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USING CBR LEARNING FOR THE LOW-LEVEL AND HIGH-LEVEL UNIT OF AN IMAGE INTERPRETATION SYSTEM

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ABSTRACT
The existing image interpretation systems lack robustness and accuracy. They cannot adapt to changing environmental conditions and to new objects. The application of machine learning to image interpretation is the next logical step.
Our proposed approach aims at the development of dedicated machine learning techniques at all levels of image interpretation in a systematic fashion.
In the paper we propose a system, which uses Case-Based Reasoning (CBR) to optimize image segmentation at the low level according to changing image acquisition conditions and image quality. The intermediate-level unit extracts the case representation used by the high-level unit for further processing. At the high level, CBR is employed to dynamically adapt image interpretation.

1 INTRODUCTION
The existing image interpretation systems lack robustness and accuracy. They cannot adapt to changing environmental conditions and to new objects. The application of machine learning to image interpretation is the next logical step.
Our proposed approach aims at the development of dedicated machine learning techniques at all levels of image interpretation in a systematic fashion.
The proposed system uses Case-Based Reasoning (CBR) [1] to optimize image segmentation at the low level according to changing image acquisition conditions and image quality [2]. The intermediate-level unit extracts the case representation used by the high-level unit for further processing. At the high level, CBR is employed to dynamically adapt image interpretation [3].
Case-Based Reasoning can be used where generalized knowledge is lacking but a set of cases is available. The CBR unit consists of a case base, which contains formerly processed cases. Each case has an entry in case base. The entry contains the features describing the particular case and the interpretation result. A new case is interpreted by looking up the case base for similar cases and by selecting the closest case with its interpretation result. Learning strategies enable the system to improve it´s system performance over time by learning the similarity or the case base according to different abstraction levels.
This strategy ensures that we can run the system without knowing the general concept description for the objects and without knowing the entire objects that should be interpreted by the system.
In section 2, we describe the proposed system architecture and the fundamental behavior of a CBR learning system. The CBR strategy of the low-level unit is described in Section 3. The feature extraction process and the high-level description of a case image are described in Section 4. In Section 5, we describe the high-level unit and give results to the system performance.

2 BACKGROUND

Learning provides adaptation of algorithms to changes in environment and uses the experience to improve recognition performance over time.
Our work aims at the development of dedicated machine learning techniques at all levels of image interpretation in a systematic fashion as shown in Figure 1.
Case-Based Reasoning is used for image segmentation and the acquisition of object description. This reasoning method is used when generalized knowledge is lacking. The method works on a set of cases formerly processed and stored in a case base. A new case is interpreted by searching for similar cases in the case base. Among this set of similar cases the closest case with it´s associated result is selected and presented to the output.
To point out the differences between a CBR learning system and a symbolic learning system, which represents a learned concept explicitly, e.g. by formulas, rules or decision trees, we follow the notion of Wess et al. [4]: "A case-based reasoning system describes a concept C implicitly by a pair (CB, sim). The relationship between the case base CB and the measure sim used for classification may be characterized by the equation:

Concept = Case Base + Measure of Similarity

This equation indicates in analogy to arithmetic that it is possible to represent a given concept C in multiple ways, i.e. there exist many pairs C= (CB_1, sim_1), (CB_2, sim_2), ..., (CB_i,sim_i) for the same concept C. Furthermore, the equation gives a hint how a case-based learner can improve ist classification ability. There are three possibilities to improve a case-based system. The system can

- store new cases in the case base *CB*,
- change the measure of similarity *sim*,
- or change *CB* and *sim*.

