A Method for Generic Object Recognition Using Fuzzy Linguistic Modeling

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Abstract

The paper describes a method for generic object recognition , using a multi-layered rule-based system. The representation of 3D objects is accomplished with fuzzy linguistic modeling. The objects to be recognized are composed of 3D volumetric primitives. As inputs for the generic object recognition we consider the contour segments obtained after the edge detection and maximum curvature points determination. The information is processed in two stages: 1) the transformation of existing information into a semantic description, and 2) generation of production rules which provide the syntactic relation between the semantic expressions. The object recognition in the proposed method are done by aspects recognition. Aspect recognition are performed by labeling his faces , taking into account local neighborhoods.

Keywords: generic object recognition, fuzzy modeling, aspect, geometric primitives, knowledge-base.

1. Generic Object Recognition

This paper addresses the problem of generic 3D object recognition from 2D gray-level images. The objects to be recognized are composed of 3D volumetric primitives, such as: truncated pyramid, cylinder, truncated cone, bent block. The set of volumetric primitives are mapped to a set of viewer-centered aspects. The recognition system would have to label the primitives that make up the object, in order to carry out a recognition by parts procedure, having the line drawings of a single view.

This type of recognition is not based on quantitative parameterized description, but rather on coarse, qualitative models representing classes of objects.

A remarkable theory ih this area of computer vision is formulated by Biederman [5] . His so called “Recognition by components” theory, based on psychological experiments, asserts that humans can recognize objects from line drawings as efficiently as from full color pictures.

Generic object recognition uses the object class concept which has been introduced in the artificial intelligence in order to imitate the human ability of associating a unique label to different objects with the same structure and functionality .

We take into consideration three properties of volumetric primitives in order to classify them:

- The type of edges forming the cross-section
- The type of axis
- The expansion function of the cross-section

The Cartesian product of the values of these properties give rise to the set of volumetric primitives taken into consideration.

The three properties enumerated can have the following values:

The edges forming the cross-section can be:

- Straight
- Curved

The symmetry axis can be:

- Straight
- Curved

The expansion function of the cross-section along the symmetry axis can be:

- Constant
- Expanding
- Contracting
- Expanding-contracting

The combination of these primitives give rise to the following set of volumetric primitives:

a) Block- rectangular cross-section, straight axis, and constant cross-section size.
b) Truncated pyramid- rectangular cross-section, straight axis, and linearly increasing cross-section size not starting from a point.
c) Truncated cone-elliptical cross-section straight axis, and linearly increasing cross-section size starting from a point.
d) Bent block –rectangular cross-section, curved axis, and constant cross-section size.
e) Pyramid-rectangular cross-section, linearly axis, and linearly increasing cross-section starting from a point.
f) Cylinder- elliptical cross-section, straight axis and constant cross-section .
g) Truncated ellipsoid-elliptical cross-section, straight axis, and expanding-contracting section .
h) Bent cylinder-elliptical cross-section, curved axis, and constant cross-section size.

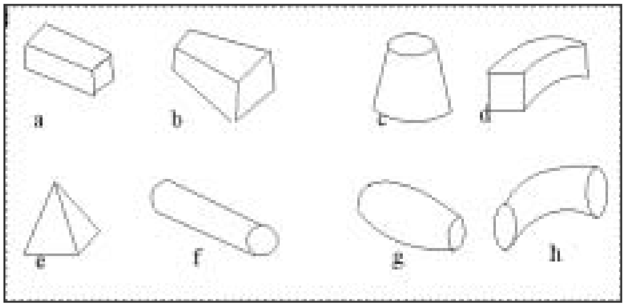

Figure. 1 The primitives

2. Generic Object Recognition Using Fuzzy Linguistic Modeling

The linguistic techniques in pattern recognition are based on the structure and relationships between features in two dimensional space. The precision of formal languages conflicts with the imprecision and vagueness of real life patterns, since the fuzzy languages , generated by fuzzy grammars are suitable for the structural relationships description. The fuzzy languages provide adequately means for generic representation and recognition.

Because this, a fuzzy linguistic modeling for generic object recognition is proposed in this paper.

The core of fuzzy modeling technique is the linguistic variable.

A linguistic variable is identified by its name and characterized by a term set.

If v is the linguistic variable, its term set is T(v). The linguistic values of T(v) are obtained by a syntactic rule, according to the semantic meaning.

The object recognition in the proposed method are done by the aspects recognition . Aspect recognition are done by labeling his faces, taking into account local neighborhoods.

The recognition method proposed uses a multi-layered linguistic rules system.

These rules form a knowledge base, built by means of a fuzzy grammar and human expert knowledge.

3. Knowledge Base Creation

We assume that the pattern space is partitioned into many subspaces. These subspaces represent the domains of the local fuzzy features. These local features correspond to linguistic features. The first layer of the knowledge base is constructed by combining the local features in the form of linguistic relations. These relations are the inputs for the first stage and conclusions are given as premises for the next stage of relations. At each level a conclusion is obtained by combining the inputs and certain relations.

