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Image Contour Extraction using Bacterial Quorum Sensing

Fredy H. Martínez S., Holman Montiel A. and Fernando Martínez S.

Technological Faculty, District University Francisco José de Caldas
Bogotá D.C., Colombia

Abstract

In this paper we present an image contour extraction strategy based on bacterial Quorum Sensing (QS). By imitating bacterial behavior, we get the bacteria or agents to navigate the image and accumulate in the areas of attraction, which correspond to special features of color. When the bacterial population begins to cluster in one or several areas of the image, the population virulence is activated, which accelerates the process of convergence. Population boundaries identify the contour sought in the images. As a result, the method achieves accurate estimation of the area related to the flame in real-time. We present experiments where our strategy accurately identifies the flame inside the furnace, which increases the performance of the oxygen estimation algorithm in which it is used.

Keywords: Embedded system, control, image contour, quorum sensing, real-time.

INTRODUCTION

In the control of the production process of activated carbon from vegetable waste, supervision and adjusting of oxygen and temperature levels inside the carbonization and activation furnaces should be performed. For these furnaces it has been proposed the use of a visual identification system for the estimation of the oxygen content in the flame [1]. The system is composed of preprocessing, segmentation, feature extraction and selection, as well as classification according to the color of the flame.

The control unit uses the temperature and oxygen level information in the furnace to adjust the fuel and air inlet valves. In the prototype we use histogram-based similarity measures on images of the flame with respect to reference images. With this tool we estimate the amount of oxygen in the process, and therefore the quality of the combustion [1, 2, 3]. To do this, we evaluate four different similarity metrics, combining the information from the four metrics to obtain the best oxygen estimate. This information is fundamental in the sensing loop of the control system, and due to background influence (refractory), shadows [4], problems of viewing angle, illumination and adjustment of the lens [5], the sensor sometimes presents errors in the estimation [6]. To reduce the error, we propose the use of an automatic segmentation system that uses the shape information from images [7]. In this way the metrics will focus their comparison on the color of the flame, reducing the error produced by the environment [5], while lowering the computational load on the processor.

However, in our application the color contrast between the flame and the interior of the furnace is very low (Figs. 2(a), 2(e) and 2(i)), reason why few traditional segmentation algorithms are suitable to extract the object contours from the surrounding environment [8].

Another key element in the algorithm design is the need for real-time work [9]. The algorithm is implemented on an embedded system in charge of the estimation of oxygen content inside the furnace [10], why should be computationally lightweight, and robust against low-quality images and geometric distortions produced by viewpoint changes.

The paper is organized as follows. Section 2 presents preliminary concepts and problem formulation. Section 3 illustrates the methodology based on bacterial QS to search regions on the images. Section 4 we present the preliminary results. And finally, in Section 5, we present our conclusions.

PROBLEM FORMULATION

The oxygen estimation system used in the carbonization and activation furnaces requires a strategy to quantify the colors without significantly degrading the color quality. Through this strategy we want to facilitate the extraction of relevant information in real time. The goal is to use a few representative colors that can be used to differentiate regions in the image.

The strategy proposes to assign labels to the coded colors to conform class-maps limited by distances between colors, using some metric. The category map can be viewed as a set of point data located on a 2D plane. Each point is characterized by its position (x,y) and its color value, a set of three matrices in some color space.

Suppose a discrete model of image perception where $O(x,y)$ corresponds to output i with coordinates (x,y) de valor $y^*u^*v^*$ in some color space (ideally a uniform color space such that linear superposition is allowed). $O(x,y)$ takes values within a limited set of classification labels.

If $\boldsymbol{I_k}$ is the k-color color for the image I, then the color plane of the perceived image is equation 1.

$$Pk(I) = Wk \times Ix \qquad (1)$$

Where W_k is the perception kernel.

