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STRUCTURED ANNOTATION OF SEMANTIC CONTENTS ON IMAGES FROM EARTHQUAKE RECONNAISSANCE

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Abstract

Post–event reconnaissance teams have a critical mission: to collect scientific data to be used to learn from disasters. Despite the large volumes of images that have been collected from past events, only a small portion of these are accessible to the public and archived with certain basic information such as date, event, or location. Thus, the capacity to access and facilitate reuse of these images based on the true visual contents on images is limited. Currently, there is no established image annotation method and formal ontology for describing visual contents in such images. This impedes the use of images for generating new knowledge, and large volumes of images remain largely unused for scientific research. To address this problem, a structured annotation method is proposed for images originating from earthquake reconnaissance. images of buildings are focused in this study, with the intention of supporting researchers focused on structural design and performance. Herein, an earthquake image ontology (EIO) is developed for formalized and structured descriptions of images. EIO consists of a large terminology and associated relationships, enabling rich descriptions of images based on their contents and the types of queries of interest to researchers. It is adequately extensible and flexible to successfully deal with a broader set of images in the future as needed. An image annotation tool assists human annotators as they choose appropriate terminologies and their relations in EIO. This facilitates image annotation and conversion of data into a searchable form. The capability and usefulness of the method is demonstrated using real-world images and their descriptions, based on a comprehensive examination of many publicly available reports, articles, and data repositories.

Keywords: Image annotation, Ontology, Structure performance, Earthquake reconnaissance

1. Introduction

After an earthquake, many images are collected by teams of trained engineers. Damaged buildings and components provide learning tools, and the lessons to be learned from the buildings that do not experience damage are often just as important. The general functions of an earthquake building investigation team are to collect perishable available data to enable scientific research intended to: (i) learn as much as possible about the nature of the event and extent of the consequences; (ii) identify possible gaps in existing research or in the application in practice of scientific, economic, engineering or policy knowledge; and (iii) help elucidate possible knowledge gaps for further investigations, and/or changes to codes, standards and design guidelines.

The value of visual data enhanced through accurate and useful annotation will empower researchers across several disciplines to distil the importance lessons that will enable engineers and researchers to improve the resilience of our communities against natural events. Determining structured and formalized descriptive information for these images will enable their scientific use and retrieval. For instance, longitudinal studies or regional studies comparing structural performance would lead to decisions regarding design practices. A structured set of descriptive information is essential for making use of these data. Long-term preservation of the large volumes of images collected is only effective if it is discoverable by future researchers. An example related to the impact of reconnaissance data, a longitudinal study directly comparing the performance of school buildings in Turkey was conducted. Images collected during the 1999 Düzce and 2003 Bingöl earthquakes were used, and both time variations and regional techniques were examined. The conclusion was that, regardless of construction quality, the use of structural walls was the single important structural characteristic impacting life safety in these schools. The presence of structural walls drastically improved performance, and prevented collapse [1]. This single example of data reuse is one of many that provide strong motivation for formalized annotation of such data to guide policy and code decisions.

