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A Qualitative Image Descriptor $QIDL^+$ Applied to Ambient Intelligent Systems

Zoe FALOMIR [a,1],
[a] *Cognitive Systems Department (CoSy), Universität Bremen*

Abstract. A model for obtaining a real-world scene logic and narrative description using qualitative features of shape, colour, topology, location and size is presented in this paper. The main aim is describing the location of target objects with respect to known or unknown objects in a scene. A logic description is also provided for reasoning about spatial locations. A proof-of-concept of an image of the top of the desk is use to illustrate the approach and promising results are obtained.

Keywords. qualitative descriptors, logics, narrative, context, scene understanding

1. Introduction

Ambient Assisted Living (AAL) applications need Ambient Intelligence (AmI) for: (i) scene understanding (i.e. to 'know' what is happening in a building); (ii) reasoning, to identify the consequences of what is happening and provide assistance if needed; and (iii) learning, to identify routine activities and 'predict' events by analogy with the past, and also identify uncommon or 'new' activities. Moreover, systems that must carry out a task in environments where people live or work need cognitive capabilities for enhancing human-machine communication. As Vernon [1] pointed out: *'Cognition implies an ability to understand how the world around us might possibly be (...) and being able to interpret a visual scene without having complete data'*. Therefore, a cognitive system should be able to describe and identify scenes without having complete information about them. (i.e., it should be able to describe objects that have not seen before and identify them by the context).

A key issue in the study of Ambient Intelligence is reasoning about context to deduce new knowledge. The main challenges of this effort derive from the imperfect context information, and the dynamic and heterogeneous nature of the ambient environments [2]. In order to provide the right information to the users at the right time and in the right place, an ambient intelligent system must 'understand' its environment, the users needs/preferences and the tasks and activities that are being undertaken. Henricksen and Indulska [3] characterize four types of imperfect context information: unknown, ambiguous, imprecise, and erroneous. Sensor or connectivity failures result in situations, where not all context data is available at any time. When the data about a context property comes

[1]Corresponding Author: Dr.-Ing. Zoe Falomir Llansola, Cognitive Systems Department (CoSy), Universität Bremen, Cartesium 3.54 Enrique-Schmidt-Str. 5, 28359 Bremen, Germany
E-mail: zfalomir@informatik.uni-bremen.de

from multiple sources, the context information may become ambiguous. Imprecision is common in sensor-derived information, while erroneous context information arises as a result of human or hardware errors. The role of reasoning in these cases is to detect possible errors, make predictions about missing values, and decide about the quality and the validity of the sensed data. The raw context data needs, then, to be transformed into meaningful information so that it can later be used in the application layer.

Some approaches which use Semantic Web-based representations to describe context and reasoning have been proposed in the literature [2]. They retrieve information from the context knowledge base, check if the available context data is consistent or derive implicit ontological knowledge, but they have some drawbacks in reasoning: they cannot deal with missing or ambiguous information (which is a common case in ambient environments) and are not able to provide support for decision making. Some of these reasoning issues are due to the fact that ontology-based models are based on open world assumption (OWA) for reasoning and there is a need to close the world for solving inferences (i.e. regarding counting individuals) [4]. Other AI techniques have been explored in this context, for example case-based reasoning [5] and temporal reasoning [6]. Qualitative Spatial and Temporal Reasoning (QSTR) [7,8] deal with commonsense knowledge without using numerical computation, therefore it can reason with non-exact data, ambiguous or incomplete. It has been applied to simulated AmI environments for reasoning about spatial configurations and dynamics [9]. This paper extends the Qualitative Image Description (QID) approach [10,11] by including qualitative sizes of the objects as a new feature and it is applied to describe logically and narratively real AmI scenes at Cartesium building at Universität Bremen.

The rest of the paper is organized as follows. Section 2 presents the qualitative image descriptors in Prolog syntax, which enables straightforward reasoning capabilities. Section 3 shows logic definitions for inferencing new information about the context. Section 4 shows a a proof-of-concept, then conclusions and future work are explained.

