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Fuzzy를 이용한 영상에서의 기체분리

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Fuzzy-based gaseous object segmentation on image plane

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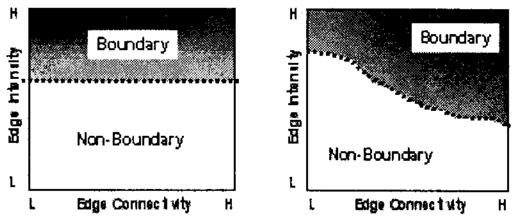
Abstract - Unlike rigid objects, the edge intensity of a gaseous object is various along the object boundary (edge intensities of some pixels on a gaseous object boundary are weaker than those of small rigid objects or noise itself). Therefore, the conventional edge detectors may not adequately detect boundary-like edge pixels for gaseous objects. In this paper A new methodology for segmenting gaseous object images is introduced. Proposed method consists of fuzzy-based boundary detector applicable to gaseous as well as rigid objects and concave region filling to recover object regions.

1. Introduction

Segmenting gaseous objects are very useful to numerous applications, for example analyzing scientific data from climate simulation, and monitoring air pollution or mountain fire. A good example of gaseous objects is a plume (i.e. smoke rising up from a chimney of the factory). Although there have been profound researches on segmenting rigid objects or model-based deformable objects, such researches for gaseous objects are rarely performed. Unlike rigid objects, the edge intensity of a gaseous object is various along the object boundary (edge intensities of some pixels on a gaseous object boundary are weaker than those of small rigid objects or noise itself). Therefore, the conventional edge detectors, such as Sobel, Pewitts, Canny edge detectors that use edge intensity only, may not adequately detect boundary-like edge pixels for gaseous objects. We observe that a weak intensity edge pixel could belong to a boundary in case it is one of the long connected edges and also a strong intensity edge pixel could be a noise-like edge in case it is isolated or on the short-connected edges. Based on this observation, we propose a new boundary-like edge detection rule applicable to gaseous as well as rigid objects. Fig. 1 compares a conventional edge detection rule and the proposed boundary-like edge detection rule. The conventional edge detectors declare every high intensity pixel as a edge pixel. However, the proposed edge detector may declare low intensity edge pixels with large connectivity (the number of connected edge pixels) as boundary pixels and declare high intensity pixels with low connectivity as non-boundary pixels. Thus, while the conventional edge detectors decision rule is a straight dotted line as shown in Fig. 1(a), the proposed edge detector forms a non-linear decision filtering as shown in Fig. 1(b)



(a) Conventional edge detection (b) Proposed edge detection

Fig. 1. Comparison of boundary edge decision rules

We propose a Fuzzy-based edge detector (FED) that uses edge connectivity as well as edge intensity. In the FED, the Fuzzy parameters are optimized through Genetic Algorithm (GA). After detecting boundary pixels, concave area-filling algorithm with morphological operations is introduced to segment object regions. Various simulation results indicate that the proposed algorithm segments both rigid and gaseous objects reasonably well.

2. Fuzzy-Based Edge Detector

The procedure of proposed FED is as follows:

Step 1: Apply a conventional edge detector (such as Sobel detector) with low threshold to produce all boundary candidates (edge pixels).
Step 2: Compute the edge intensity and connectivity).
Step 3: Apply FED to determine boundary pixels.

In step 3. the input variables for the FED are the edge intensity and connectivity and the output variable is the edge confidence that is regarded as the possibility of boundary pixel. In the FED, general triangular shapes are used for input membership functions, and singleton function is used for output function [1][2]. Let $A_1^k, A_2^k$and B^k be the fuzzy sets of intensity, connectivity and edge confidence, respectively.
For the intensity membership function, 3 cases such as *"strong "*, *"medium"* and *"weak"* are adopted. For the connectivity membership function, *" long"* , *"medium "* and *"short "* connectivities are also used. Therefore, nine rules are finally constructed. The *kth* fuzzy rule is as follows;

kth Rule: if *intensity* is A_1^k and *connectivity* is A_2^k, then *edge confidence* is B^k,(k=1,2··9)

To obtain edge confidence, the following defuzzification function is used:

$$f(x_1,x_2)=\frac{\sum_{k=1}^{l} y^k(\prod_{i=1}^{2}\mu_{A_i^l}(x_i))}{\sum_{k=1}^{l}(\prod_{i=1}^{2}\mu_{A_i^l}(x_i))} \quad (1)$$

where x_1 and x_2 are edge intensity and connectivity values and y^l is the center value of edge confidence (B^l).
Parameters for fuzzy membership functions are optimized through GA training. Two 256x256 images that include smoke rising from chimney of factory surrounded by mountain forest are used for GA training. Their edge candidates are manually classified into boundary edges and non-boundary edges. The classified pixels are used to train the parameters.