The earthquake engineering community has promoted data repositories, often integrated within science gateways, to gather various types of scientific data to generate lessons learned [2-4]. Several hundreds of thousands of photos, with tens of thousands (at least) being collected each year around the world. Despite the enormous investment involved in collection of these important data, they have not historically been carefully documented or consistently organized due to the time and resources needed to perform this activity. Several examples aiming for this objective are available with varying levels of detail. The Earthquake Engineering Research Institute (EERI) has archived a broad collection of earthquake reconnaissance data collected by multidisciplinary teams of researchers (e.g. earth scientists, engineers, social scientists) (EERI.org). Although general information can be retrieved about the event (e.g. data, event, seismic intensity and country) and other data resources are available (e.g. article, report or image), the actual image data collected in the field are categorized as "Other resources." Users are not able to identify the types of data, nor can they automatically search of their contents. Furthermore, images are not curated or widely available beyond more than just a few events. Another system, CEISMIC is designed to include a digital archive of multimedia contents related to the Canterbury earthquakes of 2010 and 2011 (ceismic.org.nz). Archived data can be filtered by several types (e.g. images, newspapers, or videos) and metadata (e.g. keyword, time, or provider). However, image search results may be limited because images are retrieved based on associated text descriptions included in related documents, and are not using specific tagged keywords. The Earthquake Engineering Online Archive and NISEE e-library is a database of literature, photographs, data and software in earthquake structural and geotechnical engineering (nisee.berkeley.edu/elibrary). Various types of data from historical earthquakes are well documented and accessed by searching matching keywords. However, this is not data-intensive repository and provides very few information including images related with recent earthquake events (e.g. Haiti, 2010 or Nepal, 2014). Lastly, "datacenterhub.org" is an ongoing project funded by Purdue University and the National Science Foundation (NSF 1443027), and provides large collections of earthquake reconnaissance data and images (datacenterhub.org). Data are curated in the form of a table to enable ready comparisons and searching. Keyword-based image searching is in progress.

As image collections from such missions continue to grow into the millions, a formalized and structured method is needed to store and retrieve earthquake reconnaissance images (hereafter, earthquake images) along with descriptive metadata of these images. The descriptions should be based on the visual contents as extracted from the images collected, and integrated with the necessary information about the location and source of the image. Mostly, the contents can be only understood using metadata, linked text, or unorganized and heterogeneous tags (keywords). Because users often generate the description and metadata using their terminology without any structure, the ability to retrieve useful data is limited without consistently annotated contents and contextual information. Also, a traditional keyword-based tagging system is too simple to overcome the large semantic discrepancy that remains between user expectations and retrieval capability. It is not sufficient for earthquake images to represent visual semantic contents and engineer's explicit interpretation and knowledge.

Herein, a high-level annotation schema is proposed for describing the visual semantic contents of earthquake images in a structured way. The method is developed to incorporate original descriptions of earthquake images by preserving the original meaning of the description. Annotated contents and images can thus be fully retrieved using a semantic query. A core idea is to annotate images using structured terms and relations constructed by Earthquake Image Ontology (EIO). With the support of the associated annotation tool, annotators can easily select proper terms and their relations for descriptions and convert them into structured forms. This study aims to initiate a discussion of the visual semantic annotation in earthquake images. The proposed method is intended to provide a significant step forward in handling these unstructured images in such a way as to be manageable and tractable.

2. Problem Statement

The term "annotation" as used in this study is defined first. *Image annotation* is defined as the practice of capturing and collecting the contents associated with image data. In general, the contents are divided into two major categories: (1) properties of the image itself, such as size, resolution, location or date, and (2) actual visual content such as properties of the object, person or abstract concept (e.g. room, wall, failure?) depicted by the image [7]. Simply, the former category answers "how, when and why was the image made or what information should be known to understand (the setting, or, to place) the content of the image?" and the latter category provides an answer to "what does the image depict or illustrate?"

The terminology for the description and documentation necessary to address the first category has been well established and standardized, for example, Exchangeable Image File Format (EXIF) or Dublin Core [7,8]. However, the second category, "what should be known to understand the content of the image," is not well established. Despite various techniques developed to annotate visual semantic contents including medical images [9] or art [10], this is still a complex problem. The challenge lies mainly in the large variation in domain terms and expressions, and its dependence on the associated application [7]. Thus, the annotation method should be designed based on a domain-specific ontology with clear definitions of the terms used, and a suitably structured model to enable retrieval.