2. The Extended Qualitative Image Logic Descriptor ($QIDL^+$)

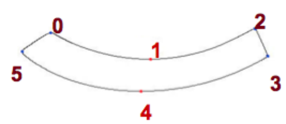
The *QID* approach [10] extracts the relevant regions detected within a digital image and describes them qualitatively by its shape, colour, topology an orientation. The *QIDL* [11] approach implemented logics for the description. Here, the $QIDL^+$ extends these logics and features to include also qualitative sizes.

2.1. Qualitative Shape Description (QSD)

Each of the relevant points of shape points ($\{P_0,P_1,...,P_N\}$) is described by a set of four features:
– Edge Connection (EC) occurring at P, described as: {*line_line, line_curve, curve_ line, curve_curve, curvature_point*};
– Angle (A) at the relevant point P (which is a not a *curvature_point*) described by the qualitative tags: {*very_acute, acute, right, obtuse, very_obtuse*}; – Type of Curvature (TC) at the relevant point P (which is a *curvature_point*) described qualitatively by the tags: {*very_acute, acute, semicircular, plane, very_plane*};

– Compared Length (L) of the two edges connected by P, described qualitatively by: {*much_shorter (msh), half_length (hl), a_bit_shorter (absh), similar_length (sl), a_bit_longer (abl), double_length (dl), much_longer (ml)*};
– Convexity (C) at the relevant point P, described as: {*convex, concave*}.

Thus, the complete shape of an object is categorized qualitatively with respect to (wrt) this descriptors as: {*triangle, quadrilateral, square, pentagon, ..., polygon*}. Figure 1 presents an example of the QSD.



qsd(EC, A|TC, L, C)
0: qsd(line-curve, obtuse, much_shorter, convex).
1: qsd(curvature-point, very-plane, similar_length, concave).
2: qsd(curve-line, obtuse, much_longer, convex).
3: qsd([line-curve, right, much_shorter, convex]).
4: qsd(curvature-point, very-plane, similar_length, convex).
5: qsd(curve-line, acute, much_longer, convex).

Figure 1. Example of shape described by the Qualitative Shape Descriptor (QSD).

2.2. *Qualitative Colour Description (QCD)*

The Red, Green and Blue (RGB) colour channels of object pixels are translated into Hue, Saturation and Lightness (HSL) coordinates, and a reference system for colour naming is built according to Figure 2 and defined as:

$$QCRS = \{uH, uS, uL, QC_{NAME1..5}, QC_{INT1..5}\}$$

where uH is the unit of Hue; uS is the unit of Saturation; uL is the unit of Lightness; $QC_{NAME1..5}$ refers to the colour names; and $QC_{INT1..5}$ refers to the intervals of HSL coordinates associated with each colour. The chosen QC_{NAME} and QC_{INT} are:
QC_{NAME_1} = {*black, dark_grey, grey, light_grey, white*}
QC_{INT_1} = {[0, 20), [20, 30), [30, 50), [50, 75), [75, 100) $\in$ UL / $\forall$ UH $\wedge$ US $\in$ [0, 20] }
QC_{NAME_2} = {*red, orange, yellow, green, turquoise, blue, purple, pink*}
QC_{INT_2} = {(335, 360] $\wedge$ [0, 20], (20,50], (50, 80], (80, 160], (160, 200], (200, 260], (260, 300], (300, 335] $\in$ UH / US $\in$ (50, 100] $\wedge$ UL $\in$ (40, 55] }
QC_{NAME_3} = {*pale_* + QC_{NAME_2}}
QC_{INT_3} = {$\forall$UH$_{INT_2}$ / US $\in$(20, 50] $\wedge$UL $\in$(40, 55] }
QC_{NAME_4} = {*ligth_* + QC_{NAME_2}}
QC_{INT_4} = {$\forall$ UH$_{INT_2}$ / US $\in$(50, 100] $\wedge$ UL $\in$(55, 100] }
QC_{NAME_5} = {*dark_* + QC_{NAME_2}}
QC_{INT_5} = {$\forall$UH$_{INT_2}$ / US $\in$(50, 100] $\wedge$UL $\in$(20, 40]}

As a baseline, the QCRS was calibrated according to the vision system used.

