On Fuzzy Rule-Based Algorithms for Image Segmentation using Gray-Level Histogram Analysis

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Abstract

One of the biggest problems in computer vision systems, analyzing images having high uncertainty/vagueness degree, is the treatment of such uncertainty. This problem is even clearest in the segmentation process. Fuzzy set theory and fuzzy logic are ideally suited for dealing with such uncertainty.
This work extends our earlier and on-going work in automated image labeled segmentation, modeled following expert's knowledge. This knowledge is represented by means of a fuzzy rule-base, wherein the membership functions associated to the labels are defined based on the analysis of the gray-value's histogram of the pixels of the training images.
The proposed system has been evaluated on two very different real data sets.

Keywords: Computer vision; Image segmentation; Membership function generation; Fuzzy rule-based system; Knowledge-based.

1 Introduction

Although fuzzy methods are not a solution to all problems, they are useful in situations in which the concepts (features, criteria, or rules) are vague. This is often the situation in computer vision.

There is uncertainty in many aspects of image processing and computer vision. Visual patterns are inherently ambiguous, image features are corrupted and distorted by the acquisition process, object definitions are not always crisp. Moreover, knowledge about the objects in the scene can be described only in vague terms, and the outputs of low level processes provide vague, conflicting, or erroneous inputs to higher level algorithms. Fuzzy set theory and fuzzy logic are ideally suited for dealing with such uncertainty [2] and [1].

In this work we consider the use of fuzzy set theoretic decision-making models and algorithms within the computer vision framework, particularly we consider problems in segmentation and object recognition.

Considering the task of segmenting an image into object regions, it is known that object boundaries and surfaces need to be described in compact terms for further processing. However, object boundaries are often blurred and distorted due to the imaging process. Moreover, in some cases, object boundaries are truly fuzzy. An alternative approach is to preserve the uncertainty inherent in the image as long as possible, until actual decisions have to be made. In this approach, each object in the image is treated as a fuzzy region represented by a fuzzy set. Such an approach would be consistent with Marr's (1982) *principle of least commitment.*

2 Fuzzy Rule-Based Algorithms for integrating expert's knowledge

When performing image understanding, we need to represent properties and attributes of image regions and spatial relations among regions. Fuzzy rule-based systems are ideally suited for this purpose. For example, a usual rule in a rule-based scene understanding system, could be:

IF *brightness* of a pixel is *high*
AND the *granularity* within a 3x3 window, centered in the pixel, is *medium* (1)
THEN the pixel belongs to · · ·

Terms as brightness, high, granularity and medium are intrinsically vague. Fuzzy set theory provides a natural mechanism to represent such vagueness effectively. Flexibility and power provided by fuzzy set theory for knowledge representation makes fuzzy rule-based systems very attractive, when compared with traditional rule-based systems. Furthermore, rule-based approaches must address the problem of conflict resolution when the preconditions for several (partially) conflicting rules are simultaneously satisfied. There are sophisticated control strategies to solve this problem in traditional systems. In contrast, with fuzzy rule-based classifier systems, problems such as these are attacked by manipulating certainty factors and/or firing strengths to combine the rules.

Going back to the segmentation problem, it is known that, in a segmented image, ideally each region should be homogeneous with respect to some characteristics or features such as gray level or texture, and adjacent regions should have significantly different characteristics or features [4].

However, if the features used to determine homogeneity don't have sharp transitions at region boundaries, won't be easy to determine if a pixel should belong to a region or not, as when features are computed using, say, a local 3x3 or 5x5 · · · window. To alleviate this situation we can insert fuzzy set concepts into the segmentation process.

In 1970, Prewitt already suggested that the results of image segmentation should be fuzzy subsets rather than crisp subsets of the image plane. In this sense, within a fuzzy segmentation, each pixel is assigned a membership value in each of the regions. If the memberships are taken into account while computing properties of regions, we often obtain more accurate estimates of region properties.

So, it can be deduced that determining appropriate membership functions is one of the fundamental issues to apply fuzzy set theory within image segmentation and understanding.

In computer vision applications, membership functions are not always subjective evaluations of vague concepts, but rather a means to model the uncertainty contained in the input information such as images and/or features extracted from images. Therefore, to get appropriate methods for membership function generations it is important that they formalize expert's knowledge and its uncertainty.

3 Proposed Algorithm

This work extends our earlier and on-going work in automated image labeled segmentation, modeled following expert's knowledge, wherein methods which incorporate the uncertainty of object and region definition, and the faithfulness of the features to represent various objects, are considered in the sense of Pal [2], and Bezdek and Sutton [1].

The type of algorithm we present is defined based on the descriptions of perceptual features of the objects to be segmented. Moreover, to retain as much vagueness as possible, these algorithms take benefit of fuzzy techniques modeled by the data of a set of training images. Because of within unseen images objects can appear sufficiently different from those in the training data, rules that attempt to capture human expertise are used to gain low-level segmentation. The fuzzy sets associated to the labels of the brightness' perceptual feature of the objects appearing at the images are defined based on the segmentation of the relevant peaks of the gray level histogram. Furthermore, Fuzzy Morphological Structural Elements (FMSE) are introduced to be used in image segmentation based on pixel classification, with the aim to reduce uncertainty problems and reduce pixel misclassification, providing accurate boundaries among different regions.

This algorithm is applied to images wherein the main, and almost the only, information is the brightness of the pixels. Specifically, they are applied for image labeled segmentation of White Blood Cell and LADAR intensity images.

