A FUZZY EXPERT SYSTEM FOR LOW LEVEL IMAGE SEGMENTATION

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ABSTRACT

In this paper a general purpose fuzzy expert system is presented for low level image segmentation. By means of approximate reasoning based on fuzzy logic, the criticality of the choice of the several thresholds and parameters which usually must be tuned to make the expert system work properly is reduced. More specifically, it is proved that, by keeping constant the number of rules the expert system consists of, the fuzzy approach permits to build a more general system, capable of giving satisfactory results for a large number of images stemming from different applications. The validity of the approach is demonstrated by comparing the effectiveness of a classical expert system with that of its corresponding fuzzy version. Upon analysis of the results, the superiority of the fuzzy system in terms of robustness and generality comes out.

1 INTRODUCTION

In the last years a wide variety of image segmentation techniques have been proposed [1]. Some of them are very simple and do not involve any kind of reasoning about the desired image partition, while others exploit the knowledge about the characteristics a good segmentation should have, to obtain a better image partition. In general, the quality of the segmentation increases with the knowledge the system has about the desired result, though at the expense of algorithm complexity.

Recently, it has been shown that good results can be obtained by means of expert systems designed to cope with the problems inherent in the segmentation task [2]. According to the kind of knowledge they have about the scene content, expert systems can be grouped into low level and high level systems. If the system is designed to match a particular application, the system is said to be a high level system. On the contrary, if only some general segmentation rules holding for a large class of images are exploited, the system is a low level one.

A problem common to many expert systems is the large number of parameters, usually thresholds, which must be tuned to achieve a satisfactory segmentation. Generally, to reduce the impact of such parameters on the output accuracy, the number of rules the system relies on must be increased, thus increasing the system complexity too. Alternatively, an accurate analysis of the class of images to be processed can be carried out, so that an optimal set of thresholds can be chosen. However, in this way the segmentation algorithm looses in generality and its validity as a general purpose system is reduced.

In the following a fuzzy expert system is presented for low level image segmentation. The use of fuzzy logic permits to reduce the criticality of the choice of thresholds, without increasing the number of rules the expert system is composed by. The validity of the fuzzy approach is proved by building a fuzzy version of the classical segmentation expert system by Nazif and Levine [2]. Actually, the Levine and Nazif system already contains some fuzzy modules, but the core of the system, the set of splitting and merging rules, is implemented according to classical binary logic. In this paper we will show how a more robust system can be obtained by designing the expert system according to the fuzzy paradigm.

The paper is organized as follows. In the next section, an overview of the Nazif and Levine system is given. In section 3, the introduction of fuzzy rules into the expert system is discussed. Experimental results and the comparison between the classical and the fuzzy systems is considered in section 4. Finally, in section 5 some conclusions are drawn.

2 EXPERT SYSTEM ARCHITECTURE

To prove that the performance of a knowledge-based system for image segmentation can be improved by implementing the knowledge rules according to a fuzzy approach, the classical expert system by Nazif and Levine [2] has been chosen.

The overall architecture of the system is reported in figure 1. The system consists of six processing modules and a set of knowledge rules. The first module to be activated is the initializer. It generates an initial image segmentation, an edge map and a set of focus of attention areas. Focus of attention areas are used for the purpose of directing the attention of the system to the part of the image which is more interesting in terms of processing needs. Three kind of focus of attention areas may be generated: smooth, textured and bounded areas, i.e. areas bounded by long and almost closed lines. The initializer also computes the features of the initial data elements.

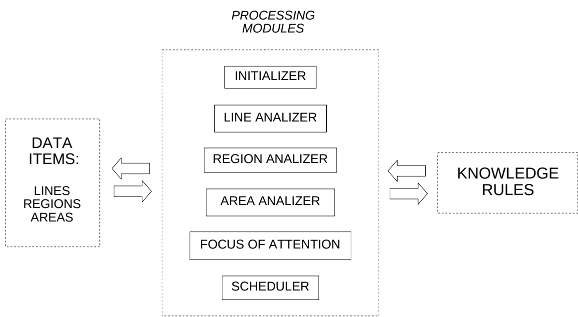

Figure 1: Main modules of the expert system by Nazif and Levine

The next three modules constitute the core of the system, their primary tasks being rule matching and data updating. More specifically, the *line analyzer* tries to match line rules and upon rule matching it activates the corresponding actions. Similarly, the *region analyzer* and the *area analyzer* are reponsible for the matching of rules concerning regions and focus of attention areas respectively.

In order to properly apply knowledge rules, a path strategy must be defined. In other words, the order by which lines, regions and areas are analyzed must be specified. This task is accomplished by the focus of attention module, which, according its own set of rules, brings data items to the attention of the system.

Finally, the scheduler monitors the overall segmentation strategy. Among the tasks the scheduler is in charge of, the definition of the order in which the other modules are activated is the most important one. To this aim a set of *metarules* is applied to determine which set of rules is to be tested next.