To better understand the intent of this research, consider the sample earthquake image in Fig. 1. This image was collected by an earthquake reconnaissance team after the 2010 Chile earthquake. This image opened a critical line of inquiry that strongly impact on the practice of structural wall design because the damage mode, called "overall wall buckling", had rarely been observed in past earthquakes [11-13]. The following statement was provided as the original description of the image: "Reinforced concrete shear wall has longitudinal crushing, spalling at the height of the wall, and buckling of vertical reinforcement at the boundary" [11]. This is a typical description and includes information about the visual contents such as the structure component type, several damage types and directions, and relative location of the damage. Keyword-based image tagging would not effectively handle so much information. For example, if reduced to keywords, "longitudinal" and "vertical" can refer to either the reinforcement or the damage, and the locations of "height" and "boundary" lost their relationship to targets in the image.

Fig. 1 – Sample image of reinforced concrete shear wall damage in the 2010 Chile earthquake [11-13]

3. Methodology

Before providing details on how to achieve this goal for earthquake images, the technology needed to support the proposed annotation method is introduced. *Resource Description Framework* (RDF) is a formal language for describing structured information [14-15]. The RDF data model defines data as a 3–tuple referred to as *triples* [14]. For example, suppose that the information to be stored is "John has a son, Brad." This data is represented as a triple using "John–hasSon–Brad". The RDF data model is mainly used as a plain format to store or exchange information, without providing any semantics. In other words, this data model explains how to represent the information as a triple but does not provide the mechanism to define names for the specific property or value. In the previous example, without knowing that "John" can have the property of "hasSon", their relationship cannot be hypothesized. Thus, a schema to define resource types and names, and their structure (or relationships) is needed. *Web Ontology Language* (OWL) is an ontology language that can be used to represent the meaning of terms and their relationships for domain applications in a more expressive way. In this study, the OWL-DL language is employed for modeling our EIO [16]. Here, DL stands for description logics, which is designed for reasoning systems [16].

The main OWL elements are *classes* and *properties*. A *class* is a set of terms that are used for describing concepts in a particular domain. A *property* expresses a relationship between two classes or with a description of an object using values. Actual data interested in this study are stored in *instances* in classes. In the previous example, "Father" and "Son" are possible classes, and these classes have instances of "John" and "Brad", respectively. Their relationship is defined through the property "hasSon". In our EIO, a class includes the terms that are needed for describing the visual content of the images, and a property is a relationship between classes. Here, the core idea underlying the proposed annotation method is that sentence-like information, such as "John has a son, Brad", can readily be converted into a triple, John–hasSon–Brad. To use this approach, the classes and properties to be used would be selected from the developed ontology.

Based on a detailed review of current practices used to describe the earthquake images in the literature, an appropriate set of multiple triples is nearly sufficient to represent the original descriptions used for earthquake images while maintaining much of the richness of expression in language. Each highly detailed description may be transformed and stored in the RDF model guided by the predefined EIO. Having done that, the features of the RDF model are exploited such as storing linked data and semantic query searching. For example, the long image description in Section 2 might be stored as multiple triples in the database. This would enable a researcher to retrieve the stored information using a simple semantic query, as illustrated in Section 6.

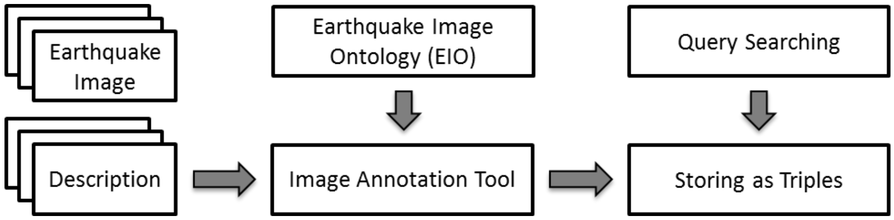


Fig. 2 – Overview of the proposed image annotation method

Fig. 2 shows the general architecture of the proposed annotation method. The overall process is that annotators exploit an image annotation tool to store the original descriptions of images. The tool would employ the pre-defined classes and their properties in our EIO, assisting annotators to apply valid class names and types while converting the original descriptions to multiple triples. With these in place, the stored information can be fully retrieved using query languages. Here, Protégé is used for developing our ontology suitable for annotating earthquake images. Protégé is ontology design software and has a user–friendly interface and support for exporting ontology definitions in the established RDF/OWL database format to compose and execute queries using RDF query languages [17-18].

