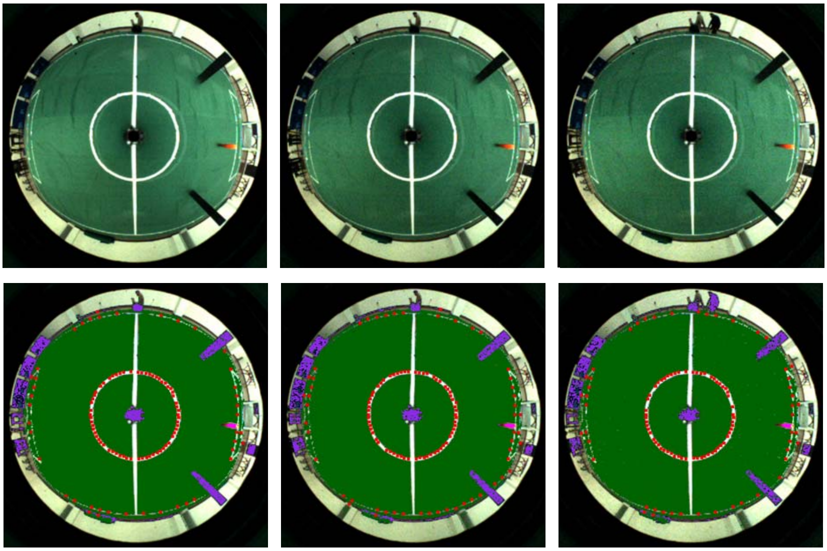


Fig. 4. The typical images along the ridge curve and the processing results in indoor experiment. (top) are the typical images. (bottom) are the processing results, and the red points are the detected white line points. The camera parameters are as follows: (left) exposure time: 34ms, gain: 13. (middle) exposure time: 18ms, gain: 18. (right) exposure time: 14ms, gain: 21.

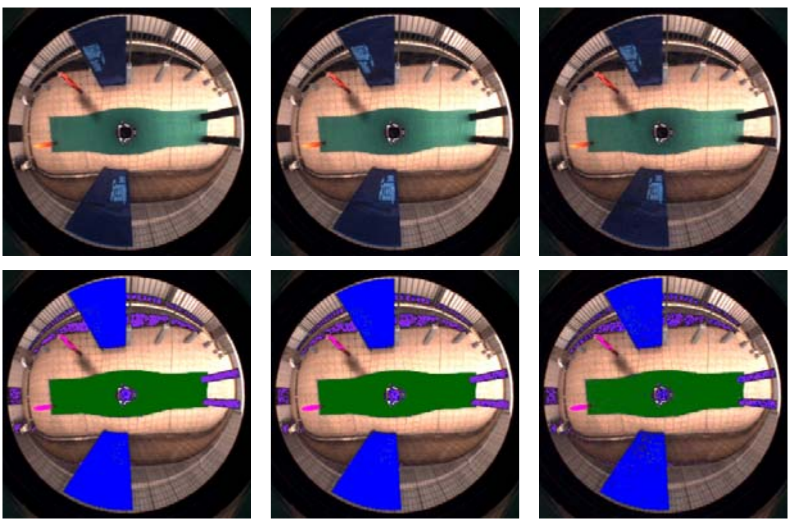
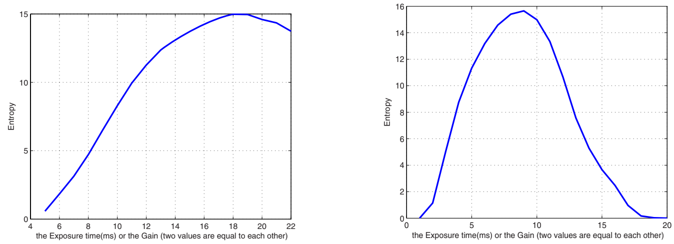


Fig. 5. The typical images along the ridge curve and the processing results in outdoor experiment. In this experiment, there are not white lines to detect. (top) are the typical images. (bottom) are the processing results. The camera parameters are as follows: (left) exposure time: 17ms, gain: 5. (middle) exposure time: 9ms, gain: 9. (right) exposure time: 2ms, gain: 18.



