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A BI–DRIVEN OPTIMAL SEARCH FOR KNOWLEDGE–BASED VISION

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Abstract. A domain–independent tree search algorithm for semantic network–based image understanding systems is proposed. The basic transition operators for this search, that provide search space expansion, have been designed for a (hierarchical) *model–to–image* match. In this paper two operators for *data–dependent* matching are additionally defined. The first operator forces an *iteration* of the model concept–to–image match, the second one concerns the instantiation of *generic relations.* At end minimal *data requirements* of conceptions are introduced, allowing the design of one additional global operator of the search space – a *data–driven* search tree pruning.

1. INTRODUCTION

In this paper the image interpretation problem is viewed as an optimal forward search in an implicit space of partial symbolic descriptions [1]. A *semantic net*–based system shell *ERNEST* [2, 3] and the A^**–tree search* algorithm constitute the basis of presented approach. The basic transition operators in *ERNEST*, that provide search space expansion, have been designed for a (hierarchical) *model–to–image* match. But one needs *data–driven* search operators in vision systems too because the number of non–competitive instances of given conception may be image–dependent (can not be predetermined in the model). Two such operators are proposed here for *data–dependent* matching. The first one causes an *iteration* of the model–to–image match. For example it can be used in following cases: an unlimited number of object instances may exist in the scene, iterative volume parts of a solid may exist, non–merged segments may exist in the image description due to segmentation faults. The second operator concerns the instantiation of *generic relations* for the verification of hypotheses and for consistency maintenance. Additionally minimal *data requirements* may be specified for each conception. They allow a global pruning of search space nodes while retaining the admissibility of search.

2. KNOWLEDGE–BASED ANALYSIS IN *ERNEST*

The semantic network in *ERNEST* provides three node types: the *concept*, the *modified concept* and the *instance*, as well as three link types: *part*, *concrete*, *specialization.* A part is *context dependent* or *not.* Part– and concrete–links of a concept are aggregated into *modality* sets, and each link is marked inside a set by one of the labels: *obligatory, optional, inherent* or *reference.*

There are three domain–independent rules for the *instantiation* of concepts and three rules for the *modification* of concepts, that describe the use of knowledge. First a *partial* instance $I_{partial}(A)$ of a concept A (or its modified concept $Q_{partial}(A)$) is computed by requiring instances of the *context independent* parts and concretes only (RULE 1). Having the partial instance of A instances of *context dependent* parts $\{M\}$ can be generated. With the instances of $\{M\}$ and due to the RULE 2 the partial instance of A can be *completed* ($I_{complete}(A)$) The RULE 3 checks whether there are instances of *optional* parts or concretes and it generates *extended* instances from a complete instance of A. Constraints can be propagated upwards (RULE 4) or downwards (RULE 5) in the knowledge hierarchy. Initial modifications of concepts are derived by the application of RULE 6 directly to the image data.

The rules for instantiation and modification in connection with the A^*–tree search algorithm form the skeleton for different control strategies. The basic *alternating* control consists of a bottom–up selection of (temporary) goal concepts and of matching them to the image data. This matching process is tailored into a top–dow *model expansion* (inverse application of the instantiation rules combined with modification of expected conceptions) and bottom–up *instantiation* until the application specified goal is reached.

3. THE BI–DRIVEN CONTROL (Table 1)

3.1 Data–driven goal selection

The primary problem of *ERNEST*–based signal analysis is to find an optimal path in the graph of modified goal concepts. This graph is extended over the concrete–of– and specialization–hierarchies of the model (and the Z axis for multiple modifications of a concept) and a path leads from some initial goal concept from the set C_g to some terminal one (from the set of most abstract and most specialized concepts in the model net). The search tree is expanded by the application of following operators:
– initilization by the application of RULE 6 to the image data; one successor node is generated for each initialized goal
– superior goal generation (applying RULE 4 to the instance of current goal); one successor node for each modified superior concept
– more specialized goal generation (applying the inheritance mechanism to the instance of current goal); one successor node for each partial instance of direct specialization concept

