Evolutionary Fuzzy Rule Construction for Iterative Object Segmentation

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Abstract: This paper presents Cellular Fuzzy Oriented Classifier Evolution (CFORCE), a generic method for constructing fuzzy rules to divide an image into two segments: object and background. In CFORCE, a pair of fuzzy classification rule sets for object and background is defined as a processing unit, and the identical units are allocated on each pixel over an input image. Each unit computes matching degree of each pixel with object and background class iteratively with considering the matching degree of neighbor units. The algorithm has mainly two features: 1) designing the fuzzy rules using Fuzzy Oriented Classifier Evolution (FORCE) which develops fuzzy rules represented as directed graphs flexibly and automatically by Genetic Algorithm, and 2) performing iterative segmentation with considering spatial relationship between pixels besides local features. In natural image segmentation, many pixels are overlapped between different clusters. Considering the spatial relationship is important to classify the overlapped pixels correctly. We applied CFORCE to three different object segmentation, and showed that CFORCE extracted object regions successfully.

1 INTRODUCTION

Image segmentation is a process to divide an image into meaningful segments (regions). It is a fundamental technique in computer vision, image understanding, etc., but hard to be achieved adequately because a large variety of segments exists and boundaries of them are likely ambiguous in natural image segmentation. To perform effective segmentation, various methods have been studied. The supervised segmentation methods using Fuzzy Rule Based Classification System (FRBCS) is one of them.

FRBCS is a classifier system using fuzzy IF-THEN rules that has good interpretability and accuracy because of an understandable rule form and ability of treating ambiguous problems by Membership Functions (MFs). MF computes matching degree of input variables with conditions of rules. The idea treating ambiguity by fuzzy logic is suitable for image segmentation which contains ambiguity, and fuzzy rule based segmentation methods have been studied (Karmakar et al., 2000). For example, Karmakar and Dooley have proposed Generic Fuzzy Rule based Image Segmentation (GFRIS) which employs three MFs based on pixel distributions, closeness of region and spatial relationships between pixels (Karmakar and Dooley, 2002). Lai and Lin have applied manually designed fuzzy inference rules with texture features to teeth segmentation of dental X-ray images (Lai and Lin, 2008). Borji and Hamidi have proposed the method to design fuzzy rules for pixel-wise color classification of images using Particle Swam Optimization (Borji and Hamidi, 2007). Stavrakoudis et al. have developed Boosted Genetic Fuzzy Classifier (BGFC) which generates fuzzy rules for segmentation using Genetic Algorithm (GA) in an iterative fashion directed by a boosting algorithm, and applied BGFC to land cover classification of remote sensing images (Stavrakoudis et al., 2011).

In fuzzy rule based segmentation, we consider that designing segmentation rules for various objects effectively and incorporating a mechanism considering spatial relationship between pixels in the rules are important. As mentioned in various studies (Karmakar and Dooley, 2002; Beevi and Sathik, 2012), many pixels are overlapped between different clusters in natural image segmentation, and considering the spatial relationship between pixels besides local features is effective to classify the overlapped pixels correctly. Hence, we propose a novel segmentation method using FRBCS, Cellular Fuzzy Oriented Classifier Evolution (CFORCE) that has mainly two features: 1) constructing fuzzy rules to classify pixels as either object or background using Fuzzy Oriented Classifier Evolution (FORCE) which develops fuzzy classification rules flexibly by GA (Otsuka and Nagao, 2013), and 2) performing iterative segmentation with considering spatial relationship between pixels. FORCE

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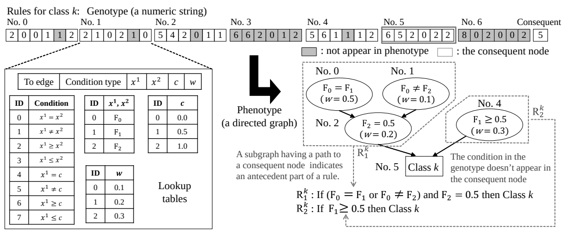


Figure 1: Example of genotype and phenotype representation of Fuzzy Oriented Classifier Evolution.

is one of Genetic Fuzzy Systems (GFSs) which design fuzzy rules by evolutionary algorithms (Herrera, 2008), and constructs fuzzy classification rules represented as directed graphs composed of nodes indicating fuzzy conditions. We expect FORCE constructs fuzzy rules for segmentation efficiently because of the compact and flexible graph representation. The second feature is inspired by Cellular Neural Network (CNN) (Chua and Yang, 1988). CNN consists of a regular array of processing units called cells connected with only their neighbor cells. Each cell computes an output value iteratively considering output of their neighbor cells besides local information. CNN has showed good performance in image filtering in spite of its simple structure. The proposed model computes matching degree of pixels with object and background iteratively with considering the matching degree of neighbor pixels as CNN computes output iteratively, to classify even the overlapped pixels correctly by considering their spatial relationship.

The remaining of this paper is organized in the following way. Section 2 reviews FORCE briefly, and details of the proposed model are described in Section 3. Experimental results are shown in Section 4. Finally, in Section 5, we conclude this work.