(a) (b)

Fig. 6. The distribution of image entropy along the defined searching path. (a) The distribution in indoor environment. (b) The distribution in outdoor environment.

From figure 6, a very good property of image entropy can be found that the image entropy will increase monotonously to the peak and then decrease monotonously along the defined searching path. So the global maximal image entropy can be found easily by searching along the defined path, and the best camera parameters are also determined at the same time. In figure 6(a), the best exposure time and gain for the omnidirectional vision system are 18ms and 18 respectively; in figure 6(b), the best exposure time and gain are 9ms and 9 respectively.

According to the special character of omnidirectional vision, the robot itself will be imaged in the central area of the panoramic images. So in the real application, robot can judge that whether it comes into a totally new environment or the illumination changes in the current environment by calculating the mean brightness value on the central part of panoramic image. If the increase of the mean value is higher than a threshold, the robot will consider that the illumination becomes stronger, and the optimization of camera parameters will be run towards the direction that exposure time and gain reduce and along the searching path. Similarly, if the decrease of the mean value is higher than the threshold, the optimization will be run towards the direction that exposure time and gain raise and along the searching path. In our experiment, we set the threshold as 20. In the optimizing process, a new group of parameters will be set into the camera, and then a new image will be captured and the image entropy can be calculated according to equation (1). The new entropy will be compared with the last one to check whether the maximal entropy has reached. This iteration will go on and on until the maximal entropy is reached. About how to choose new parameters, the technique of varying optimizing step could be used to accelerate the optimization process. When the current entropy is not far from $Max(Entropy)$, the optimizing step could be 1, which means that the change of exposure time is 1ms and the change of gain is 1. When the current entropy is far from $Max(Entropy)$, the optimizing step could be 2 or 3.

The searching path can be changed according to different requirement about the vision system in different application. In some cases, the signal noise ratio of image is required to be high and the real-time performance is not necessary, so the searching path could be exposure time= α *gain (also just equal in number value), and $\alpha > 1$. In some other application, the camera is required to output image as soon as possible and the image noise is not restricted too much, so the searching path could be exposure time= α *gain (also equal in number value), and $\alpha < 1$.

4 The Experimental Results under Different Light Conditions

In this section, we test our novel camera parameters auto-adjusting algorithm proposed in last section under different light conditions in indoor environment and outdoor environment respectively. We verify that whether the camera parameters are properly set successfully by processing the images using the same color calibration result learned in the experiments of section 2. We also evaluate the robot's self-localization based on omnidirectional vision after the camera parameters are optimized in different illumination.

4.1 The Experiment in Indoor Environment

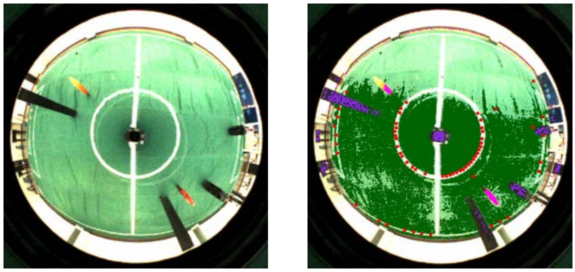
In this experiment, the weather is cloudy, and the experiment time is midday, so the illumination is influenced by artificial and natural light. We also turn off some lamps gradually to change the illumination. We use the color calibration result in the indoor experiment of section 2 to process the images for soccer robots. The outputting image and the processing result are shown in figure 7 when camera is set with the best parameters in section 2. The image is over-exposed, and processing result is terrible. After the parameters have been optimized by our method, the outputting image and the processing result are demonstrated in figure 8(a) and (b). The distribution of image entropy along the searching path is shown in figure 8(c). The optimal exposure time is 14ms and gain is 14, so the image is well-exposed, and the processing result is also good. When the illumination changes gradually, the similar results are achieved.

