Image processing using fuzzy rule sets

Heinz-Georg Fehn, Hans-Peter Wiesmath
Fachhochschule Münster, Fachbereich Elektrotechnik
Stegerwaldstraße 39
48565 Steinfurt
Germany
Phone: +49 - 2551 - 962 - 234
Fax: +49 - 2551 - 962 - 169
E-mail: Fehn@FH-Muenster.De

Abstract: In image analysis often the information about the outline and shape of an object is disturbed by the influence other object or the shape of the object itself in the region of interest. Therefore it is nesseccary to have clever algorithms, that can cope with problems of concatention between objects and unsufficient description of surface due to the fact of converting 3-D shapes into 2-D shapes during the acquisition process. An approach using fuzzy-methods in identifying concatenated object is presented with an attempt to apply the methods to reconstruct 3-D shapes.

Introduction

Since the concept of fuzzy-sets was first introduced in /Zade65/ has been applied to many different fields. Mainly fuzzy-set theory is used in control strategies (fuzzy-control), in operation researches and desicion processes (fuzzy-decision). A wide field of applications using fuzzy-set theory can be found in clustering and pattern recognition problems /Bezd81/. Generally, the integration of fuzzy-set theory in image analysis is not so commonly used as in control and decision processes. In image coding, e.g. Kong and Kosko /Kosk92/ introduces an adaptive technique using fuzzy-sets and fuzzy-variables representing the power of subimages in the frequency domain to reduce the bitrate for the image transmission or storing. Felix /Feli93/ uses fuzzy-methods as a decision support in qualitative and structural fuzzy-image analysis. In his contex "qualitative" means any form of distortion which disturbs the quality (quality control). The specific form or geometric description is less important. "Structural" means using any object characteristic which gives the capability to make a conclusion about object shape, size, position etc..

Many tasks in the field of industrial image processing deal with the subject of object description in various forms. On one hand it is important to find the outlines (conturs) of an object, e.g. for measurement, on the other hand it is neccessary to get information about the surface, e.g. for a grinding process. In both cases, the main task of the image processing system is image analysis. Image analysis is concerned with the extraction of measurement, data, or in general gathering information by automatic or semiautomatic methods (structural image analysis). Often measurement tasks, especially task using outline description, based on binary images which are easy to generate with backlighting. A binary image, for example, is shown in fig. 1. The problem to be solved is to find out how many object an which type of object are in the image. In the case that all objects are separated no difficulties may occur using method of classification and pattern regocnition.