Input: APPLICATION function to provide a list C_g of competitive goal concepts					
Initialize: search tree S= (V,E) with V={R}, E= $\emptyset$; lists OPEN= $\emptyset$, CLOSED= R					
provide APPLICATION function for initial parameters					
FOR all concepts $K \in C_g$ DO:					
	apply RULE 6 to K				
	FOR all modified concepts Q_i(K) = o_i generated by RULE 6 DO:				
		generate one successor node V_i^K of root R in search tree S DATA(V_i^K)= {o_i }; GOAL(V_i^K)= o_i; $h(V_i^K)$= judgement(V_i^K)			
		IF	K is a *minimal concept*		
		THEN	OBL_PREM(V_i^K,O_i)= T		
		ELSE	OBL_PREM(V_i^K,O_i)= F		
		refer unlimited objects in DATA(V_i^K) in ITER[V_i^K]			
		IF	the segmentation data satisfy MIN_REQUIRED[V_i^K]		
		THEN	add V_i^K to OPEN		
WHILE OPEN is not empty DO:					
	select the node N with best score from OPEN				
	remove node N from OPEN; add it to CLOSED				
	IF	the APPLICATION decides that an analysis goal or an end has been reached			
	THEN	STOP - successful end of search or end of resource			
	activate APPLICATION function to provide a (possibly empty) set S of new goal concepts				
	IF	S is not empty			
	THEN	FOR all concepts $C_i \in$ S DO:			
			apply RULE 4 to C_i		
			FOR all objects o_l generated this way DO:		
				generate one successor node V_{il} of N in S; add V_{il} to OPEN DATA(V_{il}) = DATA(N) $\cup$ { o_l }; OBL_PREM(V_{il}, o_l) = F h(V_{il}) = judgement(V_{il}); GOAL(V_{il}) = o_l	
	ELSE	IF	some object $o_l \in$ DATA(N) can be instantiated by one of the RULES 1–3		
		THEN	activate ERNEST function *instant* (N) to instantiate the model in node N determine the set Next(N) of successor nodes of N in OPEN activate ERNEST function *consistency_check* (Next(N)) FOR all nodes $N_i \in$ Next(N) DO:		
				refer all unlimited objects from DATA(N_i) in ITER[N_i]	
				FOR all unlimited objects $T_{(i)} \in$ (ITER[N] – ITER[N_i]) DO:	
					generate one successor node N_i^1 of N in S and OPEN copy N_i to N_i^1; DATA(N_i^1) = DATA(N_i) $\cup$ $T_{(i+1)}$ ITER[N_i^1] = ITER[N_i] $\cup$ $T_{(i+1)}$ extend the premises of superior objects of $T_{(i)}$ by $T_{(i+1)}$
		ELSE	IF	there is at least one object $o_l \in$ DATA(N) with OBL_PREM(N,o_l) = F	
			THEN	activate ERNEST function *expand* (N) to expand the model in N	
				determine the set Next(N) of successor nodes of N in OPEN activate ERNEST function *pruning* (Next(N)) to prune the nodes $N_i \in$ Next(N) from OPEN if the available segmentation data does not satisfy MIN_REQUIRED[N_i]	
			ELSE	IF	there is at least one object $o_l \in$ DATA(N) with OPT_PREM(N, o_l) = F
				THEN	activate ERNEST function *opt_expand*(N) to expand the model in node N
				ELSE	activate ERNEST function *opt_spec*(N) to consider optional parts and specializations
STOP – no success of analysis					

Table 1: The bi–driven search

3.2 Model–to–image matching

The parts and concrets of a concept are aggregated into a finite set of competitive *modalities* (md), i.e. subsets of parts and concrets. The match of selected goal to the image data is a combination of two search problems: a search for a best solution graph in an AND–OR graph (expanded model) M for current goal A (Fig. 1) and the search in the space of competitive instances of entities from M. The entities in M are modified concepts created for model paths starting from current goal A. These modified concepts are refered by so called *object*–data structures (denoted by Q_i) in a search space node. Due to the *identification* of equivalent paths (as specified in the model) or equivalent objects (from various modality sets of one superior object), one object can represent multiple paths.

Hence two search operators are applied during the basic matching process. Successors of a search tree node are created either for competitive premises of instantiation (due to different modalities and different modifications generated by RULE 5) or for competitive instances of every object $Q_i \in M$.

