

AUTOMATIC OBJECT IDENTIFICATION USING VISUAL LOW LEVEL FEATURE EXTRACTION AND ONTOLOGICAL KNOWLEDGE

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The present work is a part of research study aiming to develop an algorithm and a software system capable of quick identification of weapons and relations between human and a weapon in a scene. Bridging the semantic gap between the low level knowledge extracted from an image and the high level semantics needed to negotiate the weapon domain ontology is connected to the features extraction algorithms. Also, the ontology is anticipated to help facilitate the recognition part of the work. To accelerate the search process a hierarchy of attributes and concepts will be applied to cluster the ontology using a set of extracted features. The ontological structure, the clustering ideas and the feature extraction approaches and algorithms are introduced in the paper. Experimental results for boundary and convex hull extraction are shown as well. The paper ends with discussion and the future directions of the present work.

Keywords: *features extraction, hierarchy of attributes, semantics, clustering, ontology, weapons*

1. Introduction

This paper is envisaged as a contribution to the general problem of extracting meaning from low-level visual features, such as colors and shapes, and specifically applied toward the problem of automatically recognizing and identifying weapons and their relations to humans in images. The problem for real time, automatic weapons detection and finding of humans carrying weapons is a subject of great interest for national and international security agencies. The practical utility of a system capable of identifying and recognizing weapons without human intervention at runtime is obvious: potential uses could range from luggage screening at airports to surveillance camera monitoring of businesses, schools, and other public places, but could range as far as battlefield analysis (for example by discriminating between weapon-bearing and non-weapon-bearing humans). Both constraints formulated above impose the requirements for quicker solution of the problem in a time period of a second or two without user interactions. The present paper proposes an approach capable of dealing with both requirements. Initially the model is using a single image as input, but the model and the tools utilities are intended to be scalable toward the motion picture (video) problem.

The general problem of extracting meaning from images is a very complex one. A preliminary step leading to the solution of this problem is image segmentation. Multiple different approaches have been proven to deal efficiently with segmentation; however, our study will apply active contours. A very

useful survey of the main methods from this field is given in (Xu et al., 2000). Our approach consists of the integration of original research with image segmentation, and geometric features extraction, etc. with ontological semantics, on the one hand, and with data clustering, on the other, to both restrict the search space of the system once a query object has been acquired and to enhance the acquisition mechanism itself. A particular feature of the system described is that it integrates very deeply the high-level semantic information stored in the ontology, with low level semantic information typically stored outside of the ontology as well as with geometrical and other low-level visual information, typically absent from ontologies.

Since ontological semantics is a basic component of the system we are developing, we will start with the introduction to the ontology being developed for the ONTO-SEE project.

2. Ontological Semantics

Ontological semantics is a theory of meaning based on ontology. An ontology has been defined, in Artificial Intelligence (AI), as “an explicit specification of a conceptualization” (Gruber 1993: 1) or, put differently “a body of formally represented knowledge” (Gruber 1993: 1; see also Gruber 1995). The formality of the representation is essential to its algorithmization, which require unambiguous, explicit, and consistent descriptions (i.e., formalized descriptions). A “conceptualization” is the sum total of the knowledge that a given agent (for example, a robot) has available to operate with. This will include concepts such as MOVE, TURN, VEHICLE or WHEEL and their relationships (for example, turning is a kind of movement which both wheels and vehicles may engage in). Finally, an ontology will usually assume that some form of inferential logic can be applied to its axiomatic knowledge to derive theorems (so, our robotic agent would be able to deduce that if it is turning it is therefore moving). Summing up, an ontology in AI is a representation of the world of a certain agent that is both relevant and available to that agent for reasoning.

