The Semantics of Image Annotation

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Abstract

This paper presents a language for the semantic annotation of images, focusing on event types, their participants, and their spatial and orientational configurations. This language, ImageML, is a self-contained layered specification language, building on top of ISOspace, as well as some elements from Spatial Role Labeling and SpatialML. An annotation language characterizing such features surrounding an event and its various aspects could play a significant role in structured image retrieval, and a mapping of annotated semantic entities and the image’s low-level features will likely assist event recognition and description generation tasks.

1 Introduction

The role of image annotation is becoming increasingly important in the context of algorithms that allow for efficient access and retrieval of images from large datasets; for this reason, it has become an active topic of research in both the computer vision and natural language processing communities. Keyword annotation (tagging) approaches include interactive annotation games (Von Ahn and Dabbish, 2004; Von Ahn et al., 2006; Ho et al., 2009) and automatic keyword annotation, where, given an image, the system provides the appropriate (or potential) labels that describe its content (Li and Fei-Fei, 2007; Luo et al., 2009; Feng and Lapata, 2010). On the other hand, efforts in the task of image caption generation have experienced a growth due to the advances in object recognition. Here, objects as well as relations among them have to be identified, and the output must be a grammatical (and, if possible, natural) sentence that correctly describes the image content (Kiros et al., 2014). Approaches include those of Farhadi et al. (2010); Elliott and Keller (2013); Kiros et al. (2014) and Karpathy and Fei-Fei (2014), among many others.

The current MPEG-7 format encodes several dimensions of information about image structure (visual features, spatio-temporal structure, decomposition in regions or shots, etc.) and semantic content by means of its descriptors (Martinez, 2004). Semantic annotation with MPEG-7 captures events represented in the image as well as participants (objects and agents), the time, location, etc., and annotation and retrieval tools based on this format were presented in Lux et al. (2003); Lux and Granitzer (2005) and Lux (2009). The use of ontologies and thesaurus in the annotation of the semantic content of an image has been developed in the art history domain in Hollink et al. (2003); Hollink (2006) and Klavans et al. (2008), as well as in the context of multimedia semantic indexing (Nemrava et al. (2008)).

This paper approaches the annotation of image content outside the task of automatic image caption generation. Even though MPEG-7 approaches capture information about the event, its participants and the relations among them, this annotation could be enriched to include aspects that go beyond the basic categories addressed so far (location, time, event, participants), such as: the spatial relations between participants, the motion of objects, the semantic role of participants, their orientation and frame of reference, the relations among events in the image, or the characterization of the image as a whole as prototypical, given the event in question. These aspects can be included following text annotation schemes such as SpatialML (Mani et al., 2010), ISOspace (Pustejovsky et al., 2011) and Spatial Role Labeling (Kordjamshidi et al., 2010). Pustejovsky and Yocum (2014) in fact adapt ISOspace to the annotation of the
spatial configuration of objects in image captions, in particular to distinguish the way captions refer to the structure versus the content of the image. In this paper, we introduce ImageML for this purpose, and we describe how this richer information concerning the image can be incorporated as a self-contained layer annotation, making explicit reference to several embedded specifications, i.e., ISO-TimeML and ISOspace (ISO/TC 37/SC 4/WG 2 (2014); Pustejovsky et al. (2010)).

2 Problems Posed by Images

Text-based image search assumes that images have an annotation of some kind or at least a text in which to perform the query, and, that the text of the web page on which the image appears is related to the image content. These two assumptions, however, do not always hold. Content-based image retrieval approaches the problem by recording the image’s low-level features (texture, color layout, etc.) and semantic annotation of images aims to bridge the gap between those low-level features and the image semantic content.

However, efforts in keyword annotation, MPEG-7-based semantic annotation, and ontology-based annotation do not capture some aspects to which users might turn their attention when searching for an image. Although unstructured labels might be enough for image filtering or simple queries (dog running in park), more complex ones require a richer annotation that includes a description about the orientation of figures with respect to the viewer, the spatial relations among objects, their motion, appearance, or the structure of the event (including its sub-events) in which they might be involved; e.g., a user needs a picture of someone running towards the camera while listening to music.

