Qualitative Spatial Relationships for Image Interpretation by Using Semantic Graph

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Abstract. In this paper, a new way to express complex spatial relations is proposed in order to integrate them in a Constraint Satisfaction Problem with bilevel constraints. These constraints allow to build semantic graphs, which can describe more precisely the spatial relations between subparts of a composite object that we look for in an image. For example, it allows to express complex spatial relations such as "is surrounded by". This approach can be applied to image interpretation and some examples on real images are presented.

Keywords: Semantic graph, arc-consistency checking, spatial relationship, image interpretation.

1 Introduction

The large expansion of web applications leads to manipulate a huge amount of images. Then, interpreting correctly the content of images is a crucial step to obtain what we want from this huge image database. Image interpretation is also an important issue in medical images, particularly when it is necessary to find automatically anatomical structures such that cerebral structures linked to brain activity. However, a large gap persists between the semantic interpretation of an image and its low-level features. The MPEG-7 standard has been developed to introduce high-level representations (ontology) that capture the semantics of a document [10], [11]. This semantic is sometimes limited to textual descriptors of image components according to a semantic hierarchy. Other semantic descriptions may be more relevant to interpret an image.

Usually, a complex object, like an anatomical structure, is described by the shape of its components and the spatial relationships between these components. Then, a semantic model has to integrate both spatial and morphological constraints. One could think that spatial relations could be simply described by a notion of adjacency as we can find in region adjacency graph (RAG). This formalism has some interesting properties which make it very convenient to describe an image and therefore it has been chosen by many authors [2], [6], [12], [13], [14]. However, the unique notion of adjacency is too poor to describe complex spatial organization of the different parts of an object. Cohn et al. [5] proposed to describe more complex spatial relations between

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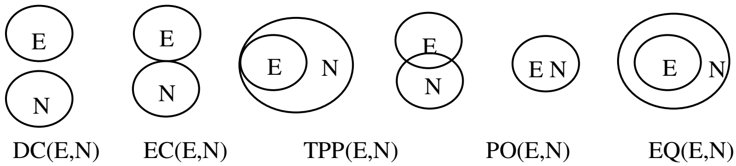

Fig. 1. Illustration of the JEPD relations

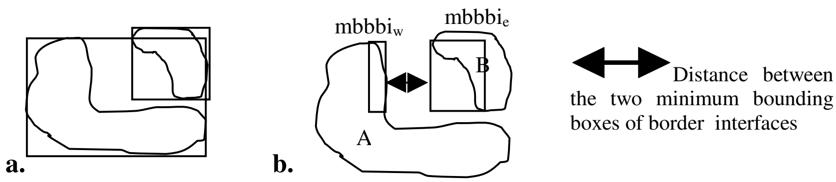

Fig. 2. a. In that case the two regions are not overlapped and the two minimum bounding boxes are overlapped. The analysis of the spatial relation between these two regions is not possible by using minimum bounding boxes**. b.** $mbbbi_w$ is the minimum bounding box of the border interface which is on the left of region A. $mbbbi_e$ is the minimum bounding box of the border interface which is on the right of region B.

regions, in a topological framework, with a set of basic relations and they create for that purpose the RCC8 formalism. RCC8 deals with a set of eight Jointly Exhaustive and Pairwise Disjoint (JEPD) relations called basic relations: DisConnected (DC), Externally Connected (EC), Partial Overlap (PO), Equal (EQ), Tangential Proper Part (TPP), Non Tangential Proper Part (NTPP) and their converses (See Fig.1). However, this formalism does not take into account the shape of the regions and the directional relations. Skiadopoulos and Koubarakis [17] circumvent this drawback by defining formally the Cardinal Direction Relations. These relations exploit the notion of *minimum bounding box* (mbb) and several authors have proposed some ways to combine topological notions with directional relations [18]. This approach has several interesting advantages: it has good properties of computation (computing the minimum bounding box of a region is fast), it is possible to inherit the properties of minimum bounding boxes inside a pyramid of adjacency graphs, it is possible to introduce a notion of absolute or relative metrics and RCC8 relation can be retrieved from it [18]. However, the topological and directional notions should take into account that the notion of distance between two regions is also a very important feature [4]. For example, the difference between different animal faces lies mainly on the difference of distances between each part of the face. The main drawback of working only on minimum bounding boxes is when the two minimum bounding boxes of two regions are overlapped (See Fig. 2.a), it is not possible to compute any useful distance. Moreover, all these works consider that each object is ideally identified. In practice, this is not the case in a segmented image where objects are often arbitrarily over-segmented.

