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Analysis of A Fire Area Detection Method Based on RGB Color Model

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Abstract

Fire can now be created and detected easily with modern technology. Various algorithms have been developed to detect fires based on their various characteristics. In this paper, a fire area detection algorithm is proposed. Initially, fire pixels are recognized based on an RGB model; then morphological processing is added to optimize the pixels; after this, the pixels are screened based on area. The algorithm is tested under different conditions, the main difference being background illumination since some objects display similar properties to fire as the camera. It is found that most disturbance terms can be eliminated, but since the model is based only on RGB, some giant light sources are also recognized as fires. Therefore, A larger number of fire-related features should be analyzed in order to reduce false alarms.

Keywords

RGB model, morphological processing, area screening, illumination, disturbance terms.

1. Introduction

Fire has been important to human society for millions of years, as it provides light and warmth. Nevertheless, owing to the pace at which the flame spreads and the hotness of the flame, the unawareness of the rise of flame can be dangerous both physically and economically, an artificial flame can have adverse ecological effects as well. The development of computer vision has made accurate flame detection possible by utilizing a camera. Color-based flame detection is one method of detecting flame that is commonly used.

It is possible to detect fire in a number of different ways, some of which are similar and others completely different. A variety of detection scenarios can be realized based on sensors and algorithms, including detection based on temperature, smoke, motion, shape, and color. Nevertheless, many of them are based on color models, i.e., calculations of RGB components of each pixel. For example, Thou-Ho Chen et al proposed algorithms for both chromatic and dynamic features, as well as the smoke of flame. In order to minimize false alarms and maximize fire detection accuracy and efficiency, three criteria are employed [1]. Ping-He Huang et al. adapted Thou-Ho Chen's color model algorithm but optimized its capture of fire's dynamic features [2]. Bruno Miguel Nogueira de Souza et al. proposed an algorithm based on color mapping, which involved RGB, HSI, YCbCr, and other color mapping functions [3]. Using multicolor detection (RGB & HSI) and a hybrid clustering algorithm, Chakraborty et al. improved their sample detection accuracy [4]. Wen-Bing Horng et al. combined the HSI color model with the invented color masking technique to eliminate the fire-like features in the image [5].

The paper proposes a method for detecting fire area based on [1], then all detected pixels are processed based on morphology and area, which would filter out some detection errors. The sensor is tested in four different environments and three different light conditions, and the color of the fire varies among the three light conditions and the four environments. Fire with

disturbance terms such as light spots is also tested. Analyzing and concluding the experiments is the final step.

2. Methodology

2.1. Fire Pixel Separation

To begin recognizing fire, it is necessary to separate it from other objects. This is done by operating the RGB component of each pixel of the image, if the values of the pixels satisfy certain criteria, the pixel will be recognized as fire. However, this is not easy since there are many fire-like objects exist, such as bright lights. [1] states that the color of fire ranges from red to yellow, with the corresponding RGB values showing $R \geq G > B$. Furthermore, the R component should be stronger and higher since red is the predominant color of fire, so, it needs to be under a certain condition, which is a threshold R_T. However, fire displays different features to the camera under different lighting conditions, that is, if the fire is in a sufficiently illuminated environment, it will display less white, while if the fire is nearly the only illuminant in the captured image, it will appear more white. In order to avoid false alarms, a threshold for S_T is used for saturation. In conclusion, the three rules are:

$$Rule\ 1: R > R_T$$

$$Rule\ 2: R \geq G > B$$

$$Rule\ 3: S \geq ((255 - R) * S_T / R_T)$$

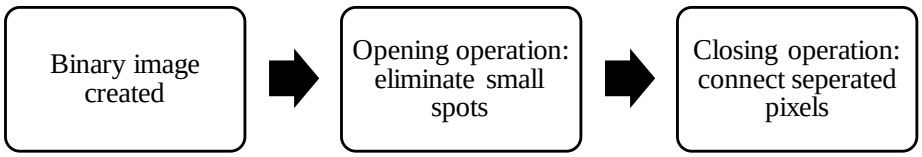
A pixel is only recognized as a fire pixel if it meets all three criteria, otherwise, it is not a fire pixel.

