Scene analysis system using a combined fuzzy logic-based technique

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ABSTRACT

This paper proposes a two-stage scene analysis scheme using a combined fuzzy logic-based technique. The first stage begins with generating fuzzy rules to describe the scene. Based on these fuzzy classification rules, each image pixel is inferred and then classified to the natural object category with the largest membership degree. The second stage involves a newly derived fuzzy K-nearest neighbor algorithm that further refines the classification result obtained. With this second stage, the proposed system is robust because it is demonstrated to be insensitive to the variations of membership functions and image noise contamination. Simulations of real world images have shown that the proposed scheme is very successful and the results are visually confirmed by human observation. The satisfactory results achieved in this paper suggest the feasibility of developing similar systems for other types of images aiming at image description problems.

I. INTRODUCTION

Image analysis is an obvious issue in computer vision research. Images are regarded as an essential variety of information media since they are the most common and rich type of information around us. The paradigm of image analysis has been utilized in various fields, including robot vision, medical diagnosis, geographical surveying and planning, aerial/satellite image understanding, (Binford, 1982; Matsuyama and Hwang, 1990; Rosenfeld, 1999) and many others. Nevertheless, interpreting and understanding a natural scene by machine automatically is still one of the most difficult fields for scientists as described below: First, in the real world, there are many natural objects existing in various classes of natural scenes. Second, natural objects viewed under realistic conditions do not have uniform shapes which can be matched against stored prototypes, and their local surface properties are too variable to be uniquely determined. Third, a natural scene may produce completely different data under different situations, for example, the time of day, the season, and the environment. Consequently, exploiting a single paradigm, such as computer vision-based (Kodratoff and Moscatelli, 1994; Yamamoto, 1995; Noronha and Nevatia, 2001), statistics-based (Kumar and Desai, 1999; Modestino and Zhang, 1992), or artificial intelligence-based (Mckeown Jr. and Harvey Jr., 1985; Strat and Fischler, 1991; Huertas *et al.*, 2000), in such a complex task of image interpretation and description is very difficult. The results for these valuable attempts are in general not satisfactory and the working algorithmic programs are very large and complex.

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Indeed, they are almost unmanageable and uncontainable.

On the other hand, observe that humans can understand a scene with little difficulty, no matter in what situation we are. When we look at an image, some information enters our brain and it is easy for us to recognize and describe what the image contains. This is because that there exists a powerful knowledge base in our brain. It is well understood that human perception and thinking adopt more or less a set of linguistically descriptive percepts because human reasoning and decision-making are approximate and based on a large database and high level scale of abstraction. Linguistic knowledge is usually given in fuzzy terms not only because they are the most common form in the representation of human knowledge but also because our knowledge about many aspects is fuzzy. Keeping this observation in mind, this paper introduces a fuzzy logic-based algorithm that can embrace human-like intelligence in analyzing an image as we humans do. The considerable amount of knowledge, often stated in linguistic form, needed to characterize or describe image regions semantically can also be efficiently encoded by the forms of fuzzy rules. As described previously, uncertainty and imprecision abound in a scene analysis problem. Such uncertainty and imprecision, existing in the image analysis problem, also suggest fuzzy logic should be a natural and effective paradigm to be exploited because fuzzy set has flexible representation ability in describing the uncertainty, vagueness, and imprecision, and also is an intuitively easy thinking process.

Works related to the use of fuzzy logic in image analysis have been found in the literature (Demko and Zahzah, 1995; Fathi *et al.*, 1998; Masui *et al.*, 1994; Miyajima and Ralescu, 1993; Nakagawa and Hirota, 1995; Terano *et al.*, 1993; Zhang and Sugeno, 1993). Some have tried a general methodology while others describe a particular application. These works remain scattered and a consensus has not yet been reached in these approaches because a general scheme of image analysis or scene understanding has been considered as very difficult.

In this study, we develop a general scene description system which can interpret not only clean images but also images contaminated with noise and/or disturbance. However, the complexity of the real world and the finite size of most knowledge bases pose significant difficulty if using only one paradigm for such a difficult task in image analysis. The use of just a single technique alone, in general, cannot produce a satisfactory result applied to a fairly complex problem in image analysis. A solution to this problem is using multiple paradigms. The use of multiple modalities is receiving increased attention

(Yasdi, 1995) as a means of overcoming some of the limitations imposed by using only one technique. A judicious integration of several different techniques for this specific application may produce advantageous results in addition to the generic merit of each paradigm.