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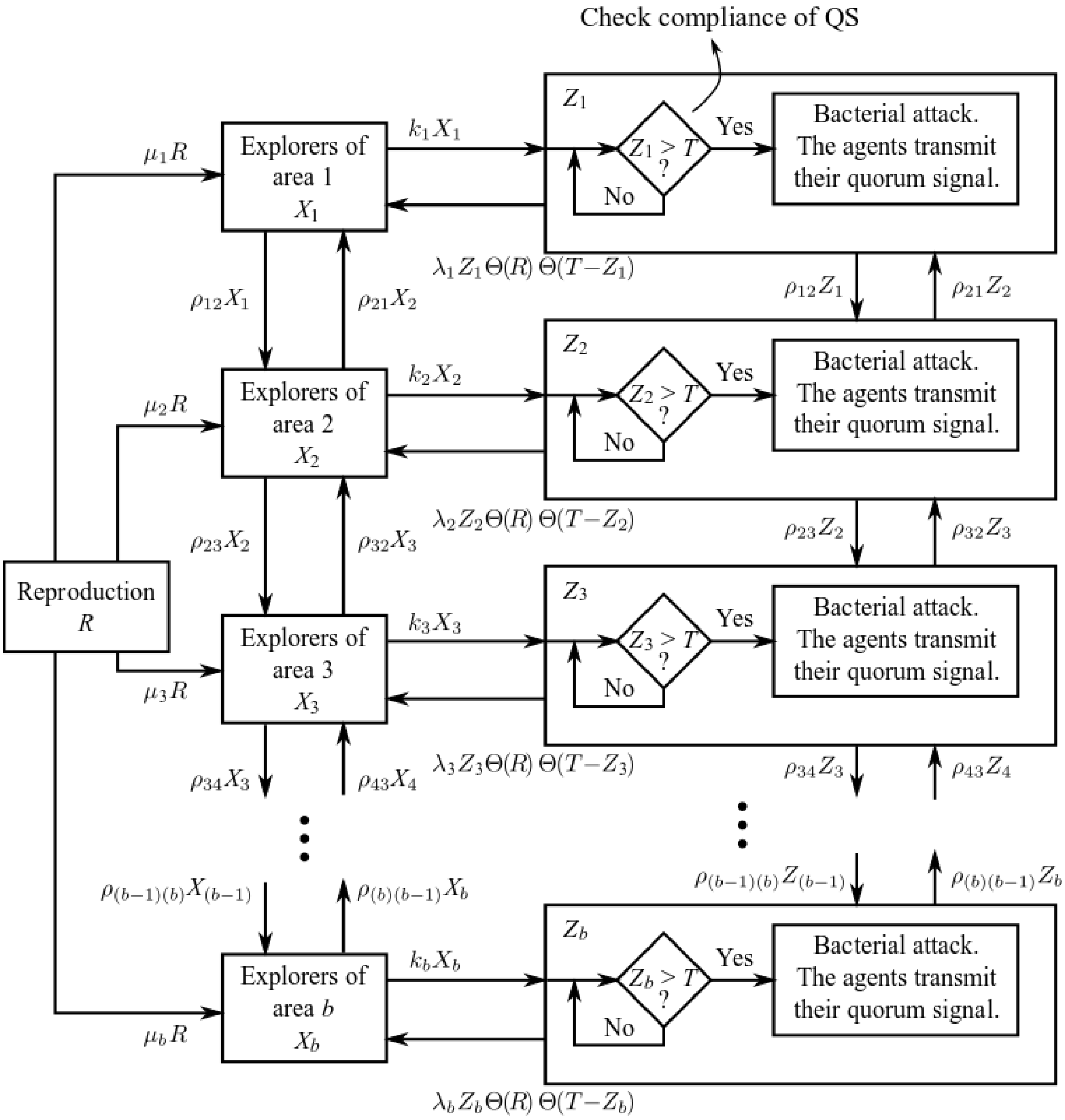


Figure 1: QS-based system architecture for image segmentation.

The quantized color plane of the discrete perception system is limited to a discrete number $\boldsymbol{Y} \subset \boldsymbol{P_k}$. Quantization is defined as an assignment of pixels to quantized colors by membership function.

In the proposed algorithm, the mapping of pixels to the class-map is done by means of a randomized search imitating the behavior of biological bacteria. The evaluation of each pixel in this scan uses similarity metrics.