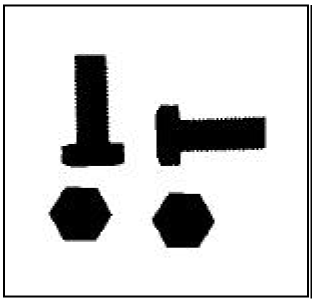

fig. 1 binary image with four objects

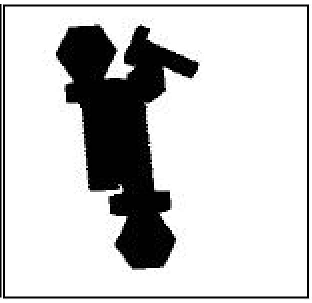

fig. 2 binary image concatenated objects

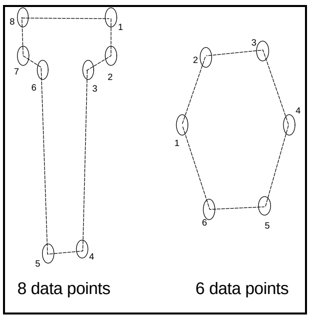

fig. 3 edge points and object outlines

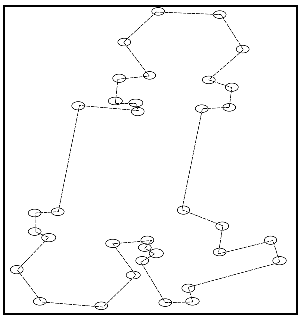

fig. 4 edge points of concatenated objects

With characteristic information from the outline, e.g. points of the edges, distances between these points, automatic method are wellknown. However, automatic methods as used for separated objects fail, if the objects in the grabbed image are concatenated as shown in fig. 2. The outline defined by characteristic points will result after some data reduction algorithms based chain coding methods /Prat91/. In fig. 3 are examples of edge points of separate objects, whereas fig. 4 shows the edge points of the concatenated objects. To solve the identification process with concatenated objects based on fig. 4 an attempt using fuzzy-methods will be developped.

Linguistic variables

A key role in the design process of the fuzzy-system in this application plays the object geometry and its parameters to be used as linguistic variables. The values of the linguistic variables are word or sentences in a natural of artifical language /Dria93/. For example, the distance D between two egde points can be rather small, small, large or very large. So the linguistic variable D is denoted by _ D with values _ D = {rather small, small, large, very large}. In case of the linguistic variable distance it can be in the interval [0 m , 10 m] and in image analysis mainly given in pixel to avoid scaling between the world coordinate system x,y and the image coordinate system given by discrete values in rows and columns of the image memory. After specifying some linguistic variables, they can represent now features of the geometry or more generalized properties of the object.

Choise of Membership Functions

The next step in the design process is the assignment of membership functions to the linguistic variables. Different type of membership functions (fig. 5) as triangular, trapezoidal or bell-shaped, linear or non-linear are

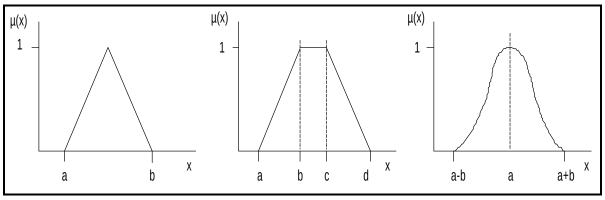

fig. 5 types of membership-functions

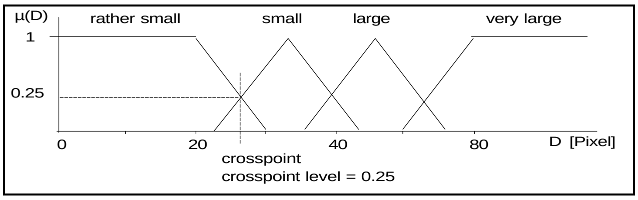

fig. 6 fuzzy-set with membership-functions

possible. The number of membership function is equivalent to the number of values of the linguistic variable. The decision which type of membership function is used, normally follows the requirements of the goal of the task to be solved. In industrial processes often the computations time to be spent time is bounded by cycle time of the process itself. Therefore the simpliest membership-function with respect to computation time is used, that means triangular or trapezoidal shape. The mapping of the subsets of the linguistic variable leads to the fuzzy-set of membership-functions (an example is shown in fig. 6). The membership-functions can overlap at cross-points with given crosspoints levels. At the crosspoints the crosspoint level defines the degree of membership to two different subsets of the same linguistic variable. However, at the long last, the right approach of the fuzzy-sets, which best fit the requirements in image analysis tends to be more or less heuristic and based on the experience of the engineer than using extensively theoretical formulations.

Fuzzy-rules

The approach to the deviration of rules most widely used today is based on the knowledge and experience of the engineer. The rules are sets of if - then statements and provide the necessary information for the proper functioning of the fuzzification modules. A fuzzy-rule describes fuzzy-relations to represent the connections between two fuzzy-propositions. A fuzzy-propositions , for example D is small, used in the if-part (aggregation) of the rule yields the proposition in the then-part (implication) of the rule as shown in fig. 7. The inference, the firing of the rule, clippes the fuzzy-set of the then-part (the shaded area). The clipping value is the degree of membership (0.7) of the crisp value 36 of the distance D. The conversion of a crisp value to a degree of membership is called fuzzification. To make rule more complex, more then one linguistic variable can be used in one rule. So, the set or subsets of the linguistic variables have to be compound, using terms as "and", "or" and "not". Using a set of rules, the implication of each rule is accumulated to get the output. The result of the accumulation is converted (defuzzification) to a crisp output by various methods, for instance the center of area (COA), center of sums (COS) etc..