2.3. *Topological Description*

The topological situation in space (invariant under translation, rotation and scaling) of an object A with respect to (wrt) another object B (A wrt B) is described as:

$$T_{Label} = \{disjoint, touching, completely\_inside, container\}.$$

The T_{Label} determines if an object is *completely_inside* another object or if it is its *container*. It defines also the *neighbours* of an object as all the other objects with the

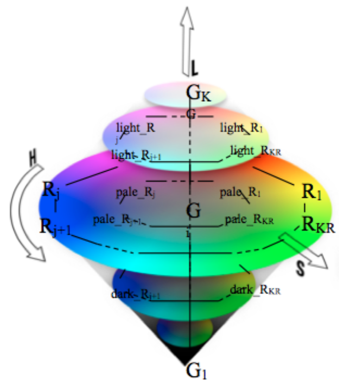


Figure 2. Reference System for the Qualitative Colour Descriptor (QCD). The vertical axis contains the colours in the *grey scale* ($G_1 \cdots G_K$) whereas the *rainbow or prototype colours* are located in the external central circle ($R_1 \cdots R_{KR}$). *Light* colours are situated above, close to *white*, and *dark* colours are placed below, close to *black*.

same container which can be (i) *disjoint* from the object, if they do not have any edge or vertex in common; (ii) or *touching* the object, if they have at least one vertex or edge in common or if the Euclidean distance between them is smaller than a certain threshold set by experimentation. Figure 3 presents a graphical representation of these relations.

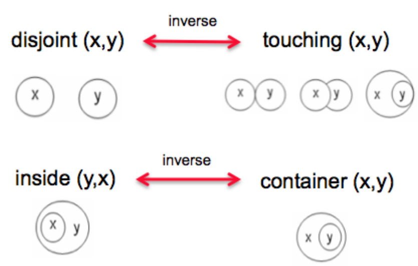


Figure 3. Topological situations distinguished by the *QIDL*$^+$.

2.4. Location Description

For obtaining the location of an object A wrt its container or the location of an object A wrt an object B, neighbour of A, the following Location Reference System (LoRS) is used which divides the space into nine regions as shown in Figure 4:

LoRS$_{Label}$= {*up, down, left, right, up_left, up_right, down_left, down_left, centre*}.

The orientation of an object is determined by the union of all the orientations obtained for each of the relevant points of the shape of the object ($\{P_0, P_1, ..., P_N\}$). The location of any object wrt the image is computed and also the location of any object wrt its *touching* neighbours.

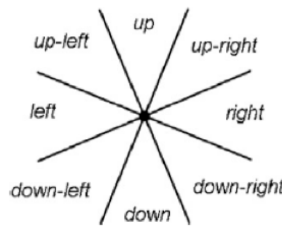


Figure 4. Locations described by the $QIDL^+$.

2.5. Qualitaive Size Descriptior

A qualitative size descriptor is built according to a reference system described by Figure 5 and defined as:

$$QSizeRS = \{relationSize, QSize_{Label}, QSize_{Int}\}$$

where $relationSize$ is the unit of reference defined as $relationSize = \frac{objectSize}{imageSize}$; $QSize_{Label}$ refers to the size labels; and QSz_{Int} refers to the intervals associated with each label, which follows a geometric serial.

The chosen $QSize_{Label}$ and $QSize_{Int}$ are:
$QSize_{Label}$ = {*huge, large, very_big, big, medium, quite_small, small, very_small, tiny*}
$QSize_{Int}$=$\{[1, \frac{1}{2}), [\frac{1}{2}, \frac{1}{2^2}), [\frac{1}{2^2}, \frac{1}{2^3}), [\frac{1}{2^3}, \frac{1}{2^4}), [\frac{1}{2^4}, \frac{1}{2^5}), [\frac{1}{2^5}, \frac{1}{2^6}), [\frac{1}{2^6}, \frac{1}{2^7}), [\frac{1}{2^7}, \frac{1}{2^8}), [\frac{1}{2^8}, 0]\}$