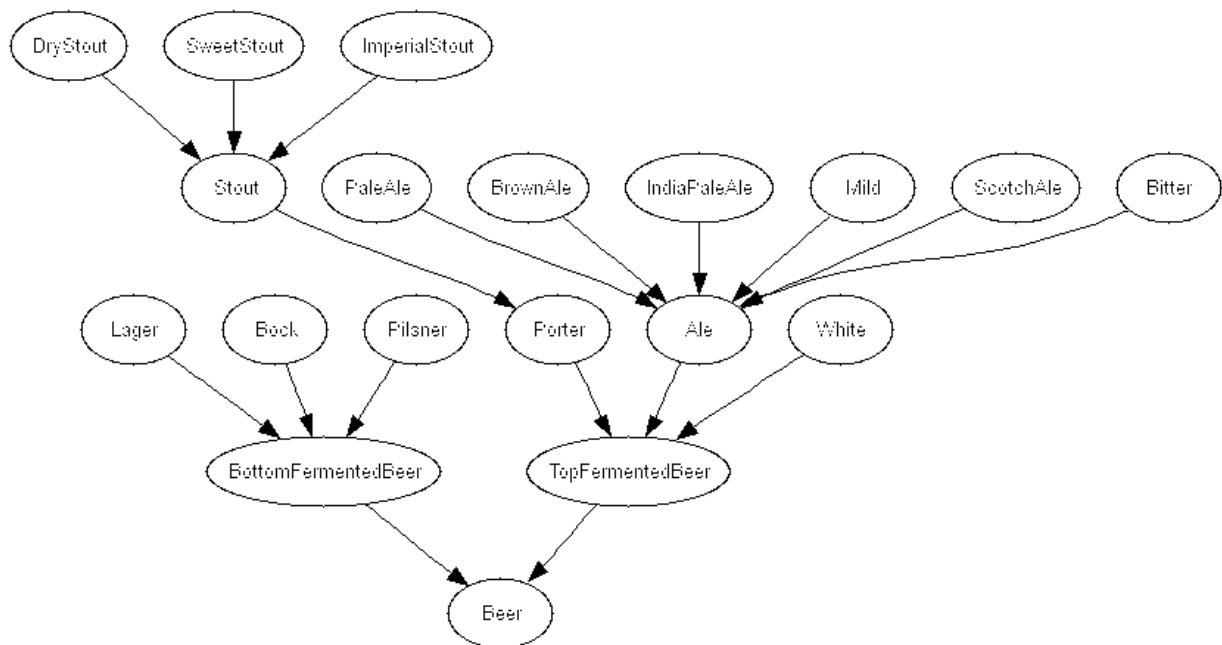


Fig. 1 The BEER domain ontology, from www.schemaweb.info notice the ISA links represented as arrows, each node representing a concept, here for a type of beer