Adherent to this concept, we propose a two-stage scene analysis system which integrates two fuzzy classification algorithms systematically. The present system interprets a scene by classifying pixels in gray-scaled images to several classes of natural objects. Each class represents a particular type of natural object, which is known *a priori*. The first stage of the proposed scene analysis system introduces a fuzzy rule-based system for pixel classification. In this fuzzy rule-based classifier, several fuzzy sets are defined to characterize the features of the image, and then fuzzy rule-based inference is facilitated to classify the image. In the next stage, we present a modified fuzzy K-nearest neighbor (fuzzy K-NN) algorithm to refine the result obtained. Owing to the fact that membership Functions are defined subjectively by humans, the result obtained after the first stage may not be objective. The degradation of classification caused by defining membership functions subjectively and/or the noise existing in the input image is greatly reduced via the proposed fuzzy K-NN scheme of the second stage. As a result, erroneously classified pixels in the first stage can be corrected to the right labels in the second stage, and the system performance should be much more reliable and less noise sensitive.

The rest of this paper is organized as follows. The overall scene analysis system is described in Sec. II. First, fuzzy sets and rules used for characterizing image pixels are defined by human observation and human knowledge. Then, fuzzy inference on these extracted rules classifies the image pixels into an appropriate category of natural element. In the second stage, a new and simple fuzzy K-NN algorithm is derived to further refine the result obtained. In Sec. III, computer simulations of real world images are conducted. Comparisons are also made with different kind of input images, membership functions, and different fuzzy K-NN schemes. The paper is summarized and concluded in the last section.

II. A TWO-STAGE SCENE ANALYSIS SCHEME

Before describing the details of our algorithm, a two-stage scene analysis scheme is outlined. Our main concept is to label image pixels into categories containing the same natural elements in the first stage and then refine the labeling classification in the second stage. The first stage involves a fuzzy rule-based

system and the second stage makes use of a newly derived fuzzy K-NN algorithm.

1. The First Stage – a Fuzzy Rule-Based System

In this section, the proposed rule-based system classifies image pixels by a set of fuzzy rules defined according to some intrinsic features of the image. The main modules developed in this stage will be discussed as follows.

(i) Feature Extraction

In order to classify the input images into different classes of natural objects, we have to extract distinct and efficient features defined as fuzzy linguistic variables useful for labeling classification. To this end, three intrinsic features, which are rather descriptive for most outdoor scenes and can also be easily extracted from the image, are chosen. These three features include (1) Gray Value (GV); (2) Vertical Position (VP); and (3) Local Standard Deviation (LSD) of a pixel, and they will be described in detail in the following.

(ii) Fuzzy Rules to Represent a Scene

To treat the frequent ambiguity and vagueness present during image analysis activities, this module employs a set of fuzzy rules to encode the domain knowledge so that they not only can interpret the image scene but also can take the inherent uncertainty and ambiguity of the image into account. Our proposed fuzzy frame structure is characterized by linguistic knowledge related to the context of images under the form of fuzzy rules. In this setting, the membership functions of the following three linguistic variables, (1) gray value; (2) vertical position; and (3) local standard deviation, are introduced to characterize the three intrinsic features we have chosen. The reference base line of the vertical position was set at the bottom of an image. We used a window mask to calculate the local standard deviation of the central pixel in the window.

In an attempt to mimic human thinking, a fuzzy rule-based knowledge for scene analysis will then be defined. For convenience, an example is used to illustrate how we established the fuzzy rules to describe a scene.

We tried to classify a given image, Fig. 1 for example, into three classes of natural elements: SKY, TREE, and ROAD (which are assumed to be known *a priori*). The qualitative and quantitative knowledge existing among these natural elements of the image are utilized to construct the linguistic rules. We can see from Fig. 1 that the SKY is bright and lies in the

Fig. 1 A source image for analysis

upper part of the image. The TREE is dark and lies in the middle of the image, while the ROAD is gray and occupies the bottom of the image. It can also be observed that the local standard deviation of the TREE is the largest; that of the ROAD is medium, and that of the SKY is the smallest. Consequently, the following three fuzzy rules to encrypt the commonsense knowledge above can be constructed, as given by

Rule 1. IF the gray value is *large* and the vertical position is *high* and the local standard deviation *small*, THEN the pixel is SKY.

Rule 2. IF the gray value is small and the vertical position is *medium* and the local standard deviation is *large*, THEN the pixel is TREE.

Rule 3. IF the gray value is *medium* and the vertical position is *low* and the local standard deviation is *medium*, THEN the pixel is ROAD.

In the rules constructed above, three linguistic values were used for each feature chosen. In this study, trapezoid membership functions were utilized for all the linguistic values involved. Here, a rule of thumb for roughly defining the trapezoid membership functions is given. First, the support of the membership function is determined from the dynamic range of the target feature. Second, the range of the kernel (the interval set with full membership degree) inside the support mostly starts around 25% and ends around 75% of the support interval, but is also adjustable by human experience. Based on these guidelines, the membership functions can be easily chosen by intuition and experience. It is to be noted that our image analysis results are rather robust in defining the membership functions as will be shown in Sec. 3 later. The flexible and intuitive way of defining the necessary membership functions further manifests the simplicity in the design of our proposed image analysis system.