Inspired by the natural behavior of a community of bacteria, a strategy of exploration and detection of areas of interest according to color is proposed, which allows segmenting images quickly and with very low computational costs. The system architecture is shown in Fig. 1.
The system consists of n bacteria (agents). All agents are identical in structure and autonomous. Agents take one of three possible behaviors: Reproduction (population size indicated by R), Explorer (population size indicated by $\boldsymbol{X_i}$, where i indicates the area that is exploring the agent), and Virulent (population size indicated by $\boldsymbol{Z_i}$, where i indicates the area that is exploring the agent).

The system starts from a bacterium in reproduction state, which doubles up to the population size defined for the problem (it is a variable defined by the programmer). The agents then move to the scan state in which they randomly move through the environment (by the image) and collect local readings to determine the performance of the area in which they are located.

The performance of the area is evaluated according to the value of the color space and its similarity with standard images according to its histogram. The displacement of the agent is inversely proportional to the distance of similarity found. If the similarity is high, the agent reduces its displacement, and if on the other hand it is low, the agent increases its displacement. When the amount of agents in an area i exceeds the value T (threshold of QS), these agents emit an additional signal that can be detected by other agents in the vicinity (autoinductors in the biological system), explorers that are nearby, but outside the area i. This signal increases the attractiveness of area i, causing nearby agents to enter the area.

The constant $\boldsymbol{\mu}$, $\boldsymbol{k}$, $\boldsymbol{\lambda}$ and $\boldsymbol{\rho}$ set the ease with which an agent toggles between behaviors. The model does not include bacterial death, so the sum of the different populations always be equal to n.

The contour of the image is the union of the n circular regions of radius r centered on the position of each agent in the system.

METHODOLOGY

The strategy operates on the description of the image in a three-dimensional color space. The selection of the color space is restricted by its usefulness in the application and by the sensor. Since the application is intended to be robust against variations of brightness and illumination, it is ideal to have a color space that encodes colors and intensity separately. The camera used (GC2035 of GalaxyCore Inc.) provides colors in RGB and YUV (CMOS with 1616V x 1232H pixel array), which is why YUV is used as color space in the system (the system does not require color space transformation).

First we perform basic image processing (resizing, rotating and translating). In order to make the processing steps faster we resize the image. Then we rotate the image to try to compare them in the same position (the furnaces are rotating continuously). We then blur the image slightly by using a bilateral filter. Bilateral filtering has the property of removing noise in the image while still preserving the actual edges. Finally, we apply our algorithm based on QS.

Within the algorithm we use the characteristic color of each oxygen concentration. This color is identified from the histogram of the reference images. This color becomes reference for the exploration of areas in the image, i.e., the algorithm looks similar areas to the four reference colors thus:

- Flame with 0% oxygen
- Flame with 40% oxygen
- Flame with 80% oxygen
- Flame with 100% oxygen

The percentage of oxygen is coded according to the level of air fed to the furnace from the burner.

If the comparison color is defined as: $\boldsymbol{Y_{S0}\ U_{S0}\ V_{S0}}$ for the case of 0% oxygen, $\boldsymbol{Y_{S40}\ U_{S40}\ V_{S40}}$ for the case of 40% oxygen, $\boldsymbol{Y_{S80}\ U_{S80}\ V_{S80}}$ for the case of 80% oxygen, and $\boldsymbol{Y_{S100}\ U_{S100}\ V_{S100}}$ for the case of 100% oxygen, then the performance of the pixel is calculated from the distance (equation 2).

$$d\,(i, [S0, S40, S80, S100]) = min[d\,(i, S0), d\,(i, S40), d\,(i, S80), d\,(i, S100)] \quad (2)$$

Being also the performance function of i. This means that we calculate three distances per pixel for each reference, one for each dimension in the color space. As the application uses four references, each performance function involves the calculation of 12 distances. This is the critical element of the algorithm that directly impacts its efficiency, since this operation must be repeated for each pixel visited by an agent. The optimization is guaranteed by the QS model, since it is not necessary to process all the pixels of the image.