During the learning phase a case-based system gets a sequence of cases $X_1, X_2, ..., X_i$ with $X_i = (x_i, class(x_i))$ and builds a sequence of pairs $(CB_1, sim_1), (CB_2, sim_2), ..., (CB_i, sim_i)$ with $CB_i \subseteq \{X_1, X_2, ..., X_i\}$. The aim is to get in the limit a pair (CB_n, sim_n) that needs no further change, i.e. $\exists n \; \forall m \geq n \; (CB_n, sim_n) = (CB_m, sim_m)$, because it is a correct classifier for the target concept C."
This behavior of the learning approach makes it useful for image segmentation as well as for image interpretation. Most segmentation techniques contain numerous control parameters, which must be adjusted to obtain optimal performance. Learning optimal parameter settings requires search in a large parameter space. The parameters within most segmentation algorithm typically interact in a complex, non-linear fashion, which makes it impossible to model the parameters behavior in an algorithmic or rule-based fashion. The variation between images causes changes in segmentation results. Thus, with fixed parameter settings, the segmentation quality varies from image to image. The technique used to optimize the segmentation quality must be able to adapt to these variations.
At the high-level stage, CBR is useful to dynamically adapt image interpretation to new object and to improve performance results.
As we noted before, the main problems concerned with CBR are [5]:

1. What is an appropriate similartiy measure for the problem?
2. How to organize a large number of cases for efficient retrieval?
3. How to acquire and refine a new case for entry in the case base?
4. How to generalize specific cases to a case that is applicable to a wide range of situations?

All these problems are concerned with learning. Clearly, a chosen organization for case base must be updated with every new stored case. A similarity measure that was chosen based on expert knowledge about the problem domain must not hold when more cases have been seen. In case generalization, specific cases are modified to create cases with more universal applicability and meaning.

In the next section, we will investigate how these problems can be solved for the low-level and the high-level unit of an image interpretation system. For each system, level we have chosen a different approach, which fulfills different requirements.