(iii) Fuzzy Rule Inference and Decision Making

To calculate the membership degrees of these

fuzzy rules, we propose the commonly used minimum operator for connective "and." Then, for every pixel x in the image, we have

$$\mu_{SKY}(x)=\min(\mu_{large}(GV), \mu_{high}(VP), \mu_{small}(LSD))$$

$$\mu_{TREE}(x)=\min(\mu_{small}(GV), \mu_{medium}(VP)$$

$$\mu_{large}(LSD))$$

$$\mu_{ROAD}(x)=\min(\mu_{medium}(GV), \mu_{low}(VP)$$

$$\mu_{medium}(LSD)) \tag{1}$$

Finally, after these membership values are computed, the pixel can be classified into the category that produces the maximal membership degree. Namely,

IF $\mu_C=\max(\mu_{SKY}(x), \mu_{TREE}(x), \mu_{ROAD}(x))$

THEN x belongs to class c $\tag{2}$

Following such a max-min inference strategy, we assigned each pixel of the image into the natural element that assumes the highest membership degree among all the classes to be differentiated.

2. The Second Stage - a Fuzzy *K*-Nearest Neighbor Classifier

Owing to the membership functions being defined subjectively by human definition and some other variations being involved, such as inevitable noise and errors, the pixel classification obtained in the first stage may not be objective and reliable enough for visual satisfaction among humans, although fuzzy set theory is a powerful tool in dealing with ambiguity found in the data. In what follows, we propose the second processing stage that aims at reducing the subjectivity effect and coping with contradictions, inconsistencies, and variations that may be present after the first stage of image analysis. In this second processing stage, the fuzzy *K*-nearest neighbor concept (Keller *et al.*, 1985; Kim and Han, 1995) is exploited to correct all the pixels undermined in the first stage because the distribution of the pixels of deceptive and non-deceptive classes was not known beforehand. Before describing the detailed algorithmic architecture of our fuzzy *K*-NN, we recall the *K*-NN approach first. In the traditional *K*-NN approach, the *K*-nearest neighbors of a new sample are selected from the mixture of classes. The new sample x_p is then classified to the class that is represented by a majority amongst the *K*-nearest neighbors. In this regard, the traditional *K*-NN rule proceeds as follows:

$$k_j=\max(k_1, k_2, ..., k_L) \quad x_p \in \Gamma_j \tag{3}$$

where $k_1+k_2+...+k_L=K$, Γ_j is the set of samples in class j, and k_j is the number of *K*-nearest neighbors that belong to Γ_j, $j=1, 2, ..., L$.

Using more than one neighbor for classification and giving each neighbor the same weight in influencing decisions, there can be a tie among classes with the same maximum number of samples amongst the *K*-nearest neighbors. The fuzzy *K*-NN algorithm was proposed to provide more suitable differentiation and can usually solve tie problems by using fuzzy set theory. Rather than assigning the input sample to a particular class in a conventional way, in the fuzzy *K*-NN algorithm, an input sample is associated with each class having a different class membership degree. Consequently, each input sample could be considered to belong to any one class to some degree, which for instance can be *very likely*, *likely*, and *unlikely*. Equivalently, an input sample is not definitely ascribed to a particular class, it rather belongs to each class with a certain degree of confidence. In this paper, encrypting this human-like idea of a fuzzy *K*-nearest neighbor routine results in a new fuzzy *K*-NN version, called the modified fuzzy *K*-NN classifier. The first step of the modified fuzzy *K*-NN is to choose the *K*-nearest neighbors. Second, every sample in these *K* selected samples is assigned a membership grade according to its distance from the input sample. Finally, among these *K*-nearest neighbors, the input sample is ascribed to the class that accumulates the maximal membership degree of belongingness. Based on the description above, the modified fuzzy *K*-NN algorithm for the image analysis problem can be stated as follows.

(i) The Modified Fuzzy K-NN Algorithm

As noted in the first stage, each image pixel has been classified to a particular class of natural objects by the inference of scene knowledge and we assume that there are L classes being labeled to each pixel of the image data. The proposed modified fuzzy *K*-nearest neighbor algorithm, which constitutes the second processing stage of the image description, is illustrated below.

Step 1: *K*-nearest neighbors selection.

Image data can be regarded as a matrix form and all the pixels are uniformly displayed vertically and horizontally. Due to such a uniform 2-D array data structure of an image, a fast and convenient *K*-nearest neighbors selection method, based on distance information, is proposed. A window mask of size $n \times n$ (n is an odd number), centered around an input pixel, is used to define the *K*-nearest neighbors of the pixel. Hence, value K is equal to the number of pixels inside the window, n^2, including the input pixel itself.

Step 2: Class membership assignment.

