

Fuzzy Invariant Indexing: A General Indexing Scheme for Occluded Object Recognition

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Abstract

In this paper we present a general indexing scheme for model-based occluded object recognition. This new technique is called fuzzy invariant indexing (FII). It is based on fuzzy if-then-classification rules and fuzzified invariant object descriptions, which can be either invariant values or invariant signatures. We describe the framework of the method and its general applicability: if invariant object descriptions can be constructed, the fuzzy invariant indexing technique can be utilized for recognizing the objects. The recognition performance of the FII-technique is demonstrated for partially occluded (quasi-)planar objects as well as for rotationally symmetric objects in real scenes.

1 Introduction

We present a general indexing scheme for the recognition of partially occluded objects. Since we use fuzzy if-then-classification rules and fuzzified invariant object descriptions, which can be either invariant values or invariant signatures, we call this approach *fuzzy invariant indexing* (FII).

In our context *indexing* means to assign extracted image features (like points, lines, curves, etc.) to adequate object models and hence to generate object hypotheses. Recent research has indicated that the use of invariant object descriptions is a powerful approach to realizing the indexing. Mathematically, invariants are values or signatures (sets of coherent points) of geometric structures which remain unaffected under particular groups of transformations (for a good introductory paper see [1]). Since the affine/projective invariants remain unaffected under the group of affine/projective transformations that are used for

modeling the camera mappings, they are most important to vision systems.

Several recognition systems based on viewpoint independent invariant object descriptions have been developed (see e.g. [2, 3, 4]). Generally, these systems perform the indexing by mapping single invariant values to object models. Invariant signatures, however, are often reduced to invariant values (see [8]). Contrary to theoretical expectations these systems have to cope with fluctuating invariant values caused mainly by noisy imaging hardware and inaccurate feature extraction. Therefore, not only single invariant values are mapped to object models but rather certain, possibly overlapping, intervals.

Using an interval based indexing technique is a problematic approach: if invariant values at the boundaries of intervals are slightly disturbed it is possible that no object hypotheses are generated, i.e. a certain geometric structure indicates an object but another one which is very similar does not. Furthermore, if the invariant values of several object models are close to one another, it may become very difficult to discriminate between observed objects, i.e. to establish an unambiguous mapping between the observation and the correct object model.

Therefore, we have designed an indexing scheme that unlike traditional indexing methods combines the geometrical strength of invariant theory with the uncertainty representation and management facilities of fuzzy set theory. We have demonstrated recently [5] that it can be successfully applied to the recognition of (quasi-)planar objects, which can be composed of geometric primitives like straight lines and ellipses. Moreover, the FII-technique may improve the performance of conventional indexing methods: firstly, it enhances the discrimination ability of object recognition systems based on invariant theory. This is true especially in the difficult case of recognizing very similar objects because the FII-technique generates object hypotheses with different credibilities. Secondly, the fuzzy if-then-classification rules are easily extensible by further (invariant or variant) attributes. This allows a system structure that

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can be flexibly adopted to different object domains.

In this paper we focus on the general applicability of the proposed method, i.e. if invariant object descriptions can be constructed, then the FII-technique can be utilized for recognizing the objects. In section 2 we illustrate the general framework of the proposed technique and show how invariant object descriptions (invariant values (Sect. 2.2.1) as well as invariant signatures (Sect. 2.2.2)), can be fuzzified. In section 3 we demonstrate some experimental results for recognizing two different types of objects: (quasi-)planar objects (Sect. 3.1) and rotationally symmetric objects (Sect. 3.2).

2 General framework

We now describe the general setting for the proposed FII-technique based on fuzzy if-then-classification rules performing the hypothesis generation and on fuzzy invariant object descriptions modeling the invariant values/signatures and their fluctuations.

2.1 Fuzzy classification rules

The structure of the disjunctively connected fuzzy-if-then-classification rules has the following form [5]:

$$\begin{aligned} \text{IF } i_{m1}^k = \tilde{I}_{m1}^k \text{ AND } \dots \text{ AND } i_{mN_m^k}^k = \tilde{I}_{mN_m^k}^k \\ \text{THEN } o_m^k = \tilde{O}^k \end{aligned} \quad (1)$$

$$\begin{aligned} \text{with } k &= 1, 2, \dots, K \\ m &= 1, 2, \dots, M^k \\ n &= 1, 2, \dots, N_m^k \end{aligned}$$

where i_{mn}^k denotes the n -th input variable of subrule m for the k -th object, \tilde{I}_{mn}^k the corresponding fuzzy invariant object description, o_m^k the output variable of subrule m and \tilde{O}^k the k -th object class modeled as a fuzzy singleton. The total amount of antecedents N_m^k depends on the number of independent invariant object descriptions of the underlying geometric structure. The total amount of subrules M^k depends on the number of different geometric configurations for object k .