4.2 The Experiment in Outdoor Environment

In this experiment, the weather is sunny, and the experiment time is from midday to dusk, so the illumination is from bright to dark decided by natural light. We also use the same color calibration result in the outdoor experiment of section 2 to process the images for soccer robots. The outputting image and the processing result are shown in figure 9 when camera is set with the best parameters in section 2. The image is also over-exposed, and processing result is unacceptable for robot vision. After the parameters have been optimized, the outputting image and the processing result are demonstrated in figure 10(a) and (b). The distribution of image entropy along the searching path is shown in figure 10(c). The optimal exposure time is 3ms and gain is 3, so the image is well-exposed, and the processing result is also good. When the experiment is run in different time from midday to dusk, all images can be well-exposed and well processed after the camera parameters have been optimized.

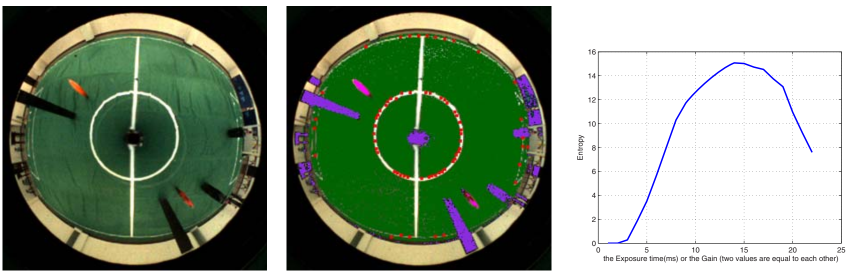
4.3 Comparison of Robot's Localization under Different Illumination

In this experiment, we compare the robot's self-localization results based on omnidirectional vision with optimized camera parameters in indoor RoboCup MSL standard



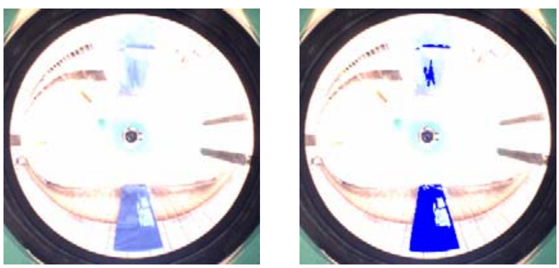
(a) (b)

Fig. 7. (a) The outputting image when the camera parameters have not been optimized in indoor environment. The best parameters in section 2 are used. (b) The processing result.



(a) (b) (c)

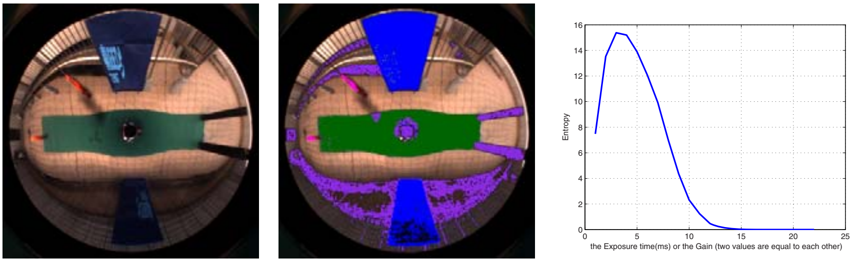
Fig. 8. (a) The outputting image after camera parameters have been optimized. (b) The processing result. (c) The distribution of image entropy along the searching path.



(a) (b)

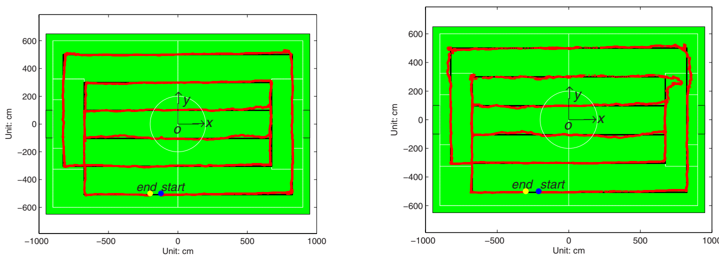
Fig. 9. (a) The outputting image when the camera parameters have not been optimized in outdoor environment. The best parameters in section 2 are used. (b) The processing result.

environment under very different illumination. The first light condition is the same as that in the indoor experiment of section 2. The second one is that the illumination is affected by strong sun's rays in a sunny day, and the optimal exposure time and gain are 12ms and 12 respectively. The robot's self-localization results by the method proposed in [19] under these two light conditions are demonstrated in figure 11. In this experiment, the robot is pushed by human to follow some straight traces on the



(a) (b) (c)

Fig. 10. (a) The outputting image after camera parameters have been optimized. (b) The processing result. (c) The distribution of image entropy along the searching path.