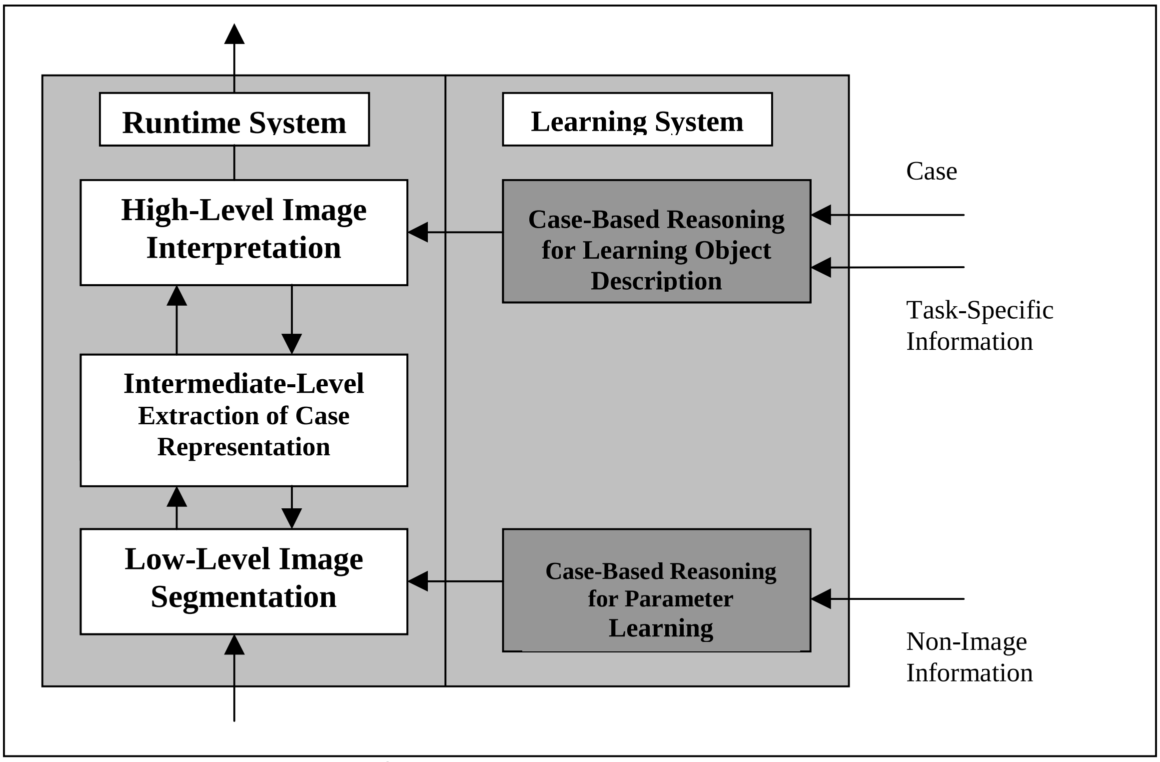


Fig. 1 Overall Architecture of the System

3 CASE-BASED REASONING FOR LOW-LEVEL VISION

Most segmentation techniques contain numerous control parameters, which must be adjusted to obtain optimal performance. The parameter selection is usually done on a large enough test data set, which should represent the entire domain well enough in order to be able to built up a general model for the segmentation. However, often it is not possible to obtain a large enough data set so that the segmentation model doesn't fit well to the data and needs to be adjusted to new data. Besides that, a general model does not guarantee the best segmentation for each image rather it guarantees an average best fit over the entire set of images. Another aspect goes along with changes in image quality caused by variations in environmental conditions, image devices, etc. Then the segmentation performance needs to be adapted to these changes in image quality. All that makes it necessary to equip the segmentation unit with learning capabilities, which can incrementally acquire new knowledge about the model for segmentation.

The case-based reasoning unit for parameter learning of image segmentation consists of a case base, in which formerly processed cases are stored by their original images, their non-image information (e.g. image acquisition parameters, object characteristics and so on), and their image segmentation parameters. The task is now to find the best segmentation for the current image by looking up the case base for similar cases. Similarity determination is done based on non-image information and image information. The evaluation unit will take the case with the highest similarity score for further processing. In case there are two or more cases with the same similarity score the first appeared case will be taken. After the closest case has been chosen, the image segmentation parameter associated with the selected case will be given to the image segmentation unit and the current image will be segmented, see Fig. 2. It is assumed that images having similar image characteristics will show similar good segmentation results when the same segmentation parameters were applied to these images.

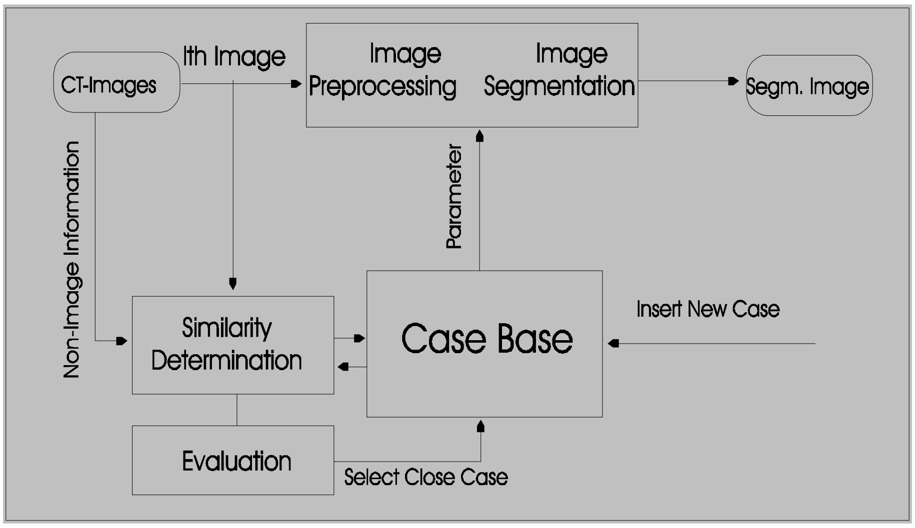


Fig. 2 Similarity-Based Image Segmentation Unit

3.1 SIMILARITY MEASURE FOR NON-IMAGE INFORMATION

We use Tversky´s similarity measure [6] for the non-image information. The similarity between a Case C_i and a new case *b* presented to the system is:

$$S(C_i, b) = \frac{|C_i|}{\alpha|A| + \beta|D| + \gamma|M|} \qquad (1)$$

$$\alpha = 1, \beta, \gamma = \frac{1}{2}$$

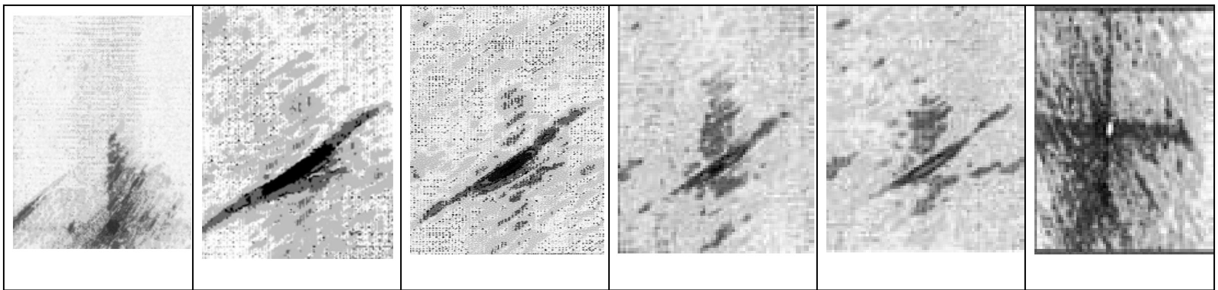
where $|C_i|$ is the set of attributes in case C_i, A is the set of corresponding attributes in case C_i and *b*, *D* is the set of attributes having different values, and M is the set of attributes having missing values.

3.2 SIMILARITY MEASURE FOR IMAGE INFORMATION

Determination of similarity is done with an algorithm proposed by Zamperoni et al. For detailed description of the algorithm, we refer the interested reader to [7]. The input to the algorithm is two images that should be compared. According to the specified distance function, the proximity matrix is calculated for one pixel at position r,s in image *A* to the pixel at the same position in image *B* and to surrounding pixel within a predefined window. The same is done for the pixel at position r,s in image *B*. Then, clustering is performed based on that matrix in order to get the minimum distance among the compared pixel. Afterwards, the average of both values is calculated. This repeats until all pixels of both images are processed. Then from the average minimal pixel distance, the distance value for the whole image is calculated and this value is given to the output. Summarizing this, the similarity is calculated in three steps: point-to-point, point-to-image, and image-to-image. The algorithm considers the distance in gray level as well as the distance in space. Therefore, the algorithm can detect changes in gray level as well as shift in space. Table 1 shows the similarity based on the algorithm of Zamperoni et al. for the images shown in Figure 3.

Image	B1_1	B2_1	B2_3	B2_4	B2_5	B4_1
B1_1	0	0,19748	0,15646	0,15748	0,16216	0,32239
B2_1	0,19748	0	0,13614	0,15844	0,16099	0,30203
B2_3	0,15646	0,13614	0	0,10337	0,10571	0,28891
B2_4	0,15748	0,15844	0,10337	0	0,09431	0,27510
B2_5	0,16216	0,16099	0,10571	0,09431	0	0,28985
B4_1	0,32239	0,30203	0,28891	0,27510	0,28985	0

Tab. 1 Similarity Values for the Images in Fig. 2



B1_1	B2_1	B2_3	B2_4	B2_5	B4_1

Fig. 3 Images used for Similarity Calculation shown in Tab. 1

3.3 SEGMENTATION PARAMETERS

Segmentation is done by thresholding in this application. The segmentation parameter, which is given to the segmentation unit, is the threshold.

3.4 MONITORING THE SYSTEM PERFORMANCE

There are several approaches for monitoring the segmentation performance possible. The most common strategy in CBR is to let the user evaluate the result of the system. Whereas at the high-level unit such an approach may be adequate since the decision is only `right answer` or `wrong answer`. At the low-level unit, a subjective decision might not be useful although this has widely been done in the past.

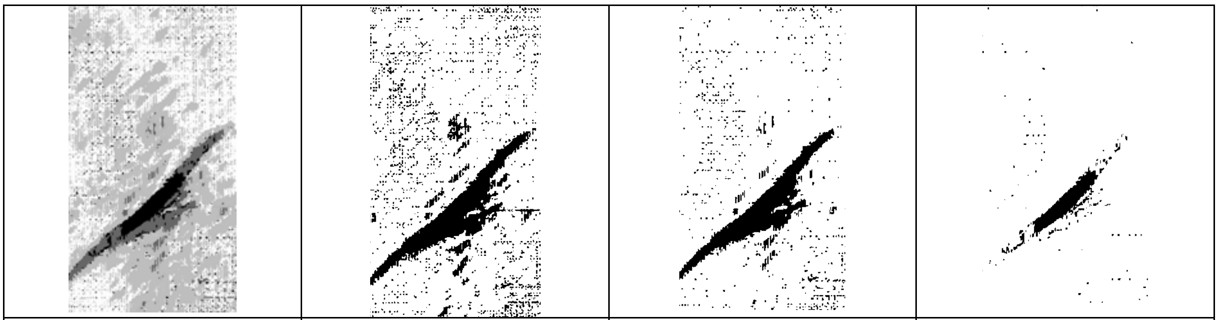
To objectify the quality of the segmentation result we calculate the similarity between the gray levels of the original image and the segmented image based on Zamperoni et al. dissimilarity measure [7]. The learning system will be called if the calculated value for similarity exceeds a predefined threshold.