More insight into the system behaviour can be achieved by re-arranging its modules according to the three levels shown in figure 2. The first level is relative to knowledge rules. At this stage, rules encode the information about the entities which define the image segmentation, namely regions and lines. Upon matching of a given rule, the corresponding action is activated, which may be the splitting of a region; the merging of two adjacent regions; the addition, deletion or extension of a line, and so on. Knowledge rules are classified by their actions, so that region rules and line rules exist.

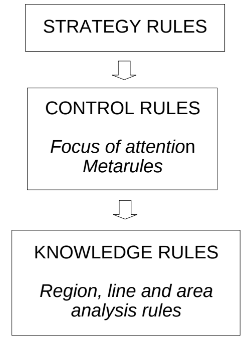

Figure 2: Different levels of rules

The second level of the system consists of control rules. They are responsible for the system control strategy: by means of a set of focus of attention rules, the next data item to be analyzed is determined, whereas the so called *metarules* define the order in which knowledge rules are applied.

Control rules are based on a set of dynamic parameters representing the status of the system. They are concerned with path strategy and rule priorities. The actual status of the system, i.e. the actual values of status parameters, is set by means of strategy rules (highest level in figure 2).

More details about knowledge, control and strategy rules may be found in [2]. In it is also demonstrated that the use of an expert system for low level image segmentation leads to higher accuracy than classical image segmentation techniques.

3 FUZZY KNOWLEDGE RULES

A drawback with the system described in the previous section and with expert systems in general, is the presence of a large number of parameters, usually thresholds, which must be set to determine the actual behaviour of the system. The impact the choice of thresholds has on the final segmentation is such that, generally, a different set of parameters should be used for different classes of images. A possible solution to reduce the sensitivity to threshold values, consists in the introduction of a number of properly designed rules takinge care of border cases. In such cases, which very often represent ambiguous situations, a set of additional rules is fired thus making the system output less sensitive to input changes.

In this paper an alternative solution is explored: by restating the rules the system relies on in the framework of fuzzy theory, a more robust system is obtained. More specifically, we aim to build a system which is less sensitive to the kind of image being analyzed, thus augmenting its value as a general purpose system.

To prove the validity of such an approach, most of the functionalities of the Nazif and Levine expert system has been re-built by resorting to the theory of approximate reasoning [3] [4].

Based on fuzzy set theory, approximate reasoning represents a powerful tool for dealing with complex systems and uncertain, vague or incomplete knowledge. In particular, by means of a set on linguistic control rules, and the corresponding concepts of fuzzy implication and compositional rule of inference, a class of systems is obtained, which reproduce the behaviour of human experts automatically.

As a matter of fact, a limited part of the original system by Nazif and Levine was already defined in terms of fuzzy rules. More specifically, some of the rules at the strategy level were built according to fuzzy concepts [5]. However, in the original work, the core of the system, i.e. knowledge rules, still relies on classical binary logic.

As an example of translation of a rule written according to classical binary logic into a fuzzy rule, let us consider the case of region merging. One of the rules used to state whereas two adjacent regions are to be merged can be expressed as follows:

RULE (802)

IF: (1) The *region size* is *very low*
(2) The *adjacency* with region 2 is *high*
(3) The *R-difference* is *not high*
(4) The *G-difference* is *not high*
(5) The *B-difference* is *not high*

THEN: merge the two regions

Rule (802) refers to the case of colour images, thus three conditions on mean value difference, (3-5), are needed to take into account the R, G, and B channels of the image.

In rule (802) the terms *very low*, *high* and *not high* refer to classical hard sets. That is a variable, e.g. *region size*, is considered as *very low* if it belongs to a predefined hard interval. On the contrary, if the same terms are considered as linguistic variables, whose values are interpreted as fuzzy sets, the fuzzy version of rule 802 is obtained. For instance, the fuzzy set corresponding to a *very low region size* can be represented by the function plotted in figure 3.

Rule (802) is quite a simple rule, however, the use of fuzzy logic tends to be more fruitful when complex rules dealing with vague concepts are involved. This is the case, for example, of splitting rules based on histogram bimodality. Due to the complexity of the concept of histogram bimodality, and to the difficulty of defining it exactly in mathematical terms, fuzzy logic can be fruitfully used to reproduce the way in which humans reasons when they are asked to decide whether a given histogram is bimodal or not.

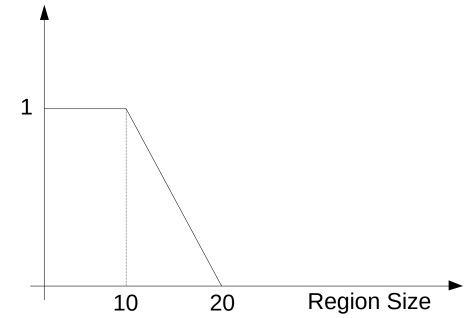

Figure 3: Fuzzy set representing a *very low region size*

4 EXPERIMENTAL RESULTS

Experimental results have been carried out in order to verify the superiority of the fuzzy approach with respect to the classical one. As a first step, the same image, i.e. an aerial image, has been used to tune both the fuzzy and the classical systems. Due to the fine tuning of the system parameters, when the training image is considered, the fuzzy and the classical systems give virtually the same results (figures 4 and 5). For the actual comparison of the generality of the systems, a completely different kind of image has been considered. As a consequence of the different image characteristics, the effectiveness of the classical system falls off, whereas the quality of the fuzzy system output does not change significantly.