2.2. Binary Image Processing

By processing each pixel by the rules above, a binary image is generated, the white pixels stand for the pixels that meet the rules, while the black pixels are those that do not. It is necessary to perform some morphological processing due to many unpredictable errors.

It is possible for white pixels to be caused by things other than fire, such as bright spots and objects that can reflect the fire. Therefore, an open operation of mathematical morphology should be performed, which is erosion followed by dilation. As a result, all the tiny spots will disappear after erosion and will not reappear after dilation, whereas the major part will not be affected due to dilation being executed, which will negate erosion.

Moreover, not all fire pixels will meet the three rules, especially the central part, then a single flame will be separated in the binary image. Thus, a close operation of mathematical morphology must be reserved, i.e., dilation followed by erosion, the opposite of an open operation. It will result in white pixels being connected while retaining the previous size and shape of the flame.



2.3. Area Screening

It is necessary to use the BFS (breadth-first search) method to screen the binary image after eliminating potential errors. The number of pixels in each group of white pixels is calculated using the BFS algorithm and then stored in a set. Different places require different levels of fire alarm sensitivity, so screening can be of help in adjusting fire alarm demand. The forest may need an alert alarm system, even a small flame of a lighter can be useful, but for places like kitchens, the fire for cooking should not trigger the fire system. In other words, different firefighting or alarm measures will only be executed if the maximum area of the fire reaches a

threshold. I_R and I_C represent the number of rows and columns in the image respectively, N_i represents the ith place in the set, P_T is a threshold that represents a proportion of the total image area ranges from 0.01% to 1%. Only if $N_i/(I_R * I_C) > P_T$, is the group identified as fire, and the pseudocode corresponds as follows:

$$FOR(i = every\ places\ in\ the\ set)$$
$$IF(N_i/(I_R * I_C) > P_T) \rightarrow fire\ pixel$$
$$ELSE \rightarrow not\ fire$$

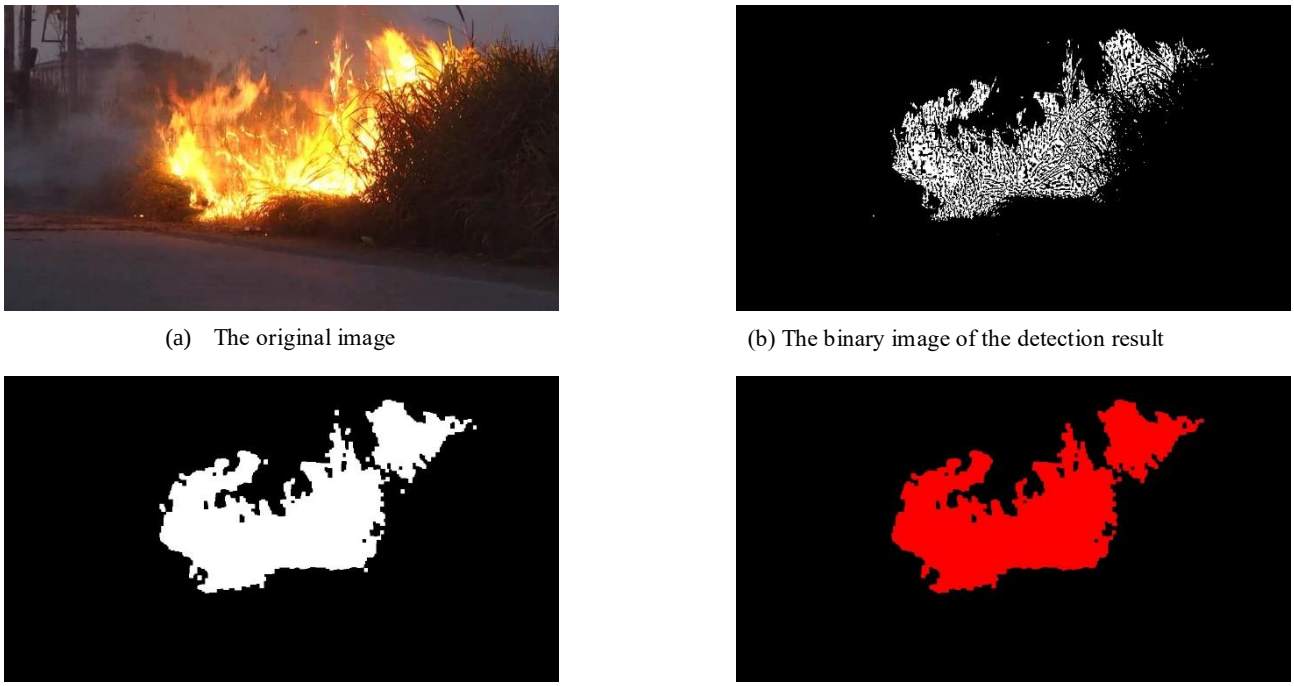
3. Experiment And Analysis

3.1. Detection Result

The fire recognition model outlined in this paper is observed under different environmental conditions to ensure it is effective and adaptable.