Technically speaking, the ontology itself can be conceptualized as a labeled graph with concepts as vertices and labeled links as edges. The labeled links describe and define relationships between concepts. Thus, for example, the two concepts CAR and VEHICLE would be connected, among other links, by an ISA link (arrows, in the BEER ontology example in Fig. 1). Significantly, the ontology is not a simple tree, but a general graph (i.e., there may be more than one path between two vertices/concepts). The formalism of the representation of the ontology is in itself unimportant, so we could represent this as a function ISA (CAR, VEHICLE), or in pseudo-code, using the common slot-filler syntax (CAR (ISA VEHICLE)), the latter representation having the advantage of being easily extended to the case in which there are more than one and in fact many links between a concept and others. For example:

```
(CAR
 (ISA VEHICLE)
 (HAS-PARTS ENGINE, WHEEL, CHASSIS, DOOR, ...))
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where the information that a car is not just a vehicle only, but that it has also parts which include an engine, wheels, etc. as represented. Such a set of links defining a concept is called a “frame” (Fillmore, 1985). It should be stressed that since the computer manipulates strings of symbols, concepts such as WHEEL or CAR are only defined as the set of links they exhibit. Any other information would be unavailable to the system. This is a common tenet in ontological semantics (Dean and Schreiber, 2004).

There are different levels of specificity among ontologies. There exist domain specific ontologies, midlevel, and general purpose ontologies. A general purpose ontology (e.g., Philpot et al. 2003) is also referred to as “upper level ontology” (e.g., the Suggested Upper Merged Ontology (SUMO), Niles and Pease, 2001). The upper level ontologies are very general concepts likely to occur across domains. For example, OBJECT, EVENT, and ACTION will most likely occur in all general ontologies. Midlevel ontologies would cover domains such as “communication,” “military,” “government,” and “geography” (all examples are from SUMO midlevel ontologies). Domain specific ontologies are even more specific: examples are “emotions” (Triezenberg, 2006), “tourism” (Mohammed, 2005), “beer” (see Fig.1) and “wine” (available at <http://www.schemaweb.info/default.aspx>). For a sample list of domain ontologies see Gomez-Perez et al. (2004: 85-102).

There are several proposals for upper level, general purpose ontologies, including SUMO (mentioned above). Lenat’s CyC is another example (Lenat, 1995; Reed and Lenat, 2002). For a review see Gomez-Perez (2004: 71-77). For a number of reasons, see for example Mahesh et al. (1996), we will be using OntoSem, the ontology developed by Hempelmann and Raskin (2008); see Nirenburg and Raskin (2004) for the theoretical background.

It should be noted that an ontology represents a set of concepts, i.e., ideas, that agents represent in their brains (or systems, in the case of a robotic agent). Concepts are not words, although the two are obviously related. Simplifying a very complex philosophical issue, words link concepts and linguistic representations. Therefore, an ontology in and of itself has no relationship with a language at all. While it is true that generally ontologies have represented linguistic information, one of the advantages of the frame-based ontology model adopted in this work, developed and justified in OntoSem, is that it is applicable to any set of information, including in our case, visual information. Frames can handle elegantly visual information, including actual images, as part of the slot-filler data structure (note for example in Fig. 3, below how actual links to images are part of the frame). The integration of semantic/linguistic information and visual information will allow us to leverage the advantages of ontological reasoning wherever possible, without being constrained by divisions.

The general upper level ontology will be integrated by a domain specific ontology for weapons (to be fully developed) and by a fragment of the onomasticon (i.e., named instances of concepts). Fig. 2 exemplifies the various levels. All the concepts below SHOTGUN belong to the onomasticon (there

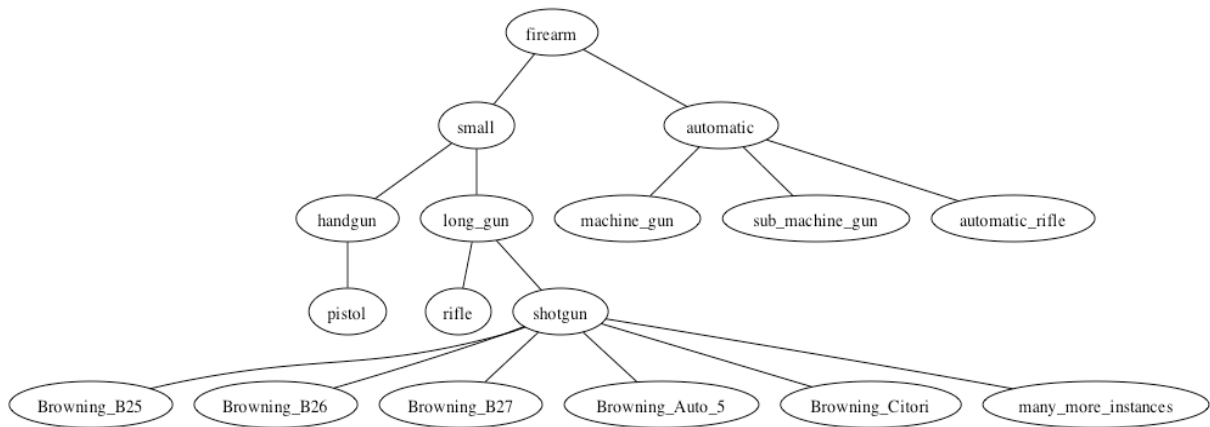


Fig. 2 A (small) fragment of Firearms ontology. The links are ISA links. No other links are represented in this image.

are 129 nodes, to be precise). All the other concepts belong to the domain specific ontology of FIREARM, itself part of the general WEAPON ontology.