Next we present a brief explanation of the steps followed by the algorithm.

3.1 Selection of Training Images

To construct a robust and effective *automated image segmentation algorithm*, which simulates the human process, a prior knowledge about the scene content has to be used. It is necessary to be well up on the objects appearing into the scene, and how they appear, to fix the perceptual characteristic features distinguishing them. Besides, some information regarding the geometrical and morphological properties of the objects and its spatial relation should be gathered.

Therefore, a previous, but very important step, consists in performing an exhaustive heuristic analysis to track down the suitable images making up the training set. As these images must allows to define and carry out all the steps of the algorithm, modeling the expert knowledge, this analysis must take into account that training images have to contain all the elements appearing within the images, and retain all the vagueness and variability enclosed within these elements.

3.2 Representation of Expert's Knowledge

Once the training images have been selected, and the elements identified, these are described by means of perceptual features. Then some labels are associated to the features, in order to describe the elements according to the descriptions given by the technician.

Following the framework of [7], and considering variability and vagueness within the images, and linguistic descriptions of the elements, next step consists in represent the fuzzy knowledge by a fuzzy rule base.

To represent this knowledge, the description of the elements is transformed into Mamdani rules, so defining a fuzzy rule-based computer vision system.

The inputs to the rules are the degrees of satisfaction of labels, and the outputs are the aggregated degree of satisfaction of the inputs. Thus, the problem reduces to (1) determining the structure of the aggregation functions to be used, (2) determining the nature of the connectives at each input of the network, and (3) computing the input supports (degrees of satisfaction of labels) based on observed features. The final structure depends on the problem at hand. The connectives used at each rule are based on fuzzy union, fuzzy intersection, and OWA operators, depending on the kind of attitude expected from the aggregation connective.

3.3 Obtaining the Membership Functions

As said previously, the main problem consists in defining the membership functions associated to the input labels. In this paper we introduce a method to get the membership functions, which is based on the analysis of the gray-values' histogram of the pixels within the training images.

This analysis lies in locate the *"relevant peaks"*, that is to say, the peaks of the histogram providing qualitative and quantitative relevant information regarding the gray-level intervals related to the labels.

The process consists in performing cuts at different frequency values (*frequency-cuts*), looking for the brightness-values, the frequencies of which are greater than the *frequency-cut*. The maximum and minimum frequencies wherein the cuts start and finish, as well as the gap between successive *frequency-cuts*, are gotten from the heuristic analysis of the training images.

For each *frequency-cut* -$freq_k$,- the information of the *relevant gray-level intervals* is laid away. A gray-level interval $I_j(freq_k)=[g\text{-}l\text{-}min_j, g\text{-}l\text{-}max_j]$ is considered *relevant* if satisfy next two conditions:

1. $frequency(g\text{-}l_j) \geq$ *frequency-cut*, $\forall\ g\text{-}l_j \in I_j(freq_k)$
2. $\#(I_j(freq_k)) \geq n$

Where n (usually equal to 10) is determined by the heuristic analysis of the histograms of the training images. After performing all *frequency cuts*, the information of the *relevant gray-level intervals* laid away is fussed, to get the gray-level intervals associated with the *relevant peaks*. Once the peaks have been located, they must be related to the labels. In this paper some rules that attempt to capture human knowledge and expertise, regarding the elements appearing within the images, are introduced to carry out this process, so getting the labels' gray-level intervals.

Then, following the framework of [6] and [7] the fuzzy sets, for the individual labels of the inputs, are obtained as approximations of the probability density and distribution functions.

Next step consists in getting the outputs of the rules, describing the elements (similar to the one given at (1)), which constitute the fuzzy rule-base. To do it we select the suitable connectives allowing implementing the rules in such a way that the system simulates human way of work.

3.4 Improvement of the results

Finally, with the aim to get an accurate detection of elements appearing within the images, it is necessary to eliminate false alarms and misclassifications. Therefore, as in [7], we use Fuzzy Morphological Structural Elements (FMSEs) [8]. The goal of these elements is to decrease the membership degree to a fuzzy set of the pixels within an area of the image, if there are very few pixels having high membership degree to this fuzzy set.

We use erosive and dilative FMSEs, depending on the characteristics of the images. Their size, shape, and structures characterize these elements, contributing to reduce misclassifications, false alarms, and noise effects, providing accurate boundaries among different regions.

Moreover, these elements are divided into regions in order to allow a better analysis of the uniformity of the membership degree distribution in the neighborhood.

Results and Conclusions

The system presented has been evaluated on seventy images from a database collected at the Ellis Fischel Cancer Center of the University of Missouri, to detect White Blood Cells. We obtained an accurate detection in the ninety three per cent of them.

It has been also trained on four images and tested on 44 images. LADAR intensity data were provided by the Naval Air Warfare Center (NAWC), China Lake, Ca. In this case we had to detect roads and pipes within the images. The system has shown to give very accurate detection results at almost all the images. Anyway, over some images wherein roads appear very thin, these pixels are assigned to pipe.

The results obtained by the proposed system show the effectiveness of fuzzy techniques in vagueness treatment. The improvements introduced within the histogram segmentation make easier to apply this technique to very noisy images having a very high degree of variability, obtaining accurate brightness membership degrees. Furthermore, the structural element is seen to be effective for segmentation based on pixel classification, when uniformity and gray level must be analyzed locally. On the other hand, the way this element has been applied allows us to obtain convex and compact regions

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