2 FUZZY ORIENTED CLASSIFIER EVOLUTION

Figure 1 illustrates an overview of FORCE. FORCE represents fuzzy classification rules as a directed graph composed of two types of nodes: condition nodes and a consequent node that indicate conditions and a predefined consequent of rules (classification class) respectively. In the graph, series connections of condition nodes are defined as AND operation of the conditions and parallel connections are defined as OR operation. A subgraph of the graph having a path to a consequent node indicates an antecedent part of a rule whose consequent part is defined by the consequent node. Namely, one graph represents one rule set for predefined class k such like that illustrated in Figure 1. The rule set computes matching degree m^k of data with class k. The graph is converted into a numeric string (genotype) indicating connections and parameters of each condition node and a consequent node number, and developed by optimizing the string by GA.

FORCE is expected to constructs fuzzy rules more flexibly and efficiently than conventional GFSs based on simple GA or Genetic Programming (Koza, 1992) because of the compact graph representation. FORCE has been applied to image classification tasks and classification of benchmark data sets in comparison with conventional methods, and constructed compact and accurate classification rules (Otsuka and Nagao, 2012; Otsuka and Nagao, 2013).

3 CELLULAR FUZZY ORIENTED CLASSIFIER EVOLUTION

3.1 Model Overview

An overview of CFORCE is described in Figure 2. In CFORCE, a pair of graphs representing fuzzy classification rules for object (obj) and background (bkg) class is defined as a processing unit, and the identical units are allocated on each pixel over an input image. The graphs of each unit output matching degree of each pixel with obj and bkg class iteratively with considering local features (LFs) and feedback features (FBs). LFs are such like standard statistics computed from pixel values in a local window, and FBs indicate magnitude of the matching degree of neighbor pixels. After defined number of output iteration, each pixel is classified as either obj or bkg associated with the highest matching degree. In region segmentation, spatial relationship between neighbor pixels is important as well as local features. That is, neighbor pixels tend to belong to be the same class. FBs are expected to enable CFORCE to consider the relationship and process complex object segmentation in which clusters of pixels are overlapped.

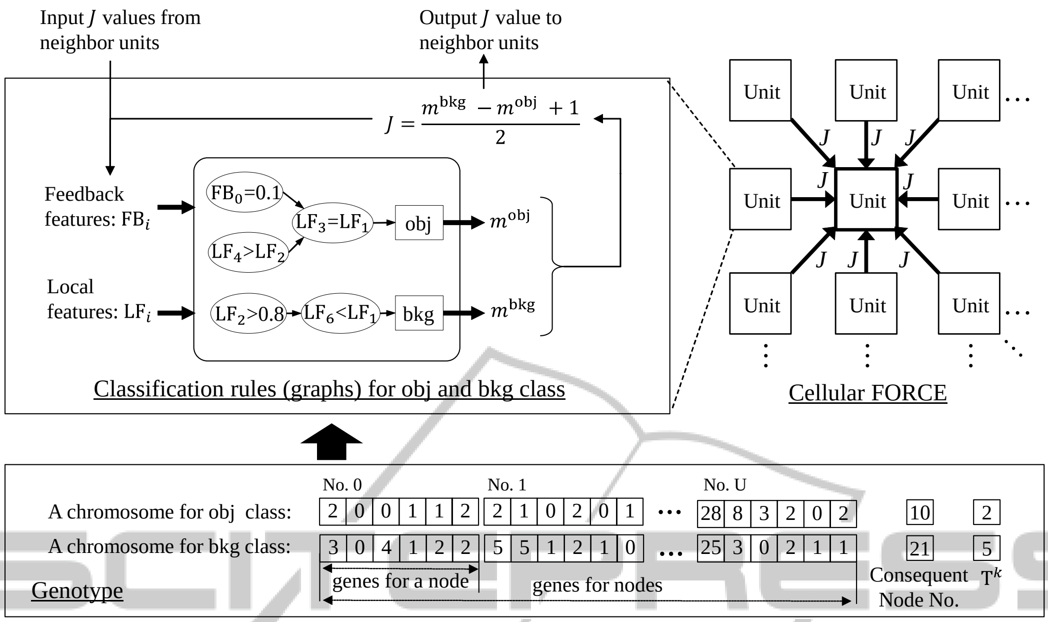


Figure 2: Overview of the proposed model.

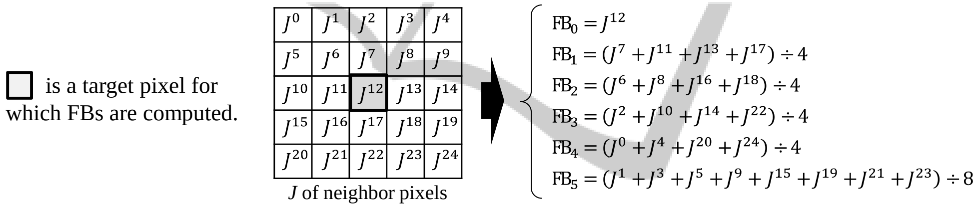


Figure 3: Feedback template: how to merge J values of neighbor units to six rotation invariant feedback features.