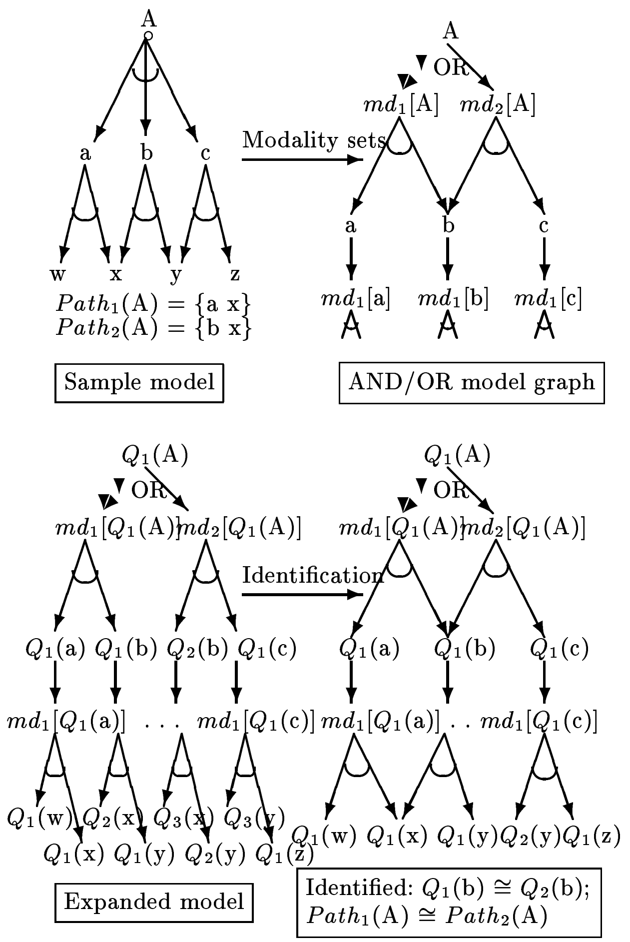


Figure 1: Model expansion with path identification

Actually the model expansion mechanism is more complex than the one presented on Fig. 1 because the elements of one modality are additionally classified into obligatory or optional. For a given goal concept the *obligatory model*–to–

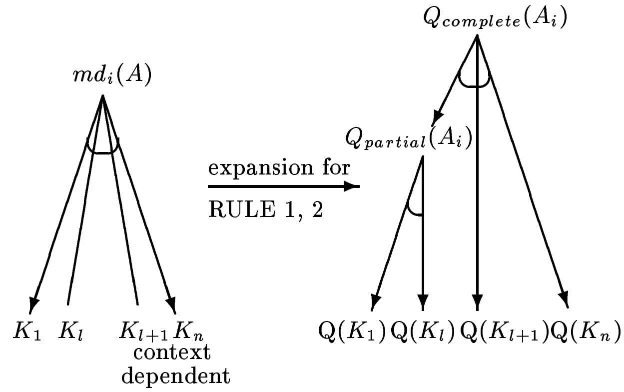


Figure 2: Expanded obligatory model

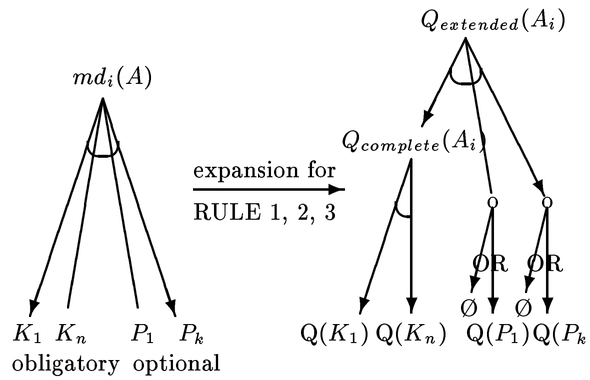


Figure 3: Expanded optional model

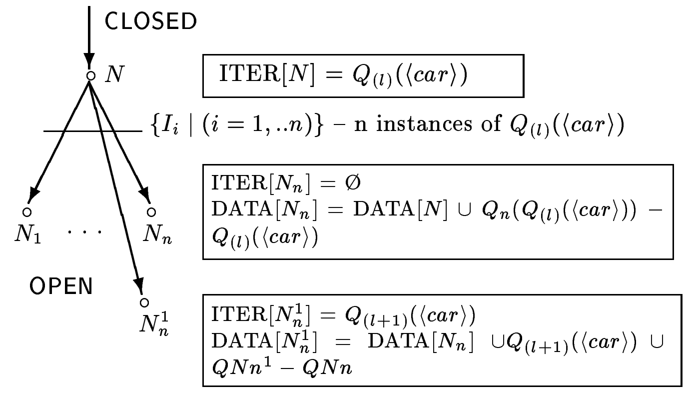
image match is performed. In this case RULE 1 and RULE 2 are considered only during the model expansion process (Fig. 2). Due to the optional parts, required by the RULE 3, the *optional model*–to–image match can be distinguished. Before an *extended* instance can be created from the *complete* one, instances of optional parts are searched for (empty instances are allowed) (Fig. 3).

The matching process consists of interlaced expansion– and instantiation–steps. The instantiation step has always the greatest priority. By applying RULES 4 and 5 to new generated instances, the object domains from the data set DATA(N) can be more constrained. In this way the later expansion of each such object can be restricted to those premises only, which satisfy the new constraints.

For the judgement of search space nodes an estimation of the goal object judgement with respect to the set DATA(N) is performed. This measure satisfies the admissibility requirements for the A^*–tree search algorithm.