After the K-nearest neighbors are selected by the associated window mask, the membership degrees of belongingness of these K-nearest neighbors will be given. Let S_m, $0 \le m \le (n-1)/2$ be the set of pixels in the window different from the input pixel x_p by m, the larger one either different from the abscissa or ordinate, pixels. For simplicity, we called S_m the mth layer of the window centered at input pixel x_p. For a labeled sample $x \in S_m$ (say x in class l) of the K-nearest neighbors, the membership degree of belonging to class j, μ_j is assigned according to the following equation:

$$\mu_j(x \in S_m) = \begin{cases} 1 - \dfrac{2m}{n+1}, & \text{if } j = l \\ 0, & \text{if } j \ne l \end{cases} \qquad (4)$$

Equation (4) attempts to fuzzify the memberships of the labeled samples based on their distances, in terms of layers, from the central input pixel. In this way, each labeled pixel in the same layer will be assigned by the same membership degree belonging to its known class and zero in all other classes. The labeled samples in a farther layer from the central input pixel are given by a smaller membership degree of their own classes. As a consequence, the central pixel will be less affected by the pixels in the farther layer, and vice versa. It is to be remarked that our modified K-NN algorithm shares the same spirit as the fuzzy K-NN algorithm (Keller *et al.*, 1985), but the assigned membership functions are influenced according to the simple equation of Eq. (4), rather than the inverse of the Euclidean distances of conventional fuzzy K-NN.

Step 3: Reclassification

After all neighbors of input x_p are assigned, the class membership values of Eq. (4), to which class the input sample belongs, becomes evident. Let Ω_j denote the cumulative membership degree of μ_j for all the K neighbors. That is,

$$\Omega_j = \sum_{x \in S_m} \mu_j(x), \ j = 1, 2, ..., L, \ 0 \le m \le \frac{n-1}{2} \qquad (5)$$

Finally, the input pixel x_p is categorized to the class with the largest Ω_l. Namely,

$$\Omega_l = \max(\Omega_1, ..., \Omega_L) \Rightarrow x_p \in \Gamma_l \qquad (6)$$

III. SIMULATION AND RESULTS

In this section, we illustrate our proposed

algorithm by analyzing several outdoor scene images. The images considered are monochromatic and of size 128×128. In order to confirm the validity of the proposed algorithm, we present the following two simulations. In the first simulation, an outdoor scene image was used. We conducted experiments on the following two different parameter selections: (1) different membership function selections in the first stage and (2) different K selections in the second stage of the proposed system. Moreover, randomly generated noises were added to the outdoor scene image to test the noise tolerance capability of the image analysis system. Regarding the effect of the second stage on the proposed system, a comparison between our modified fuzzy K-NN algorithm and other fuzzy K-NN algorithms (Keller *et al.*, 1985) was also made. In the second simulation, two different images taken from the campus of Chiao Tung University were analyzed to test the generality and consistency of the proposed scene analysis system.

1. Simulation 1

Example 1:

In this example, an outdoor image, as shown in Fig. 1, was analyzed. For this image, the following three label regions, SKY, TREE, and ROAD, would be recognized. According to the procedure in Sec. II-1, we defined several membership functions of linguistic labels used for the *a priori* knowledge base. As shown in Fig. 2, trapezoidal functions are used for the membership functions involving gray value, vertical position, and local standard deviation. The *a priori* knowledge of this scene justifies three fuzzy IF-THEN rules that have been stated in Sec. II.1.2. The resultant image after the rule inference is shown in Fig. 3.

In the second stage, we selected different values of K, i.e., n^2, to optimize the classifier performance. The results after several selections of K are shown in Fig. 4. The CPU processing time running on a PIII-600 for K=9,25,49 and 81 are 8.9, 18.6, 33.2, and 56.3 sec., respectively. The largest K, 81, produces the best result (visually) but requires the longest CPU processing time, as should be anticipated.

Example 2:

The purpose of this example was to test how sensitive the system is when the shapes of involving membership functions are changed. In this example, we used another set of membership functions, Fig. 5, for defining the rule base of the first stage. Figs. 6(a) and 6(b) display the first stage and final results, respectively. These results reveal that the proposed first stage is rather insensitive to subjective variations
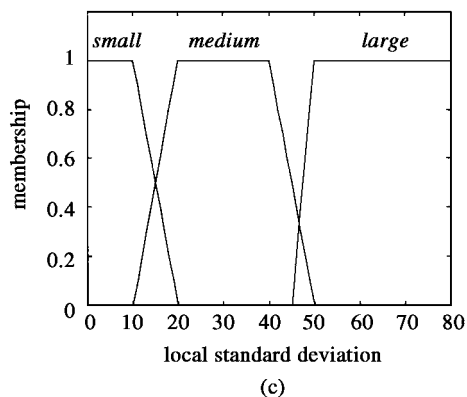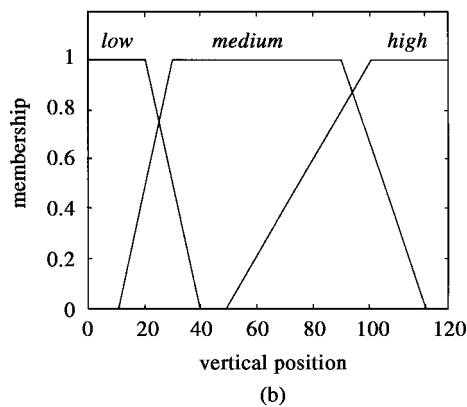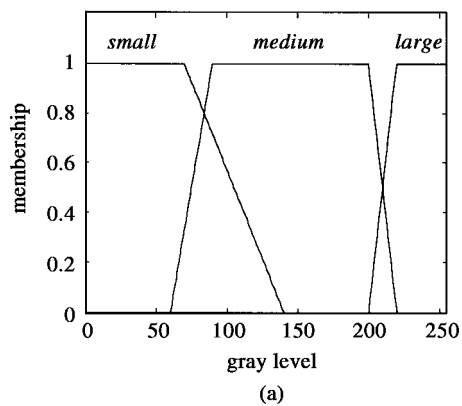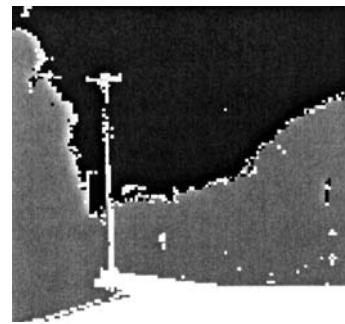
Fig. 3 The resultant image after the first stage

Fig. 2 The membership functions for Fig. 1

Fig. 4 The resultant images after the second stage for (a) K=9; (b) K=25; (c) K=49; (d) K=81

in defining membership functions of fuzzy sets utilized in the fuzzy rules. After the second stage with K=81, the final result is also quite successful visually.

Example 3:

During the courses of storage, transmission, and retrieval, an image source may be inevitably corrupted by noise and induced by computational errors. Hence, the noise tolerance capability of a scene analysis system is also very important. In this example, random noise was added to the images to

test the noise immunity of the proposed model. The noise corrupted outdoor images are shown in Fig. 7 at several signal-to-noise ratio (SNR) levels, defined in the mean-square sense. We selected K to be 81 and used the same membership functions shown in Fig. 2. Fig. 8 shows the result after the first stage and Fig. 9 displays the final resultant image. From these figures, our proposed scene analysis system produced consistent and stable results regardless of whether the noise level was high or low. Hence, it can be concluded that the proposed system is very noise tolerant.

Next, the effectiveness of the noise tolerance capability achieved in the second stage via our modified fuzzy K-NN algorithm (second stage) or the conventional fuzzy K-NN algorithm (Keller *et al.*, 1985) will be compared. In the conventional fuzzy K-NN algorithm, two methods of membership assignment

(a)

Fig. 6   (a) The resultant image after the first stage of Example 2;
(b) The final resultant image of Example 2

(b)
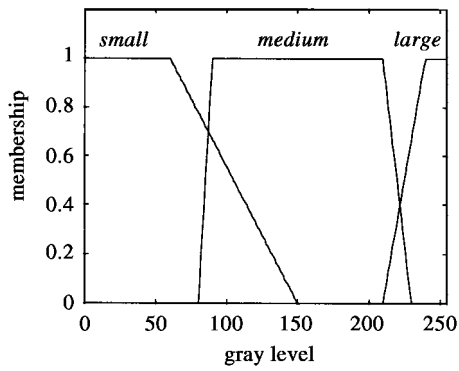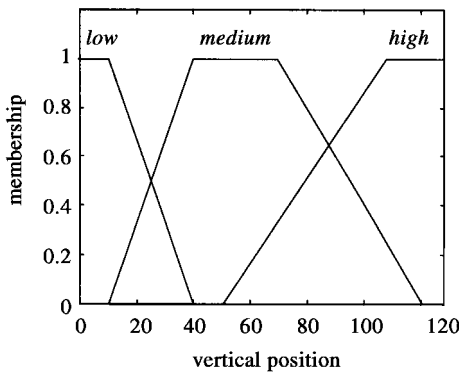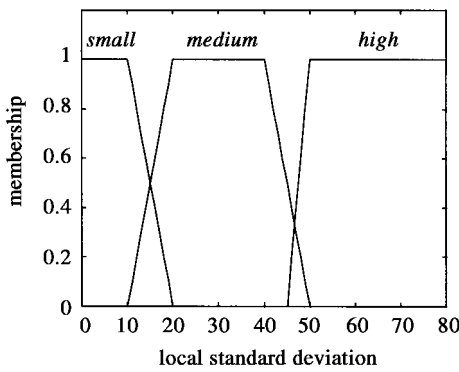
Fig. 5 Other membership functions for Fig. 1
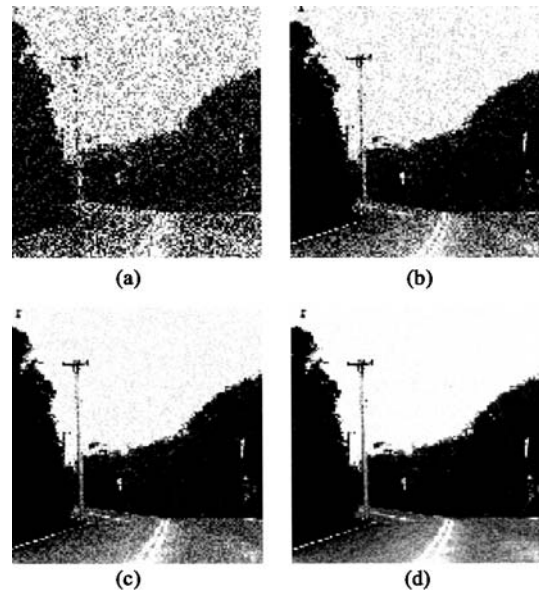
Fig. 7   The noise images with different SNRs, (a) 5dB; (b) 10dB;
(c) 15dB; (d) 20dB