As for rule 3, the saturation value can be calculated in a variety of ways. The formula given in [1] is not the exact formula and in this experiment, the formula given is one common method of calculating saturation:

$$S = 1 - (3\min(R, G, B))/(R + G + B)$$



(a) The original image (b) The binary image of the detection result

(c) The binary image after morphological processing (d) The binary image with pixels that meet the proportion threshold

Figure 1. The process and result of the fire recognition model proposed in this paper

3.2. Light Condition

The detection results vary depending on the light conditions, which means that different threshold values (R_T, S_T, P_T) should correspond to different illumination conditions. It is known from [1] that fire will display differently to the camera, therefore the RGB components should be analyzed separately under different illumination conditions.

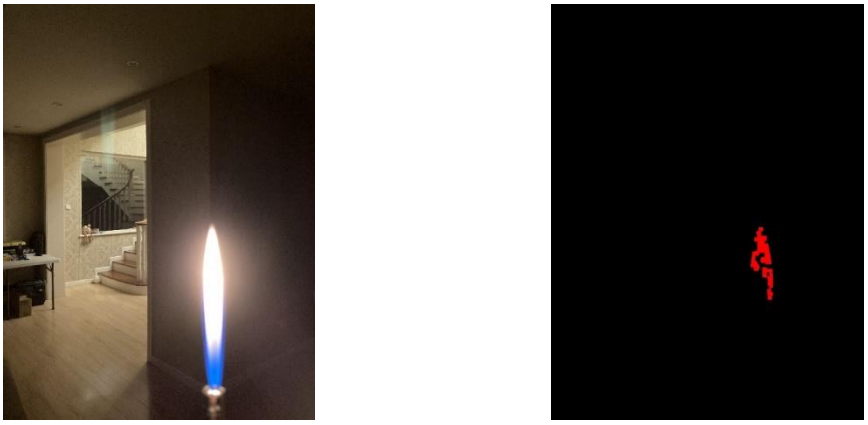
3.2.1. Daily illumination

(a) The original image (b) The final detection result

Figure 2. Original image and detection result of fire image under daily illumination

The fire is neutral to the camera, and the colors appear close to white as well as saturated red. According to rule 1, R_T should be set to the lowest R component value among all the fire pixels. However, if R_T is too small, the denominator in rule 3 will be small, resulting in the fraction gaining in value. Then, rule 3 will be harder to be met, while this can be adjusted it is possible to adjust this through controlling S_T, since as S_T decreases, the fraction value will decrease. In other words, the balance between R_T and S_T is crucial to optimizing this fire detection algorithm. When $R_T = 170$, $S_T = 40$, $P_T = 0.01\%$, a good combination is found. P_T is not significant in this detection since there are nearly no small white pixels.

3.2.2. Dark illumination

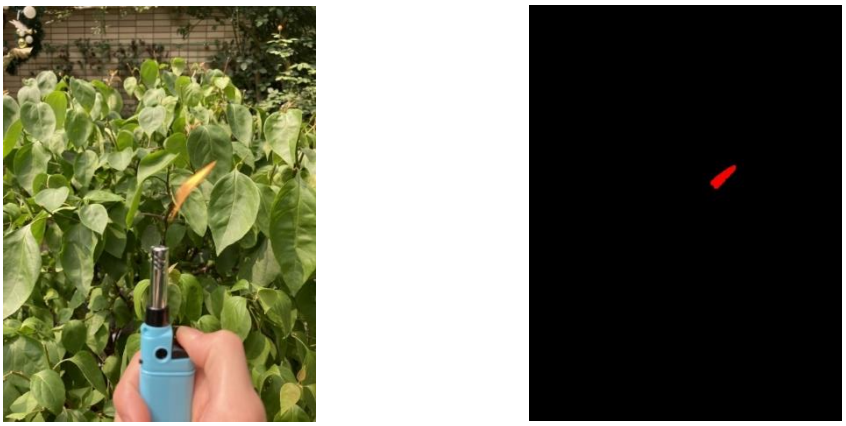


(a) The original image (b) The final detection result

Figure 3. Original image and detection result of fire image under dark illumination

