

Describing the *where* – improving image annotation and search through geography

Ross S. Purves, Alistair Edwardes and Mark Sanderson

Department of Geography, University of Zurich
ross.purves@geo.uzh.ch; Alistair.edwardes@geo.uzh.ch
Department of Information Science, University of Sheffield
mark.sanderson@sheffield.ac.uk

Abstract. Image retrieval, using either content or text-based techniques, does not match up to the current quality of standard text retrieval. One possible reason for this mismatch is the semantic gap – the terms by which images are indexed do not accord with those imagined by users querying image databases. In this paper we set out to describe how geography might help to index the where facet of the Pansofsky-Shatford matrix, which has previously been shown to accord well with the types of queries users make. We illustrate these ideas with existing (e.g. identifying place names associated with a set of coordinates) and novel (e.g. describing images using land cover data) techniques to describe images and contend that such methods will become central as increasing numbers of images become georeferenced.

Keywords: Image retrieval, image indexing, geography.

1 Introduction and motivation

1.1 Image retrieval and the semantic gap

The performance of image retrieval systems is currently recognized as lagging behind that of text retrieval in terms of both the quality of the results returned for individual queries and the overall ubiquitousness of image retrieval techniques as a first port of call for search for a particular illustration [11]. The two main approaches to image retrieval – content-based image retrieval (CBIR) and retrieval of images based on text surrogates [13] have significant limitations. In general, CBIR techniques work best within domains where the expected structures and forms of the images are limited, for example in the retrieval of medical images [7]. However, at the time of writing, CBIR is not in a state where it can be applied to large collections of what might be termed “general photographs”, such as those typically held in large stock image collections.

Text-based image retrieval (TBIR) is predicated on the use of appropriate terms to describe an image. These terms can be drawn from a range of possible sources, including terms freely chosen by indexers [1]; terms selected by indexers from some controlled keyword list and text thought to be related to the content of an image (e.g.

figure captions or filenames associated with images embedded in documents). Although in principle images annotated in such a way are amenable to identical approaches to those applied in full text document search, the quality of TBIR is handicapped by the quality of the annotation. This appears to be primarily due to the relative sparseness of the description of an image, which will tend to be based on the purpose for which the image itself was being indexed and the cultural background of the indexer. This in turn means that image search requires that users are, for example, familiar with the controlled keyword lists used to describe images or that they have similar backgrounds and expectations to those describing images with free text. A similar mismatch between user expectations and indexing methods has been identified in the context of CBIR, where it is termed the *semantic gap*. Smeulders *et al.* [24] defined this gap as follows:

“...the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation.” (p.1353)

In effect, the key problem with image search is centered on this mismatch between the data describing content and the expectations of those searching for content. In contrast to document search, both CBIR and TBIR index images using proxies for content, which it is hoped will describe the images indexed as fully as possible. Thus, a key challenge in image retrieval must be to develop methods which will describe images in as universal and rich a way as possible, in order to bridge this semantic gap.

1.2 Describing images

Clearly, if we wish to describe images universally, we must first formalize the ways in which images may be described. Shatford [21] set out to do exactly this, refining the work of Pansofsky to develop the Pansofsky-Shatford facet matrix (Table 1). This matrix contains three levels, termed the *specific of*, the *generic of* and *about*. Each of these levels has four associated facets: *who*, *what*, *where* and *when*. We will term individual entries in the matrix (e.g. “*who/specific of*”) as elements.