Figure 4 shows the similarity between the original image and the processed image for different thresholds. The subjective chosen threshold gives also the best similarity.

3.5 LEARNING

If the learning system was called by the evaluation unit, the run-time system will give the recent case (the image and the non-image information) to the learning system. In an off-line process, the right threshold will be chosen interactively by the user so that the similarity measure will be less than the predefined threshold. Afterwards, the segmentation parameter, the image and the non-image information is collected to a new case and stored into the case base.

In principal, all case-based management and learning functions for the case base described at the high-level unit are applicable here as well. But we restricted our work at this level to the kind of learning described above since we use a parallel system for the processing, which guaranties us the efficiency in computation time.



B2_1	Threshold =190	Threshold=169	Threshold=100
	D=0,170983	D=0,161021 Best	D=0,169589

Fig. 4 Different Segmentation Results for Image B2_1 and the Similarity Values

3.6 ORGANIZATION OF CASE BASE AND RETRIEVAL

The case base is organized as a flat structure. The cases are stored one behind the other in the case base. To ensure the efficiency of the retrieval process we implemented the low-level unit on a parallel system (4 node processor based on Power PC 604). The case base is partitioned into three equally portions. Each of these three portions is distributed to one of these three processor nodes. A query is given to each of these three nodes. Each processor calculates the similarity to each of the cases in its case base. The similarity values are given to the fourth processor node to score out the highest similarity. The image segmentation parameters associated to the close case are given to the fourth processor. Afterwards, the original image is processed by the segmentation unit and the result is evaluated. If the segmentation result is not satisfactory, the recent case is interactively processed. The final segmentation parameter together with the original image and the non-image information are stored into one of the three processor node so that the cases are equally distributed.

4 EXTRACTION OF FEATURES AND HIGH-LEVEL DESCRIPTION OF A CASE

After the image is processed by the segmentation unit, the intermediate-level unit calculates the high-level description of the image, which is given as case representation to the CBR unit at the high-level stage [8].

A single image, following called case, is represented by objects, their attributes (e.g. graylevel = light, gray, black; size = large, middle and small) and the spatial relations (e.g. left_behind, right etc.) between the objects. That gives a structural representation for an image represented as an image graph. Images of that kind are for example ultra sonic images for defect classification shown in Figure 5. The images were acquired by the SAFT ultra sonic system [9]. Thresholding technique is used for segmentation (s. Fig. 6), preprocessing is done by using morphological operators like dilation and erosion (s. Fig. 7) and afterwards the objects are labeled by the line coincidence method. Symbolic transformation of the numeric information of an object is done with the help of a functional model for space [10], size and gray level. The symbolic description of the image is used since it is natural to an operator to describe images in these terms. The final representation of a case is shown in Fig. 8.