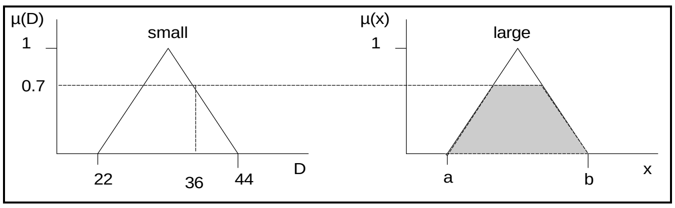

fig. 7 graphical repesentation of firing a rule. For example:
if D is small then X is large

To simplify the defuzzification process, the output of the rule, is the result already. Of course, if there is a set of rules all implications must be taken into account.

Technical approach in image analysis

Starting from a grabbed gray-scaled image of a scence with an unknown number of objects in the scence, a fuzzy-method identifies the object independent from the case of concatenated image data only by the outline. Surely, there is first an interactive teaching step neccessary to introduce all object to identify to the system. The result of the teaching process is a set of parameters describing the object, for example the edge point as shown in fig. 3 so, that different values as distances, angles, center of gravity could be calculated in advance or when neccessary during the identification process. After converting the image to a two-level (binary) image (or directly with backlighting) the outline is found and is described by the chaincode. A data reduction process removes redundant information, for example the pitches of the screw thread. The dataset after the reduction ist shown in fig. 4. Next, a pattern matching algorithm has to be developped which is able to cope with the problems of spatial image quantization, nonadaptive binarisation thresholds and possible defocussed lenses. These effects can influence the shape of the outline. As a result distances and especially calculated angles differ from the stored parameter set. A second obstacle in the pattern matching process are the concatenated objects in the image. Due to the concatenation, never a complete outline of one object will be found, except in the case that the objects are separeted already. To cope with the first problemes the following linguistic variable are created

_ DI euclidian distance of two points extracted from the image
_ DD distance difference (DD = DT - DI; DT=euclidian distance of two points of teached objects
_ DA difference in angle
_ P point of the outline resp. the contur

and the following fuzzy-sets (fig. 8) are used /Topp94/. The values of the x-axis was matched to scaling factor of the image system. It is important to mention at this point, that the minimum distances between to edge points should not be less then ten to fifteen pixels. To guarantee this, use a lens with sufficient focal length. The shape of the membership -functions takes the computation time and the influence of the spatial quantization into account. In the case of distance measurement the trapezoidal shape fits best and the number of subset for _ DI and _ DD = {small, medium, large} are sufficent to solve our problem. To make the decision about a point belonging to a contur - the linguistic variable _ P = {bad, good} is clipped by the firing of the rules - and the defuzzification is done by COA. The scaling of this fuzzy-set produces COA - values between zero (point does not fit) to ten (point fits best) with respect to integer calculations. All values greater or equal five means the the point fits a teached contur. We used the rules

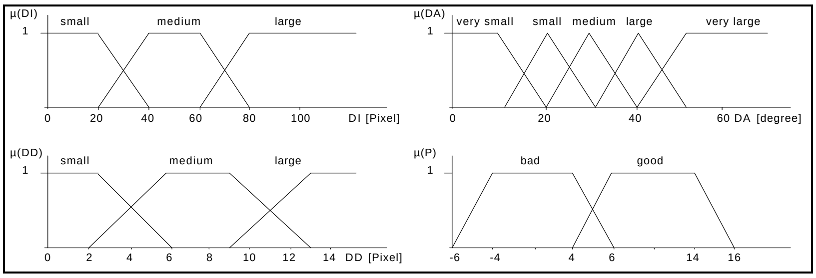

fig. 8 used fuzzy-set for point matching

IF (DD is medium and AD is small) or (DD is small and (AD is small or AD is medium)) **then** point is good
IF DD is large or (DD is medium and (AD is medium or AD is large) or AD is large)) **then** point is bad

The linguistic variable _ AD is formed directly by the implication from rules, which I called sub-rules.