3.2 Feedback Features

FBs represent magnitude relation between matching degree of neighbor pixels with obj and bkg class calculated by neighbor graphs in the previous output. In the t-th output, FBs of a pixel are calculated using J_{t-1} of neighbor pixels computed by the following formula:

$$J_{t-1} = \frac{m^{\text{bkg}}_{t-1} - m^{\text{obj}}_{t-1} + 1}{2}, \quad (1)$$

where m^{obj}_{t-1} and m^{bkg}_{t-1} are matching degree of a pixel with obj and bkg class respectively computed by a pair of graphs placed on the pixel in the (t-1)-th output. J_{t-1} indicates magnitude relation between m^{obj}_{t-1} and m^{bkg}_{t-1}. m^{obj}_{t-1}, m^{bkg}_{t-1} and J_{t-1} are real numbers in range $[0,1]$. In this work, six types of 90 degrees rotation invariant FBs are computed from neighbor J_{t-1} in 5×5 pixels using a template illustrated in Figure 3. In the template, a target pixel is placed on the center. FBs are used in condition nodes in the same way as the other input features except when $t = 1$. When

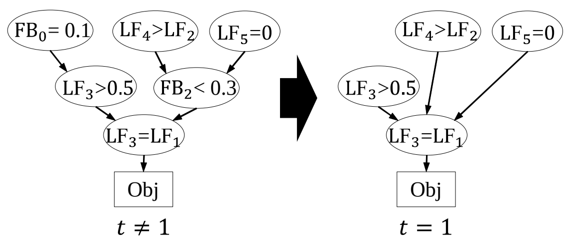


Figure 4: Example of graphs when $t \neq 1$ and $t = 1$.

$t = 1$, FBs cannot be computed because m^{bkg}_0 and m^{obj}_0 are undefined. Therefore, condition nodes using FBs are not used when $t = 1$. That is, they are simply ignored such like that illustrated in Figure 4.

3.3 Graph Structure and Genotype

The structure of graphs is the same as that of FORCE except that CFORCE employs FBs. In the graph, a condition node represents a condition in a form of "x^1_i *Operator V*", where x^1_i is the i-th input feature,

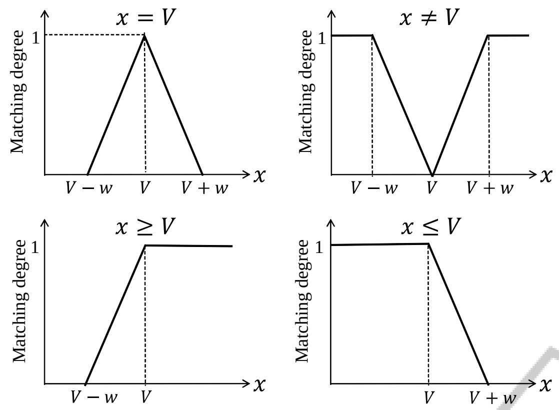


Figure 5: Membership functions used in this work.

Operator is a comparison operator $\in \{=, \neq, \geq, \leq\}$, and V is a constant c or input feature x_i^2 compared with x_i^1. In addition, each condition node has a parameter w for MFs. Figure 5 shows MFs corresponding to each comparison operator used in the proposed model. w determines slope and V (i.e., c or x_i^2) determines position of MFs.

The genotype for a graph is a numeric string in which genes deciding parameters for each condition nodes (i.e., to edge, condition type, x_i^1, x_i^2, c and w), a consequent node number, and an output iteration number T line up. Table 1 shows the parameters for graphs used in this work. Genes for condition nodes are ID numbers associated with the parameters, and each condition node is converted from the genes using lookup tables. Figure 6 illustrates an example of converting genes to a condition node using Table 1. Note that, genes for x_i^1 and x_i^2 indicate ID numbers of input features including FBs. The length of the genotype for a graph is fixed: $6\text{U}+2$, where U is the maximal number of nodes used for a graph. However, the number of nodes appearing in the phenotype (active nodes) is variable because nodes not having a path to a consequent node do not appear in the phenotype (inactive nodes). The graph is feedforward graph as each node is allowed to connect to only nodes having a larger node number than itself. The genotype of CFORCE is a pair of the numeric string representing graphs for obj and bkg class.

3.4 Object Segmentation Procedure

Using $k \in \{\text{obj}, \text{bkg}\}$ and G^k indicating a graph for class k, the procedure of object segmentation by the proposed model is described as follows:

1. $t = 1$.
2. Execute the following procedure for each class k.

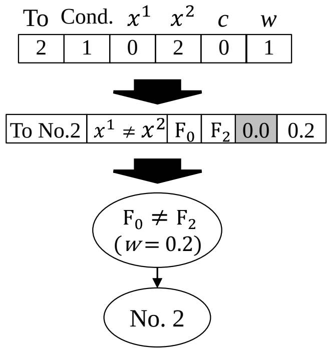


Figure 6: Example of converting genes to a condition node.