Table 1. The Pansofsky-Shatford facet matrix (Shatford [21], p. 49)

<i>Facets</i>	<i>Specific Of</i>	<i>Generic Of</i>	<i>About</i>
<i>Who?</i>	Individually named persons, animals, things	Kinds of persons, animals, things	Mythical beings, abstraction manifested or symbolised by objects or beings
<i>What?</i>	Individually named events	Actions, conditions	Emotions, abstractions manifested by actions
<i>Where?</i>	Individually named geographic locations	Kind of place geographic or architectural	Places symbolised, abstractions manifest by locale
<i>When?</i>	Linear time; dates or periods	Cyclical time; seasons, time of day	Emotions or abstraction symbolised by or manifest by

The Pansofsky-Shatford matrix has been extensively used in information science, particularly in the classification of image queries. For example, Armitage and Enser [3] examined queries posed to a number of image libraries, and allocated each query to one or more elements of the matrix (e.g. the query “Churchill’s funeral” is allocated to the “*specific of/ what*” element). Armitage and Enser demonstrated that both the “*specific of*” and “*generic of*” levels were commonly used in queries submitted to image archives, whilst those represented by the more abstract “*about*” level were rarely identified.

The matrix suggests a variety of ways in which images might be queried or indexed. For example, CBIR techniques capable of face recognition [26] might allow us to annotate the “*specific of/ who*” element (a picture of Jim), whilst CBIR techniques capable of face spotting [30] would allow annotation of the “*generic of/ who*” element (a picture of some people). Moreover, the matrix also suggests how proxy data might be profitably be used to help us describe images – for instance use of a time-stamp and location associated with an image and a local almanac would allow generation of annotation related to the “*generic of/ when*” (a picture at night). Such tools, taking account of ancillary information to annotate images have been developed as part of, for example, the MediAssist and NameSet projects [21, 20, 19].

The *where* facet is, we would argue, particularly interesting and relevant to image annotation for a number of reasons. Firstly, previous studies have shown that location is an important element in both indexing and searching for images (e.g. [3]). Secondly, the volume and content of spatial data describing the semantics of locations has grown exponentially in recent years, providing a wide variety of potential sources of ancillary data to describe the *where* facet. Thirdly, and crucially, images increasingly carry information related to *where* within metadata created at the time of capture, storing at a minimum a set of image coordinates, but potentially also information about the camera’s orientation (azimuth, pitch and roll).

In this paper we aim to briefly introduce ideas from existing work on the notion of *place* from a geographic perspective, which provides a potential theoretical framework in considering how location can be used to annotate images. We then explore existing work from a variety of research areas which has attempted to described locations and introduce ongoing research within the European Project Tripod which aims specifically to describe images through their location. All of this research is positioned within the framework of the *where* facet of the Pansofsky-Shatford matrix which we contend, together with an understanding of *place*, will allow us to address challenge of developing methods to richly and universally describe images.

2 Geographic perspectives on *place*

The explosion of devices which are location aware and of resources which contain references to location has led to a wide variety of research in, for example, Location-Based Services and Geographic Information Retrieval. In general, much of this research has been dominated by researchers from computing, information and geographic information science and has paid relatively little attention to more

theoretical work deriving mainly from human geography. This has in turn, led to a conflation of terminology with location, place and space being used interchangeably by many researchers and generally being considered to be represented by the assignment of a set of geometric coordinates or a *toponym*¹ to a resource.

However, in geography *place* is considered to lie at one end of a continuum of viewpoints with the other extreme being *space*. Place relates geography to human existence, experiences and interaction and therefore cannot be considered as purely an abstract property of a set of geometric coordinates [9]. Space on the other hand encompasses a more abstract and objective geometric view of the world, such as is typically encoded in spatial data stored in computers. Thus a key challenge in describing images is to include not only the objective and geometric notion of space but also the more subjective and potentially everyday idea of place.

3 Methods to describe *where*

We set out here to consider a range of methods to achieve our aim of describing both space and place, and consider how these methods can be positioned within the Pansofsky-Shatford matrix. These methods can be considered to be a means of addressing many of the issues set out by Egenhofer in his discussion of a semantic geospatial web [7].