In this paper, we propose new topological and directional relations able to better describe complex spatial relations between two objects made up of several segmented regions. A concrete implementation of these relations is proposed to use it in the context of a constraint satisfaction problem with bilevel constraints. These relations are used as spatial constraints associated with the arcs of a semantic graph. Indeed, this formalism can describe many objects of an image [1], [3], [7], [15], [19]. In section 2, we describe the new spatial relations. In section 3 an implementation of these relations in the context of a CSP with bilevel constraints is proposed. In section 4, we present some experiments with different kinds of models applied on real images.

2 Complex Spatial Relations Between Two Composite Objects

2.1 Cardinal Direction Formalism

In the framework of the cardinal Direction Formalism (CDF), Skiadopoulos and Koubarakis [17] formally defined nine cardinal directions relations. (See Fig. 3). Let A be a region, the greatest lower bound of the projection of A on the x-axis (respectively y-axis) is denoted by infx(A) (respectively infy(A)). The least upper bound of the projection of A on the x-axis (respectively y-axis) is denoted by supx(A) (respectively supy(A)). The minimum bounding box of A, denoted by mbb(A), is the box formed by the rectangle where the coordinates of the left inferior corner are x1=infx(A), y1=infy(A) and the coordinates of the right superior corner are x2=supx(A), y2=supy(A). The single-tile cardinal direction relations can be defined as follows:

A O B iff infx(B)≤infx(A), supx(A)≤supx(B), infy(B)≤infy(A) and supy(A)≤supy(B)
A S B iff supy(A) ≤ infy(B), infx(B) ≤ infx(A) and supx(A) ≤ supx(B)
A SW B iff supx(A) ≤infx(B) and supy(A) ≤infy(B)
A W B iff supx(A) ≤ infx(B), infy(B) ≤ infy(A) and supy(A) ≤ supy(B)
A NW B iff supx(A) ≤ infx(B) and supy(A) ≤ supy(B)
A N B iff supy(B) ≤ infy(A), infx(B) ≤ infx(A) and supx(A) ≤ supx(B)
A NE B iff supx(B) ≤ infx(A) and supy(B) ≤ infy(A)
A E B iff supx(B) ≤ infx(A), infy(B) ≤ infy(A) and supy(A) ≤ supy(B)
A SE B iff supx(B) ≤ infx(A) and supy(A) ≤ supy(B)

Each multi-tile cardinal direction relation can be defined as follows:

a R1 : … : Rk b, 2 ≤ k≤ 9 if there exists regions a1, …, ak such that a= a1 ∪ … ∪ak and a1 R1 b, a2 R2 b, …, ak Rk b.

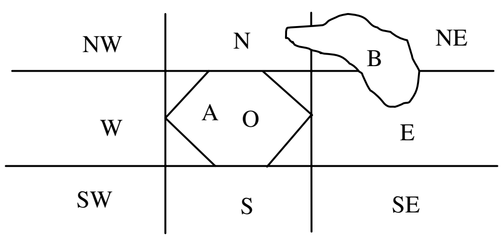

Fig. 3. cardinal direction relation between two regions A and B

2.2 The Connectivity-Direction-Metric Formalism (CDMF)

The minimum bounding boxes of two regions give some information about their spatial relations but this information is sometimes very poor, for example when one box overlapped another (Fig. 2a). In order to describe more complex spatial organization, we use three kinds of basic information:

(1) The notion of connectivity expressed in the topological framework of RCC8 by the primitive dyadic relation C(x,y) read as "x connects with y".