MPEG-7-based annotation effectively captures the ‘narrative world’ of the image (Benitez et al., 2002), but does not provide a thorough annotation of the representation of figures or a characterization of their motion according to different frames of reference. Furthermore, image captions alone have a fixed frame of reference (viewer) and descriptions might refer both to image structure or image content; cf. (Pustejovsky and Yocum, 2014), which makes the annotation of this distinction an important task towards a more accurate image retrieval.

By capturing information about: (1) the event (type of event, any sub-events, any motion triggered by it, or any other event the image might refer to, if it is ambiguous); (2) the participants of the event (their type of entity, their semantic roles, their appearance, and their representation); and (3) the setting and the time of the depicted situation, ImageML would not only contribute to a more precise image querying capability, but it could also assist in event recognition and automatic caption generation tasks.

3 Annotating Spatial Relations in Images with ISOspace

The annotation of spatial information in text involves at least the following: a PLACE tag (for locations, entities participating in spatial relations, and paths); LINK tags (for topological relations, direction and orientation, time and space measurements, and frames of reference); and a SIGNAL tag (for spatial prepositions). ISOspace has been designed to capture both spatial and spatiotemporal information as expressed in natural language texts (Pustejovsky et al. (2012)). We have followed a strict methodology of specification development, as adopted by ISO TC37/SC4 and outlined in Bunt (2010) and Ide and Romary (2004), and as implemented with the development of ISO-TimeML Pustejovsky et al. (2005) and others in the family of SemAF standards.

There are four spatial relation tags in ISOspace, that are relevant to the definition of ImageML, defined as follows:

1. QSLINK – qualitative spatial relations;
2. OLINK – orientation relations;
3. MLINK – dimensions of a region or the distance between them.

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1 Roser and Pustejovsky (2008); Lee (2013).
2 The initial specification of a semantic annotation for images is first outlined in Bosque-Gil (2014).
3 For more information, cf. Pustejovsky et al. (2012).
d. MOVELINK – for movement relations;

QSLINKs are used in ISOspace to capture topological relationships between tag elements captured in the annotation. The `relType` attribute values come from an extension to the RCC8 set of relations that was first used by SpatialML. The possible RCC8+ values include the RCC8 values Randell et al. (1992), in addition to `IN`, a disjunction of TPP and NTPP.

Orientation links describe non-topological relationships. A `SPATIAL_SIGNAL` with a `DIRECTIONAL` `semantic_type` triggers such a link. In contrast to qualitative spatial relations, OLINK relations are built around a specific frame of reference type and a reference point. The `referencePt` value depends on the `frame_type` of the link. The `ABSOLUTE` frame type stipulates that the `referencePt` is a cardinal direction. For INTRINSIC OLINKS, the `referencePt` is the same identifier that is given in the `ground` attribute. For RELATIVE OLINKS, the `referencePt` for the viewer should be provided as to the `referencePt`. When the document type is `IMAGE`, all `olinks` are interpreted as relative FR relations (unless otherwise stated), with the “VIEWER” as the `referencePt`.

ISOspace also allows one to identify the source and type of the text being annotated. This is done with the `document creation location (DCL)` attribute. This is a distinguished location that serves as the “narrative or reference location”. While useful for narratives and news articles, captions associated with images pose a different problem, in that the document describes a `representation artifact`, such as an image or a Google Street View scene; hence, the document type is distinguished as an `IMAGE`. To account for this, (Pustejovsky and Yocum, 2014) introduce a new attribute, `domain`, which can take one of two values: `STRUCTURE` and `CONTENT`. This allows the spatial relations to differentiate the kinds of regions being identified in the caption. Furthermore, this means that the DCL can take two values: an `Image Structure Location`, for reference to the image as an object; and an `Image Content Location`, which is what the picture refers to (as in the default DCL for most texts).

4 The ImageML Model

In this section, we describe ImageML, a model for the semantic annotation of images. The conceptual schema provides an introduction to the information covered, its elements, and the relations among them.