All terminology used in the remainder of this paper are those used in Protégé. Vocabularies (objects or terminologies) are referred to as a *Class* and their relations (object property) and relation to value (data property) are described using a *Property* [17-19]. There is no mandatory naming convention for OWL-DL classes and properties, but in EIO all class names begin with a capital letter with no space between words, and property names start with 'has' or 'is' and have no spaces and use capitalization for the remaining words. This choice of convention helps clarify the intent of the property to annotators [19]. Hereafter, all class and property names are written using the italic font.

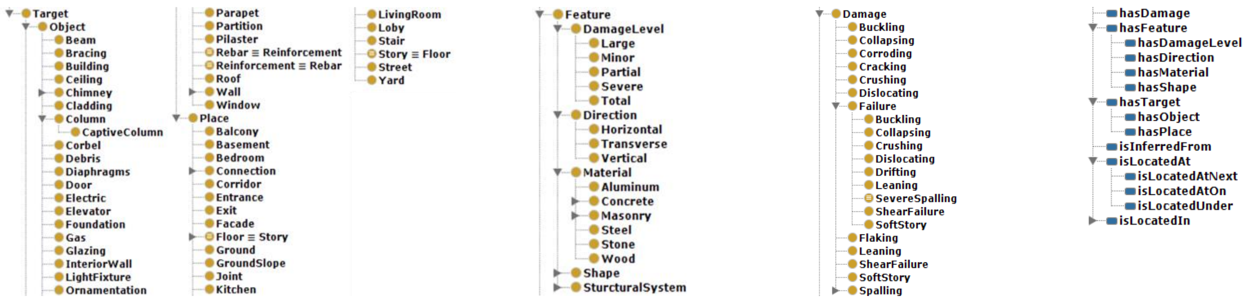
4. Earthquake Image Ontology

The development of EIO is intended for annotating earthquake image using a broad, but still focused, the range of standardized terminology and structures. EIO is highly tailored to provide rich and natural descriptions of visual semantic content in earthquake images. EIO has been designed based on image descriptions in published articles, reconnaissance reports, and manuals related with earthquake building reconnaissance [20-23]. It is meant to be quite flexible, permitting changes and expansion of classes and properties over time. All classes and properties are designed using English, and the use of all morphological variants of a word, such as plurals of nouns or inflected forms of verbs (e.g., collapse, collapsing, collapsed) are ignored. Thus, they all point to one single class defined in EIO.

EIO has two top classes; *Visual* and *Metadata*. This division is based on whether or not the information can be collected from visual semantic content. As mentioned in Section 2, this study focuses on the visual semantic content included in *Visual*. Note that "semantic" means other non-semantic visual contents are not considered here such as color, texture or pattern across the images unless they contain a particular semantic meaning.

In *Visual*, there are three subclasses. Together these cover most of the classes appearing in existing image descriptions. The three subclasses are: *Target*, *Feature* and *Damage*. Figs. 3(a-c) provide a list of the subclasses in Protégé and these subclasses inherit the characteristics of the superclasses. *Target* refers to the subject of an image. In *Target*, there are two broad classes, *Object* and *Place*. *Object* is a thing that has a visually clear boundary and illustratable shapes, such as *Column*, *Wall*, or *Chimney*. *Place* as the name suggests, is a space having a particular purpose, such as *Balcony*, *LivingRoom*, or *Basement*. This is typically inferred from the existence of objects and their spatial configuration. *Feature* includes any characteristics of a *Target* such as material, shape, or direction. *Feature* always modifies *Target; Feature* cannot modify other classes in *Feature*. Lastly, a special class named *Damage* is a frequently used class to describe the damage state of *Target*. However, classes in *Damage* can be used as either *Target* or *Feature* in the context of the original description. For example, "*Vertical Cracking*" indicates that *Vertical* in *Feature–Direction* describes a direction of *Cracking* in *Target–Damage*. On the other hand, “*Collapsing Wall*”, *Collapsing* is used as a characteristic (*Feature*) of *Wall* in *Target–Object*. Classes having the same semantic meanings may be used in the earthquake image description, and are registered as an equivalent class such as *Rebar* ≡ *Reinforcement*, or *Floor* ≡ *Story*. Also, a class that requires clarification may include subclasses. For example, *Failure* is a superclass of a kind of severe damage such as collapsing or leaning, explained in Section 6.