(2) the notion of minimum bounding box introduced in the Cardinal Direction Formalism. Several properties can be deduced from this notion:

- The surface, width and height of a region can be computed.
- The directional relations between two regions. In our context we define four directional relations: N (North), S (South), W (West) and E (East).

a N b iff supy(b) ≤ infy(a), a S b iff supy(a) ≤ infy(b),
a W b iff supx(a) ≤ infx(b), a E b iff supx(b) ≤ infx(a)

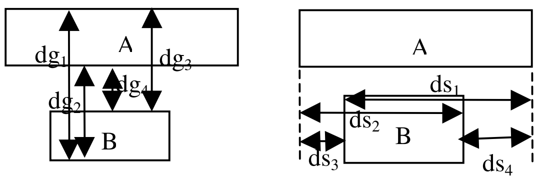

Fig. 4. The 8 metrics between two minimum bounding boxes: distances between A and B and lateral shifts between A and B

- Several metrics between two regions so long as the minimum bounding boxes of the two regions are not overlapped. Eight metrics between two minimum bounding boxes can be defined (see Fig. 4). For the north/south orientation, the definitions are: dg_1(A,B) = supy(A)-infy(B) , dg_2(A,B) =infy(A)-infy(B), dg_3(A,B) = supy(A)-supy(B), dg_4(A,B)= infy(A)-supy(B), ds_1(A,B)= supx(A)-infx(B), ds_2(A,B)= supx(B)-infx(A), ds_3(A,B)= infx(B)-infx(A), ds_4(A,B)=supx(A)-supx(B). The definitions for the east/west orientation are similar. The eight relations defined in the CDF can be easily retrieved from our relations with the appropriate metrics.

(3) A new notion of minimum bounding box of border interfaces (mbbbi) between two regions for each main cardinal direction (N, S, E, W). This notion is defined in the following section.

Minimum bounding boxes of border interfaces between two regions. In order to make a more accurate spatial analysis we define the notion of minimum bounding boxes of "border interfaces". We mean by "border interface" the border part of a region which, given a cardinal direction, is in front of another region (See Fig. 2b).

Definition 1. Let R be a region (a set of connected pixels), we note p(x,y) a pixel of R. E(R)={p(x,y) ∈ R | ∃p(x',y') one of the 8 connected neighbors of p(x,y), p(x',y') ∉ R}. Let be A and B two regions:

- The border interface Cw(A,B) is defined by {p(x,y) ∈ E(A) such that ∃p(x' ,y) ∈ E(B) and ∀ p(x'',y) such that x< x''<x' p(x'',y) ∉ A and p(x'',y) ∉ B }
- The border interface Ce(A,B) is defined by {p(x, y) ∈ E(A) such that ∃p(x', y) ∈ E(B) and ∀ p(x'', y) such that x> x''>x' p(x'', y) ∉ A and p(x'', y) ∉ B }
- The border interface Cn(A,B) is defined by {p(x, y) ∈ E(A) such that ∃p(x ,y') ∈ E(B) and ∀ p(x, y'') such that y< y''<y' p(x, y'') ∉ A and p(x, y'') ∉ B }
- The border interface Cs(A,B) is defined by {p(x, y) ∈ E(A) such that ∃p(x ,y') ∈ E(B) and ∀ p(x, y'') such that y> y''>y' p(x, y'') ∉ A and p(x, y'') ∉ B }

Definition 2. The minimum bounding box of a border interface in the direction *d* ($mbbbi_d$) is defined by (infx(C*d*(a,b)),infy(C*d*(a,b))),(supx(C*d*(a,b)),supy(C*d*(a,b)))

We can see on the example of Figure 2 that the two mbb of the regions A and B are overlapped. On the contrary the $mbbbi_w$ and the $mbbbi_e$ are not overlapped. Then, it is easy to know on this example that the region A is on the left side of region B.