The fire appears white to the camera, there is barely red color. Therefore, all RGB components are close to 255, rule 1 is easily met, the numerator $(255 - R) * S_T$ in rule 3 is small since $(255 - R)$ approaches 0, and if S_T and R_T are adjusted as well, rule 3 is easily met as well. There are some fire pixels, especially at the center of the fire, that is completely white. This means the RGB component values are all 255, thus rule 2 cannot be met. So, for dark detection, there is likely to be a hole inside the fire since that area is completely white, if rule 2 is changed from $R \geq G > B$ to $R \geq G \geq B$, this problem can be solved, but at the same time, all the white area in the image will be recognized as fire. For the detection above, $R_T = 200$, $S_T = 40$, $P_T = 0.05\%$.

3.2.3. Bright illumination:



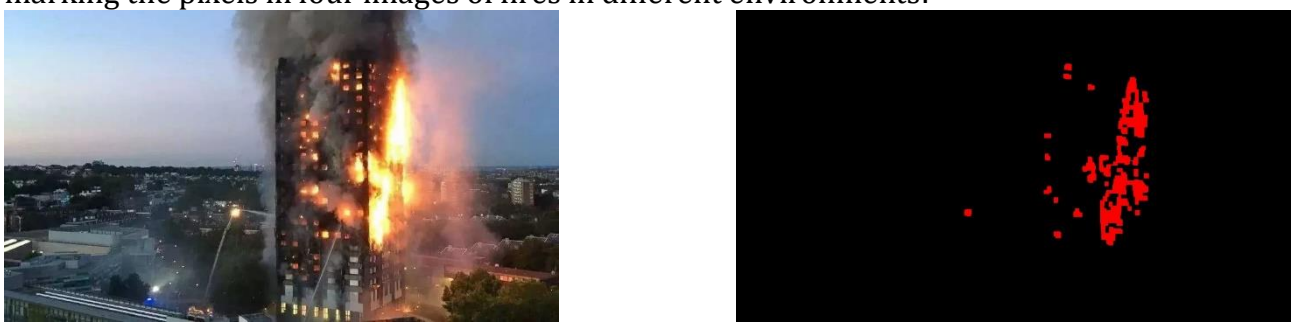
(a) The original image (b) The final detection result

Figure 4. Original image and detection result of fire image under bright illumination

The fire appears darker color to the camera since the surrounding brightness is comparable to or even brighter than the fire itself. Therefore, rule 2 is easy to be met and R_T should be smaller than it is in the dark illumination, at the same time the value of the fraction in rule 3 will increase, however, consider the value the saturation, $S = 1 - (3\min(R, G, B))/(R + G + B)$, the smallest value among RGB can be very small, so the fraction will be small, resulting in a larger S value. The values at both sides of the inequation increase, no problem should arise, if it does, S_T, as the numerator, may be adjusted smaller to reduce the difficulty in meeting this rule. For the detection above, $R_T = 140$, $S_T = 30$, $P_T = 0.15\%$.

3.3. Different Environments

As the fire detection system is used in different environments, the demand for alarm varies, so the 3 threshold values should be adjusted. figure 5 to 8 shows the results of detecting and marking the pixels in four images of fires in different environments.



(a) The original image (b) The final detection result

Figure 5. Original image and detection result of fire in city

The threshold values for the detection above are $R_T = 140$, $S_T = 70$, $P_T = 0.01\%$. Most of the fire is detected, if P_T is slightly increased, both the light spots on the left side of the building and small flames shown in some windows will not be seen, leaving only the huge flame on the right side.

The threshold values for the detection above are $R_T = 210$ $S_T = 20$, $P_T = 0.01\%$. A part of the fire is detected, both the part below that is separated by the trees and the highest part of the flame that is going to fade away cannot be detected. P_T is at minimum value since the forest requires sensitive detection of fire.