IF (DI is small and (DA is very small or DA is small or DA is medium)) or (DI is medium and (DA is very small or DA is small)) or (DI is large and DA is very small) **then** AD is small
IF (DI is small and DA is large) or (DI is medium and (DA is small or DA is medium)) or (DI is large and DA is small) **then** AD is medium
IF DA is very large or (DI is medium and DA is large) or (DI is large and (DA is medium or DA is large or DA is very large)) **then** AD is large

This sub-rules does not have any membership function. The result is the firing of the rule. For the explanation of _ DA consider the following geometrical interpretation. The first point of a teaches contur is translates into the origin of a cartesion coordinate system. Then the system is rotated by an angle, so that the second point of the teached object matches the x-axis (fig. 9). Next, the first point of the image contur is also tranlated into the origin and then rotated by the same angle. Because of the influence of lighting, spatial quantization, binary threshold etc. the second point in the image does not match the second point of the teached object, even this two points belong to identically objects. The angle difference AD is calculated in the rotated coordinate system and depends dramatically on the distance DI, resp. the distance DT. For example, if the distance DT of teached point are small, may be 10 pixels, and the y-coordinate of the image point in the rotated systems differs by only one pixel an angle difference of 5.7 degree occur. If, by the same length, the y-coordinate differs by two pixels, the angel difference is 11.3 degree. If the length DT increases, the angle difference decreases and become less important or by _ AD = {small, medium, large} with respect to _ DI and _ DA as given in the three sub-rules.

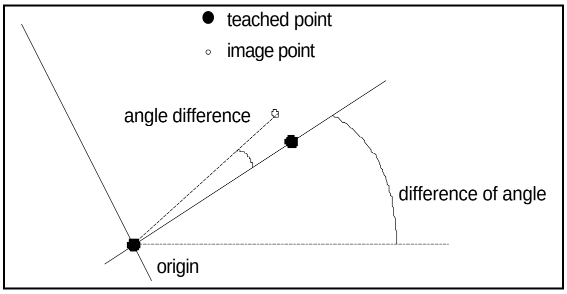

fig. 3 sketch for explanation of difference of angle

The following sketch of an algorithm was implemented properly in a C-program running under windows and tested with object of various sizes as shown in fig. 1.

```
Initilize system and roboter
  Grab image and calculate edge points
use with a first and second edge points of the image
          use first and second point of first teached object
                              use fuzzy method
                                        defuzzificate
                                        discard point, if COA less then five
                              store point, object number and defuzzification value if COA greater or equal five
                              use first and second point of the next object teached
                              replace point and object number, if defuzzification value of next object is better
                    repeat for all objects teached
                              shift points by one
                    repeat for all points of teached objects
                    shift points of image by one
repeat until all image points are used
calculate degree of matched points
calculate center of gravity
calculate rotation angle for image object for robots hand correction
remove object
  repeat until all object identified removed
  remove unidentified objects
end of program
```

To test the efficency of the algorithm, a set of letters (FUZZY) was teached. The image outline of concatenated letters is shown in fig. 10. In the image, one Z is missing. Despite humans have to think about the orientation of the letters in fig. 10, the algorithm up to now never failed.

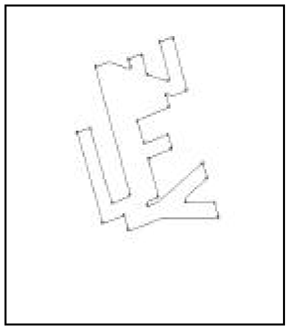

fig. 4 letters FUZ(Z)Y

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