Inferring the fuzzy rules generates object hypotheses. Firstly, the fuzzy if-then-classification rules are evaluated separately:

$$\mu_{o_m^k} := \min_{1 \leq n \leq N_m^k} \mu_{\tilde{I}_{mn}^k}^k(i_{mn}^k) \quad (2)$$

where $\mu_{o_m^k}$ is the output of m -th subrule for object k and \tilde{i}_{mn}^k are the measured invariant object descriptions. Subsequently, these subresults are connected disjunctively:

$$\mu_{o^k} = \max_{1 \leq m \leq M^k} \mu_{o_m^k} \quad (3)$$

The final result is the indexed k -th object model with the measured credibility μ_{o^k} .

2.2 Fuzzy invariant object descriptions

The main problem in generating the fuzzy rules (1) is to find appropriate membership functions to model the fuzzy invariant object descriptions \tilde{I}_{mn}^k for a given object. As mentioned, we distinguish between two different types of descriptions: fuzzy invariant values and fuzzy invariant signatures.

2.2.1 Fuzzy invariant values

The most commonly used invariant object descriptions are invariant values. These values result from evaluating invariant functions based on geometric structures which can be extracted for an object to be recognized.

For example, consider the well-known projective invariant function of four collinear points called *cross ratio* [6]:

$$I(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3, \mathbf{x}_4) = \frac{|\mathbf{x}_3 - \mathbf{x}_1|}{|\mathbf{x}_3 - \mathbf{x}_2|} : \frac{|\mathbf{x}_4 - \mathbf{x}_1|}{|\mathbf{x}_4 - \mathbf{x}_2|} \quad (4)$$

where $\mathbf{x}_i, 1 \leq i \leq 4$ are four points on a straight line.

As we have already shown [5], the fluctuations of invariant values observed in different perspective views can be adequately approximated by bell-shaped membership functions $\mu_{\tilde{I}_{mn}^k}^k$:

$$\mu_{\tilde{I}_{mn}^k}^k(u) = e^{-\frac{(u - \alpha_{mn}^k)^2}{2\beta_{mn}^k}}, \quad u \in \mathbb{R} \quad (5)$$

where the parameters $\alpha_{mn}^k, \beta_{mn}^k$ determining the shape of the functions are chosen as the mean of the fluctuating invariant values, $\alpha_{mn}^k = \frac{1}{N} \sum_l I_l$, and the standard deviation, $\beta_{mn}^k = \left(\frac{1}{N} \sum_l (I_l - \alpha_{mn}^k)^2\right)^{\frac{1}{2}}$, where the invariant values $I_l, 1 \leq l \leq N$ are taken for an object in N different training images.

2.2.2 Fuzzy invariant signatures

The other type of invariant object descriptions are invariant signatures, which consist not only of single invariant values but rather of complex invariant curves. These invariant curves are constructed by transforming an imaged curve to a particular coordinate frame, in which any measurement act as an invariant (e.g. the canonical frame [7]).

Since most of the invariant indexing methods can only employ invariant values as indices distinguishing object models, the invariant signatures must normally be reduced to invariant values by applying measure functions like moments that are found heuristically [8].

The following approach holds the potential of performing much better: unlike other known procedures it does not compare sparse sample feature points of the signatures but the *whole discretized signature* of an object. If we denote $\vec{I}(p)$ as the parameterized signature curve of the model and $\vec{i}(p)$ as the parameterized signature of the object's image then we proceed as follows:

1. Represent observed invariant signatures \vec{i} as discrete parameterized curves $\vec{i}(p), 1 \leq p \leq P$, where P denotes a certain upper limit for the number of curve fitting points.
2. Compare observed signatures $\vec{i}(p)$ with model signatures $\vec{I}(p)$ of the object models by a least square distance measure:

$$D_{\vec{I}}(\vec{i}(p)) = \frac{1}{P} \sqrt{\sum_{p=1}^P |\vec{I}(p) - \vec{i}(p)|^2} \quad (6)$$

3. Depending on the value of the dissimilarity measure $D_{\vec{I}}(\vec{i}(p))$, determine the credibilities for the objects that are described by the model signatures \vec{I} (see [9]):

$$\mu(\vec{i}(p)) = \begin{cases} 1 - \frac{D_{\vec{I}}(\vec{i}(p))}{D}, & 0 \leq D_{\vec{I}}(\vec{i}(p)) \leq D \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

where D is an upper bound for tolerated distances.

This matching algorithm can be easily applied to the FII-technique by defining the membership functions of the fuzzy invariant object descriptions in (1) as the membership functions (7). During the recognition process the hypothesis generation is realized in the same way as described in section 2.1.

3 Experimental results

We have integrated the proposed fuzzy invariant indexing technique into an object recognition system (for details see [5]), which consists of the following modules: (a) edge detection, (b) feature fitting, (c) invariant calculation, (d) hypothesis generation and (e) verification.

To demonstrate the general applicability of the proposed method we employ this system to recognize two quite different types of objects: (quasi-)planar objects and rotationally symmetric objects. So far the system uses only fuzzified invariant values for performing these tasks, not yet the whole signatures according to section 2.2.2.

3.1 Recognition of (quasi-)planar objects

To recognize the object domain of (quasi-)planar wooden toy objects like slats, rims and tyres as shown in figure

1a, we use the two projective invariants of a pair of coplanar conics and of a conic and two straight lines (see [5]) as indices into the object models.