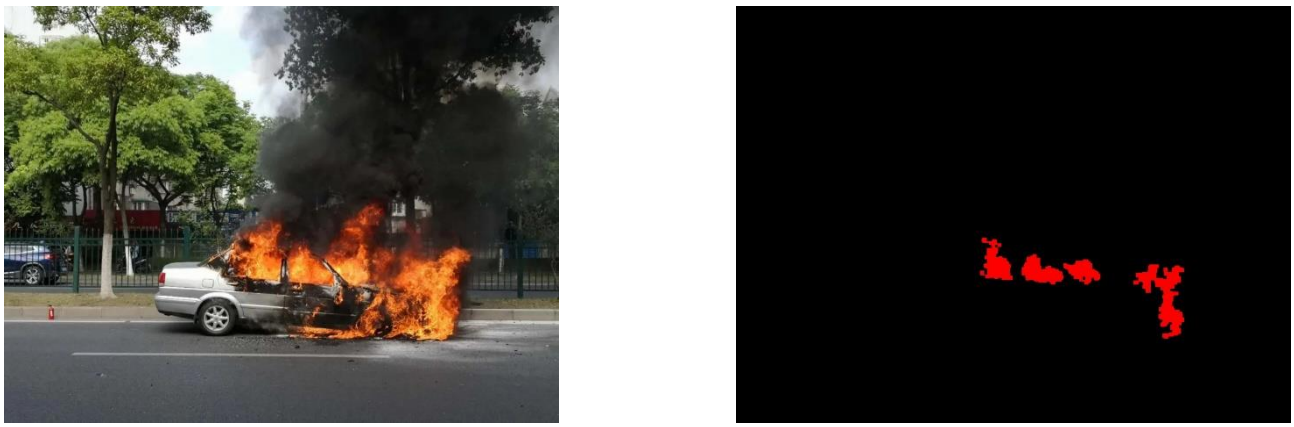
(a) The original image (b) The final detection result

Figure 6. Original image and detection result of fire in forest

(a) The original image (b) The final detection result

Figure 7. Original image and detection result of fire in cooking

The threshold values for the detection above are $R_T = 170$ $S_T = 40$, $P_T = 0.1\%$. Most of the fire is detected, the bright light at the upper part of the image is eliminated by adjusting the value of P_T to 0.1%. As fire is almost necessary for cooking, the sensitivity of fire detection in cooking should be lower than in the forest and city. Only if a fire gets too big should an alarm be sounded.



(a) The original image (b) The final detection result

Figure 8 Original image and detection result of fire on road

The threshold values for the detection above are $R_T = 150$ $S_T = 20$, $P_T = 0.05\%$. Most of the fire is detected, along with the forest detection, but the lower parts and the rapidly fading parts cannot be detected. P_T is adjusted to 0.05% to eliminate some reflections caused by the car.

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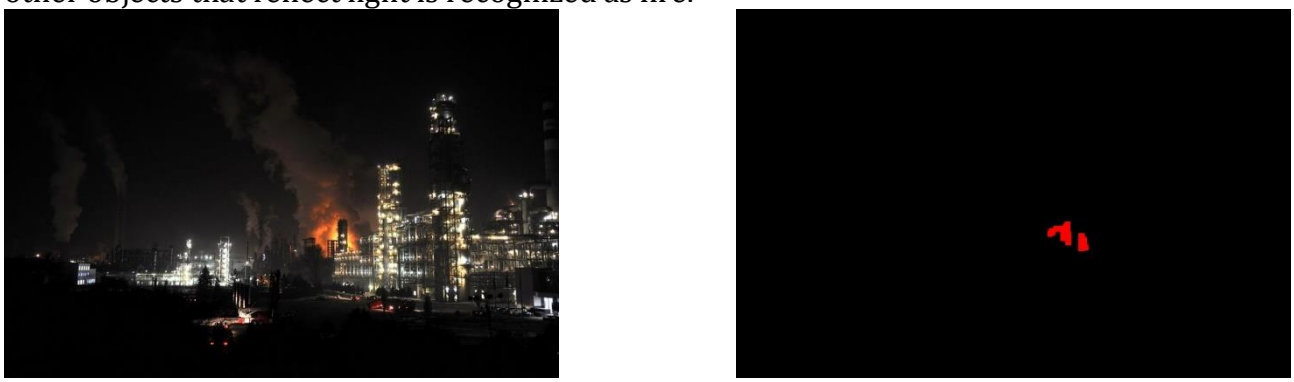
3.4. Disturbance Terms

As fire and light have similar characteristics, especially in dark illumination, sometimes light or other objects that reflect light is recognized as fire.