Fig. 3 is a sample frame, which describes one of the concepts under PISTOL, and namely the Swiss-made SIG P220. An image of the object along with its boundary and convex hull extracted with an active contour are shown in Fig. 9.

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(SIG_P220
(ISA pistol)
(material metal, stainless_steel, aluminum)
(color black)
(weight 800, 1130) ; unit: grams
(length 198) ;unit: millimeters
(has_parts magazine)
    (variants p245, p225, p6, p220_rail, p220_carry,
    p220_compact, p220_combat)
(image
(contour SIG-220_ob_b_500_10_10_15.JPG)
    (convex_hull SIG-220_CH_100_10_10_15.png))
(texture coarse, smooth, regular)
(ratio 1x7)
)
  
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Fig. 3 Sample frame for the SIG P220 (see Fig.9). Comments follow semicolons and are merely for the convenience of the human acquirer, as are indentations; alternate fillers for each slot are separated by commas.

Finally, it is worth noting that the ontology developed in OntoSem and applied in ONTO-SEE is partly hierarchical (the ISA hierarchy) and partly an n-dimensional construct. As we mentioned above the usefulness of the ontology is further enhanced by using clustering techniques, which are presented in the next section.

3. Clustering With Object Properties

Clustering consists of grouping together similar data items into clusters. Hierarchical clustering is one of the most frequently used methods in unsupervised learning and in design of workflow models (Zerguini 2004). The idea of hierarchical clustering (Sang, Nikhil and Young, 2006), is to begin with each point from the input as a separate attribute. We then build concepts by merging attributes that are related to each other, if we keep merging, we end up with a single concept that contains all points. Conceptual clustering is a technique that forms concepts out of data incrementally by subdividing groups into subclasses iteratively.

An important property of conceptual clustering is that it enhances the value of existing databases by revealing patterns in the data. These patterns may be useful for understanding trends, for making predictions of future occurrences from historical evidence, or for synthesizing data records into meaningful clusters. A conceptual clustering system accepts a set of object descriptions (properties, events, observations, facts) and produces a classification scheme over the observations (Nicolas, et al., 2007). These systems use an evaluation function to determine classes with "good" conceptual descriptions. A learning of this kind is referred to as learning from observation (as opposed to learning from examples). Typically, conceptual clustering systems assume that the observations are available indefinitely so that batch processing is possible using all observations.

It is observed that searching for concepts, rather than regular terms, increases the opportunity of retrieving object relevant to the associated properties (object descriptors) and decreases the possibility of retrieving non-relevant objects (Soon, Ying and Lee, 2009). The reason behind this observation is that concepts are originally extracted and analyzed with respect to the object descriptors.

4. Multi Faceted Representation of Object Information Using Object Ontology and Hierarchy of Attributes and Concepts

In this representation of object information, we maintain 3 important structures:

1. Object Feature Representation Table (OFRT).
2. Object Ontological Relation Table (OORT).
3. Hierarchy of Attributes and Concepts, (HAC). (Sang, Nikhil and Young, 2006).

Detecting the features of the object is very important to support automatic object extraction from image. We have developed an OFRT, where each object is defined with their corresponding features as shown in Fig. 4. In order to have a better illustration of our idea, we still consider the example with three product variants: AR10A4BSN, BP40DTCC and CR10001 in this context. A collection of product information related to each of the product variants, such as information from the Web, Text Corpus or an third party manufacturer is collected in the first place (Huan, Xing, Liang and Tan, 2008) and (Soon, Ying and Lee, 2009). The product entity extraction process is then performed on these collections of product information to extract the properties of the product which forms the object feature representation table; an instance of this table is shown in Fig. 4.