   (a) If t is T^k and less, G^k executes (b) and (c).
   (b) Compute matching degree $\mu_{C_s^k}(\mathbf{X})$ between input features $\mathbf{X}$ of each pixel with an antecedent part C_s^k defined by the s-th subgraph of G^k by the following fuzzy logic operators.

$$\mu_{\text{A}\cap\text{B}}(\mathbf{X}) = \min\{\mu_\text{A}(\mathbf{X}), \mu_\text{B}(\mathbf{X})\}, \quad (2)$$

$$\mu_{\text{A}\cup\text{B}}(\mathbf{X}) = \max\{\mu_\text{A}(\mathbf{X}), \mu_\text{B}(\mathbf{X})\}, \quad (3)$$

   where A and B are arbitrary fuzzy conditions, and μ is matching degree of $\mathbf{X}$ with the conditions. Matching degree of $\mathbf{X}$ with a condition of each condition node is computed by MF.
   (c) Integrate $\mu_{C_s^k}(\mathbf{X})$ into matching degree $m^k(\mathbf{X})$ of $\mathbf{X}$ with class k on each pixel by the following formula:

$$m^k(\mathbf{X}) = \frac{\Sigma_{s=1}^{\text{S}^k} \mu_{C_s^k}(\mathbf{X})}{\text{S}^k}, \quad (4)$$

   where S^k is the number of the subgraphs of G^k. More detailed process (b) and (c) are described in Algorithm 1.
3. If t is less than $\max\{\text{T}^{\text{obj}}, \text{T}^{\text{bkg}}\}$, execute the following procedure.
   (a) Compute J on each pixel by Equation 1.
   (b) Compute FBs on each pixel by the template described in Figure 3.
   (c) $t = t + 1$, and go back to 2.
4. Classify each pixel as class k associated with the highest $m^k(\mathbf{X})$.

3.5 Rule Evolution

The two graphs are optimized simultaneously using GA employing simple two-point crossover and random mutation as genetic operators. The fitness is described by mainly two indicators of evaluation: “F” and “IMP”. F is F-measure indicating classification

Table 1: Parameters of CFORCE.

Parameters	ID										
	0	1	2	3	4	5	6	7	8	9	10
Condition	$x^1 = x^2$	$x^1 \neq x^2$	$x^1 \geq x^2$	$x^1 \leq x^2$	$x^1 = c$	$x^1 \neq c$	$x^1 \geq c$	$x^1 \leq c$	-	-	-
c	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
w	0.1	0.2	0.3	0.4	0.5	-	-	-	-	-	-
T	1	2	3	4	5	-	-	-	-	-	-

input : A pixel with input features $\mathbf{X}$
An iteration number t
output: Matching degree m^k of $\mathbf{X}$ with $\mathrm{G^k}$

if $t = 1$ **then**
    $\mathrm{G}' \leftarrow \mathrm{G^k}$ without nodes using FBs;
else
    $\mathrm{G}' \leftarrow \mathrm{G^k}$ with nodes using FBs;
end
$i \leftarrow 1$;
$n_i \leftarrow$ the i-th active node in G';
while *n_i is not the consequent node* **do**
    $from \leftarrow$ a set of nodes connected to n_i;
    if *$from$ is not empty* **then**
        $\mu_{\max} \leftarrow \max_{n_j \in from} \left\{\mu_{n_j}\right\}$;
    else
        $\mu_{\max} \leftarrow 1$;
    end
    $\mu_{n_i} \leftarrow \min\{\mu_{\max}, \mathrm{MF}_{n_i}(\mathbf{X})\}$;
    $i \leftarrow i+1$;
    $n_i \leftarrow$ the i-th active node in G';
end
$from \leftarrow$ a set of nodes connected to n_i;
if *$from$ is not empty* **then**
    $\mathrm{S}^k \leftarrow$ the number of nodes in $from$;
    $m^k \leftarrow \frac{\Sigma_{n_j \in from}\left(\mu_{n_j}\right)}{\mathrm{S}^k}$;   /* $\mu_{n_j} = \mu_{C_s^k}$ */
else
    $m^k \leftarrow 0$;
end

Algorithm 1: How to compute $m^k(\mathbf{X})$ using $\mathrm{G^k}$.

accuracy, and IMP evaluates importance of obtained rules. F is calculated by the following formula:

$$\mathrm{F} = \frac{2 \times \mathrm{N_{correct}}}{\mathrm{N} + \mathrm{N_{detect}}}, \tag{5}$$

where N is the number of obj pixels, $\mathrm{N_{correct}}$ is the number of obj pixels classified correctly, and $\mathrm{N_{detect}}$ is the number of pixels classified as obj class. IMP is the average product of Confidence (CD) and Support (SP) of rules for each class, both represent importance of rules. IMP is calculated by the following formula:

$$\mathrm{CD}^k = \frac{\Sigma_{n=1}^{\mathrm{N}^k} m^k\left(\mathbf{X}_n^k\right)}{\Sigma_{l=1}^{\mathrm{N}} m^k\left(\mathbf{X}_l\right)}, \tag{6}$$