Additional relations between two regions. Minimum bounding boxes of border interface ($mbbbi_w$, $mbbbi_e$, $mbbbi_n$, $mbbbi_s$) allow to describe additional relations. The four spatial relations between A and B linked to the corresponding $mbbbi_d$ can be defined as follows:

A Ei B iff supx (Cw(B,A)) ≤ infx(Ce(A,B)),
A Wi B iff supx(Cw(A,B)) ≤ infx (Ce(B,A)),
A Ni B iff supy(Cn(A,B)) ≤ infy(Cs(B,A))
A Si B iff supy(Cn(B,A)) ≤ infy(Cs(A,B)),

All these relations may be associated with the metric d defined as follows: d(A,B)= infz(A)-supz(B) where z = y for Ni or Si relationship, and z = x for Ei or Wi relationship.

Elementary relations in CDMF. CDMF allows to define very complex relationships by a combination of elementary relationships. An elementary relationship is a relation:

- (1) of connectivity or non connectivity
- (2) of directional relationship between mbb with none or one metric relation chosen among the metrics dsi and dgi (i=1…4) defined before (with inferior and superior limits). In that case, we have four directional relationships: N (North), S (South), W (West) and E (East).
- (3) of directional relationship between mbbbi with one metric relation d defined before (with inferior and superior limits). In that case, we have four directional relationships: Ni, Si, Wi and Ei.

Property 1. For each elementary relation ℜe between A and B, A ℜe B ⇒ ∃a ∈ A and ∃b ∈ B, a ℜe b.

Proof: ℜe of type (1). It is straightforward that
A connected to B ⇒ ∃a ∈ A and ∃b ∈ B, a connected to b.
A not connected to B ⇒ ∃a ∈ A and ∃b ∈ B, a not connected to b.

$\Re e$ of type (2). Let R be one of the four relations N, S, E, W and d_i be one of the eight metrics defined between two mbb (i=1 …8). Let min and max be the inferior and superior limits (in number of pixels) of the distance d_i. It is straightforward that A R B and min $\leq d_i$ (mbb(A),mbb(B)) $\leq$max $\Rightarrow \exists a \in A$ and $\exists b \in B$, a R b min $\leq d_i$ (mbb(a),mbb(b)) $\leq$max.

$\Re e$ of type (3). Let R be one of the four relations Ni, Si, Wi, Ei defined by using the mbbbi in section 2.2. Let d be the metric associated with the two mbbbi. Let min and max be the inferior and superior limits (in number of pixels) of the distance d. It is straightforward that A R B and min $\leq$d ($mbbbi_R$ (A),$mbbbi_R^{-1}$(B)) $\leq$max $\Rightarrow \exists a \in A$ and $\exists b \in B$, a R b min $\leq$d ($mbbbi_R$ (a),$mbbbi_R^{-1}$ (b)) $\leq$max. R^{-1} is the opposite direction of R.