(a) (b)

Fig. 11. (a) The robot's localization result when the illumination is not affected by natural light. (b) The robot's localization result when the illumination is affected greatly by strong sun's rays.

Table 1. The statistic of robot's self-localization error under different illumination. In this table, x , y , θ are the self-localization coordinate related to the location x, y and orientation.

	Under the first light condition			Under the second light condition		
	mean error	standard dev	maximal error	mean error	standard dev	maximal error
x (cm)	5.907	7.334	30.724	6.416	12.431	95.396
y (cm)	5.967	7.117	35.595	5.544	7.381	33.063
θ (rad)	0.044	0.052	0.286	0.067	0.093	0.580

field shown as black lines in figure 11. The statistic of localization errors is shown in Table 1. The robot can achieve good localization results with the same color calibration result even under very different light conditions, though sometimes the effect from sun's rays is so strong that the maximal localization error under the second light condition is much larger. This experiment also verifies that our camera parameters adjusting method is effective.

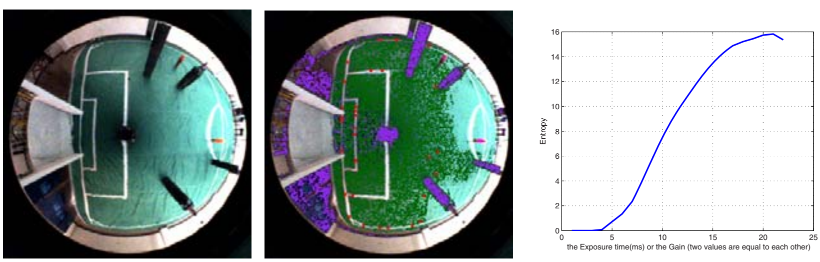
5 Discussion

According to the analysis and the experimental results in above sections, our method can make the camera's output adaptive to different light conditions, so the images can describe the real world as consistently as possible. Our method also provides an objective camera setup technique when robots come into a totally new environment, so users don't need to adjust camera parameters manually according to experience.

Although only exposure time and gain are adjusted in our experiments, our method can be extended to adjust more parameters (if supported by hardware). Besides omnidirectional vision, our method can also be applied in other vision systems, but maybe some special object should be recognized and then used as reference image area to judge whether the illumination changes for camera parameters auto-adjustment.

About the real-time performance of our method, for the light condition will not change too suddenly in real application, it only takes several cycles to finish the optimizing process. And it takes about 40ms to set the parameters into our camera for one time. So camera parameters adjustment can be finished in maximal several hundred ms, and there is not problem for our method in real-time requirement.

However, there are still some deficiencies in our algorithm. For example, our method can not deal with the situation that the illumination is highly not uniform. Because image entropy is a global appearance feature for image, it may be not the best optimizing goal in this situation. As shown in figure 12, though the camera parameters have been optimized as 21ms and 21, but the image processing result is still unacceptable for robot vision. Maybe object recognition or tracking technique should be integrated in our method, and camera parameters can be optimized according to local image features near the object area on the images.



(a) (b) (c)

Fig. 12. (a) The outputting image with optimal parameters when illumination is highly not uniform. (b) The processing result. (c) The distribution of image entropy along searching path.

6 Conclusion

In this paper, a novel camera parameters auto-adjusting method is proposed to make the output of robot vision adaptive to different light conditions. Firstly we present the definition of image entropy, and use image entropy as optimizing goal for the optimization problem of camera parameters after verifying that image entropy can indicate whether the camera parameters are properly set by experiments. Then how to optimize the camera parameters based on image entropy is proposed to adapt to different illumination. The experiments in indoor RoboCup MSL standard field and outdoor RoboCup-like environment show that our algorithm is effective and the color constancy to some extent in the output of vision systems can be achieved.

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