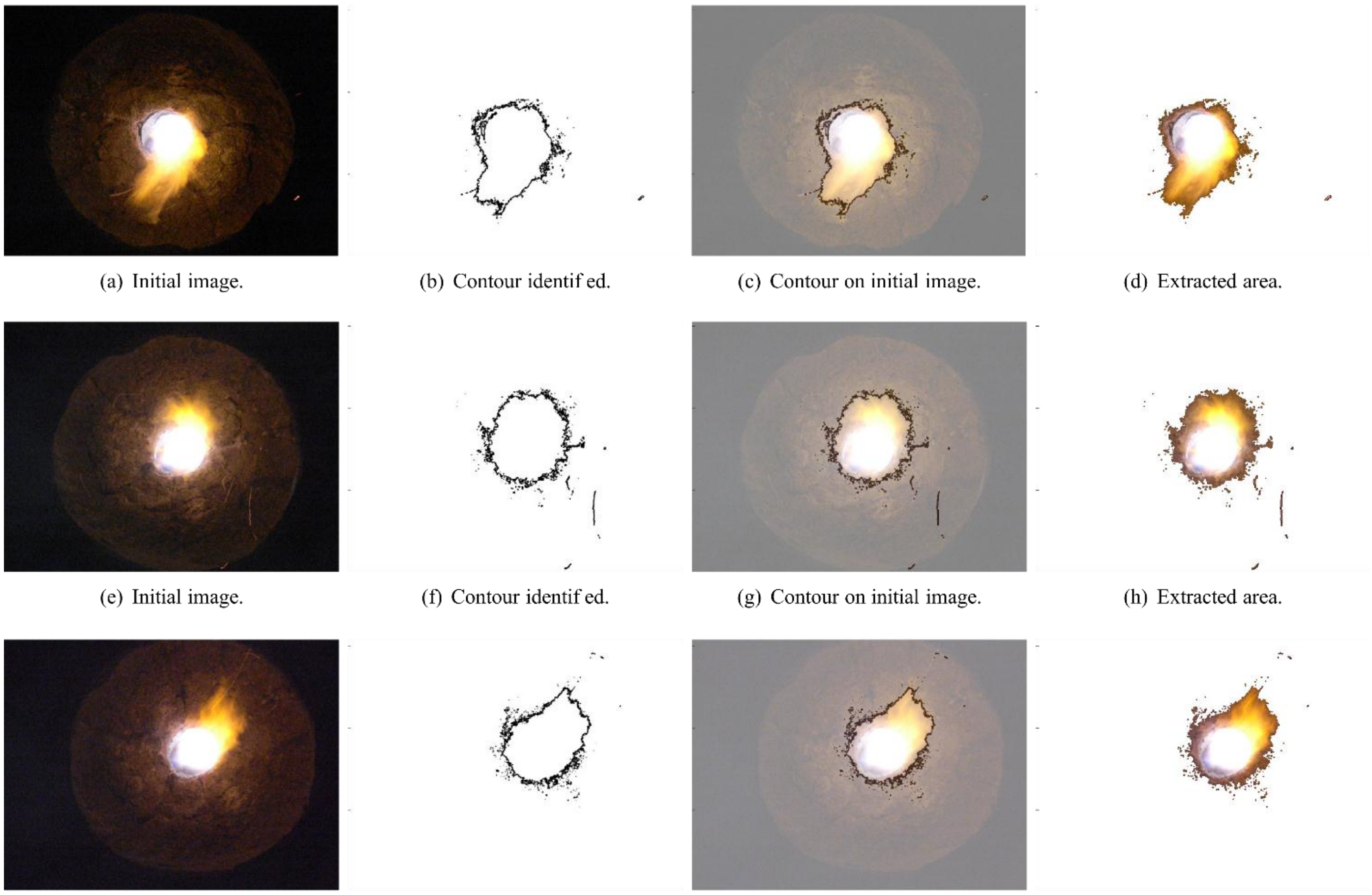
Distances were assessed using four metrics: Correlation, Chi-Square, Intersection and Bhattacharyya.

RESULTS AND DISCUSSION

The implementation of the algorithm was carried out on the prototype of an intelligent sensor of an industrial furnace. This sensor is supported on an embedded platform around a Allwinner H3 quad core Cortex A7 @ 1.2 GHz processor with a ARM Mali GPU-400MP2. The operating system is a Debian Linux ARM variant with video capture drivers in the kernel. The requirement for extraction of the flame contour, and segmented of the area for extraction of characteristics, was evaluated as an alternative to increase the reliability and robustness of the sensor. The hardware platform uses a GC2035 CMOS sensor from GalaxyCore Inc. designed for smartphones and laptop computers.

