Integration of Low Level and Ontology Derived Features For Automatic Weapon Recognition and Identification

Nikolay Metodiev Sirakov[1], Sang Suh[2], Salvatore Attardo[3]
Dept of Mathematics[1]; Dept of Computer Science and Information Systems[1,2]; College of Arts and Sciences[3], Texas A&M University – Commerce, Commerce, TX 75429, USA

ABSTRACT

This paper presents a further step of a research toward the development of a quick and accurate weapons identification methodology and system. A basic stage of this methodology is the automatic acquisition and updating of weapons ontology as a source of deriving high level weapons information. The present paper outlines the main ideas used to approach the goal. In the next stage, a clustering approach is suggested on the base of hierarchy of concepts. An inherent slot of every node of the proposed ontology is a low level features vector (LLFV), which facilitates the search through the ontology. Part of the LLFV is the information about the object's parts. To partition an object a new approach is presented capable of defining the objects concavities used to mark the end points of weapon parts, considered as convexities. Further an existing matching approach is optimized to determine whether an ontological object matches the objects from an input image. Objects from derived ontological clusters will be considered for the matching process. Image resizing is studied and applied to decrease the runtime of the matching approach and investigate its rotational and scaling invariance. Set of experiments are preformed to validate the theoretical concepts.

Keywords: Ontology, weapons, acquisition, clustering, partitioning, matching

1. INTRODUCTION

This paper continues the research that has been presented in [1] elaborating the main components of an autonomous approach for weapons identification. The main requirement to such an approach is high accuracy in a short time period. The present method uses low-level features extracted from image and utilizes them for a search in the weapons ontology in order to retrieve high-level (meta) information. Such information is not possible or very difficult to extract from an image or sequence of images.

The algorithm implementing the above mentioned main goals of the method is described as follows.

1. The input to the method is an image containing multiple subjects of interest. The image may come from different modalities and could be very noisy. Although the image enhancement problem is important, it is out of the scope of the present paper, where the image is considered in "good conditions" for further processing and analysis;

2. On the next step, a segmentation tool will automatically extract the objects from the image background [1]. Then the set of objects will be split to separate objects. An active contour (AC) model based on the exact solution of a specific form of the heat partial differential equation will be used to perform the task [2];

3. Low level features will be extracted from every single object. Such of features are: geometric- ratio between major and minor excess [1], number of concavities [3], object's parts, ratios of areas [4]; colors; texture [5]. Active convex hull and active concavity models will be used to extract the geometric [3, 4] and some of the color features;

4. Low level features will be used for objects partitioning. The parts subjects of interest are considered as branches (convexities). The second derivative test will be applied on the extracted object's boundary to determine convex parts (branches) of the objects;

5. The low level features extracted from an object and its branches will be used for the generation of a LLFV;

6. An algorithm is to be designed to search weapons ontology for knots with LLFV which most closely match the feature vector of the input object;

7. The set of knots which contain LLFV most similar to the input one will form an ontological cluster. Ontological information may be used at this stage to further narrow down the candidates for similarity with the input object;

8. At this stage a matching algorithm will be employed to match the shape of the initial object with shape of the object at every knot from the extracted ontological cluster;

9. If match is found a weapon is detected in the input image. The entire ontological information is available to the user for decision making;

10. If no match is found the conclusion is “either the input object is no weapon or a new weapon is detected”.

As one may tell from the above algorithm the weapons ontology is a major component of the weapons identification approach and system. To comply with this importance the present paper develops a new algorithm for automatic generation of a weapons ontology. The algorithm will provide automatic updates of the ontology with new items or parts of items. This will provide an opportunity for development of a fast and accurate algorithm for surfing through the ontology using vectors of low level features. The algorithm will perform also automatic and quick clustering of the ontology using the low level features and hierarchy.

The future work will concentrate on the design of a method to automatically provide the links between the knots in the extracted cluster. This will define new shortcuts between the knots in the entire ontology and may provide important information about the relations between ontological objects which may look different.