Object properties are defined based on the relationship between two classes, shown in Fig. 3(d). The relationship between classes is not unique and various object properties can be defined (but there are not many). For the above example, *hasDirections* is an appropriate object property linking *Cracking* and *Vertical*. Object properties also have hierarchical subproperties, For instance, some subproperties of *isLocatedAt* are *isLocatedOn*, *isLocatedNext*, and *isLocatedUnder*.



(a) Target (b) Feature (c) Damage (d) Object property

Fig. 3 –*Target*, *Feature* and *Damage* and object properties in Earthquake Image Ontology (EIO)

5. Image Annotation Tool

The image annotation tool is designed to assist annotators to seek to write structured image descriptions. The tool is intended to support them by providing a normative selection of appropriate names of classes and properties. Also, based on EIO, the tool can perform several functions such as identifying synonyms (e.g., *Rebar* and *reinforcement*), autocompletion (e.g., a user types a few characters of a term and the tool suggests a proper class or property), or clarifying ambiguity in words used to specify the meaning (e.g., *Failure* in Section 6). Once a proper description is written, the tool generates multiple triples in a semi-automated manner [10,24,25]. Here, “semi-automated” indicates that annotators can select appropriate class names or properties from a list supplied by the tool.

As a result of our comprehensive review of earthquake image descriptions used in the literature, a major annotation pattern was identified in the annotations of earthquake images. The pattern consists of an illustration of the main target object by its characteristics, conditions, or spatial location about other objects. For example, “collapsing masonry wall”, “circular column” or “spalling column” (for further examples see Fig. 4). Thus, the following template is proposed, which is best suited for rich annotation using such descriptions:

<u>Feature 1</u> <u>Target 1</u> (Object property) <u>Feature 2</u> <u>Target 2</u>

where each underlined slot is a single class field, and each slot in the parenthesis is a single object property.

Feature 1 and Feature 2 would contain a class from *Feature* or *Damage*, and Target 1 and Target 2 would contain a subclass from *Target* or *Damage*. These are denoted as F1, T1, F2, and T2, respectively, in the sequence. A description using this template is referred to as a statement and considered to represent an English sentence. Roughly speaking, (F1 and T1), (Object property), and (F2 and T2) represent the subject, verb, and object or adjective, respectively). All fields are not necessarily required in such a statement. However, in each statement, annotators have to enter T1, which is the subject of the statement. A class in T1 (or T2) is automatically stored as *Image–has*{*}–T1 (or T2). Here, *Image* is a class that stores the annotation information. “–“ represents a delimiter for tuples in a triple, and “{*}” is the top subclass name of the corresponding class in *Target*, *Feature or Damage*.