3.3 Iterative match for "unlimited" objects

If the *dimension* item of some (optional) link is equal to the number "unlimited" then it will be searched for an image–dependent number of instances of the appropriate concept. This is represented in the expanded model by an *unlimited* object. The set of such objects in a node N is recognized by the operator ITER[N]. After n instances of an *unlim-*



$QNn = \{\ q \mid q \in \mathrm{DATA}[N_n],\ Q_{(l)}(\langle car\rangle) \in \mathrm{Premise}(q)\ \}$
$QNn^1 = \{\ q^1 \mid \exists q \in QNn,\ \mathrm{Premise}(q^1) = \mathrm{Premise}(q) \cup Q_{(l+1)}(\langle car\rangle)\ \}$

Figure 4: Iterated search for object $\langle car\rangle$

ited object (for example object $Q_{(l)}$ of concept $\langle car\rangle$) have been created, the search space node N is firstly expanded by nodes $N_1, ..., N_n$ as usual (Fig. 4). After one of the nodes N_i (i=1,...,n) has been selected for expansion one additional successor node N_i^1 of node N is created. From this new node the model–to–data match for this unlimited object will be iterated – a next version $Q_{(l+1)}(\langle car\rangle)$ of the unlimited object is added to the set DATA(N_i^1). The premises of all superior objects of the unlimited object have to be changed in order to include the next version of this object. The iteration stops because of the limited image data – no data can be interpreted twice on one path in the search space. Thus in the subsequent iteration only this data can be matched, which is not interpreted by instances from DATA(N) yet.

3.4 R–objects for generic relations

A specific unlimited object, called the *R–object*, is given if its part– and concrete–links have all the *reference* labels. These links are not expanded – new objects are not generated for concepts reached by them. For each object tuple from the expanded model that satisfy the premise of the R–concept one appropriate R–object is generated in the expanded model (Fig. 5). This set may be extended by new objects generated during the analysis if some link of the R–object refers to an "unlimited" object.

One application example of generic relations is the representation of relationships for consistency maintenance of the search space. After some inconsistent DATA set has been discovered (so called *NOGOOD* search space node) the procedure *inconsistency_check* tries to detect inconsistent subsets. Nodes which contain at least one of the detected inconsistency can be removed from the OPEN set.

3.5 Minimal data requirements for non–expanded objects

The third operator concerns a data–driven pruning of search space nodes. A set MIN_REQUIRED is specified for each search node. It contains the minimal image data requirements for the non–expanded object set of given search node.

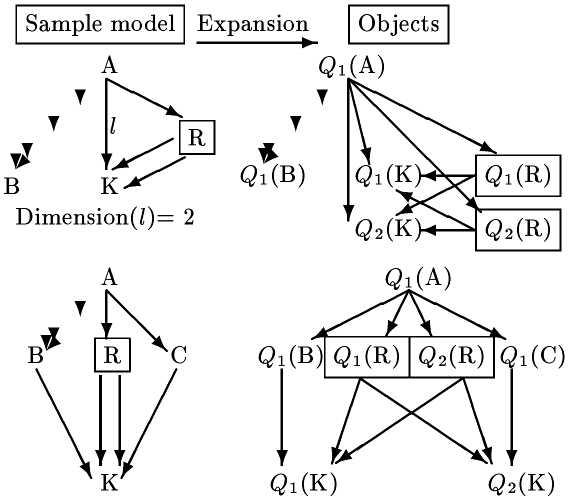


Figure 5: Expansion of the R–concept R

In order to pass the pruning test the subset of image data, that is available in a node, should include the appropriate MIN_REQUIRED set.

4. CONCLUSION

Two data–driven search operators have been proposed for knowledge–based image understanding and they have been integrated in a model–driven optimal search algorithm. Contrary to the basic model expansion prinicple the number of some objects ("unlimited", "R–objects") is not determined by the model but depends on the current analysis results. The specification of minimal (remaining) data requirements implies a data–dependent global pruning of the search space.

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REFERENCES

[1] Niemann H. et al: *A Knowledge Based System for Analysis of Gated Blood Pool Studies*, **IEEE Trans.Patt.Anal.Mach.Intell., 7(1985)**, 245–259.

[2] Sagerer G., Kummert F.: *Knowledge Base System fo Speec Understanding*, In: [Nieman H. et al (Ed.): **Recent Advances in Speech Understandina and Dialog Systems**, NATO ASI Series, F46, Springer, Berlin, 1988], 21–458

[3] Niemann H., Sagerer G., Schr"oder S., Kummert F.: *ERNEST: A Semantic Network System for Pattern Understanding*, **IEEE Trans.Patt. Anal.Mach.Intell., 12(1990)**, 883–905.