2. AUTOMATIC AND SEMI-AUTOMATIC ONTOLOGY ACQUISITION

It is a truth universally acknowledged among ontology builders that ontology acquisition is a difficult and time-consuming operation [6,7.8]. Conversely, the acquisition of domain ontology, let alone a general all-purpose ontology, requires hundreds of thousands of concepts.

The above considerations explain the move toward automatic or semi-automatic acquisition of concepts and/or semantic relations in the ontology. Most approaches use corpora, either dynamically acquired internet “corpora” [9,10], traditional corpora [11] or corpora of convenience, e.g., corporate literature [12] or keywords from search engines [13]. Other use structured resources (e.g., machine readable dictionaries, such as WordNet, [14], or glossaries, such as the financial glossary used in [15] to expand Cyc) which encode semantic information that can be used to build (parts of) the ontology. The methodologies vary, ranging from simple syntactic patterns [16], to statistical patterns [17], data mining [18] and clustering [19,20].

All these approaches share the same problems: 1) reliability of the information, 2) completeness of the information, and 3) updating of the information. Concerning points 1 and 2, it is obvious that a machine acquired or augmented ontology, at best, can only be as good as its sources, and at worst require significant human input, thus eliminating the advantage of automatic acquisition.

Given the purpose of the system in which our ontology needs to operate (i.e., the recognition of weapons from images), our problem reduces to populating the terminal nodes of the ISA hierarchy of a general ontology, to a level of specificity that is generally not necessary or possible for general-purpose ontologies (see Fig. 1, for a fragment of the ISA hierarchy of the subdomain of the ontology we are concerned with). Hence we designed a collection algorithm that uses the freely available Wikipedia source to gather both a list of weapons and some basic factual information to populate the individual frames in the ontology. Wikipedia contains an enormous amount of highly specific information both organized as lists (in our case, lists of guns, pistols, rifles, etc.) and hierarchically. Moreover it provides images of many entries, a