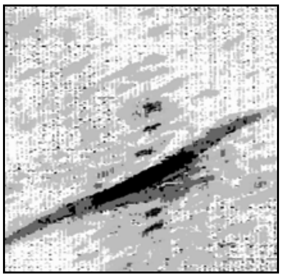


Fig. 5 Original Image

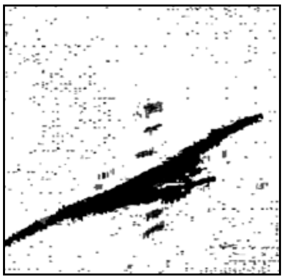


Fig. 6 Binary Image

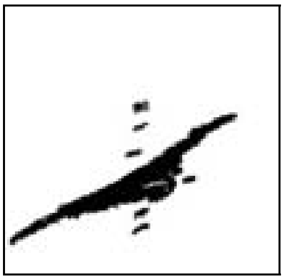


Fig. 7 Result

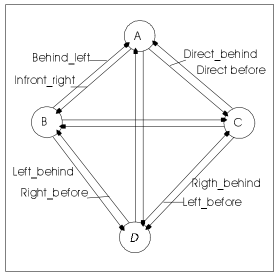


Fig. 8 Representation

5 CASE BASED REASONING FOR IMAGE INTERPRETATION

The basis for the development of our system is a set of cases $CB = \{G_1, G_2, ..., G_i, ..., G_n\}$, each case is a 3-Tupel $G_i = (N, p, q)$, which is a structural symbolic representation of an image, and a similarity measure δ for structural representations. For the current image an image graph is extracted by image analysis. This structure is used for indexing . The interpretation of a current image S is done by case comparison: Given an image $S = (N_s, p_s, q_s)$, find a case G_m in the case base *CB* which is most similar to the current image. Output the case G_m and the stored solution (e.g. in our case, the defect name)[11][12].

5.1 SIMILARITY DETERMINATION

For similarity determination between our image graphs, we chose part isomorphism [12] :

Definition 1

Two graphs $G_1 = (N_1,p_1,q_1)$ and $G_2 = (N_2,p_2,q_2)$ are in the relation $G_1 \leq G_2$ iff there exists a one-to-one mapping f: $N_1 \rightarrow N_2$ with (1) $p_1(x) = p_2(f(x))$ for all $x \in N_1$

(2) $q_1(x) = q_2(f(x), f(y))$ for all $x,y \in N_1$, $x \neq y$.

Is a graph G_1 included in another graph G_2 then the number of nodes of graph G_1 is not higher than the number of nodes of G_2. In order to handle the unsharp attributes and distortion in a graph representation we relaxed the required correspondence of attribute assignments of nodes and edges in such a way that we introduced ranges of tolerances according to the semantic terms [12].

5.2 ORGANIZATION OF CASE BASE

If we have many cases in case base then it can becomes very time consuming to find the closest case to an actual case. We have seen before that we can speed up the retrieval process by using a parallel platform for our processing unit. Another way to improve the efficiency of our CBR system is to develop an index structure which allows us to find the closest case without examining all existing cases for similarity in case base. On way to impose constraints on retrieval is to index cases using a case base hierarchy [11][12]. Elements in the case base are representations between graphs. As an important relation between this graph we have considered similarity based on part isomorphism. Because of this characteristic, it is possible to organize the case base as directed graph.

In the following, we define the case base as graph that contains the before described image graphs (or only a pointer to this image graphs) in the nodes:

Definition 2

Given is H, the set of all image graphs.

A case base graph is a Tupel CB = (N,E,p), with

(1) $N \subseteq H$ set of nodes and

(2) $E \subseteq N^2$ set of edges.

This set should show the part isomorphism in the set of nodes, meaning it should be valid

$x \leq y \Rightarrow (x,y) \in E$ for all $x,y \in N$.

(3) $p: N \rightarrow B$ mapping of attribute assignments to the image graph (also the attribute values for the description of the defect classes and categories).

Because of the transitivity of part isomorphism, certain edges can be directly derived from other edges and do not need to be separately stored. A relaxation of top (2) in definition 5 can be reduced storage capacity.

5.3 LEARNING

By the development and usage of the case base, it is to consider that the case base may be permanently changing during learning process. The initial case base may be built up by existing cases therefore; a nonincremental learning procedure is required. During the use of the system, new cases may be stored in the case base. They should be integrated in the already existing case base. Therefore, we need an incremental learning procedure.

Now, the task is to build up the graphs of CB in a supergraph by a learning environment. After the expert or operator has done the assignment for the defect category or class, the system is able to find automatically an answer to the given image graph. Formally, this task is to solve permanently:

Input is:

case base Supergraph $CB = (N, E)$ and

image graph $x \in H$.

Output is:

modified case base Supergraph $CB' = (N', E')$

with $N' \subseteq N \cup \{x\}$, $E \subseteq E'$,

At the beginning of the learning process or the process of construction of case base N can be an empty set.