3.1 Methods to describe “*where/ specific of*”

“*Where/ specific of*” is characterized in the Pansofsky-Shatford matrix as the use of terms describing “individually named geographic locations”. Thus, a caption which associates a toponym with an image (e.g. “A church in *Bristol*”) can be considered to be describing this matrix element. An initial challenge in deriving image metadata from geographic information is therefore simply to find the most appropriate toponym to describe an image. This task at first seems trivial, requiring a database lookup to identify the nearest place name from a *gazetteer*² and applying the selected toponym to the image. However, typical gazetteer data will include objects of widely varying *granularities* (varying from individual houses to the centroids of large administrative regions) and representing very different *feature types* (from mountain summits to the names of individual pubs). Research on *salience* in navigation, that is to say perceptually or cognitively prominent objects, has an important role to play in deciding which toponym is most appropriate in the labeling of an image. However, to date most research in this area has focused on objects of similar, relatively fine granularities which are appropriate to navigational systems.

Naaman *et al.*[20] took the problem of identifying appropriate toponyms to describe images one step further, and asked the question, “*given a set of diverse geographic coordinates, find a textual name that describes them best*”. Their system,

¹ Toponyms are names allocated to some location on the Earth’s surface

² A gazetteer is a dictionary of toponyms, usually with associated coordinates and a hierarchy of related toponyms

NameSet, identified appropriate toponyms from a polygon-based dataset by testing for containment within regions such as cities and parks and nearby cities. They included a proxy for salience by using what they termed the “Google count” (number of documents in Google that match a query word) and the population for individual city names to weight distances, allowing locations with larger populations and higher Google counts to have a larger zone of influence.

Typically when we describe locations we do so with qualifiers which represent the *spatial relationship* between the object of interest and the referencing toponym. These spatial relationships may be metric (10 km from Edinburgh), directional (north of Berlin), topological (in Belgium) or vague (near Bern). In practice, combinations of spatial relationships in natural language are used to reduce ambiguity and refine information (e.g. 10 km east of Edinburgh on the A1 road). Representing metric spatial relationships is straightforward and was implemented in the NameSet prototype [20]. However, the representation of vague spatial relationships is less trivial and requires development of both computational techniques to represent and process vagueness and empirical research to identify how people use spatial relationships [29].

Typically, in everyday language we commonly use *vernacular names* which are not found in gazetteers and whose spatial extent is ill-defined [18]. This problem has been recognized by those working on administrative gazetteers as a pressing issue [14]. Recent research has used datamining techniques to identify toponyms with entries in gazetteers which co-occur with known vernacular names and to define potential spatial extents related to vernacular names [16]. However, most work has so far addressed relatively large regions (such as Mid-Wales or the South of France), though work is currently ongoing on the automated identification and definition of vernacular names with finer granularities [22]. The techniques so far developed have not reached a level of accuracy such that they can be used to automatically generate appropriate vernacular names for any given set of coordinates, and also do not address the issue of identifying vernacular names.

3.2 Methods to describe “*where/ generic of*”

The “*where/generic of*” element of the Pansofsky-Shatford matrix is characterized as representing “kinds of geographic place or architecture”. The first task in defining this element is therefore to understand what “kinds of geographic place or architecture” are, before we consider how we can develop techniques to annotate images.

A logical first step is to identify *basic levels* of geographic kinds – that is to say informative exemplars which particularly characterize a geographic scene in terms of, for example, typical attributes, types of related activities and component parts [28]. Within geography, previous research has examined the terms most commonly used as basic levels in empirical experiments by asking subjects to give exemplars of natural earth formations, with a number of researchers finding that “mountain” was a particularly popular term [4, 26]. The advent of large volunteered datasets as part of Web 2.0 gives rise to a new sources of data for investigating such questions. We have been experimenting with data obtained from Geograph (www.geograph.org.uk), a

project with the aim to collect “geographically representative photographs and information for every square kilometer of the UK and the Republic of Ireland.” The project allows contributors to submit photographs representing individual 1km grid squares, and after moderation these images are uploaded together with descriptions to a publicly available web site. Using these data, we have identified the most commonly given terms from a set of basic levels derived from earlier empirical research [8]. Table 2 illustrates the top 20 nouns identified in the Geograph data, together with their frequencies in the collection. Here, we assume that a reference to a road, whilst possibly naming a specific location (e.g. “London Road”) is also, in most cases, likely to illustrate a generic example of the matrix element. Further work will be necessary to test this assumption.