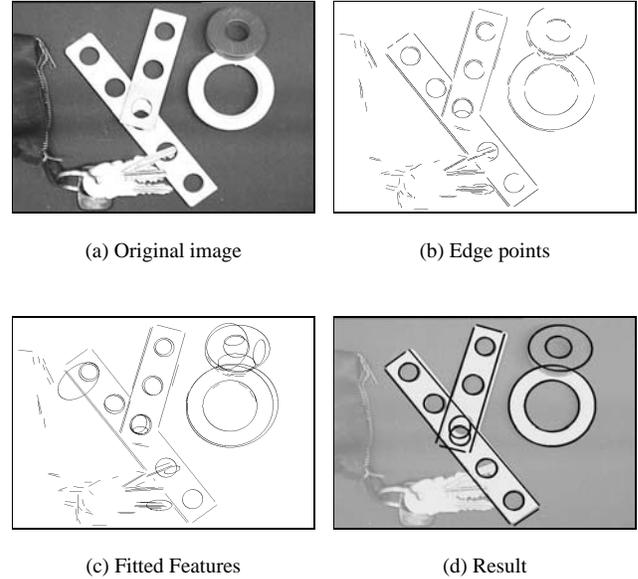


Fig. 1. Recognition of (quasi-)planar objects I

The recognition proceeds for a test scene as shown in figure 1. At first, the edge points (Fig. 1b) of the original image (Fig. 1a) are extracted using the Canny edge operator. Then, straight lines and ellipses are fitted to the edge points, shown in figure 1c. These features are used to calculate the invariant values, which are applied to the fuzzy if-then-classification rules (1). The recognized objects, i.e. the associated object models projected into the image plane, are shown in figure 1d (marked black), whereas the object not belonging to the object domain (the bunch of keys) does not interfere with the recognition process.

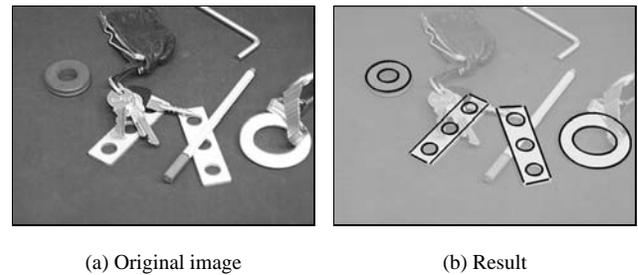


Fig. 2. Recognition of (quasi-)planar objects II

Another recognition result is illustrated in figure 2. Although the scene is taken at an angle of about 40° and the

objects are partially occluded, the system is able to recognize all of the a priori known objects correctly.

3.2 Recognition of rotationally symmetric objects

For the recognition of the object domain of rotationally symmetric 3D objects (chess figures) we use the invariant construction method from [10]. This method employs bitangents and the symmetry axis of an object to reduce the object shape to a unique 1D geometric structure, for which the cross ratio (4) can be calculated.

The recognition process proceeds as described in section 3.1 where the feature extraction and invariant calculation stage of the recognition system was adopted to the new object domain.

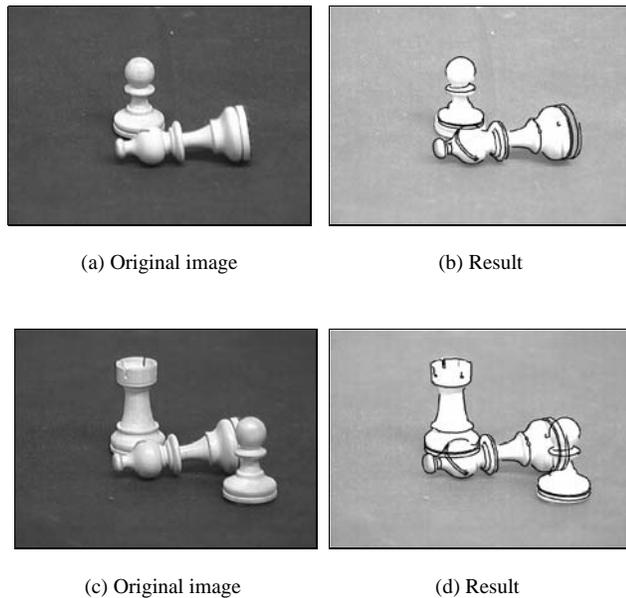


Fig. 3. Recognition of chess figures

Recognition results for two test scenes are shown in figure 3. Again, the chess figures can be recognized successfully although the chess figures are partially occluded.

4 Conclusions

In this paper we have shown that the proposed fuzzy invariant indexing technique (FII) is a general framework for the hypothesis generation of recognition systems based on invariant object descriptions. Whenever invariant object descriptions, invariant values or invariant signatures can be constructed for the objects to be recognized, the FII technique can be utilized. Future work will concentrate on the

recognition of different types of 3D objects and the integration of the procedure for evaluating not only invariant values but whole object signatures.

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