The inclusion $N' \subseteq N \cup \{x\}$ says that the image graph x can be isomorphic to one in the case base contained image graph y, so $x \leq y$ and also $y \leq x$ hold. Then, no new node is created that means the case base is not increased.

The algorithm for the construction of the modified case base CB' can also use the circumstance that no image graph is part isomorphic to another image graph if it has more nodes then the second one.

For technical help for the algorithm there are introduced a set N_i. N_i contains all image graphs of the case base CB with exactly i nodes. The maximal number of nodes of the image graph contained in the case base is k then it is valid:

$$N = \bigcup_{i=1}^{k} N_i$$

The image graph, which has to be included in the case base, has l nodes ($l \rangle 0$). By the comparison of the current image graph with all in the case base contained graphs, we can make use of transitivity of part isomorphism for the reduction of the nodes that has to be compared.

Algorithm

E' := E;
Z := N;
for all $y \in N_l$
if $x \leq y$ **then** [CB' := CB; return];
N' := N $\cup$ {x};
for all i with $0 < i < l$;
  for all $y \in N_i \setminus Z$;
  for all $y \leq x$ **then** [Z := Z \ {u _ u ≤ y, u ∈ Z};
      E' := E' $\cup$ { (y,x)}];
for all i with $l < i \leq k$
  for all $y \in N_i \setminus Z$
  if $x \leq y$ **then** [Z := Z \ {u _ y ≤ u, u ∈ Z };
      E' := E' $\cup$ { (x,y)}];

If we use the concept of [12] for uncertainty handling, then we can use the algorithm without any changes. However, we should notice that for each group of image graphs that is approximately isomorphic, the first occurred image graph is stored in the case base. Accidentally, this can be a "bad" image graph. Therefore, it is better to calculate of every instance and each new instance of a group a prototype and store this one in the case base. Thus, we can learn the appropriate instance_of.
The described approach allows to learn new cases and store the new case into the case base according to the similarity relation to the already existing cases in case base. If we relax the part isomorphism relation to the concept for uncertainty handling then in each node of the hierarchy is stored a class of cases, which is represented by a prototype. The generalization ability of the algorithm can be described as follows: Given a set of structural relations and two cases x and y, then construct a case g such that $g \succ x$ and $g \succ y$. Then g is the most specific common substructure of the two cases, which gives a generalization of the two cases. In this learning approach, the learned hierarchy depends on the chosen threshold for similarity. An approach were no threshold is necessary is shown in our further work in [13].

5.4 INDEXING AND RETRIEVAL

Retrieval is done as follows: The current case is matched according to the case base hierarchy. The case class with the maximal structural similarity is indexed. Among the members of the indexed case class the closest cases is determined.

6 EVALUATION OF THE SYSTEM

Accuracy (A = (number of right recall / number of samples) * 100) was calculated based on 100 samples [8]. The information „no similar case“ was only taken as an error if there was a similar case in case base but the system could not call it based on the chosen similarity. Among this data set were 5 cases, which are not related to any case in case base. Accuracy was 95%.

7 CONCLUSION

In image interpretation, we are often faced with the problem that it is easier to acquire cases than a compact vision model for reasoning. This makes it interesting to use Case Based Reasoning for an image interpretation system. We have shown how Case-Based Reasoning can be employed for the low-level and high-level unit of an image interpretation system. It can be used for reasoning as well as for learning. At the low-level stage, we can learn incrementally a better system performance of the segmentation unit and at the high-level stage, we can learn a more compact case representation for the objects. The main problem is to find an appropriate measure for similarity. For the low-level unit, we have shown how the similarity measure of Zamperoni et al. works for finding similar cases by comparing the image matrix and for evaluating of the segmentation result. At the high-level unit, the nature of the cases requires a structural representation and because of that, a structural similarity measure is needed. The case base can be organized in different ways. As flat structure if the system platform allows retrieving cases in suitable short time and as hierarchical structure, which speeds up the time since not all cases needs to be matched. The nature of the CBR process allows learning incrementally new cases and/or the case base, which improves the performance of the system over time. Therefore, a CBR can be used for an interpretation task although not all objects have been observed yet, which is the case in large domains like interpretation of technical drawings or in inspection tasks.

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