When T1 is in *Target*, {*} can be either *hasObject*, *hasDamage* or *hasPlace* for the object property. Then, annotators can enter other fields in the template for constructing a given statement. F1 always describes the characteristics of T1, and the "has{*}" property between them is automatically assigned. Thus, a triple of T1–*has*{*}–F1 is generated. For instance, the statement of "F1: *Collapsing*, T1: *Wall*" is converted as *Image–hasObject–Wall* and *Wall–hasDamage–Collapsing*. *Damage* is the superclass of *Collapsing*. If both F2 and T2 are entered, a triple is generated between F2 and T2 in a similar fashion as (T2–*has*{*}–F2) and (Object property) in the template is selected based on the object properties between T1 and T2. The annotation tool suggests a list of possible object properties and the annotator selects an appropriate property that can best describe the meaning of the original description. If the annotator only provides an entry for F2, the property is selected according to the relationship between T1 and F2. For example, the statement "F1: *Concrete*, T1: *Wall*, F2: *Collapsing*" is converted as *Image–hasObject–Wall*, *Wall–hasMaterial–Concrete* and *Wall–hasDamage–Collapsing*.

The actual usage of this template for image annotation is straightforward. For example, annotation of the original long description in Section 2 is demonstrated in Table 1. The original description can be represented as six statements, and 15 triples are generated, allowing for search and ready retrieval in the future. Note that the integration of multiple triples results in a description that includes almost the same information and has the same meaning as the original description.

Table 1. Annotation example using the description "Reinforced concrete shear wall has longitudinal crushing, spalling at height of the wall, and buckling of vertical reinforcement at the boundary."

Statements	**Triples**
F1: *ReinforcedConcrete*, T1: *ShearWall*, F2: *Longitudinal*, T2: *Crushing*	*Image – hasObject – ShearWall* *Image – hasDamage – Crushing* *ShearWall – hasDamage – Crushing* *ShearWall – hasMaterial – ReinforcedConcrete* *Crushing – hasDirection – Longitudinal*
T1: *ShearWall*, F2: *Longitudinal*, T2: *Spalling*	*Image – hasDamage – Spalling* *ShearWall – hasDamage – Spalling* *Spalling – hasDirection – Longitudinal*
T1: *Spalling*, T2: *ShearWall*	*Spalling – isLocatedInTop – ShearWall*
T1: *Crushing*, T2: *ShearWall*	*Crushing – isLocatedInTop – ShearWall*
F1: *Vertical*, T1: *Reinforcement*, T2: *Buckling*	*Image – hasDamage – Buckling* *Image – hasObject – Reinforcement* *Reinforcement – hasDamage – Buckling* *Reinforcement – hasDirection – Vertical*
T1: *Reinforcement*, T2: *ShearWall*	*Reinforcement – isLocatedInSide – ShearWall*

* Note that overlap triples that are generated in the previous statement are removed.

More examples are shown in Fig. 4. All images or original descriptions in this figure have been extracted from published sources including data repositories, reports or articles, which document image data in previous earthquake events. On the whole, regardless of an inevitable unnaturalness coming from the use of template annotation and triple conversion, the original meanings of descriptions can be preserved in the triples.

(a)

(b)

(c)

(d)

(e)

(f)

Fig. 4 – Example annotations of real-world earthquake images:

(a) Description: Vertical cracks along the Orthogonal Wall (Italy, 1998) [23]
Statements: (F1: *Orthogonal*, T1: *Wall*, F2: *Vertical*, T2: *Cracking*)
Triples: (*Wall – hasDamage – Cracking*), (*Wall – hasShape – Orthogonal*) and (*Cracking – hasDirection – Vertical*)

(b) Description: Failure of an unreinforced masonry wall in a building (USA, 1989) [21]
Statements: (F1: *UnreinforcedMasonry*, T1: *Wall*, F2: *Failure*) and (T1: *Wall*, T2: *Building*)
Triples: (*Wall – hasMaterial – UnreinforcedMasonry*), (*Wall – hasDamage – Failure*) and (*Wall – isLocatedAt – Building*)

(c) Description: Collapse of a tilt–up bearing wall (1994, Northridge earthquake) [22]
Statements: (F1: *Collapsing*, T1: *TiltWall*)
Triples: *TiltWall – hasDamage – Collapsing*