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*These are represented as `phys_obj` • `info` complex types (dot objects), and inherit the properties of both type elements. Pustejovsky (1995).*
This annotation model is an attempt at capturing the semantic of images representing events, in contrast to images of landscapes and other non-dynamic representations. For this reason every annotated image includes at least one element of type EVENT.

The tags EVENT, FIGURE, OFIGURE, SETTING and TIME aim at encoding most of the information about the represented situation, both from a semantic perspective as well as from a formal one dealing with the specific way the elements are portrayed. In our view, participants of events have certain characteristics, such as their physical appearance or their type (an object, a person, etc.), are involved in events that affect their posture (e.g. sitting, standing), might have a gesture that viewers interpret as them having an emotional attitude (which is valuable information for image descriptions), and are represented in a limited number of ways with respect to the viewer (back view, full body, etc.). Relation tags serve three purposes: first, capturing how a figure relates to an event and how the figure’s specific representation is coupled with the characteristics of the motion involved in the event (if any); second, accounting for event ambiguity; and third, recording frequent sub-events of a main event which involve two participants (e.g. holding, gazing, facing). We included the latter relations because they provide information that complements topological and spatial annotations without overcomplicating the annotation task. The modeling of these latter events as relations responds to the need to capture them in numerous images.

4.1 IMAGE

This tag records the type of image (e.g. photo) and the camera angle. Going back to Bloehdorn et al. (2005)’s knowledge base of prototypical instances, its attribute prototypical encodes whether an image could be considered a canonical instance of the event it depicts, which is valuable information for the event recognition task.

4.2 EVENT

The EVENT tag comes from TimeML (Pustejovsky et al., 2003; ISO/TC 37/SC 4/WG 2, 2012) and here it captures the activity, event, or change of state that is represented in the image. Its attribute stage encodes the phase of the event and the attribute type indicates whether the event is a sub-event of a main event or the main event itself, in which case its sub-events are also listed as values for the attribute subevents. Holding events that on first sight could have been thought of as EVENTS of type sub-event are here captured by links (HOLDINGLINK) to facilitate the annotation process. In this way, in a picture of someone taking notes holding a notebook and a pencil, only the event take notes would be recorded as EVENT, in this case of type main and with two HOLDINGLINKs, one for the pen and one for the notebook.

4.3 FIGURE and OFIGURE

FIGURES are those objects in an image that are participants of an event or are involved in a holding relation. An object takes part in an event if it plays a semantic role (agent, theme, experiencer, etc.) in it, which is captured by the ROLELINK relation. This point is worth mentioning in order to distinguish FIGURES from other objects that appear on the image but do not take part in any event, hence their description is outside the scope of this specification.

The type of object is encoded in the type attribute, which takes its values from the ACE Entity types\textsuperscript{5}, from MPEG-7 semantic descriptor values (object and person), and from SpatialML (place). The way the figure is portrayed with respect to the viewer in terms of a vertical axis (front, profile-lateral, etc.) and its perceivable extent (whole, waist_up, etc.) are recorded by the attributes view and extent respectively. Other properties such as physical appearance, attitude, or their state (e.g., open, broken, etc.) are also accounted for.

Figures not present in the picture but inferred by the reader when interpreting the image content are captured by the OFIGURE tag. Common examples are images in which a figure interacts with the

\textsuperscript{5}ACE: Automatic Content Extraction 2008 Evaluation Plan (ACE08), http://www.itl.nist.gov/ia/ace/2008/doc/.
viewer (waving the hand at the camera, for instance), or close-up shots where the agent is not visible. An example of this is given below in Figure (2).

![Figure 2: The OFIG is the agent of the event stir, the spoon is just the instrument.](image)

4.4 SETTING and TIME

The SETTING tag aims at capturing information about the location of the events, any background elements or any background figures taking part in an event. Its attribute figureID distinguishes the overall setting of the events (e.g., a street) from specific objects in the image in which the event takes place (reading on a bench on the street), which are FIGURES with a role. The scene attribute records general aspects about the background of the image (e.g., outdoors and the attribute type encodes more specific information (e.g., street). Similarly, the TIME tag, inspired by TimeML TIMEX tag, encodes the time of the events and information deducible from the background.