Table 2. Most common terms occurring in Geograph and their frequencies

45768	road	15815	bridge	9892	railway	9060	line
21119	farm	14737	river	9829	building	8563	valley
17242	lane	14150	square	9327	centre	8532	station
16232	hill	13690	house	9240	park	8416	way
16157	church	12707	village	9234	footpath	8331	track

Within the Tripod project, we are currently developing an ontology of scene types together with their relationships, qualities, elements and related activities through a three-pronged approach utilizing analysis of existing datasets such as Geograph, empirical experiments where subjects are asked to describe images and a literature study of previous work from a diverse range of fields ranging from landscape architecture through psychology to remote sensing in order to explore how landscapes are classified and described. This *concept ontology* can be seen as a description of the “*where/ generic of*” and is illustrated in Fig. 1 for land cover and landforms.

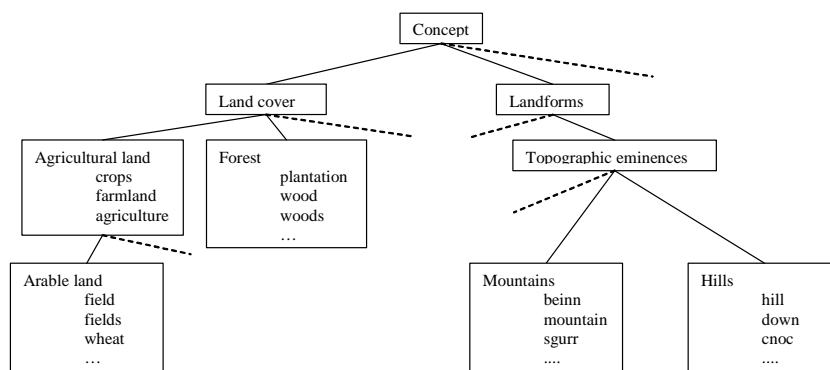


Fig. 1. Excerpt from a concept ontology – dashed lines indicate that other concepts exist at this level, and indented terms were identified in Geograph

Our working hypothesis is that using such a concept ontology, it will be possible to develop methods which exploit spatial data to describe “*where/ generic of*”. This

hypothesis can be illustrated through two examples, one exploring the identification of *land cover* and *land forms*.

Land cover is typically described in spatial data which ensure that every location is allocated a single land cover value. Within Europe, the CORINE project has produced a dataset describing land cover for 12 countries at a nominal scale of 1:100000, with a resolution of 100m. CORINE has 3 levels of description, a top level with 5 classes, an intermediate level with 15 classes and a detailed level with 44 classes. Given either a point location, or a bounding box it is possible to retrieve the associated land cover classes with this location. Fig. 2 shows a set of georeferenced images taken in Peloponnes, Greece and the land cover classes associated with the point locations of these images. In these 3 cases, it can be seen that the land cover classes describe, to different degrees, the content of the image. The third image which lies in coniferous forest clearly illustrates some of the challenges of this approach. Firstly, the position of the photographer is different from that which was photographed and the photographer's location may not reflect the image contents. Secondly, this image contains two dominant land covers – natural grassland and coniferous forest, and a method purely based on associating a point with a land cover cannot represent multiple land covers. Thirdly, this simple approach does not consider errors either in GPS position or classification and the likely cumulative error in the associated land cover. The first picture illustrates a further problem – CORINE has a resolution of 100m and an associated scale of 1:100000 – therefore close-up images of objects such as this fallen tree are not represented.