3 Application of the CDMF Relations to Over-Segmented Objects: Integration of the CDMF in a CSP with Bilevel Constraints

High level interpretation of images consists usually in matching each part of the image with a meaningful representation. The graph formalism is a very natural and convenient way to represent the semantic content of an image and the CDMF may be used to define node and arc constraints. Among several strategies [6], [16], we choose to perform this matching by solving a constraint satisfaction problem (CSP), because it better deals with complex directional spatial relationships. This aspect has been discussed in [9]. To reduce the time complexity of matching a graph with the different subparts of a shape, it is possible to only take into account local constraints. In practice, as problems are usually over-constrained, the arc-consistency checking is enough. Several authors [3], [15], [19] have proposed fast arc-consistency checking algorithms. These algorithms try to associate only one value with one node. This assumption supposes an ideal segmentation (one node of the graph is associated with only one region). In our context, the data are not ideally segmented and usually the objects present in an image are over-segmented in an arbitrary way depending on the grey level distribution in the image. The problem is: assuming A and B as two objects (regions) in an image, such that A $\Re$ B with $\Re$ a combination of $\Re e$ of CDMF, how to define the relation $\Re'$ between any subpart $a \in A$ and $b \in B$ such that a $\Re'$ b $\Rightarrow$ A $\Re$ B ?

The elementary relationships of CDMF have an interesting property seen previously. For each elementary relation $\Re e$ between A and B, A $\Re e$ B $\Rightarrow \exists a \in A$ and $\exists b \in B$, a $\Re e$ b. Then the $\Re e$ representing arc constraints in the graph formalism are valid to represent constraint on subparts of objects candidate to be matched with a node. However, due to the over-segmentation, a subpart of an object does not always satisfy all the constraints that make classical CSP fail. A solution was described in [7] by introducing two level of constraints in the classical CSP. The first level is the classical constraint between nodes, and the second level called $\mathcal{C}_{mpi}$ is an intra-node constraint. This second level defines how any subpart of an object, which does not satisfy a given inter-node constraint, has to satisfy an intra-node constraint with another region satisfying the inter-node constraint. In the following section, the notion of arc consistency checking with bilevel constraints is defined. Then, an example of its implementation and an example of using CDMF in this context are described. In particular, we will see how to express the complex spatial relationship like “is surrounded by”.

3.1 Constraint Satisfaction Problem and Arc Consistency Checking with Bilevel Constraints

We use the following conventions:

- Variables are represented by the natural numbers 1, ... n. Each variable i has an associated domain D_i. We use D to denote the union of all domains and d the size of the largest domain.
- All constraints are binary and relate two distinct variables. A constraint relating two variables i and j is denoted by C_{ij}. $C_{ij}(v,w)$ is the Boolean value obtained when variables i and j are replaced by values v and w respectively. Let $\mathcal{R}$ be the set of these constraining relations.

We defined the Finite-Domain Constraint Satisfaction Problem with Bilevel Constraints ($FDCSP_{BC}$). One level of constraint is between each couple of nodes (spatial relations between objects associated with a node) and the other one level of constraint is between each couple of regions classified inside one node (spatial relations between subparts of the object associated with a node). These constraints are called $\mathcal{C}_{mpi}$ with i=1 … n. This problem is defined as follows:

Definition 3. Let $\mathcal{C}_{mpi}$ be a compatibility relation, such that $(a,b) \in \mathcal{C}_{mpi}$ iff a and b are compatible. Clearly $\mathcal{C}_{mpi}$ is reflexive. Let C_{ij} be constraint between i and j. Let be a pair S_i, S_j such that $S_i \subset D_i$ and $S_j \subset D_j$, $S_i, S_j \mapsto C_{ij}$ means that (S_i, S_j) satisfies the oriented constraint C_{ij}.

$S_i, S_j \mapsto C_{ij} \Leftrightarrow \forall a_i \in S_i, \exists(a'i, aj) \in S_i \text{ x } S_j$, such that $(a_i, a'_i) \in \mathcal{C}_{mpi}$ and $(a'_i,a_j) \in C_{ij}$

and $\forall a_j \in S_j, \exists(a'_{j,ai}) \in S_j \text{ x } S_i$, such that $(a_j, a'_j) \in \mathcal{C}_{mpj}$ and $(a_i,a'_j) \in C_{ij}$.

Sets $\{S_1 \dots S_n\}$ satisfy $FDCSP_{BC}$ iff $\forall C_{ij}$ $S_i, S_j \mapsto C_{ij}$.