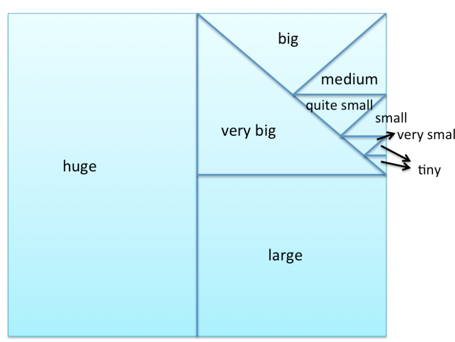


Figure 5. Reference system for the size descriptor used in $QIDL^+$.

2.6. Logics Generated for $QIDL^+$

The $QIDL^+$ approach describes a complete image by a set of facts:

$[[\mathrm{QSD}_1, \mathrm{QCD}_1, \mathrm{Topology}_1, \mathrm{Location}_1, \mathrm{QSize}_1], \ldots, [\mathrm{QSD}_n, \mathrm{QCD}_n, \mathrm{Topology}_n, \mathrm{Location}_n, \mathrm{QSize}_n]]$ where n is the number of objects.

A knowledge base (KB) can be built as a set of formulas in first order logic [12] constructed using four types of symbols (constants, variables, functions, and predicates). First-order KBs are usually built using Horn clauses [13], which contains at most one positive literal. Prolog programming language [14] is based on Horn clause logic.

The $QIDL^+$ can be generated in first-order logic following the Prolog notation shown in Table 1.

Table 1. Logics facts extracted for the objects in the images based on the qualitative descriptors.

α_1	$\mathsf{QIDLogics} \sqsubseteq \forall \mathsf{Object} \in \mathsf{Image}\ \exists \mathsf{QD}$
α_2	$\mathsf{QD} \sqsubseteq \forall \mathsf{P} \in \mathsf{Object}\ \exists \mathsf{hasQSDpoint}(\mathsf{Object}, \mathsf{P}, \mathsf{xy}(\mathsf{X}, \mathsf{Y}), \mathsf{qsd}(\mathsf{EC}_{\mathsf{Label}}, \mathsf{ATC}_{\mathsf{Label}}, \mathsf{C}_{\mathsf{Label}}, \mathsf{L}_{\mathsf{Label}}))$.
α_3	$\mathsf{QD} \sqsubseteq \exists \mathsf{hasQSDcategory}(\mathsf{Object}, \mathsf{Name}, \mathsf{Regularity}, \mathsf{Convexity})$.
α_4	$\mathsf{QD} \sqsubseteq \exists \mathsf{hasQCD}(\mathsf{Object}, \mathsf{colourPoint}(\mathsf{xy}(\mathsf{X}, \mathsf{Y}), \mathsf{rgb}(\mathsf{R}, \mathsf{G}, \mathsf{B}), \mathsf{hsl}(\mathsf{H}, \mathsf{S}, \mathsf{L}), \mathsf{QC}_{\mathsf{NAME1..5}})$.
α_5	$\mathsf{QD} \sqsubseteq \exists \mathsf{LoRS}_{\mathsf{Label}}(\mathsf{Object}, \mathsf{Image})$.
α_6	$\mathsf{QD} \sqsubseteq \exists \mathsf{completely\_inside}(\mathsf{Object}, \mathsf{ObjectInside})$.
α_7	$\mathsf{QD} \sqsubseteq \exists \mathsf{touching}(\mathsf{Object}, \mathsf{ObjectTouching}, [\mathsf{LocationList}])$.
α_8	$\mathsf{QD} \sqsubseteq \exists \mathsf{hasQSize}(\mathsf{Object}, \mathsf{RelationSize}, \mathsf{QSize}_{\mathsf{Label}})$.