for the labeled neighbors are considered. The first technique assigns each labeled sample complete membership in its known class and zero membership in all other classes (Keller *et al.*, 1985). This type of fuzzy K-NN is referred to as "fuzzy K-NN with crisp initialization" in this comparison. The second technique assigns memberships to the labeled samples according to an additional K-nearest neighbor rule (Keller *et al.*, 1985). For a labeled sample x (say x in class l) in the K-nearest neighbors, the membership of x in each class is assigned according to the following equation
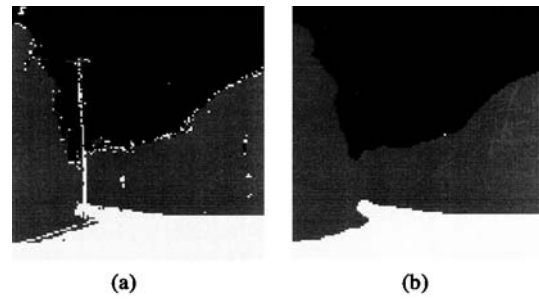

Fig. 8 The resultant images of Fig. 7 after the first stage

Fig. 9 The final resultant images of Fig. 7
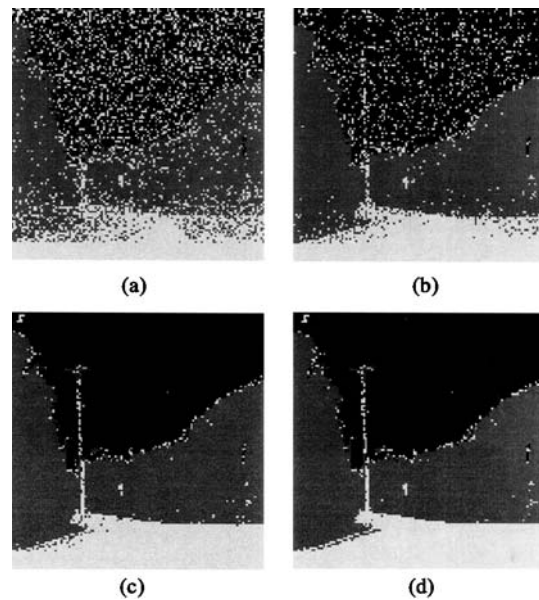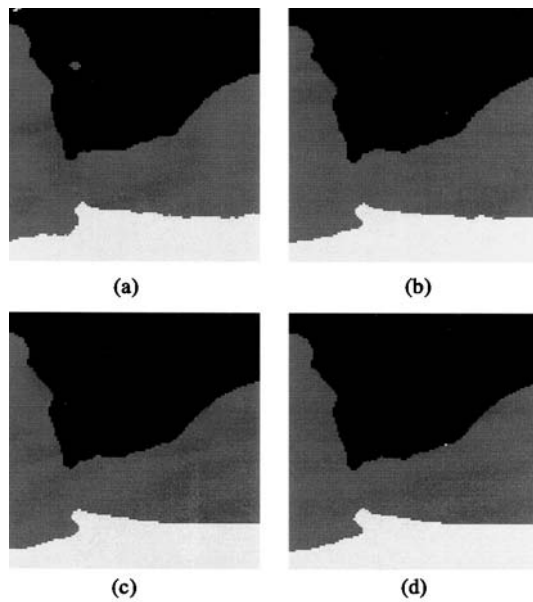
$$\mu_j(x) = \begin{cases} 0.51 + \dfrac{n_j}{K} \times 0.49, & \text{if } j = l \\[2mm] \dfrac{n_j}{K} \times 0.49, & \text{if } j \neq l \end{cases} \quad (7)$$

where value n_j is the number of the K-nearest neighbors that belong to the jth class. This type of fuzzy K-NN algorithm is named "fuzzy K-NN with fuzzy initialization" hereafter.