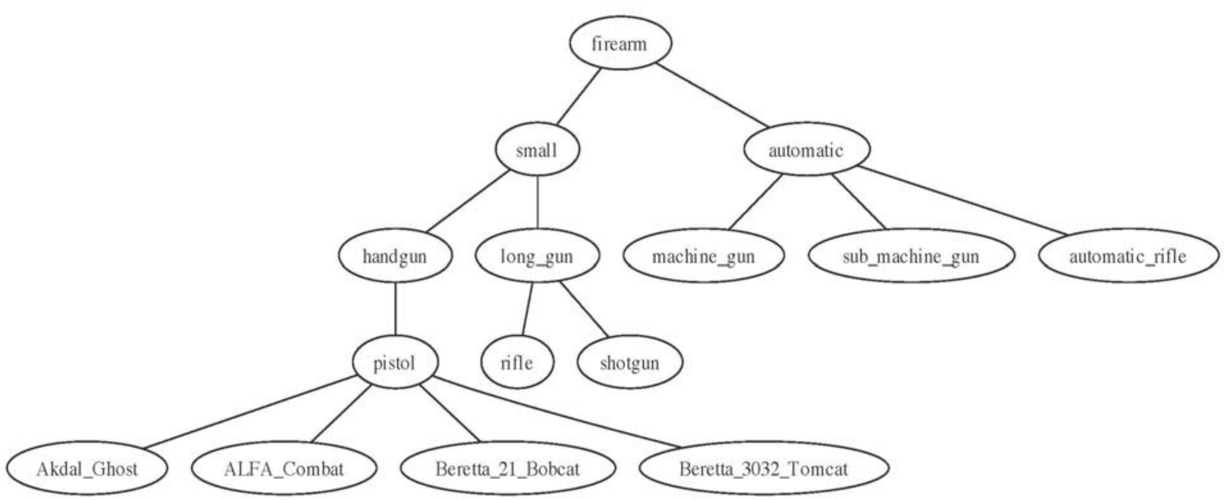


Figure 1. A fragment of the ISA hierarchy of the WEAPON sub-domain

particularly valuable resource in our case. In this manner, we were able to acquire in a simple test run for PISTOL over a thousand nodes, populated with some basic information (detailed in Fig. 2 below). Wikipedia has been used before in ontology-building situations [21,22]; see a review of various approaches in [23]. Since for this project we are working on a very specific domain, we were able to use an ad hoc solution, which, while not scalable to a general ontology, can however be applied to numerous other domains. We anticipate acquiring in this manner around 20,000 nodes in the subdomain WEAPON for our system.

Clearly, the information needs to be verified for both reliability and completeness, using other available sources (manufacturers' catalogs, rosters of weapons allowed for sale from government sources, hobbyist catalogs, etc.), but such automatic acquisitions allow us to both reduce acquisition time and to keep the database up to date. The acquisition algorithm uses the knowledge encoded in the higher-level frames of the ontology to collect some of the information. For example, the frame for PISTOL includes a meronymy list, the HAS-AS-PARTS slot, which can be used to locate information relevant to the various parts of each pistol in the relative Wikipedia entry. (see Fig. 2)

The slot "image" in Fig. 2, will contain a "Low-Level Features Vector," (LLFV) i.e., a vector consisting of the numerical presentation of low-level image features of the weapon, such as for example, geometric- ratio between major and minor excess [1], number of concavities [3], object's parts, ratios of areas [4]; colors; texture [5]. This enables fast searches in the ontology using the LLFV.

```
(Arsenal P-M02
        (ISA pistol)
        (material NA)
        (color NA)
        (weight 760 g (26.81 oz))
        (length 180 mm (7.09 in))
        (HAS-PARTS    (magazine 15-round))
        (variants NA)
        (image
                (countour  NA)
                (convex-hull  NA)
                (texture NA)
                (ratio NA)
                (JPG Arsenal_P-M02.jpg)
                (LLFV)
        ))
```

Figure 2. sample frame generated by the automatic acquisition search in Wikipedia. Note that information not available from this particular source is labeled NA.

3. ONTOLOGY CLUSTERING APPROACH

In [24], a hierarchical clustering methodology for conceptual organization is presented. Hierarchical clustering is an approach to unsupervised knowledge acquisition, based on identifying common features across data points, which are then iteratively agglomerated until the inherent hierarchical organization of the conceptual information emerges. The most significant aspect of hierarchical clustering is that it will reveal "hidden" patterns in the data, of which the producers, or even analysts, need not be aware.

The Hierarchy of Attributes and Concepts (HAC) approach developed in [24] is implemented based on a database which compresses the original data and associates a set of features with each data point. HAC can be represented diagrammatically as a directed graph (essentially a binary tree). HAC as hierarchical algorithm constructs a hierarchical description of the structural data by iteration of the substructure. "This hierarchy provides varying levels of interpretation that can be accessed based on the specific data analysis goals" [24]. "The idea of hierarchical (also known as agglomerative) clustering is to begin with each point from the input as a separate cluster." [24] We then build clusters by merging clusters that are close to each other: repeatedly merge the two clusters that are closest to each other out of all pairs. Conceptual clustering builds semantic structures out of the data incrementally by connecting a group of terms and attributes into subclasses. HAC accepts a database of structured data (relationships) as input. Further, an unstructured data is formed as structured data, forming a (maintaining) relation (concept) table for every attribute and concept in this particular domain of weapon database.