4.5 ROLELINK and HOLDINGLINK

Kordjamshidi et al. (2010) introduce an annotation scheme similar in design to the task of semantic role labeling and classifies the arguments of spatial expressions in terms of their spatial roles. In this spirit, the tag ROLELINK addresses some spatial relations by indicating the source or goal of a movement, but it mainly encodes the semantic roles participants of events play, turning to the semantic roles used in VerbNet (Schuler, 2005): agent, recipient, instrument, experiencer, etc. The HOLDINGLINK relation was introduced in section 4.2 and stands for holding sub-events: it links a figure (agent) that holds a figure (theme). Just as events, these relations have a manner attribute.

![Figure 3: HOLDINGLINK expresses a sub-event hold, in which one figure holds another figure.](image)

4.6 MOTIONLINK and DIRLINK

The tag MOTIONLINK is taken directly from ISOSpace’s MOVELINK tag. It associates to the event that triggers the motion, general information about the causer of the motion, the source and goal of it, and the path and medium through which the motion occurs. The orientation of the motion according to the different frames of reference is captured by the DIRLINK (direction link) relation, which combines attributes from SpatialML RLINKs and ISOSpace OLINKs. The idea is to record fine-grained information about the orientation of the movement from the perspective of the object in motion, the causer of the movement and the viewer.
4.7 FACELINK AND GAZELINK

The relations FACELINK and GAZELINK draw upon the idea that eye gaze is an important semantic cue for understanding an image (Zitnick and Parikh, 2013). Facing and gazing could be thought of sub-events, but are here captured as links in a way resembling the relation HOLDINGLINK introduced earlier. Further, since a figure facing another figure does not imply that it is actually directing its gaze towards it, the FACELINK tag accounts for the way two figures are oriented towards one another, whereas the GAZINGLINK tag encodes eye-gaze relations between the two figures.

4.8 EXLINK

EXLINKS take as arguments at least two events and express the fact that they are mutually exclusive. Some images might be ambiguous in the event they represent: a plane landing or taking off, someone parking the car or maneuvering to leave the spot, closing or opening a book, etc. The idea behind including both potential events is to allow for an association of the same low level features to both types of events in the context of automatic event recognition as well as for a retrieval of the image if the user searches for images of any of the two events.

5 Annotation Examples

To illustrate the descriptive nature of ImageML, let us consider an image that exploits many of the specification elements described above. This image is an instance of someone taking notes in a notebook. The associated annotation identifies the event as “note-taking”, along with the attributes of “holding a pen”, the setting as being an interior location, the background being a bookshelf, and so on.

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6Extracted from Google Image Search. Source: Flicker user Marco Arment (marcoarment).
Figure 6: Brainstorming.

Rather than merely annotating all events in the image equally, it is important to note that there is a topic event (“note-taking”), and that other salient eventualities, such as the pen being held in a hand, etc., are captured as relational attributes to the main event. This would not be sufficient for a general event description protocol, such as that promoted in ISO-TimeML, but for image descriptions, it appears particularly well-suited, at least in the context of images that we have so far studied. Obviously, this is an issue that deserves further empirical study.

6 Conclusion

In this paper we have presented ImageML, a model for the semantic annotation of images which draws largely upon ISOspace, as well as some aspects of Spatial Role Labeling and SpatialML, to capture fine-grained information about the events depicted in an image, the motion involved (described from different frames of reference), as well as information about the participants, their orientation, and the relations among them. The setting and time of the situation are also accounted for. By its very design, ImageML is a layered annotation, incorporating elements and values from the embedded specification
languages of ISOspace and ISO-TimeML.\footnote{Features from SpatialML are already incorporated into ISOspace, and the relations in Spatial Role Labeling are captured through the relation tags in ISOspace.}

While not yet created, a database of images annotated with this information along with the spatial configuration of objects should be of potential use to structured image retrieval, event detection and recognition, and automatic image caption generation. We are currently pursuing the creation of such a corpus.

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