(d) Description: Failed captive column in the basement (1999, Turkey earthquake) [1]
Statements: (F1: *Failure*, T1: *CaptiveColumn, T2: Basement*)
Triples: (*CaptiveColumn – hasDamage – Failure*) and (*CaptiveColumn – isLocatesdAt – Basement*)

(e) Description: Soft story failure (2015, Nepal earthquake) [26]
Statements: (F1: *SoftStory*, T1*: Building*)
Triples: *Building – hasDamage – SoftStory*

(f) Description: Shear failure reinforced concrete column next to collapsed masonry wall (2015, Nepal earthquake) [26]
Statements: (F1: *ShearFailure*, T1: *Column*, F2*: Collapsing*, T2*: Wall*) and (F1: *ReinforcedConcrete*, T1: *Column*, F2*: Masonry*, T2*: Wall*)
Triples: (*Column – isLocatedNext – Wall*), (*Column – hasDamage – ShearFailure*), (*Wall – hasDamage – Collapsing*), (*Column – hasMaterial – ReinforcedConcrete*) and (*Wall – hasMaterial – Masonry*)

* Parentheses in statements and triples are used to separate entries for clarity.
** Triples of *Image-has*{*}-T1 (or T2) in Triples are omitted.

Although our triple representation uses the names of classes in EIO, the actual annotated data are stored as individuals (instance in OWL) in the corresponding classes. For example, suppose that the description of a specific image is "collapsing wall". An individual, <u>Image1,</u> in *Image* is created and all annotation data related to the corresponding image are stored (hereafter, an underline for the name of each individual is used). Individuals

Collapsing1 and Wall1 are also generated. Then, the actual triple statements to be stored become Images1–*hasObject*–Wall1 and Wall1–*hasDamage*–Collapsing1. This statement is interpreted as "wall" in the description of a specific wall in *Wall* in the corresponding image, and this wall is named as Wall1.

6. Image Retrieval

The RDF data model and query searching languages are well established and already in use in many application domains [27]. Thus, the readers are recommended to review how to use RDF query languages for data retrieval and to provide the capability of query searching for data already written in triples. Rather, our focus in this section is to demonstrate how closely query searching results can yield ground-truth original descriptions, and through that process the effectiveness of the proposed annotation method is validated. Protégé provides a powerful query searching utility called DL–query. The query language (class expression) supported by the plugin can compose and execute queries with the Manchester OWL syntax, a user–friendly syntax for OWL-DL used in Protégé [17-19,27]. However, as long as identical triple information produced from original image description is stored, search query results are almost identical regardless of the query languages or platforms.

For demonstration purposes, the images are annotated shown in Fig. 4 based on their descriptions. The annotation data for image Figs. 4 (a-f) store the individuals Image1~6, respectively. The annotated classes in each image produce individuals having the same naming convention, for example having a number as suffix. The annotation example of Fig. 4(a) is presented in Fig. 5. the data are visualized using *OntoGraf* in Protégé [17]. All individuals, their classes, and object properties between classes ("Arc Types" son the right of Fig. 5) that are used for annotation of Fig. 4(a) are visualized.

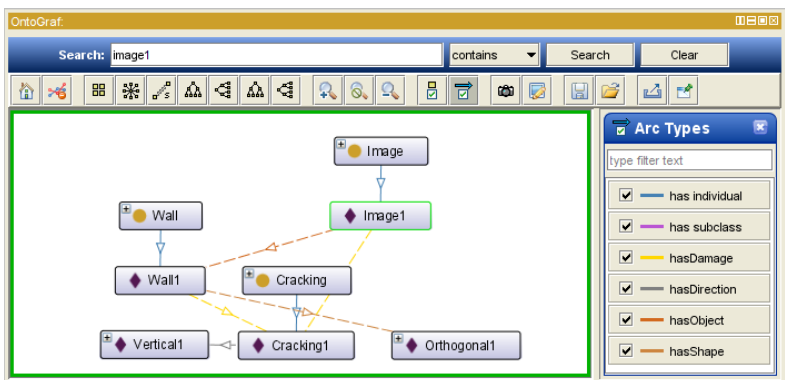


Fig. 5 – Visualizing the annotation data of Fig. 4(a) using the *OntoGraf*

Some sample queries that can be used for retrieving annotated data are examined below. Note that when individuals in DL-query like Fig. 6 are checked, a query is used for searching an individual in a corresponding class, which stores actual annotated data.