In the implementation of HAC for this project, the method is applied to the ontology itself, thus allowing for the discovery of clusters of concepts that would not be directly encoded in the ontology's hierarchy, for example, all nodes with a "15-round" filler in the "magazine" slot, thus revealing a connection between the Smith & Wesson M&P40 and the Beretta 92 pistols, for example.
In Fig. 3, clusters will be formed for various pistol types. The attributes here in this cluster are different types of pistols i.e., Alfa_Combat, Alfa_Depender. Clustering these attributes forms the concept Alfa. Thus here, different attributes will be clustered to form the related concepts. While demonstrating the role of Conceptual Hierarchies in the Weapons Domain, the base Concept will be the Fire arm followed by the next levels. Attributes forms the root level from which concept groupings are evolved. For the concept pistol, the parent concept will be Hand gun which is followed by concept small in the Hierarchy. All these concept sets falls under the node firearm. At each level of hierarchy, every concept is followed with sub classifications. This approach lends itself particularly well to clustering by low-level features of the kind indexed in the LLFV and is thus a first step toward deriving features from the ontology itself.

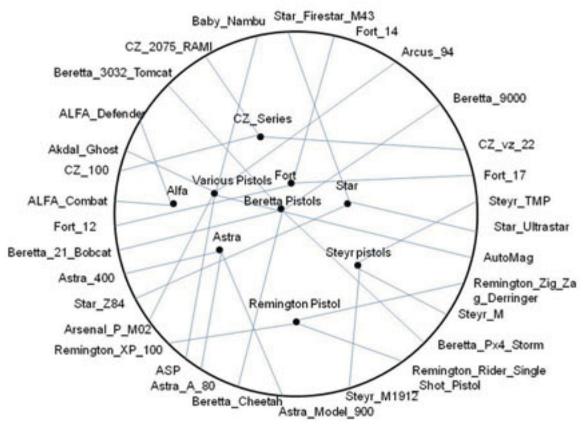


Figure 3. Clustered representation of pistol types

4. OBJECTS PARTITIONING

The present section discusses the weapons partitioning problem. Splitting an object into parts is a complex and open problem from theoretical and practical view point. Its proper solution directly relates to the problem of objects (shape) description. A number of mathematical fields are applied to tackle this problem: Probability, Graph Theory, Group Theory, Active Models, Manifolds, Differential Equations [25].
Two kinds of object segmentation may be considered: high-level and low-level. High-level segmentation may be achieved if metadata or semantic knowledge is used or conceptual object segmentation is performed. Low-level segmentation relies on low-level object's features like color, texture and/or geometry. In [26] the authors first detect the object edge using a set of filter banks. Next they use "low-level grouping cues" and build up a graph where every node corresponds to a single pixel. An advantage of the piecewise work is in its high accuracy which is achieved for the price of slower partitioning.
The present section develops a new low-level object partitioning approach, which uses the vertices of the extracted [1,2] object's boundary. To partition an object this approach assumes that every weapon has a basic convex portion (which may contain voids) and the object' parts are represented as convexities which are additions to the basic part. To extract the object's convexities the second derivative test is employed to determine concavities. To reach the goal the following discrete form of the test is employed to find "the sign of every boundary vertex" [3].

$$(x_i - x_{i-1})(y_{i+1} - y_i) > (x_{i+1} - x_i)(y_i - y_{i-1}) \qquad (1)$$

Thus a boundary vertex has a sign "+" if the above equation is satisfied [3]. Otherwise the sign is "zero", which means no sing is attained or "-". No sign is given to a vertex if the above equation is satisfied for equality relation "=".
Recall the object's boundary and its convex hull vertices are extracted by using shrinking active contour model [1], which we will call S-ACES. It will be assumed also that two consecutive positive vertices represent the end points of the boundary of an object's part. The length or the area can not be used as a distinguishing property of a part of an object, as one may tell from Fig. 4b). Only high level information may be of help to distinguish a small object's part from

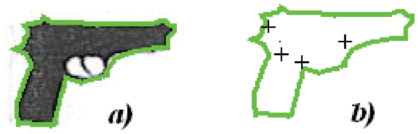


Figure 4. **a)** This figure shows a pistol and its boundary extracted by S-ACES in the range of milliseconds. **b)** the boundary alone with positive concavities change.

a shape distortion that may be created by the image noise or by S-ACES. The positive boundary vertices on Fig. 4 b) define the following pistol's parts: handle, trigger and the end of the grip. Since the points with positive sign are know the objects partitioning will be performed using the contour extracted by S-ACES (Fig. 4 b)).