In the initial tests the system was able to process images of 169x128 pixels at 15 fps. Fig. 2 shows three sample images segmented using the proposed algorithm. The first column shows the original image captured by the camera, the second column shows the contour of the image identified by the proposed algorithm, the third column shows the contour overlayed on the original image, and the fourth column shows the extracted area of the image using the contour.

For the results in Fig. 2, the algorithm used a bacterial population of n = 500, a QS threshold T = 10, and switching between behaviors $\boldsymbol{\mu}$, $\boldsymbol{k}$, $\boldsymbol{\lambda}$ and $\boldsymbol{\rho}$ all equal to 1. The performance test was performed with 20 images, and the inclusion of contour segmentation algorithm was able to increase the oxygen correct estimate by 3.2%.



(a) Initial image. (b) Contour identif ed. (c) Contour on initial image. (d) Extracted area.

(e) Initial image. (f) Contour identif ed. (g) Contour on initial image. (h) Extracted area.

(i) Initial image. (j) Contour identif ed. (k) Contour on initial image. (l) Extracted area.

Figure 2: Image in different stages of processing for three images inside the furnace: Initial image, calculated contour, contour overlayed on the initial image and area extracted from the contour.

CONCLUSIONS

According to the results of the furnace oxygen estimation process, it is possible to observe that the proposed method to identify the contour of the flame, and its use in the segmentation of the images, provides a quick and precise identification of the relevant area. This significantly increases the performance of the intelligent sensor and the control system. According to the navigation of the bacteria in the image, and the color patterns used in the local readings of each agent, the scheme quickly identifies the area corresponding to the flame, facilitating its extraction of the image, regardless of the low level of contrast or fuzzy image. There is not manual intervention in the throughout extraction process. The final performance evaluation was performed on actual images taken at the production plant.

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REFERENCES

[1] F. Martínez, A. Rendón, and P. Guevara, "Combustion quality estimation in carbonization furnace using flame similarity measure," Similarity Search and Applications, vol. 9939, pp. 125–133, 2016.

[2] L. Sabeti and J. Wu, "New similarity measure for illumination invariant content-based image retrieval," in International Conference on Automation and Logistics, pp. 279–283, 2008.

[3] C. Beecks, A. Zimmer, T. Seidl, D. Martin, P. Pischke, and R. Kneer, "Applying similarity search for the investigation of the fuel injection process," in 4th International Conference on Similarity Search and Applications (SISAP 2011), pp. 117–118, 2011.

[4] C. Wei, T. Po, and C. Yung, "Contour extraction for breast tumor in ultrasound image," in International Conference on Machine Learning and Cybernetics ICMLC 2014, vol. 2, pp. 533–537, 2014.

[5] A. Mitra, S. Roy, and S. Kumar, "Morphologically contour extraction of decisive objects from image," in First International Conference on Automation, Control, Energy and Systems ACES 2014, pp. 1–5, 2014.

[6] G. Ghazi, C. Rappaport, and J. Martinez, "Improved SAR imaging contour extraction using smooth sparsity-driven

regularization," IEEE Antennas and Wireless Propagation Letters, vol. 15, pp. 266–269, 2015.

[7] L. Zhu, Y. Gao, V. Appia, A. Yezzi, C. Arepalli, T. Faber, A. Stillman, and A. Tannenbaum, "A complete system for automatic extraction of left ventricular myocardium from ct images using shape segmentation and contour evolution," IEEE Transactions on Image Processing, vol. 23, no. 3, pp. 1340–1351, 2014.

[8] Z. Fang and L. Jun, "Microbial contour extraction based on edge detection," in 8th International Conference on Wireless Communications & Signal Processing WCSP 2016, pp. 1–5, 2016.

[9] A. Amor, A. Ruiz, F. Moreno, and A. Sanfeliu, "On-board real-time pose estimation for uavs using deformable visual contour registration," in IEEE International Conference on Robotics and Automation ICRA 2014, pp. 2595–2601, 2014.

[10] A. Barrero, M. Robayo, and E. Jacinto, "Algoritmo de navegación a bordo en ambientes controlados a partir de procesamiento de imágenes," Tekhnê, vol. 12, no. 2, pp. 23–34, 2015. ISSN 1692-8407