By using the previous Prolog predicates, the $QIDL^+$ approach allows query logic to retrieve information from the KB. For example, the following query could be written:

```
which_size_colour_location(Size,Colour, Object, Location):-
    hasQSize(Object, _, Size),
    hasQCD(Object, _, _, _, Colour),
    find_location_in_image(Object, Location).
```

where the variables *Size*, *Colour*, $Object$ and *Location* can take any value. That is, this query can be asked by using a size (i.e. *small*) and all the *small* objects in the scene will be retrieved together with their colour, location and their name. It can also be asked using combinations of variables, for example:

```
which_size_colour_location(small, pale_yellow, Object, Location).
```

and it will retrieve the objects which are *small* and *pale yellow* and their locations in the scene.

3. Domain Knowledge in $QIDL^+$

The context is reflected by the domain knowledge introduced in the $QIDL^+$, which consists on:
(i) Logic definitions to categorize objects based on their qualitative descriptors. For example:

$$\begin{aligned}
&\forall X\ category(X, wall) \rightarrow [has_QCD(X,_,_,_,white) \vee \\
&\qquad has_QCD(X,_,_,_,light_grey)] \wedge \\
&\qquad [up(X, image) \vee up_right(X, image) \vee up_left(X, image)] \\
&\forall X\ category(X, postit) \rightarrow [has_QCD(X,_,_,_,yellow) \vee \\
&\qquad has_QCD(X,_,_,_,light_yellow) \vee has_QCD(X,_,_,_,pale_yellow)] \wedge \\
&\qquad hasQSize(X,_,small)
\end{aligned} \tag{1}$$

(ii) Images of target objects already 'known' by the system which are used to detect the reference objects in the scene. The properties of QSD, QCD, QSize, Topology and Location are inherited by these target objects after a matching of their features to a region identified by the $QIDL^+$ approach.

The category inferred can also be included in the query logic in order to retrieve information from the KB. Then queries as the following can be formulated:

```
which_size_colour(Size, Colour, Object, Name):-
    hasQSize(Object, _, Size),
    hasQCD(Object, _, _, _, Colour),
    category(Object, Name).
```

where the variables *Size*, *Colour*, *Object* and *Name* can take any value. That is, this query can be asked by using a name (i.e. *wall*) and all the objects categorized as *wall* in the scene will be retrieved together with their colour, size and their object identifier:

```
which_size_colour(Size, Colour, Object, wall).
```

And the following query which can retrieve locations of any object:

```
which_location(Object, Location, Name):-
    find_location_in_image(Object, Location),
    category(Object, Name).
```

For example, objects categorized as postit's and located *up*:

```
which_location(Object, up, postit).
```

or ask about any location of any object by its name or by its object identifier, i.e. *where is the postit?*: `which_location(Object, Location, postit).`

4. A Proof-of-concept

The Spatial Interactive Laboratory (SIL) [15] located at Cartesium building, Universität Bremen (Figure 6), incorporates *intelligent door tags* (computers) installed in the walls next to every office. SIL is an scenario suitable to obtain pictures of a daily living environment and to study different situations in ambient intelligence.

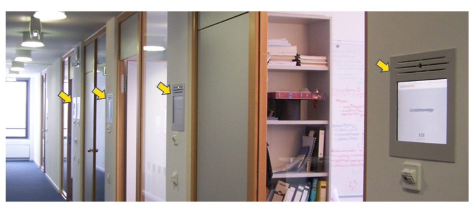


Figure 6. An office floor in the Cartesium building: arrows indicate intelligent door tags.

In this context, let us consider a picture taken at the Cartesium building, which may be obtained by SIL or by a robot incorporating a camera as a visual sensor. As Figure 7 shows, the *QIDL*$^+$ approach presented extracts the qualitative descriptors from the input image applying a colour segmentation method [16] and then obtains the closed boundary of the relevant regions detected. This process is automatic and it does not depend on the picture taken or the domain knowledge of the system. For each of the regions detected, qualitative descriptors of shape, colour, topology, location and size are obtained, as described in Section 2. From these descriptors, first order logics in Prolog syntax are obtained, as explained in Section 2.6. These qualitative descriptors combined with definitions of objects in the domain, allow to categorize regions previously unknown in the image (i.e. 'wall' or 'postit') as described in Section 3.