$$\mathrm{SP}^k = \frac{\Sigma_{n=1}^{\mathrm{N}^k} m^k\left(\mathbf{X}_n^k\right)}{\mathrm{N}^k}, \tag{7}$$

$$\mathrm{IMP} = \frac{1}{2}\Sigma_{k \in \{\mathrm{obj,bkg}\}}\left(\mathrm{CD}^k \cdot \mathrm{SP}^k\right), \tag{8}$$

where $\mathbf{X}_n^k$ indicates input features of the n-th pixel labeled as class k and N^k is the number of pixels labeled as class k. Finally, the fitness function is represented as follows:

$$\text{fitness} = \mathrm{F} \times \mathrm{IMP} + \frac{\varepsilon}{\mathrm{N_{cond}}}, \tag{9}$$

where $\mathrm{N_{cond}}$ is the total number of condition nodes used in graphs, and the last term evaluates compactness of rules. ε is a small weight value ($\varepsilon = 0.001$ in this paper).

4 EXPERIMENTS

4.1 Overview of Experiments

We tested CFORCE using three different object segmentation tasks to evaluate performance of the model.

- Crack extraction (grayscale)
  This task requires extracting cracks in concrete wall from images containing cracks and lines not cracks. Figure 7 shows training images, and Figure 8 shows test images not used in training and used to examine the performance of obtained rules. The images are 128×128 pixels.
- Coin extraction (color)
  This task requires extracting several coins from images containing coins and other objects. Figure 9 and Figure 10 show training and test images respectively. The images are 128×128 pixels.
- Human extraction (color)
  This task requires extracting human's busts from images in varied light conditions and various

backgrounds. Figure 11 and Figure 12 show parts of training and test images respectively. We selected 10 images for training and 20 images for test from the MSRC Object Category Image Database v2[1]. Originally these images are 320×213 pixels and labeled roughly. In this experiment, we reduced them to 100×67 pixels and labeled them precisely.

For comparison, we also applied four comparative methods to the same tasks: the original FORCE, Support Vector Machine (SVM) (Vapnik, 2000), C4.5 (Quinlan, 1993), and a graph cuts based segmentation method (GC). GC is a method based on Interactive Graph Cuts (Boykov and Jolly, 2001) which divide an image into object and background regions using graph cuts to find globally optimal segmentation. Interactive Graph Cuts use seeds marked pixels as object or background by a user to provide hard constraints for segmentation and to compute histogram for object or background intensity distributions. GC does not use seeds and computes the histogram from pixel values of training images.

4.2 Experimental Settings

Input features used in the experiments are shown in Table 2. The features were standard statistics computed from pixel values in a local window of 5×5 pixel size, six FBs, and six rotation invariant pixel values $\mathrm{I_i}$ computed from neighbor pixel values using the same template as FBs. For color images, we used L*a*b* color space, and the input features except FBs are computed from each color component. The "Groups" indicates the groups of input features allowed to be compared each other in CFORCE. A condition comparing input features x_i^1 and x_i^2 in different groups is changed to a condition comparing an input feature x_i^1 and a constant c.

CFORCE and FORCE were tested six times with different random seed in each experiment using the following parameters: the number of generations was 10000, the population size was 50, the crossover rate was 0.7, and the mutation rate was 0.02. Minimal Generation Gap model [15] was used as a generation alternation model, and the number of children was 30. The maximal number of nodes U for each graph was 60. These parameters are based on the previous work. SVM and C4.5 were run using WEKA (Hall et al., 2009). SVM employed RBF kernel, and γ of the RBF kernel and the complexity parameter C were selected from $\{2^n|n = -7,-6,..,1,2\}$ and $\{2^n|n = -2,-1,..,6,7\}$ respectively by grid search in each task. The minNumObj and confidenceFactor of C4.5 were also selected from $\{0,1,2,3,4,5\}$ and $\{0.1,0.2,0.3,0.4,0.5\}$ respectively by grid search. For GC, we selected BIN# of histogram from $\{16,32,64,128,256\}$, σ of boundary penalty function from $\{0.1,0.3,0.5,0.7,0.9,1.1,1.3,1.5\}$ and λ a parameter for edge weights from $\{1,2,4,8,16,32,64\}$ to maximize F-measure for training images in each task.

[1]http://research.microsoft.com/en-us/projects/ObjectClassRecognition/

Table 2: Input features used in this work.