5. MATCHING OBJECTS AS REGIONS

There are two different object matching approaches. One of them compares objects' boundaries, while the other one matches the objects' regions. The necessary conditions for a matching to be reliable and useful for practical applications are to posses rotation and scaling invariant properties, to be accurate and run in real time.

The method presented in [27] is a boundary comparing technique and uses shape symmetry. The method is fast and satisfies the rotation and scaling invariant requirement. But it would not be useful for application in weapons matching since the shape of many weapons is not symmetric as it can be observed from Fig.4.

Another advanced and fast method for matching boundaries is used in [28]. This method applies Earth Mover's Distance and Manifolds of shapes. Its calculation complexity is in the order of $O(nd\log\Delta)$, where n is the number of used shape features (obtained by shape context local descriptor), d is their dimension, while Δ is the diameter of the feature space. The authors reported a median query time, for a database containing 136,500 shapes, 1.56 sec, which shows a useful time of comparison. The method requires a use of a boundary extraction approach, such as the one described in [2], and the final result will depend on the accuracy and the speed of the extracting approach.

In the present study, we first considered a region based matching approach presented in [5]. To find the correlation value between the mask μ (template image) and the pixels beneath this mask the method employs the following equation [5]:

$$C(x,y)=\frac{\sum_s\sum_t(f(x+s,y+t)-\mu_I)\sum_s\sum_t(w(s,t)-\mu_M)}{\{\sum_s\sum_t(f(x+s,y+t)-\mu_I)^2\sum_s\sum_t(w(s,t)-\mu_M)^2\}^{\frac{1}{2}}}\quad, \tag{2}$$

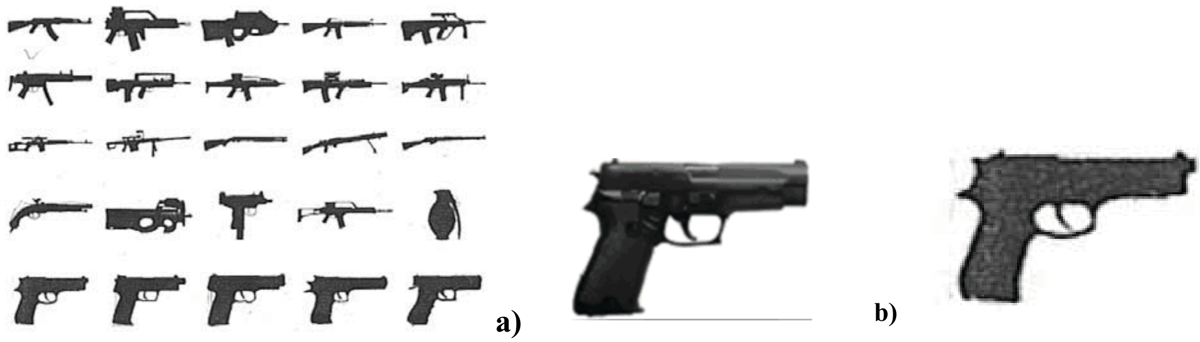
where *C(x,y)* is the correlation value at the pixel *(x,y)* of the image $f(x,y)$, μ_I is the mean of $f(x,y)$, whereas $w(s,t)$ is the mask and μ_M is the mean of the mask (template image). Since Eq. 2 works for gray level 8 bit images only the following correlation formula, reported in [29], has been adopted and employed for color images:

$$C(x,y)=\frac{\sum_{s=1}^{m}\sum_{t=1}^{n}[f_R(x+s,y+t)w_R(s,t)+f_G(x+s,y+t)w_G(s,t)+f_B(x+s,y+t)w_B(s,t)]}{\{\sum_{s=1}^{m}\sum_{t=1}^{n}[f_R(x+s,y+t)^2+f_G(x+s,y+t)^2+f_B(x+s,y+t)^2]^{1/2}\sum_{s=1}^{m}\sum_{t=1}^{n}[w_R(s,y)^2+w_G(s,t)^2+w_B(s,t)^2]^{1/2}}\,. \tag{3}$$