Target objects are provided to the system according to the task to accomplish and they are detected by the Speeded-Up Robust Features (SURF) invariant descriptor [17]

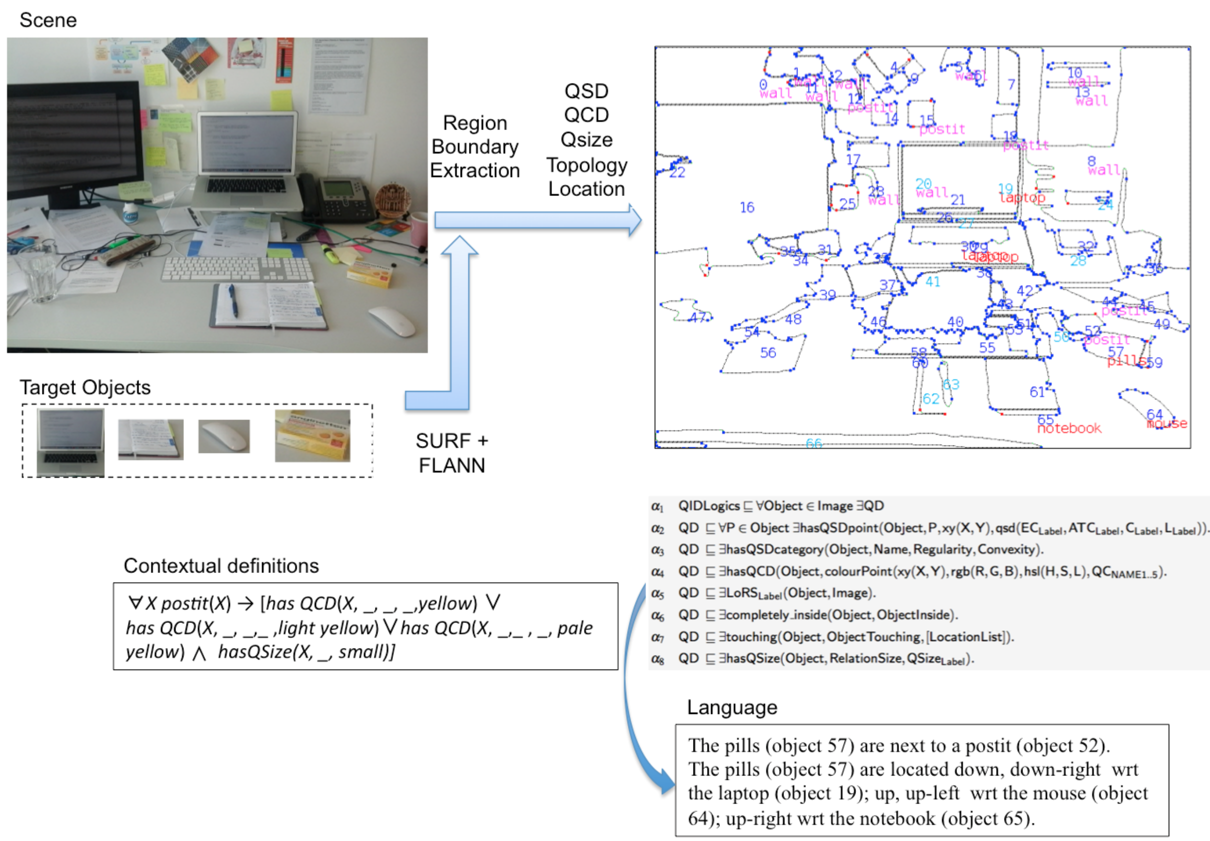


Figure 7. Outlook of the $QIDL^{+}$ approach presented.

and the fast approximate nearest neighbours (FLANN) detector [18]. As Figure 7 shows, in this proof-of-concept, the target objects are a *laptop*, a *notebook*, a *mouse* and some *pills*.