As inputs for the generic object recognition we consider the contour segments obtained after the edge detection and maximum curvature points determination.

The information processing stages in the generic object recognition are presented in fig. 2. These stages are:

1) the transformation of existing information into a semantic description
2) generation of production rules which provide the syntactic relation between the semantic expressions.

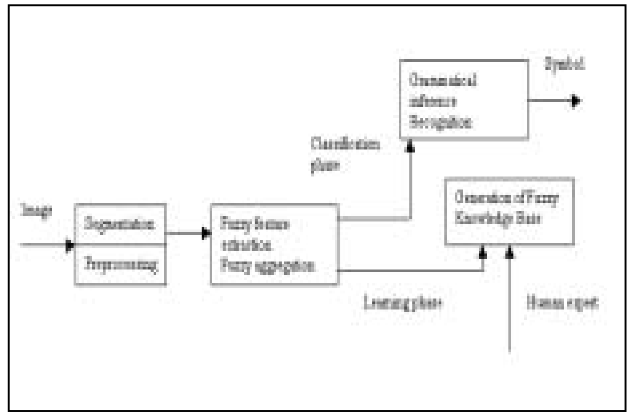

Figure.2 The information processing stages in the generic recognition system.

At each recognition level, the fuzzy membership of all patterns (segment, face , aspect) is evaluated for all level classes (straight line or arced line for contour segments, parallelogram or circle for faces). Each geometrical class corresponds to a linguistic variable characterized by a set of terms. We have defined nine linguistic terms with Π-shaped membership functions. These membership functions are presented in the Table .1

Table 1: Linguistic terms

	Symbol	Membership function
Zero	Z	$\mu=\Pi(x,0.3,0)$
Very very low	VVL	$\mu=\Pi(x,0.3,0.15)$
Very low	VL	$\mu=\Pi(x,0.3,0.3)$
Low	L	$\mu=\Pi(x,0.3,0.4)$
Medium	M	$\mu=\Pi(x,0.3,0.5)$
High	H	$\mu=\Pi(x,0.3,0.7)$
Very High	VH	$\mu=\Pi(x,0.3,0.8)$
Very very high	VVH	$\mu=\Pi(x,0.3,0.85)$
Excellent	E	$\mu=\Pi(x,0.3,0.1.00)$

The generic objects description in this method is performed with the symbols of the GENLANG language.

The symbols of this language define the classes specific for each stage processing, their attributes and their relationships.

Table 2: Fuzzy objects

Basic feature	**Abbreviation**
Straight- Line	LD
Arced-Line	LC
Pair of parallel lines	PL
Face types	FA1-FA10
Neighborhood types	NG1-NG100
Number of segments	NSEG

Table 3 Modifiers

<table>
<tr><th>Modifier type</th><th>Symbol</th></tr>
<tr><td>Between modifier</td><td>||</td></tr>
<tr><td>Great or equal modifier</td><td>></td></tr>
<tr><td>Less or equal modifier</td><td><</td></tr>
</table>

Table 4 GENLANG operators

<table>
<tr><th>Semnification</th><th>Symbol</th></tr>
<tr><td>Separator between linguistic terms and feature</td><td>#</td></tr>
<tr><td>AND operator</td><td>&</td></tr>
<tr><td>NOT operator</td><td>~</td></tr>
<tr><td>OR operator</td><td>|</td></tr>
</table>

The knowledge base is formed by the production rules set through a grammatical inference process. The terminal and non-terminal vocabulary of the grammar is the extracted feature space. The production rules use the following symbols:

- start symbols-the geometric primitives of fig.1
- the terminal symbols-straight-line and arced line, the fuzzy objects of table 2, the modifiers of table 3, the operators of table 4.
- Non-terminal symbols-pairs of parallel lines, the types of faces, the neighborhood types.

The syntax of production rules includes basic primitives related to attributes through operators. A GENLANG production rule can be written as follows:
S->primitive->description
Description->Face&neighborhood
Face->segment+segment+{segment}
Neighborhood->Face&Face&{Face}
If we take into consideration the processed elements , we can define four levels in the proposed generic recognition system
Level 1- Contour segments
Level 2 –Pairs of adjacent segments
Level 3 –Faces
Level 4- Aspects

Level 1 and 2 correspond to the first stage processing, the transformation of existing information into a semantic description.
Level 3 and 4 correspond to the second stage, production rules generation or grammatical inference.
At Level 1 the contour segments are classified to straight lines or arced-lines taking into consideration the curvature values along the segments.
In a given segment , ratio of the distance between end points to the total arc shows its arced-ness. If we consider the measure of arced-ness and the measure of straight-ness to be two complementary fuzzy linguistic terms of the fuzzy linguistic variable shape, then these two measures can be expressed as follows:

$$\mu_{Arc}(S_j) = \left[1 - \frac{d_{pj0\;pjk}}{\sum\limits_{k=0}^{kj-1} d_{pjk\;pj(k+1)}} \right]^{\beta} \qquad (1)$$

$$\mu_{dr}(S_j) = \left[\frac{d_{pj0\;pjkj}}{\sum\limits_{k=0}^{kj-1} d_{pjk\;pj(k+1)}} \right]^{\beta} \qquad (2)$$