Eq. 3 is used to determine correlation between image $f(x,y)$ with size *NxM* and a mask $w(s,t)$ with size *nxm* . The indexes R, G, and B denote the red, green and blue channels of the RGB color model. Once the correlation value *C(x,y)* is calculated, for every image pixel *(x,y)*, the best match is determined by finding the $\max\{C(x,y), x=1,...,M; y=1,...,N\}$.

The definition of the maximum value has calculation complexity *O(MN)* whereas the complexity of the correlation algorithm is in the order of *O(MNmn)*. Although the method is very accurate the latter formula suggests a long run time of the algorithms.

The matching algorithm on the base of Eq. (3) has been coded in Java and tested on a number of weapon images. Experimental results obtained with this software running on a PC with an Intel core2duo processor with 2.23 GHz, and 4 GB of RAM memory are given below.

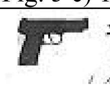


a) b) c)

Figure 5. **a)** Shows an image with size 813x549; **b)** The query image is of size 125x83; **c)** The image retrieved from **a).**

The weapon that most closely matches the pistol in Fig. 5 b) is extracted in 1072 sec from the image shown in Fig. 5 a) and is presented in c). This is the most left pistol from the bottom row in Fig. 5 a). Since the run time reported is too long for a real time weapons search it has been experimentally determined that a resizing of the searched and/or the query images keeping a ratio approximately 2:1 between the objects will dramatically reduce the run time (see Table 1.)

Table 1. Results of resizing the investigated and the query images from Fig 5a) and 5b) respectively

	Investigated Image	Query Image	Run time	Output image
Size	813x549	125x83	1072 sec	Fig. 5 c) 1^{st} from the bottom row
Reduced size 1	271x183	55x37	09 sec	 3^{rd} from the bottom row
Reduced size 2	223x158	55x37	06 sec	 3^{rd} from the bottom row

Analyzing Table 1 one may tell the run time has been significantly improved but the output of the extracted object may vary once the image is resized. Although the type of the extracted object is stable the different results come from the object details lost in the resized images.
Since in many practical cases only part of the weapon may be visible experiment was performed to validate the present matching method. The image in Fig. 5 a) has been queried with an image of the handle of the pistol from Fig. 5 b) in size 125x83. Both, the query and the closest match are shown in Fig. 6. Since the investigated image is from Fig. 5 a) and the query image has a size of 125x83 the run time of the algorithm was again 1072 sec. The pistol extracted in this case is the third one from the bottom row (see Fig.6 b)).

a) b)

Figure 6. **a)** The handle of the pistol from Fig. 5 b) in size 125x83; **b)** The closest match from Fig. 5 a).

In the next experiment an image of the barrel and the trigger of the pistols has been used. The investigated image is in size of 334 x 237 whereas the template image is 55x23 pixels. The retrieved image in 22 sec is shown in Fig. 7 b). This is again the 3^{rd} pistol from the bottom row.

a) b)

Figure 7. **a)** The barrel and the trigger of the pistol from Fig. 5 b) ; **b)** The closest match from Fig. 5 a) in size 334x237.

To demonstrate the ability of the matching approach to handle rotations experiments were performed using the AK-42 machine gun from the image in Fig. 5a). Rotations to 15° and 35° has been used for the object in the template image (Fig.8a) and c)) which were resized to 71x45, and 65x51 respectively. The searched image was resized to 225x160 and the run time to retrieve the machine guns, presented in Fig. 8b) and 8d), was 4 sec. An experiment has been performed also using a rotation on 25° and the extracted gun, again in 4 sec, was the same as the gun shown in Fig. 7 b) and d).

a) **b)** **c)** **d)**

Figure 8. **a)** The first object from the top row of Fig. 5a) rotated to 15° and presented in a template image of size 71x45; **b)** the extracted gun which is the 4th one from the 4th row; **c)** the object from a) rotated to additional 35° and presented on an image of size 65x51; **d)** the extracted gun is the same as the one in b).