The noise tolerance capability comparison of these three methods started with adding random noise to Fig. 1 at different SNRs. Four SNR levels, 5; 10; 15; and 20 dB, were simulated. At each SNR level, 50 noisy images were generated and then tested. All the noisy images were inferred (first stage) by the rules stated in Sec. II-1-ii with membership functions shown in Fig. 2. After the first stage, the resultant images were tested by three fuzzy K-NN algorithms, i.e., our modified fuzzy K-NN, fuzzy K-NN with crisp initialization, and fuzzy K-NN with fuzzy initialization. In this test, parameter K for these three algorithms is set to 81.

By these three fuzzy K-NN techniques, the results are presented in Table 1. Under the same criterion of manually assigning each image pixel to a best-matched natural object, the numbers of the average wrongly classified pixels over 50 images, for these three methods, were calculated. Upon comparison of the results obtained from these four levels of SNR, we see from Table 1 that the noise tolerance capability of the fuzzy K-NN with crisp initialization is weak since its wrongly classified pixels on the average are significantly higher than the other two techniques. Table 1 also reveals that our method produced lower

Table 1 Classification accyracy comparison of three fuzzy K-NN algorithms

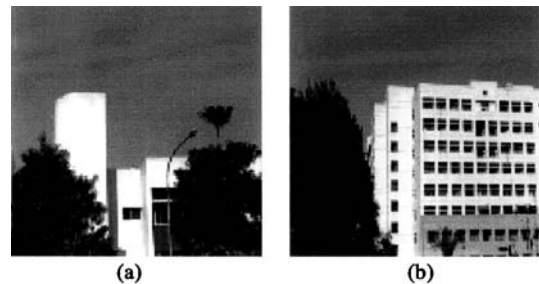| SNR	Modified fuzzy K-NN	Fuzzy K-NN with fuzzy initialization	Fuzzy K-NN with crisp initialization
5dB	14.6	33.6	113.3
10dB	2.4	8.5	38.4
15dB	0.8	2.5	33.4
20dB	0.6	2.1	26.4

Fig. 10 The test images

average wrongly classified pixels than the fuzzy K-NN with fuzzy initialization at different levels of SNR. In addition, when the amount of contamination noise is not large (SNR=15 or 20 dB), the average wrongly classified pixels produced by our method is less than one pixel. From this comparison, we found that the noise immunity gained in the second stage of our modified fuzzy K-NN algorithm outperforms the other two fuzzy K-NN techniques.

2. Simulation 2

For this simulation, two different outdoor images, Figs. 10(a) and 10(b), taken from the campus of Chiao Tung University were used to test the generality and consistency of the proposed system. As in the previous simulation, three image features, gray value, vertical position, and local standard deviation, were considered. The following three regions, SKY, BUILDING, and TREE, have to be segmented for scene interpretation.

Linguistic knowledge, which complies with human linguistic practice, employed to semantically label the characteristics of these two images is encoded as three fuzzy if-then rules below:

Rule 1. IF the gray value is medium and the vertical position is high and the local standard deviation is *small*, THEN the pixel is SKY.
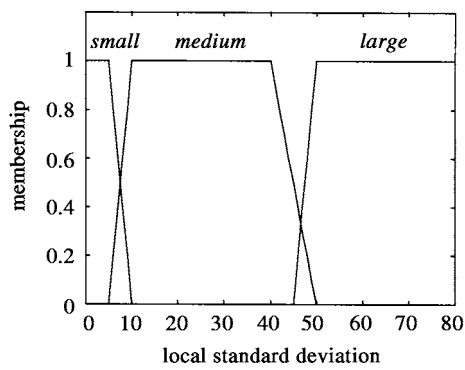
Rule 2. IF the gray value is large and the vertical position is *medium* and the local standard deviation is *medium*, THEN the pixel is
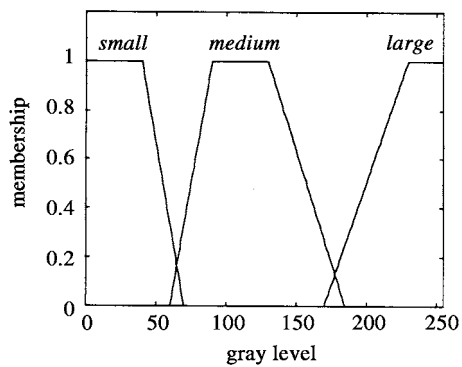
(a)
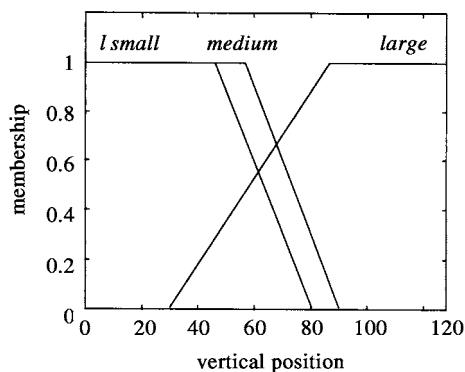
(b)