Groups	Features
0	Max, Min, Mean, Median, First quartile, Third quartile, Six rotation invariant pixel values: $\mathrm{I_i}$
1	Standard deviation
2	Range
3	Averaged edge magnitude
4	Skewness
5	Kurtosis
6	Six feedback features: $\mathrm{FB_i}$

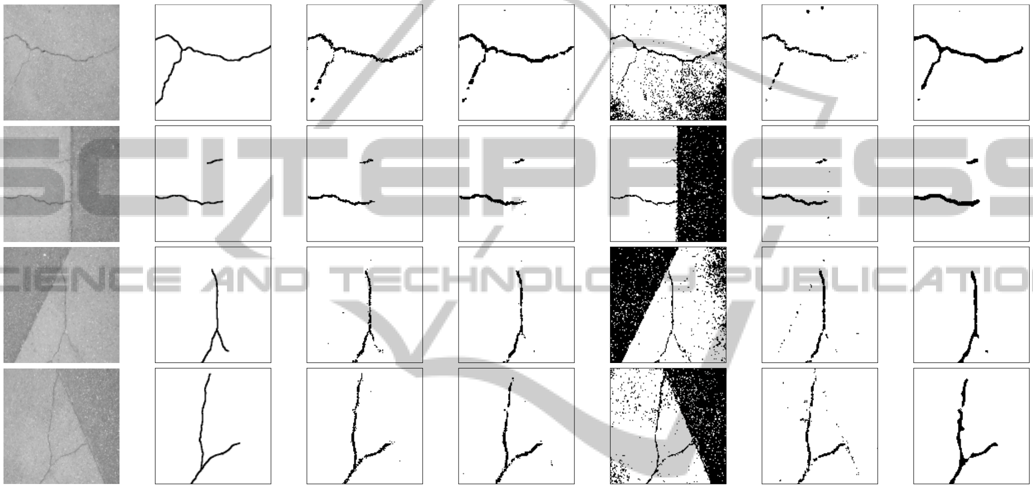
4.3 Results and Discussion

Accuracy results (F-measure) of the experiments are summarized in Table 3. The values in parentheses of FORCE and CFORCE are averaged results over six runs, and the other values of them are results of the elitist rules obtained in training. SVM and C4.5 processed the training images better than CFORCE in coin and human extraction, but for the test images, the elitist rules of CFORCE showed the most accurate results in all experiments. That is, CFORCE prevented rules from overfitting the training images better than SVM and C4.5. GC showed better results for the test images in the coin and human extraction than SVM, C4.5 and FORCE, although it hardly processed crack extraction because the histogram based on gray level is too simple to represent differences between cracks and background.

The result images processed by each method are shown in Figure 7-12. The feature of processing by CFORCE is that extracted regions tend to be united with little noises (small misclassified regions), although boundaries between regions are likely imprecise a little. We consider this feature is caused by FBs because results of FORCE without FBs do not show such features, and some results of GC considering relationship between pixels have similarity to those of CFORCE. SVM and C4.5 produced good results with precise boundaries for the training images, but the test results of them have more noises than those of CFORCE. Figure 13 illustrates an exam-

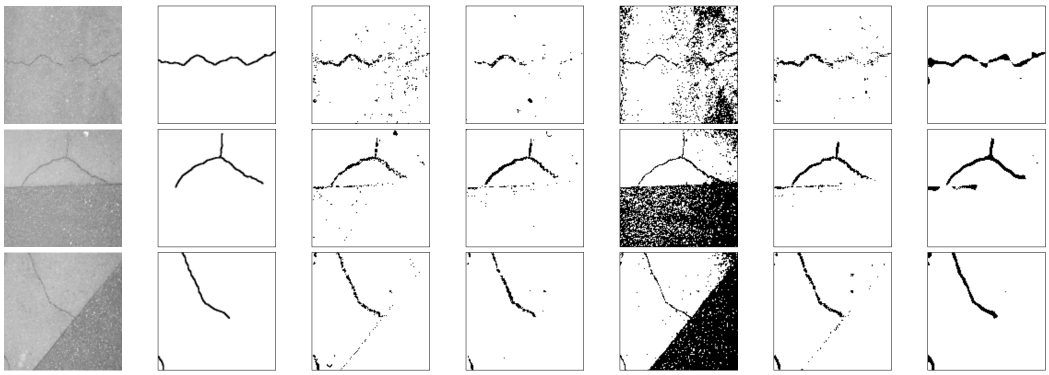
Table 3: Accuracy results (F-measure) of each method.

		SVM	C4.5	GC	FORCE Best (Avg.)	CFORCE Best (Avg.)
Crack	Training	0.910	0.930	0.061	0.788 (0.764)	0.930 (0.891)
	Test	0.665	0.567	0.056	0.712 (0.718)	0.827 (0.829)
Coin	Training	1.000	0.997	0.938	0.915 (0.896)	0.997 (0.989)
	Test	0.936	0.928	0.958	0.931 (0.915)	0.968 (0.972)
Human	Training	1.000	0.998	0.851	0.843 (0.826)	0.904 (0.855)
	Test	0.755	0.720	0.759	0.718 (0.714)	0.794 (0.744)
Avg.	Training	0.970	0.975	0.616	0.849 (0.829)	0.944 (0.912)
	Test	0.785	0.739	0.591	0.787 (0.782)	0.863 (0.848)



(a) Training images (b) Ground truth (c) C4.5 (d) SVM (e) GC (f) FORCE (g) CFORCE