(a) The original image (b) The final detection result

Figure 9. Original image and detection result of fire with light as the disturbance term

The threshold values for the detection above are $R_T = 210$ $S_T = 20$, $P_T = 0.06\%$. The value of P_T is very precise, even if it is 0.05%, some light spots will be detected, and if it is 0.07%, the right part of the fire cannot be detected. However, light in dark illumination will not affect the detection result severely, meaning that in most cases, the light can be eliminated by adjusting the threshold values.

(a) The original image (b) The final detection result

Figure 9 Original image and detection result of fire with reflections as the disturbance term

The threshold values for the detection above are $R_T = 170$ $S_T = 40$, $P_T = 1\%$. In this case, there are two reflecting parts: the upper left part (1) and the lower right part (2). The area of part 2 is smaller than part 1, so it can be eliminated by increasing the value of P_T, however, the area of part 1 has exceeded the maximum value of P_T (1%), so this part is recognized as fire. In a real kitchen, the camera may be placed farther, so that the reflections are less noticeable.

It is found that small light spots will not be recognized, but light with a similar area to the fire area will be recognized unless the threshold values are adjusted very precisely and specifically, however, this will cause the sensitivity to decrease.

4. Conclusion

From the experiment data, the algorithm proposed in [1] is able to detect fire pixels, after the morphological processing and the area screening method proposed in this paper, fire with distinct color to the surrounding can be detected. If there is only fire in the signal, the detection result will be better. The threshold values R_T, S_T, and P_T can be adjusted within the range of 140 to 210, 20 to 70, and 0.01% to 1% respectively.

However, there will be false detection and errors as a result of applying this algorithm, especially for red or white objects and light sources, which are very likely to be detected as fire. It is found that the threshold values for different illuminations can be similar, 170 for R_T and 40 for S_T can usually be used. Moreover, the threshold values for detection will not be affected by any minor adjustments.

Under different environments, small light sources and reflections can be eliminated by adjusting the value of P_T, depending on the location of the camera settings and the sensitivity required of the detection, this value can be very different. However, under certain illumination, the disturbance terms that have similar areas with the fire can still be detected, so the RGB model is applicable for simple fire detection. If more precise detection is needed, more elements need to be considered and analyzed [1] such as the dynamic features of fire in video and the smoke of the fire. Other sensors can also be used, such as temperature or infrared sensors.

References

[1] Thou-Ho Chen, Ping-Hsueh Wu and Yung-Chuen Chiou, "An early fire-detection method based on image processing," 2004 International Conference on Image Processing, 2004. ICIP '04., 2004, pp. 1707-1710 Vol. 3, doi: 10.1109/ICIP.2004.1421401.

[2] P. Huang, J. Su, Z. Lu and J. Pan, "A Fire-Alarming Method Based on Video Processing," 2006 International Conference on Intelligent Information Hiding and Multimedia, 2006, pp. 359-364, doi: 10.1109/IIH-MSP.2006.265017.

[3] B. M. Nogueira de Souza and J. Facon, "A fire color mapping-based segmentation: Fire pixel segmentation approach," 2016 IEEE/ACS 13th International Conference of Computer Systems and Applications (AICCSA), 2016, pp. 1-8, doi: 10.1109/AICCSA.2016.7945741.

[4] I. Chakraborty and T. K. Paul, "A Hybrid Clustering Algorithm for Fire Detection in Video and Analysis with Color Based Thresholding Method," 2010 International Conference on Advances in Computer Engineering, 2010, pp. 277-280, doi: 10.1109/ACE.2010.12.

[5] Wen-Bing Horng, Jian-Wen Peng and Chih-Yuan Chen, "A new image-based real-time flame detection method using color analysis," Proceedings. 2005 IEEE Networking, Sensing and Control, 2005., 2005, pp. 100-105, doi: 10.1109/ICNSC.2005.1461169.