As Figure 7 shows, the target object *pills* are detected in the image by feature detectors and matched to the segmented object-57 which inherits all the qualitative characteristics of shape, colour, size, topology and location. According to the scene, the Prolog predicates obtained are the following:

```
hasQSDcategory(object-57, octagon, convex, irregular).
hasQCD(object-57, xy(542,356), rgb(170,164,130), hsl(51,8,58), pale_yellow).
hasQSize(object-57, 0.58, small).
right(object-57, image).
down_right(object-57, image).
touching(object-57, object-50, [up_left, left]).
touching(object-57, object-52, [up, up_left, left]).
touching(object-57, object-59, [down_right, right]).
category(object-57, pills).
```

And excerpt of the corresponding narratives generated are those showed in Figure 7. The rest of the narratives can be downloaded[3].

Moreover, using the Prolog logic predicates in the KB and the testing platform

SwiProlog[2] [19] logic queries were solved, such as asking the location of an object (categorized or not) or asking all the objects located in a specific location. For example:

a) the following query finds out the location of the mouse as *down_right*:

```
?- which_location(Object, Location, mouse).
Object = object-64, Location = down_right .
```

b) the following query finds out all the objects categorized as *postit*'s and indicates also their size, colour, and location in the scene:

```
?- which_size_colour_location(Size, Colour, Object, Location, postit).
 Size = small, Colour = pale_yellow, Object = object-12, Location = up_left ;
 Size = small, Colour = pale_yellow, Object = object-12, Location = up ;
 Size = small, Colour = pale_yellow, Object = object-15, Location = up ;
 Size = small, Colour = pale_yellow, Object = object-18, Location = up_right ;
 Size = small, Colour = pale_yellow, Object = object-44, Location = right ;
 Size = small, Colour = pale_yellow, Object = object-52, Location = right ;
 Size = small, Colour = pale_yellow, Object = object-52, Location = down_right ;
```

c) the following query indicates the size and colour of an object not categorized, such as the screen or object-16:

```
?- which_size_colour_location(Size, Colour, object-16, Location, Name).
 Size = big, Colour = dark_grey, Location = up_left, Name = object ;
 Size = big, Colour = dark_grey, Location = left, Name = object ;
```

The complete data files obtained for this scenario can be downloaded and analyzed intuitively[3]. For easily testing logic queries, the on-line platform Pengines[4] can be used.

5. Conclusions and Future Work

This paper presents the extended *QIDL*$^+$ which describes any digital image by providing qualitative features of shape, colour, topology, location and size for each of the objects within the image.

When detecting objects by colour segmentation, the shape and size obtained are approximated and imperfect. However, the qualitative descriptors used can deal with imprecise, incomplete and imperfect knowledge on a symbolic level, since they are defined on approximate range of values. Moreover, qualitative descriptors also provide *symbol-grounding* [21] that allows cognitive concepts to be aligned with human perception. By writing the qualitative descriptors using logic definitions, objects can be characterized depending on the context (i.e. building, office, situation).

Context information is also introduced when providing images of a-priori-known objects or target objects, which can be detected using the SURF and FLANN feature object detectors. If object recognition is successful, then it contributes to the *QIDL*$^+$ approach which can name some of the objects in the scene. If the object recognition is not correctly obtained (i.e. the object has not enough texture features to match or the illumination conditions are not suitable), then the *QIDL*$^+$ approach can still categorize

[2]SWI-Prolog: `http://www.swi-prolog.org/`

[3]Download the data files corresponding to the results from: `https://sites.google.com/site/zfalomir/projects/cognitive-ami`

[4]Pengines by SWI-Prolog: `http://pengines.swi-prolog.org/apps/swish/index.html`

some objects using the qualitative descriptors or provide a 'broad' description of the object based on its shape, colour, size, location and topology or combinations of them (i.e. the small yellow object on the right).

The proof-of-concept presented shows the usefulness of the $QIDL^+$ approach. Qualitative logic descriptors allow reasoning using query logic and further knowledge can be inferred. Since the qualitative concepts are aligned with human perception, they can be easily translated to generate narratives for enhancing machine-user communication.

As future work, it is also intended to: (i) enhance the cognitive adequacy of the logics/narratives by selecting the features of the object which are more salient objects depending on the context [20]; (ii) extend the reasoning capabilities of the approach to detect changes and to learn about the context.

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