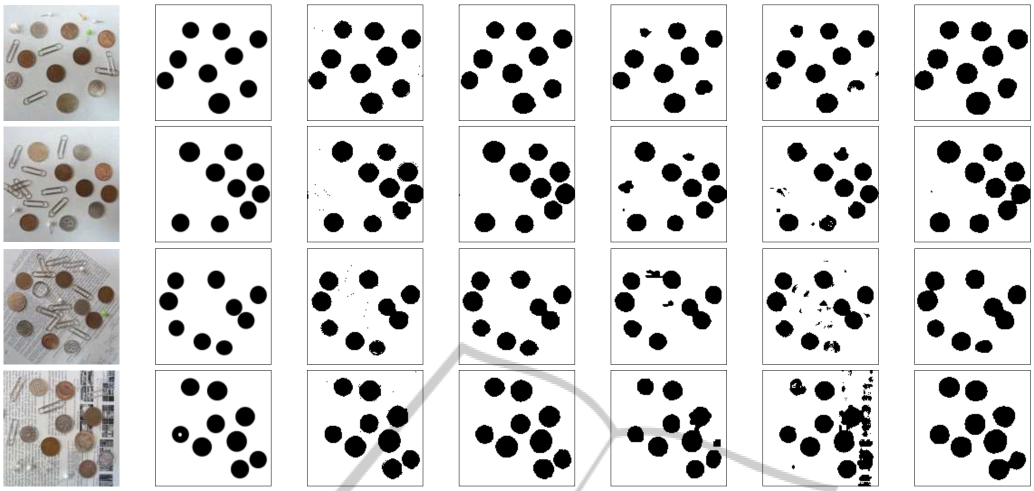
Figure 7: Training images and results of each method in crack extraction.



(a) Test images (b) Ground truth (c) C4.5 (d) SVM (e) GC (f) FORCE (g) CFORCE

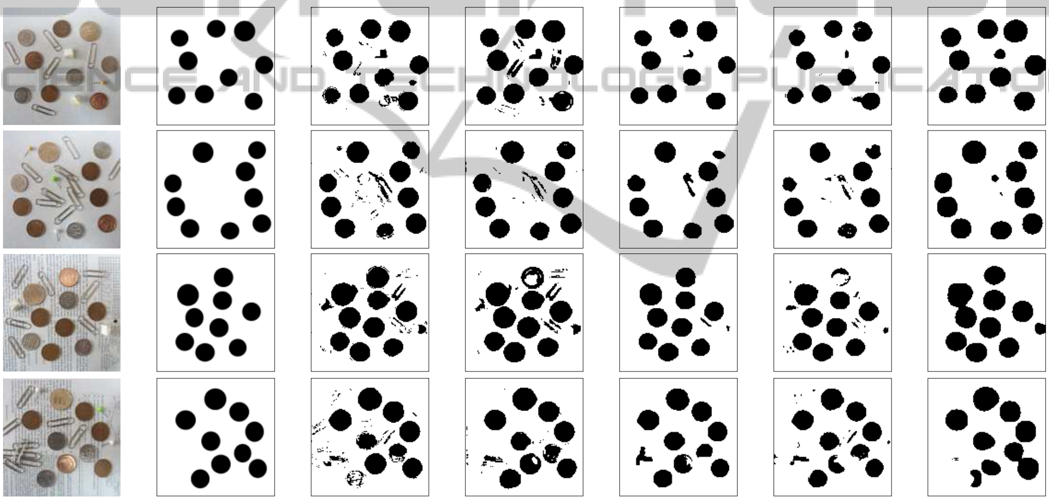
Figure 8: Test images and results of each method in crack extraction.

ple of crack extraction by the elitist rule developed by CFORCE. The brighter pixels indicate higher values in each image. We can see that each graph intensifies m^k of pixels belonging to class k gradually by considering their neighbor J values (FBs), and decreases the number of misclassified pixels which are hard to be classified by only local features. These visualized results show that iterative process with FBs worked efficiently for segmentation. Note that, in CFORCE, the number of output iteration is decided by a gene, and does not consider convergence of processing. Therefore, if output process iterates over defined times, undesirable results can occur, i.e., misclassified regions can increase. The relationship between the iteration



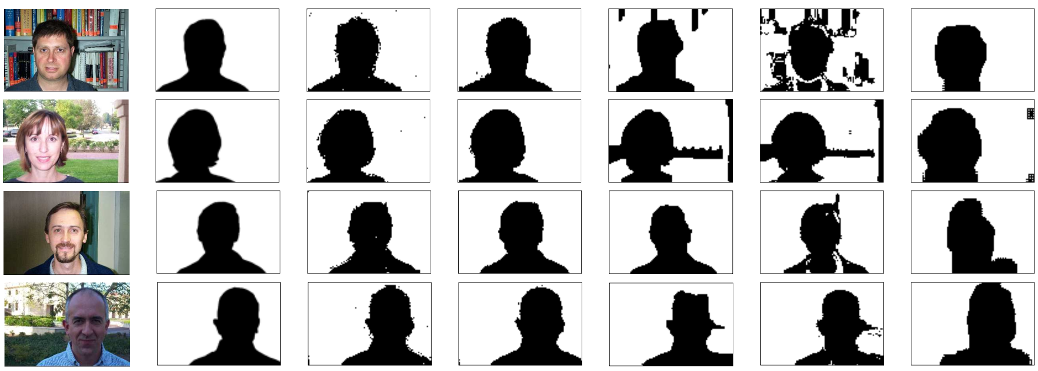
(a) Training images (b) Ground truth (c) C4.5 (d) SVM (e) GC (f) FORCE (g) CFORCE

Figure 9: Training images and results of each method in coin extraction.