Figures 6 and 7 show the results described above. In particular, the segmentations of the standard *pepper* image obtained with the classical and the fuzzy systems are reported. As it can be seen, the fuzzy system is more robust than the classical one, in that it gives better results when dealing with an image which is considerably different from that used in the training phase.

5 CONCLUSIONS

To make rule-based segmentation systems less sensitive to thresholds and parameters, the use of fuzzy logic (approximate reasoning) represents a viable solution. In this way, the generality of a given segmentation system can be augmented without increasing the number of rules used to represent the knowledge about the desired output. The validity of such an approach has been demonstrated by re-implementing a classical low level image segmentation expert system according to the fuzzy paradigm and by comparing its validity as a general purpose system with that of the original technique.

For the analysis carried out so far the architecture of the system has not been modified, however, a further improvement could be achieved by re-designing the system from scratch on the basis of approximate reasoning theory.

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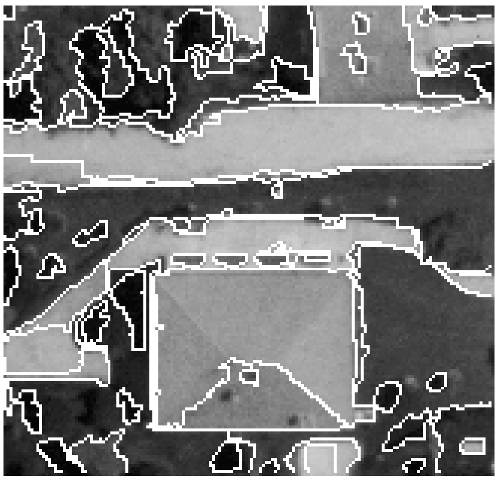

Figure 4: Segmentation of the training image by means of the classical expert system. Parameters and thresholds have been set by trial and error

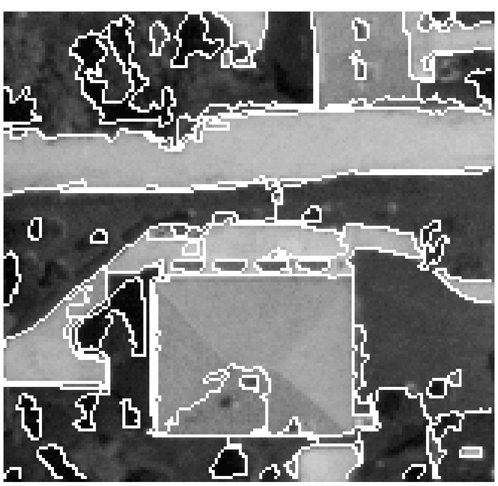

Figure 5: Segmentation of the training image by means of the fuzzy expert system. Parameters and thresholds have been set by trial and error

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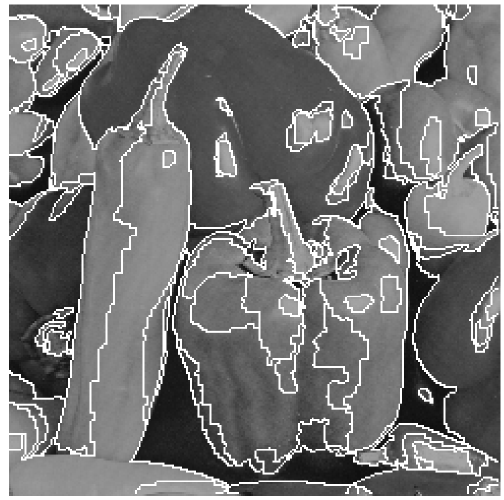

Figure 6: When a different kind of image is processed, the performance of the classical expert system gets worse due to the sensitivity to threshold setting

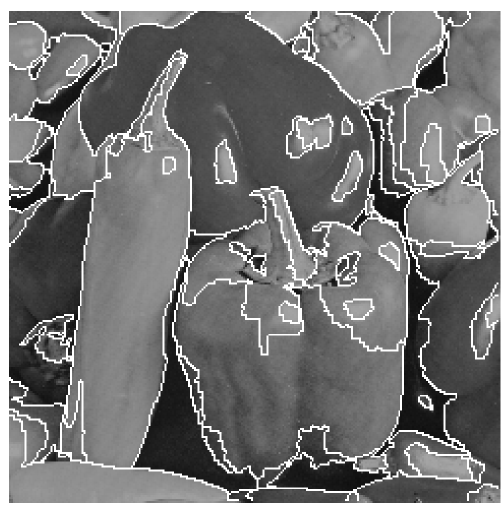

Figure 7: Though thresholds have been set by making reference to the the aerial image of figure 4, the effectiveness of the the fuzzy system does not deteriorate when a different kind of image is analyzed