β introduces a compression or a expansion of the defined membership function in order to adapt the relation to the respective operating range.
At the first level we construct a contour graph representation. The nodes of this graph contain a structure formed by a list of coordinate pairs corresponding to each segment, and the corresponding membership values for the two classes(LD, LC).The arcs of the graph represent the adjacency relationships between segments.
At Level 2 the faces graphs are generated. For each node of the contour graph, we follow a sequence of segments until the start node is encountered. For each pairs of non-adjacent edges the membership function to the parallelism pair wise relationship is defined , as in (3).

$$\mu_{pl} = \frac{min(l_a, l_b, l_c, l_d)}{max(l_a, l_b, l_c, l_d)} \cos\theta \qquad (3)$$

where , la,lb,lc,ld represent the distances from each edge endpoint to the opposite edge, and θ is the angle between the two edges.
At Level 3 the faces classification is accomplished. For the geometric primitives accepted in this method, we have the face types as in fig. 3.

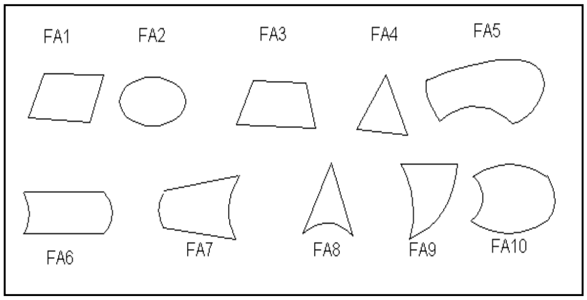

Figure. 3: Faces dictionary

The number NSEG of segments in a face can be:1,3,4. For these numbers we have defined three linguistic term: small, medium, high (L,M,H).

The measure of membership to the defined types of faces are done with a set of production rules which take into consideration the number of segments, the parallelism membership values, and the straight-ness and arc-ness of the segments.

The production rules for the faces are expressed as follows:

FA1 rule: (H#NSEG)&(>H#PL)

High number of segments, and High or more membership value for two pairs of parallel lines.

FA2 rule: (L#NSEG)&(>VH#LC)

Small number of segments and very high or more arced-line(LC).

FA3 rule(H#NSEG)&(>VH#PL)&(>VH#CL)

High number of segments and one pair with very high or more PL and very high or more CL.

At Level 4 we identify the aspect at which the face belongs.

For each face type we define a dictionary of possible neighborhoods for all primitives taken into consideration. Each neighborhood are attached a label and a linguistic variable.

Fig 4 illustrates the dictionary of neighborhoods for three types of faces.

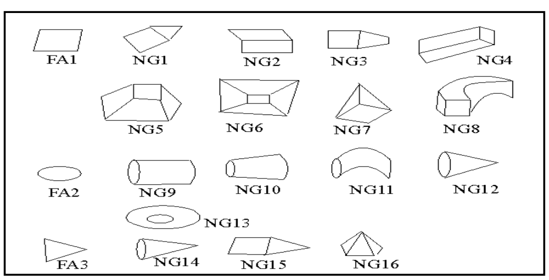

Figure 4: Dictionary of neighborhoods

For each neighborhood, a set of production rules are defined. We present some of them .

NG1 rule: (>VH#FA4)

One face with very high or more FA4.

NG2 rule: (>VH#FA1).

One face with very high or more FA1.

NG5 rule: (>VH#FA3)&(>VH#FA3)

Two faces with very high or more FA3.

For each face we determine the membership function value to the face's classes and neighborhood classes.

Similarly we can built rules for the primitives:

RP1 (block) rule:

((>VH#FA1)&(>VH#NG2))|((>VH#FA1)&(>VH#NG1) &(>VH#NG3))}((>VH#FA1)&(>VH#NG9)).

Interpretation:

(Very high or more FA1 and very high or more NG2) or (very high or more FA1 and very high or more NG1 and very high or more NG3).

RP2 (truncated pyramid rule):

((>VH#NG5)&(VH#FA1))|((>VH#NG6)&(>VH#FA1))

Interpretation:

(FA1 face and neighborhood NG5 with very high or more attribute) or (FA1 face and neighborhood NG6).

The inference engine performs the following stages:

- For each input determines the conditions achievement.
- Determines the level of rules activation.
- Selects the output with the maximum level of activation.

4. Conclusions

The paper describes an original method for generic object recognition , using a multi-layered rule-based system. The object recognition in the proposed method are done by the aspects recognition . Aspect recognition are done by labeling his faces, taking into account local neighborhoods. The first layer of the knowledge base is constructed by combining the local features in the form of linguistic relations. The generic objects description in this method is performed with the symbols of the GENLANG language.

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5.References

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