(c)

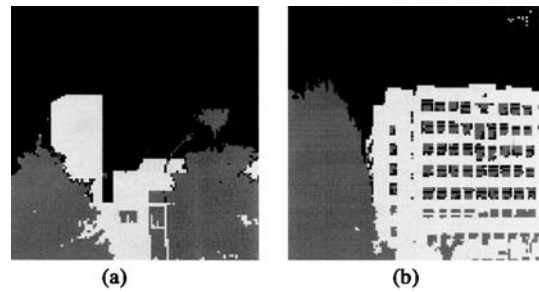Fig. 11 The membership functions for Fig. 10

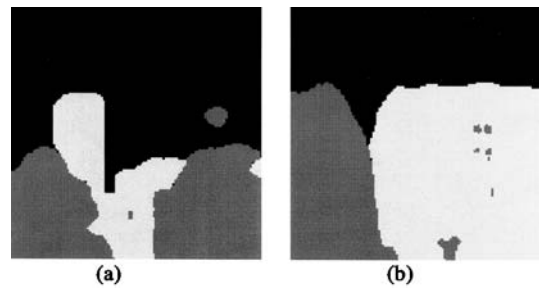Fig. 12 The resultant images after the first stage of Fig. 10

Fig. 13 The final resultant images of Fig. 10

images. These results reveal again that our system is quite flexible in choosing the membership functions used in the fuzzy rules. In Fig. 13, the output images have been semantically labeled very well, the same way as we humans do.

IV. CONCLUSION

In this paper, we have developed a two-stage scene analysis system which integrates two different fuzzy paradigms. Fuzzy logic has been shown to contribute significantly to the field of image processing, especially in scene analysis because scene understanding and interpretation involve human-like intelligent information processes. The fuzzy if-then rules needed in the first stage can be easily extracted from human commonsense knowledge that describes the task image. As demonstrated in the examples, the fuzzy rules needed for the image description are very simple and the way of choosing the membership functions defined for linguistic variables has also been shown to be rather robust to their differences in selection. A new and efficient fuzzy K-NN algorithm for relabeling the image pixels is presented in the second stage. It outperforms, in pixel classification accuracy, the other two fuzzy K-NN algorithms in the literature. Aside from its effectiveness in the image description shown, the proposed fuzzy K-NN scheme could also be very useful in refining image segmentation, region analysis, and noise removal. Integrating these two techniques leads the proposed scene

BUILDING.

Rule 3. IF the gray value is *small* and the vertical position is *low* and the local standard deviation is *large*, THEN the pixel is TREE.

The trapezoidal membership functions needed to define the fuzzy sets used in fuzzy rules for the images are shown in Fig. 11 and they were applied to both images. Figs. 12 and 13 show the first stage and the final segmented image, respectively. Fig. 12 demonstrates that the proposed first stage procedure produced very successful results by using the same rules and membership functions to test different

analysis system to have the benefits of both techniques. The proposed system can be generalized to analyze different task images by merely changing the commonsense knowledge base existing in the image to be processed.

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NOMENCLATURE

Γ_j the set of samples in class j
k_j the number of K-nearest neighbors that belong to Γ_j
S_m the mth layer of the working window centered at input x_p
$\mu_j(x)$ the membership function of belonging to class j for sample x

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利用整合性模糊邏輯技術於景物分析系統

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摘　要

　　本論文提出一個利用整合性模糊邏輯技術之兩級式景物影像的分析方法。第一級爲以模糊規則描述景物影像，根據模糊法則推論，影像的每一個像素被初步分類成有最大歸屬值之自然物。第二級提出一新型模糊 *K* 最近點分類法（fuzzy *K*-nearest neighbor classifier），進一步精確調整第一級分類的結果。由於有加入第二級分類法，此景物影像分析方法對歸屬函數（membership function）的變動或影像雜訊的干擾，相當不敏感而顯示其強健性。最後，經由對一些眞實影像的模擬，其結果可證明我們所提出的模糊分類法分析景物的效果。本篇成功的研究成果可容易地推展應用於其他影像的分析與描述。

關鍵詞：景物分析，自然物分類，模糊法則影像分析，模糊*K*最近點分類法。