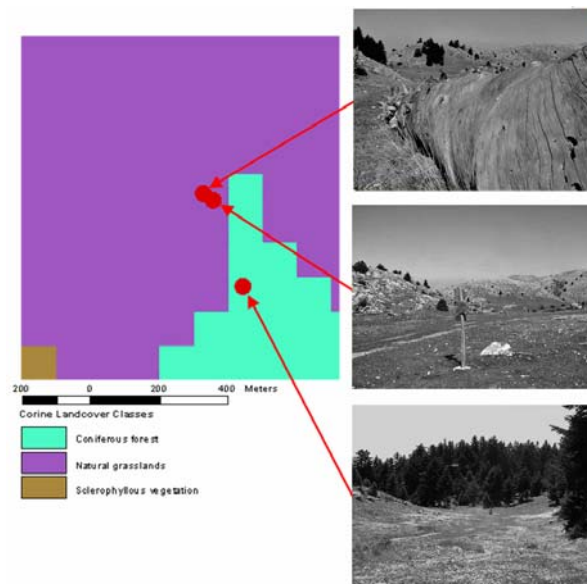


Fig. 2. Comparing Corine landcover classes with images from georeferenced images Peloponnes, Greece

To assess more quantitatively whether this approach can represent the “*where/generic of*” we carried out a preliminary study to rate the accordance of land cover

classes with images for 225 georeferenced images from Greece, Italy and the Netherlands. For the top level descriptions (5 classes), we found that 73% of land cover classes had a good or fair accordance with the images whilst for the detailed descriptions (44 classes) 47% of land cover classes had a good or fair accordance with the images.

Although data sets describing land cover at a European scale exist, this is not the case for land forms (e.g. mountains, valleys, plains, etc). Research to, for example, answer the question “Which locations within this region can we delineate as mountains?” has investigated “mountainousness” through empirical studies [25], methods which seek to delineate features using digital elevation models (DEM)³ [15] and methods which recognize that the scale at which one observes the surface of the earth influences the nature of the features that can be identified [12]. At the simplest level it is possible to assign an image whose coordinates lie at the peak of a mountain (and thus are near to a toponym representing an object belonging to the feature class mountain) to the class mountain. However, at what point do we move from being on a mountain to being in a valley? Research to investigate this issue must consider perceived properties of mountains from a particular viewpoint and aim to provide a probability function describing the extent to which a location belongs to the class mountain for a set of users with a particular background.

3.3 Methods to describe “*where/about*”

The “*where/about*” element of the Pansofsky-Shatford matrix is described as representing “*places symbolized, abstractions manifest by locale*”. In their analysis of queries submitted to image libraries Armitage and Enser [3] found that the abstract facet in general was a rarely used query form. However, they emphasized that this result is probably related to the nature of the image archives studied, and suggested that for stock-photo libraries providing images to, for example, advertising agencies, abstract concepts, such as “peaceful scenes”, are important. Such qualities are good examples of abstract properties of place and also relate closely to the geographic notion of place as being related to experience and interaction.

Although at first glance it may appear unlikely to be possible to describe such qualities using spatial data, there are in fact a number of examples of research to define such qualities. For instance, a recent study in the UK has, through participative research, firstly explored what *tranquility* is, and secondly attempted to map variation in tranquility within the UK [17]. Other, similar studies have explored how qualities such as wilderness can be modeled in space [5]. A common factor of such research is that locations are placed on a continuous scale describing some relative quality, but that the identification of a location as being, for instance, tranquil is dependent on the perceptions and experiences of those who visit a location.

We have attempted to explore abstract qualities of locations which might describe the notion of place by investigating the co-occurrence of adjectives commonly used to

³ A Digital Elevation Model (DEM) is a regular, usually gridded, tessellation of space where each grid cell represents a single height value. Attributes of topography such as gradient and aspect can easily be derived from DEMs)

describe landscapes [6] with typical classes which we have identified in our concept ontology (Fig 1.). For example, the following 10 adjectives were mostly commonly used in the Geograph dataset in conjunction with the land cover class *beach*: *sandy*; *deserted*; *eroded*; *soft*; *rocky*; *warm*; *glacial*; *low*; *beautiful and lovely* [8]. Thus, a prototypical beach picture might represent abstract qualities such as being *deserted*. This property could be modeled using a similar approach to that adopted by Carver et al. [5], using, for instance, accessibility models. Images identified as belonging to the “*where/generic of*” element associated with beaches, through use of, for example, land cover data as discussed in §3.2, might then be rated in terms of their accessibility and thus assigned a probability of representing the abstract quality of desertion.