GA training is performed as following steps:
Step 1: Initialize all tuning parameters (Edge intensity and connectivity.).
Step 2: Represent the tuning parameters as GA chromosomes.
Step 3: Tune the parameters on membership functions by GA operations (reproduction, crossover, mutation) so as to maximize the following fitness function

$$Fitness=\frac{1}{\sum_{i=1}^{N_E}(1-F_i^E)^2+\sum_{i=1}^{N_N}(F_i^N)^2} \quad (2)$$

where N_E is the total number of boundary pixels, N_N is the total number of non-boundary pixels, F_i^E is the fuzzy reasoning result of the i^{th} boundary pixel, and *FiN* F_i^N is the fuzzy reasoning result of the *ith* non-boundary pixel.
Step 4: Entire steps are repeated until the fitness reaches the appropriate value.

In our case, the crossover probability, mutation probability, maximum number of generation, and population size are set as 0.7, 0.1, 50, 50, respectively. Decision threshold to classify boundary pixel and non-boundary pixel can be specified in terms of the percent recognition rate which is calculated as R_E = (C_E/N_E) *X 100*, where C_E is the number of correctly decided boundary pixels. In the GA training, threshold level is also adjusted to satisfy the appropriate recognition rate, R_E.
Fig. 2 compares the edge detection performances of the Canny edge detector and the proposed FED. Canny edge detector with low threshold confuses boundary-like edges with noisy edges. On the contrary, Canny detector with high threshold may not detect the edges with weak intensity. However, the proposed FED detects most of gaseous boundary edges without confusing boundary-like edges with noisy edges.

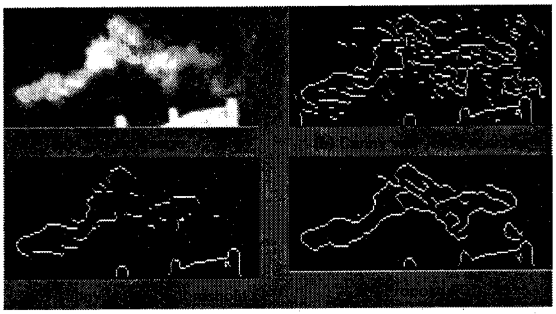
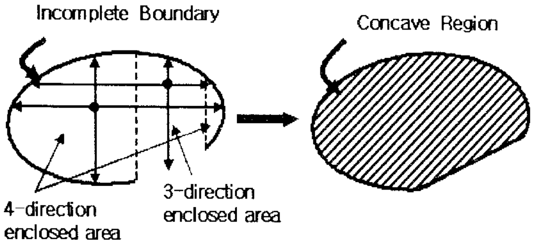


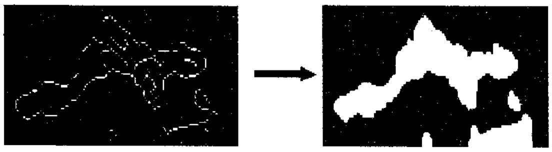
Fig. 2. Comparisons of the boundary detection performances of the Canny edge detector and the proposed FED

3. Segmenting objects from detected edges

When weak edge intensity regions on a gaseous object boundary are long, the detected edges may not enclose the whole interior of a gaseous object. Thus, we need to fill concave regions to recover the regions not enclosed by the boundary. From each non-edge pixel, lines of the four major directions (up, down, left, right) are drawn. If at least three of these lines encounter an object boundary, the pixel is labeled as objects interior region. Fig. 4 depicts the object area filling process and the reconstructed objects from detected edges.



(a) Concave Region filling method



(b) Object area filling with concave filling method

Fiig.3 Concave Region Filling Method

3. Conclusion

We present a new algorithm for segmenting and identifying gaseous objects on image plane. First, we present a new edge detector applicable to gaseous object as well as rigid objects. Then, the morphological processing for segmenting gaseous objects are proposed. Finally, the chain code correlation function is proposed to identify gaseous objects among segmented objects.

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