6. FUTURE WORK

This study will continue with the completion of a weapon ontology example with a tool providing automatic update. The ontology clustering algorithm will be completed and tested on the ontological example. The run time of the matching algorithm will decrease along with improvement of the rotational and scaling invariance. Low level features extracting approaches will improve performance in term of noise handling and objects multiplicity.

ACKNOWLEDGEMENT

The authors would like to express thanks to the computer science students J. V. Nagendra Raja for coding the matching algorithm in Java and performing some of the experiments, and to Sheena Mathew for improving the code and performing part of the experiments.

REFERENCES

[1] Sirakov, N. M., Suh, S., Attardo, S., "Automatic Object Identification Using Visual Low Level Feature Extraction And Ontological Knowledge", *Proc of Society for Design and Process Science-SDPS*, Dallas, Texas, June 6-11, 2010, 1-9 (2010).

[2] Sirakov, N.M., Ushkala, K., "An Integral Active Contour Model for Convex Hull and Boundary Extraction", G. Bebis et al. (Eds.), Lecture Notes in Computer Science 5876, *Springer Verlag*, ISVC'2009, 1031-1040 (2009).

[3] Sirakov, N.M., Simonelli, I., "A New Automatic Concavities Extraction Model", Published by IEEE, Computer Society, 2006, USA, 178-182(2006).

[4] Sirakov, N.M., "Monotonic Vector Forces and Green's Theorem For Automatic Area Calculation", Proc. IEEE ICIP2007, San Antonio, Sep. 2007, Vol. IV, 297-300 (2007).

[5] Gonzalez, R.C., Wood, R.E., [Digital Image Processing], 3rd Edition, Pearson Prentice Hall, (2008).

[6] Harb, Ali, Hajlaoui, K, "Enhanced Semantic Automatic Ontology Enrichment", Intelligent Systems Design and Applications (ISDA), 2010 10th International Conference, (2010).

[7] Shao, W., Yong-ping, H , Peng-fei, Z, "An Ontology Learning Method for Product Configuration Domain" Management and Service Science, 2009 MASS '09. International Conference, (2009).

[8] Hoxha, J., Agarwal, S, "Semi-automatic Acquisition of Semantic Descriptions of Processes in theWeb", 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, (2010).

[9] Reinberger, M., Spyns, P., Daelemans, W., and Meersman, R. Mining for Lexons: "Applying Unsupervised Learning Methods to Create Ontology Bases." in Proc. of CoopIS/DOA/ODBASE. 2003, 803-819 (2003).