4 Conclusions

We have set out in this paper to consider how Text-based Image Retrieval (TBIR) might be improved through the use of index terms describing the *where* facet of the Pansofsky-Shatford matrix. We contend that such methods will become not only possible, but indispensable, as increasing numbers of images are georeferenced⁴. Indeed, we would contend that the WorldExplorer system [1], implicitly describes the *where* facet of the Pansofsky-Shatford matrix by aggregating Flickr tags from multiple users to generate useful labels for groups of pictures. We have illustrated how a wide range of existing methods might be used to describe images not only in terms of their locations (as represented through a set of coordinates), but also in terms of the notion of *place*. Broadly speaking, methods which go beyond analyzing notionally objective datasets, such as administrative gazetteers or land cover data, can be considered to address place-based geography. Thus, for example, methods to identify vernacular names or describe prototypical scene types and their qualities rely on the development of methods which can, for instance, exploit volunteered datasets representing experiential data. However, an important note of caution must also be sounded here – descriptions of place derived from such datasets are inevitably *situated* according to the perspective of their contributors. This in turn requires that if we wish to develop methods describing both space and place that we do so critically.

Acknowledgements

This research reported in this paper is part of the project *TRIPOD* supported by the European Commission under contract 045335. Simone Bircher is thanked for her hard work on image collection and the Corine experiments. We would also like to gratefully acknowledge contributors to Geograph British Isles, see <http://www.geograph.org.uk/credits/2007-02-24>, whose work is made available under the following Creative Commons Attribution-ShareAlike 2.5 Licence (<http://creativecommons.org/licenses/by-sa/2.5/>).

⁴ For example, by 3 Nov., ‘07, over 30 million Flickr images were associated with coordinates

References

1. Ahern, S., Naaman, M., Nair, R., Yang, J.: World Explorer: Visualizing Aggregate Data from Unstructured Text in Geo-Referenced Collections. In Proceedings, Seventh ACM/IEEE-CS Joint Conference on Digital Libraries, (JCDL 07), June 2007, Vancouver, British Columbia, Canada. (2007)
2. Ahn L. von., Dabbish, L.: Labeling Images with a Computer Game. In ACM Conference on Human Factors in Computing Systems. ACM, New York (2004) 319-326
3. Armitage, L.H., Enser, P.G.B.: Analysis of user need in image archives. *J. Info. Sci.* 23 (1997) 287–299
4. Battig, W. F., Montague, W. E.: Category norms for verbal items in 56 categories: a replication and extension of the Connecticut Norms. *J. Expt. Psych.* 80 (1969) 1–46.
5. Carver, S., Evans, A.J., Fritz, S.: Wilderness attribute mapping in the United Kingdom. *International Journal of Wilderness.* 8 (2002) 24-29
6. Craik, K.H.: Appraising the Objectivity of Landscape Dimensions. In: Krutilla, J.V. (ed): *Natural Environments: Studies in Theoretical and Applied Analysis.* John-Hopkins Uni. Press, Baltimore (1971) 292–346
7. Deselaers, T., Müller, H., Clough, P., Ney, H., Lehmann, T.M.: The CLEF 2005 Automatic Medical Image Annotation Task. *International Journal of Computer Vision.* 74 (2007) 51-58
8. Edwardes, A.J and Purves, R.S. A theoretical grounding for semantic descriptions of place. To appear in Proceedings of W2GIS.
9. Edwardes, A.J.: *Re-placing Location: Geographic Perspectives in Location Based Services*, Ph.D Thesis, University of Zurich (2007)
10. Egenhofer, M.J.: Toward the semantic geospatial web. In: Voisard, A. and Chen, S.C. (eds.): *Proceedings of the 10th ACM International Symposium In Geographic Information Systems.* ACM Press, New York (2002) 1–4
11. Enser, P.: Visual image retrieval: seeking the alliance of concept-based and content-based paradigms. *Journal of Information Science.* 26 (2000) 199-210
12. Fisher, P., Wood, J., Cheng, T.: Where is Helvellyn? Fuzziness of Multiscale Landscape Morphometry. *Transactions of the Institute of British Geographers.* 29 (2004) 106-128
13. Goodrum, A. A.: Image Information Retrieval: An Overview of Current Research. *Informing Science.* 3 (2000), 64–67
14. Hill, L.L., Frew, J., Zheng, Q.: Geographic names. The implementation of a gazetteer in a georeferenced digital library. *Dig. Lib.* 5 (1999)
15. Iwahashi, J., Pike, R.J.: Automated classifications of topography from DEMs by an unsupervised nested-means algorithm and a three-part geometric signature. *Geomorphology.* 86 (2007) 409-440
16. Jones, C.B., Purves, R.S., Clough, P.D AND Joho, H.: Modelling Vague Places with Knowledge from the Web. *Int. J. of Geog. Info. Sci.* (In press)
17. MacFarlane, R., Haggett, C., Fuller, D., Dunsford, H. and Carlisle, B. (2004). *Tranquillity Mapping: developing a robust methodology for planning support*, Report to the Campaign to Protect Rural England, Countryside Agency, North East Assembly, Northumberland Strategic Partnership, Northumberland National Park Authority and Durham County Council, Centre for Environmental & Spatial Analysis, Northumbria University.
18. Montello, D., Goodchild, M., Gottsegen, J., Fohl, P.: Where's Downtown?: Behavioral Methods for Determining Referents of Vague Spatial Queries. *Spatial Cognition and Computation* 3 (2003) 185–204.
19. Naaman, M., Harada, S., Wang, Q., Garcia-Molina, H., and Paepcke, A.: Context data in geo-referenced digital photo collections. In: Proceedings of the 12th Annual ACM international Conference on Multimedia (MULTIMEDIA '04) ACM Press, New York (2004) 196-203.