A graph G is associated to a constraint satisfaction problem as follows: G has a node i for each variable i. Two directed arcs (i,j) and (j,i) are associated with each constraint C_{ij}. Arc(G) is the set of arcs of G and e is the number of arcs in G. Node(G) is the set of nodes of G and n is the number of nodes in G.

A class of problems called arc-consistency problems with bilevel constraints (AC_{BC}), associated with the $FDCSP_{BC}$ is defined as follows:

Definition 4. Let $(i,j) \in arc(G)$. Arc (i,j) is arc consistent with respect to $\mathcal{P}(D_i)$ and $\mathcal{P}(D_j)$ iff $\forall Si \in \mathcal{P}(Di)$ $\exists Sj \in \mathcal{P}(Dj)$ such that $\forall v \in Si$ $\exists t \in Si$, $\exists w \in Sj$, $\mathcal{C}_{mpi}(v,t)$ and $C_{ij}(t,w)$.(v and t could be identical)

Definition 5. Let $P= \mathcal{P}(D_1) \text{ x .... x } \mathcal{P}(D_n)$. A graph G is arc-consistent with respect to P iff $\forall (i,j) \in arc(G)$: (i,j) is arc-consistent with respect to $\mathcal{P}(D_i)$ and $\mathcal{P}(D_j)$.

The purpose of an arc-consistency algorithm with bilevel constraints is, given a graph G and a set P, to compute P', the largest arc-consistent domain with bilevel constraints for G in P.

3.2 Implementation of the Arc-Consistency Checking Algorithm with Bilevel Constraints

The AC4 algorithm proposed by Mohr and Henderson [12] has been adapted to solve the AC_{BC} problem. We call this algorithm AC_{4BC} (See [7] for the details of the algorithm). In AC_{4BC}, a node belonging to node(G) is made up of a kernel and a set of interfaces associated with each arc, which comes from another linked node. In addition, an intra-node compatibility relation $\mathcal{C}_{mpi}$ is associated with each node of the graph. It describes the semantic link between different subparts of an object, which could be associated with the node. As in algorithm AC_4, the domains are initialized with values satisfying unary node constraints and there are two main steps: an initialization step and a pruning step. However, whereas in AC_4 a value was removed from a node i if it had no direct support, in AC_{4BC}, a value is removed if it has no direct support and no indirect support obtained by using the compatibility relation $\mathcal{C}_{mpi}$. The indirect supports are found thanks to the notion of interfaces.

3.3 Example of Implementation of the Relation "Is Surrounded" by Introducing the CDMF in the CSP_{BC}

Using the CDM Formalism, it is possible to define the notion "is surrounded by" with over-segmented regions (The graph can be seen in Fig. 5.1). "A is surrounded by B" is defined as follows: $\forall a \in A, \forall R \in \{N, S, W, E\}\ \exists c \in A$ or $\exists c \in B$, a connected to c and a R c. The possibility to authorized an "or" between the two constraints the consequence of the notion of quasi arc-consistency in AC_{BC} described in [8].

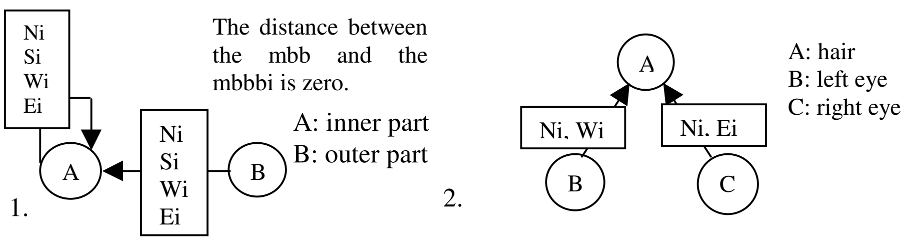

Fig. 5. 1. Graph used to work with the relation "is surrounded by" (for example, centre (A) is surrounded by petals (B) in a flower) 2. Graph used to work with "is partially surrounded by" (for example eyes are partially surrounded by hair)