Query 1. Which image has a collapsed wall? (Fig. 6(a)): This is a relatively simple query. All classes *Image* having an object *Wall* with damage *Collapsing* are founded. However, strictly speaking, individuals in *Image* that include a specific wall having collapsing damage are founded here. The query expression is "*Image* and *hasObject* some (*Wall* and *hasDamage* some *Collapsing*)". The query result is Image3 and Image6. Interestingly, Image2 is not captured with this query because of its damage types as *Failure*. *Failure* is ambiguous and has no specific definition regarding image annotation. However, typically, as saying "failure of the components", it indicates that the components have severe damage and are not serving their function. Thus, in EIO, *Failure* is classified as a superclass of *Buckling*, *Collapsing*, *Crushing*, *Drifting*, *Dislocating*, *Learning*, *StoftStory*, *ShearFailure*, and *SevereSpalling*. Here, *SevereSpalling* is defined as "*Spalling* and (*hasDamageLevel* some (*Large* or *Severe*))", which means "large or severe spalling". Thus, Figs. 4(b) and (d) were acceptably described as containing "failure".

Unfortunately, there is no way to retrieve Image2 using above query expression because *Failure* subsumes *Collapsing*. However, based on EIO, the tool suggests that annotators must specify the type of *Failure* in the annotation stage or retrieve Image2 when images using a different query *Failure* (Query 2) are searched.

Query 2. Which image has a failure? (Fig. 6(b)): The query expression is “Image and hasTarget some (hasDamage some Failure)”. The query result is Image2 ~6 and all images having a *Failure* target are detected. Note that Image2 is detected in this query despite of having no syntactic match (*Failure ≠ Collapsing*). Here, *hasTarget* is a superclass of *hasObject* and *hasPlace*, which can find damaged objects and places. Thus, the above query is identical to “Image and (*hasObject* some (*hasDamage* some *Failure*) or *hasPlace* some (*hasDamage* some *Failure*))”.

Query 3. Which damaged object is located in the basement? (Fig. 6(c))**:** A specific object with a certain condition is retrieved. The query expression is “Object and (*hasDamage* some *Damage* and *isLocatedAt* some *Basement*)”. This query will detect all images with damaged objects located in the basement. The query result is CaptiveColumn4, which is a captive column in Fig. 4(d). When images containing these objects are searched, a query of “*Image* and *hasObject* some (above original query expression)” can be written.

(a) Query 1 (b) Query 2 (c) Query 3

Fig. 6 – Examples of query searching results using annotated data in Fig. 4.

7. Conclusion

This study introduces an ontology and annotation tool that enables documentation and retrieval of visual semantic contents in earthquake images. EIO is created based on vocabularies and their relationships frequently used for descriptions of earthquake images. Using EIO and image annotation tool, it is demonstrated that the meaning of original descriptions can be transformed into a searchable form using triples to facilitate future retrieval based on the visual contents. Our annotation method can store these descriptions without any degradation or loss in the original meaning. Stored annotation data using the proposed approach can be fully retrieved with various semantic queries.

This annotation method has been designed for earthquake images and is focused, to date, on images of buildings and intended for researchers focused on structural design and performance. It might be possible to extend it to apply to describe the contents of images used for other purposes, which is worth consideration in the future. As it stands, this method represents a major step forward toward the development of an ontology and associated annotation method to support scientific research.

8. Acknowledgements

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