20. Naaman, M., Song, Y.J., Paepcke, A., Garcia-Molina, H: Assigning textual names to sets of geographic coordinates, *Comp. Env. and Urban Sys.* 30 (2006) 418-435
21. O'Hare, N., Lee, H., Cooray, S., Gurrin, C., Jones, G.J.F., Malobabic, J., O'Connor, N.E. Smeaton, A.F., Uscilowski, B.: MediAssist: Using Content-Based Analysis and Context to Manage Personal Photo Collections. In: *Proceedings of the 5th International Conference on Image and Video Retrieval (CIVR 2006)*. Tempe, AZ, U.S.A., (2006) 529-532
22. Pasley, R.C., Clough, P. and Sanderson, M.: Geo-Tagging for Imprecise Regions of Different Sizes. In: *Proceedings of GIR07*. ACM, New York (2007) 77-82.
23. Shatford, S: Analyzing the subject of a picture: a theoretical approach. *Catalog. and Class. Quart.* 6 (1986) 39-62
24. Smeulders A.W.M., Worring, M., Santini, S., Gupta, A. Jain, R.: Content-Based Image Retrieval at the End of the Early Years, *IEEE Trans. on PAMI* 22 (2000) 1349-1380
25. Smith B., Mark D. M.: Do mountains exist? Towards an ontology of landforms. *Environment and Planning B: Planning and Design.* 30 (2003) 411-427
26. Smith, B. and Mark, D.M.: Geographical categories: an ontological investigation. *Int. J. of Geog. Info. Sci.* 15(2001) 59-612
27. Turk, M.A., Pentland, A.P.: Face Recognition Using Eigenfaces. In: *Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR)*. (1991) 586-591.
28. Tversky, B. and Hemenway, K.: Categories of Environmental Scenes. *Cogn. Psych.* 15 (1983) 121-149.
29. Worboys, M. F.: Nearness relations in environmental space. *Int. J. of Geog. Info. Sci.* 15 (2001) 633-651
30. Yang, M-H., Kriegman, D.J.; Ahuja, N.: Detecting faces in images: a survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence.* 24 (2002) 34-58