[10] Maedche, A.; Staab, S.; "Ontology learning for the Semantic Web," Intelligent Systems, IEEE , vol.16, no.2, pp. 72-79 (2001).
[11] van der Plas, Lonneke, Bouma, G., Marr, J, “Automatic acquisition of lexico-semantic knowledge for question answering.” In C-C Huang, N. Calzolari, A. Gangeni, A. Lenci, A. Oltramari, L Prévot (eds.) Ontology and the lexicon. A natural language Processing perspective. Cambridge, Cambridge University Press. 271-287 (2010).
[12] Navigli, R., Velardi, P., “Learning domain ontologies from document warehouses and dedicated web sites. Computational Linguistics,” 30(2), 151–179 (2004).
[13] Shim, Joon , Lee, H., ”Automatic Ontology Generation Using Extended Search Keywords” ,4th International Conference on Next Generation Web Services Practices 2008 IEEE, (2008).
[14] O’Hara, T. K. Mahesh, S. Nirenburg. Lexical acquisition with WordNet and the Mikrokosmos ontology. Proc. of the COGLING/ACL Workshop on Usage of Wordnet in Natural Language Processing Systems. Montreal, Canada, (1998).
[15] Novalija, Inna and Dunja Mladenic, “Content and Structure in the Aspect of Semi-Automatic Ontology Extension”, Proceedings of the ITI 2010 32nd Int. Conf. on Information Technology Interfaces, June 21-24, (2010).
[16] Hearst, M. A., “Automatic Acquisition of Hyponyms from Large Text Corpora.” Proceedings of the Fourteenth International Conference on Computational Linguistics. COGLING 1992 Nantes, (1992).
[17] Maedche, A., Er Maedche, Volz., R, “The Ontology Extraction Maintenance Framework Text-To-Onto.” In Proceedings of the ICDM’01 Workshop on Integrating Data Mining and Knowledge Management, (2001).
[18] Faure, D., Poibeau, T, “First experiments of using semantic knowledge learned by ASIUM for information extraction task using INTEX.” In: S. Staab, A. Maedche, C. Nedellec, P. Wiemer-Hastings (eds.), Proc. of Workshop on Ontology Learning, 14th European Conf. on Artificial Intelligence ECAI’00, Berlin, Germany, (2000).
[19] Khan L., Luo, F., “Ontology construction for information selection.” In Proceedings of 14th IEEE International Conference on Tools with Artificial Intelligence, pp.122–127, Washington, USA, 2002. IEEE –CS, (2002).
[20] Khan, L., Luo, F., Yen, I., “Automatic ontology derivation from documents," Proc. of the 15th Conference On Advanced Information Systems Engineering (CAISE '03), (2003).
[21] Medelyan, O. & Legg, C., “Integrating Cyc and Wikipedia: Folksonomy Meets Rigorously Defined Common-Sense,” The AAAI Workshop on Wikipedia and Artificial Intelligence, Chicago, Ill pp. 13-18, (2008).
[22] Sarjant, S., Legg, C., Robinson, M., and Medelyan, O., “All You Can Eat" Ontology-Building: Feeding Wikipedia to Cyc,” 2009 IEEE/WIC/ACM Int. Joint Conf. on Web intelligence and intelligent Agent Technology - Volume 01. Web Intelligence & Intelligent Agent. IEEE Computer Society, Washington, DC, pp. 341-348, Sep. (2009).
[23] Al-Rajebah, Norah I. and Hend S. Al-Khalifa, “Semantic Relationship and Ontology Building using Wikipedia: A Comprehensive Survey.” International Journal of Computer Applications. 13:3. 6-12, (2010).
[24] Suh, S.,C., Saffer, S.I., Anaparthii, S.G., Sirakov, N. M., "Basics of Concepts Representation for Document Summarization", INC, IMS and IDC, 2009 Fifth International Joint Conference on 25-27 Aug. 2009 Page(s), 1374 - 1380 (2009).
[25] Grenander, U., Miller, M.I., [Pattern Theory], Oxford University Press, (2007). ISBN: 0-19-850570-1
[26] S. X. Yu, R. Gross, J. Shi, “Concurrent Object Recognition and Segmentation by Graph Partitioning”, Neural Information Processing Systems, Vancouver, Dec 9-14, (2002).
[27] Aslan, C., Tari, S. , “An Axis Based Representation for Recognition.” In: ICCV, pp. 1339-1346, (2005)
[28] Grauman, K., Darrell, T., “Fast Contour Matching Using Approximate Earth Mover’s Distance,” Proc. of the IEEE Conf. CVPR2004, Washington DC, June, (2004).
[29] Fanjun, L., Binggang, C., Junping, W., Kai, Z., Xi’an Jiaotong, “Color Image Similarity Measurement and its Application in Matching.” 2nd International Conference on Intelligent Computation Technology and Automation, China 2009, DOI 10.1109/ICICTA, (2009),143, IEEE Xplore.