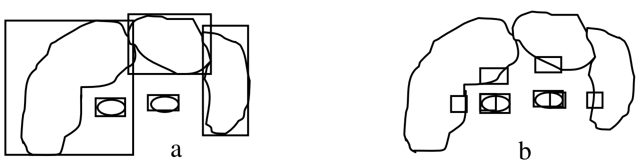

Fig. 6. a) With classical minimum bounding boxes it is not possible to compute the distance between the left eye and the hairs, b) with the mbbbi of the CDMF, it is possible to compute a distance

Another kind of relation is "partially surrounded by" with a given distance. This case can be encountered in the identification of the eyes and hair in a human face (See Fig. 6). In that case, the nodes representing the eyes and the node representing hair have to be related by the three constraints Ni, Ei and Wi. The distance d_{g4} is associated with the three relations (The graph can be seen on Fig. 5.2).

4 Experiments: Application to Check the Semantic Consistency of a Segmentation

Several kinds of test images representing different objects have been chosen. A set of images represents human faces, another set represent cars and finally another set represent flowers. For each kind of objects a semantic graph describing them has been built. The semantic consistency checking has been applied on the segmentation obtained with a pyramidal merging process [12] to stop automatically the merging at the

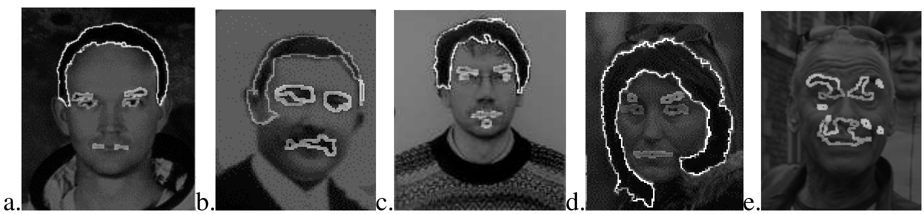

Fig.7. Interpretation of segmentation results of faces. Regions labelled as eyes, mouth and hair are shown by overlapping their edges with the original images.

Fig. 8. Interpretation of segmentation results of cars (Labelled regions are tyres and lateral windows)

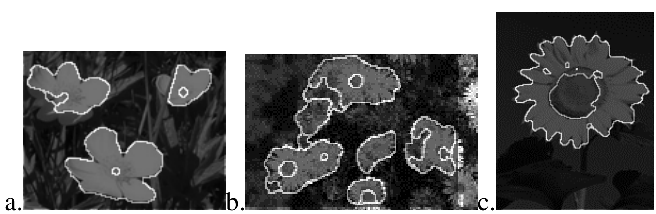

Fig. 9. Interpretation of segmentation results of flowers (labelled regions are centre and petals)

more meaningful pyramidal level (but it could be applied to other methods of segmentation providing a succession of embedded results with respect to the values of their parameters). On Figures 7,8 and 9 the regions with white edges are the obtained segmented regions correctly interpreted by the semantic analysis. In Fig. 7, the use of the quasi-arc consistency checking was necessary [8] to interpret the images because the node ”hair” may be empty (see image ’e’ of the Fig. 7).

5 Comments and Conclusion

In this article, we have proposed a new way to express complex spatial relation. We have shown that this set of new relations makes possible the expression of cardinal direction relations as well as crucial topological relations such as “is surrounded by “. Thanks to these relations, it is possible to build very precisely semantic graph describing an object made up of several subparts. With the $AC4_{BC}$ algorithm, this semantic graph can be used to retrieve objects inside an image. Some experiments have been made on real images, and we have shown that it is possible to detect very different kind of objects such as faces, cars, and flowers. This approach can be useful in the framework of image indexing to find some categories of images inside very large image databases. This work can be a theoretical foundation and embedding this approach into the MPEG-7 standard or into a realistic system can be a future work.

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