(a) Test images (b) Ground truth (c) C4.5 (d) SVM (e) GC (f) FORCE (g) CFORCE

Figure 10: Test images and results of each method in coin extraction.



(a) Training images (b) Ground truth (c) C4.5 (d) SVM (e) GC (f) FORCE (g) CFORCE

Figure 11: Examples of training images and results of each method in human extraction.

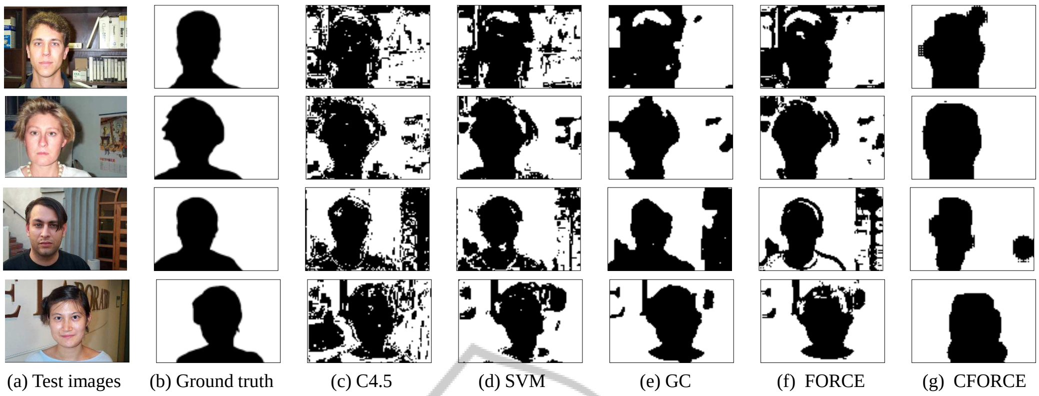


Figure 12: Examples of test images and results of each method in human extraction.

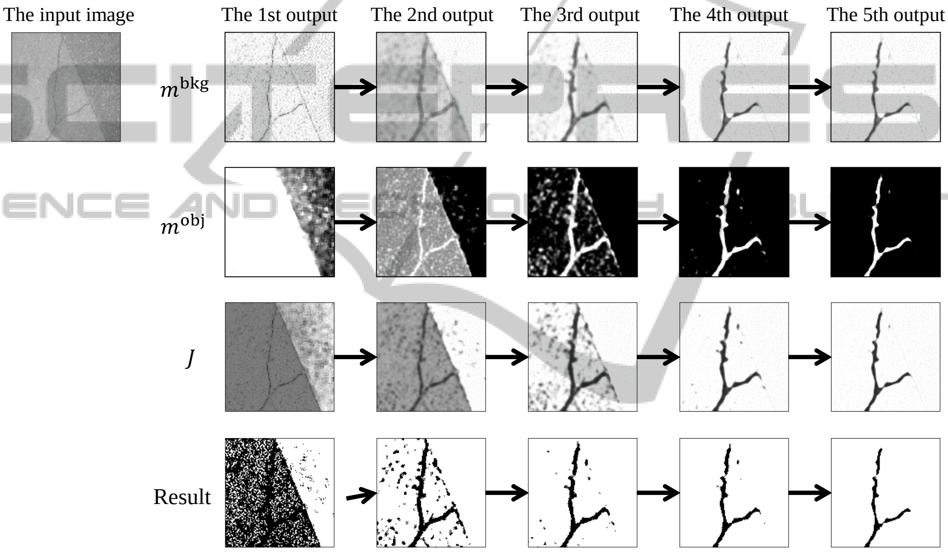


Figure 13: Example of output transition of CFORCE obtained in crack extraction.

times and convergence should be investigated in future works.

5 CONCLUSIONS

In this paper, CFORCE the novel method to construct fuzzy classification rules for image segmentation was presented. The algorithm has mainly two features: 1) designing fuzzy rules for object and background classification using FORCE which develops fuzzy rules represented as directed graphs automatically by GA, and 2) performing iterative segmentation with considering spatial relationship between pixels. In natural image segmentation, many pixels are overlapped between different clusters. Therefore, considering the spatial relationship besides local features is important to classify the overlapped pixels correctly. The proposed model constructs fuzzy classification rules in which spatial features considering the spatial relationship are incorporated, and extracts object region by the rules in iterative process even if the clusters of pixels are overlapped. The experimental results showed that CFORCE constructed fuzzy rules for three different image segmentation successfully.

In this work, the number of output iteration was decided by a gene, and it did not relate to convergence of segmentation process. Investigating relationship between the iteration times and convergence is one of our future works. Additionally, we also plan to extend the model to multi-class segmentation.

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