As discussed in (Soon, Ying and Lee, 2009), the properties of the relations in Table 1 can be explained as the following, 'IS_A' relation is transitive which means if A is a B, and B is a C, we can infer that A is a C. When one defines a property P to be a transitive property, this means that if a pair (x, y) is an instance of P then we can infer the pair (y, x) is also an instance of P. Reflexive relation is a 'is equal to' relation. The relation 'part of' is reflexive. Part of relation would only be added between A and B if B is necessarily part of A: wherever B exists, it is as part of A, and the presence of the B implies the presence of A. However, given the occurrence of A, we cannot say for certain that B exists. The Anti symmetric relation implies "is a greater than or equal" relation.

Once the features have been extracted from the text corpus, we start extracting the relations among the objects and their domains using semantic dictionaries such as Word Net. All the possible relations that can exist between any two entities are shown in Table 1. Therefore the Object Ontological



CR100016

MNFT_PROPER

Manufacturer: Comanche
Category: Firearms - Handguns
UPC: 0000062266008

TECHNICAL

Type: Revolver
Action: Single/Double
Caliber: 22 Long Rifle
Barrel Length: 6 inch
Capacity: 9 rd
Safety: Transfer Bar
Grips: Rubber
Sights: Adjustable
Weight: 39oz
Finish: Stainless
Width: 3 inch
Length: 10 inch
Stock: ----



BP40DTCC

MNFT_PROPER

Manufacturer: Bersa
Category: Firearms - Handguns
UPC: 091644911917

TECHNICAL

Type: Pistol
Action: Double
Caliber: 40 S&W
Barrel Length: 3.2 inches
Capacity: 6+1
Safety: Ambidextrous
Grips: Black Synthetic
Sights: Adjustable
Weight: 22oz
Finish: Duo-Tone
Width: 2 inch
Length: 6 inch
Stock: -----



AR10A4BSN

MNFT_PROPER

Manufacturer: Armalite
Category: Firearmsactical Rifles
UPC: -----

TECHNICAL

Type: Rifle
Action: Semi Automatic
Caliber: 308 Winchester
Barrel Length: 20 Match
Capacity: 20 rd
Trigger: National match 2 Stage
Sights: -----
Weight: -----
Finish: Stainless/ Black
Width: 8 inch
Length: 28 inch
Stock: Black Synthetic

Fig. 4 OFRT: Formal representation of Object Feature Representation Table

Table 1 Set of all Relations that can subsist between any two entities

Relation	NAME	TRANSITIVE	REFLEXIVE	ANTISYMMETRIC
R1	IS_A	+	+	+
R2	PART_OF	+	+	+
R3	INTEGRAL_PART_OF	+	+	+
R4	PROPER_PART_OF	+		
R5	LOCATED_IN	+	+	
R6	CONTAINED_IN			
R7	ADJACENT_TO			
R8	TRANSFORMATION_OF	+		
R9	DERIVES_FROM	+		
R10	PRECEDED_BY	+		
R11	HAS_PARTICIPANT			
R12	HAS_AGENT			
R13	INSTANCE_OF			

Relation Table (OORT) clearly shows that one or more relations exist between any given two entities or a domain. A part of the firearms ontology is shown in Fig. 6. The set of relations stated in Fig. 6 are: Trigger **PART_OF** Pistol, **INTEGRAL_PART_OF** pistol is Trigger, Trigger **PART_OF** Rifle, Rifle **IS_A** Hand gun, BP10614 **INSTANCE_OF** Pistol, Pistol **IS_A** Hand gun. As Sang et al. (Sang, Nikhil and Young, 2006) said, the Hierarchy of Attributes and Concepts (HAC) is both a hierarchical and conceptual clustering system that organizes data so as to maximize inference ability. The application of the clustering will get the substructure in the data which reduces the data and represents structural concepts in the OORT. The proposed idea is useful for image semantic extraction to determine relation between different objects in an image. The discovered substructures allow abstraction over detailed structures in the original data. Iteration of the substructure discovery process constructs a hierarchical description of the structural data in terms of the discovered in OORT, as explained above. This hierarchy provides varying levels of interpretation that can be accessed based on the specific data analysis goals by building the clusters based upon the features extracted (Huan, Xing, Ling and Tan, 2008) from surveillance cameras, for example.

5. Automatic Retrieval of Object using Ontology

An object feature representation table which consists of the name of the object and its corresponding features is created by identifying object categories and features from web and text corpora. Some instances of the object and their corresponding features are shown in Fig. 4. The relations mentioned in Table 1 are formed between the objects based on the extracted features and some domain based knowledge sources such as Word Net. Based upon similarity of features we group them leading to the formation of the object-ontological relation table. Fig. 6, represents a part of the weapons' ontology formed from the OORT which is too complex to traverse and retrieve the target object based upon the features extracted. In order to eliminate the fuzziness inherent in traversing unnecessary relations between objects, we create a hierarchy of concepts and their attributes which is a

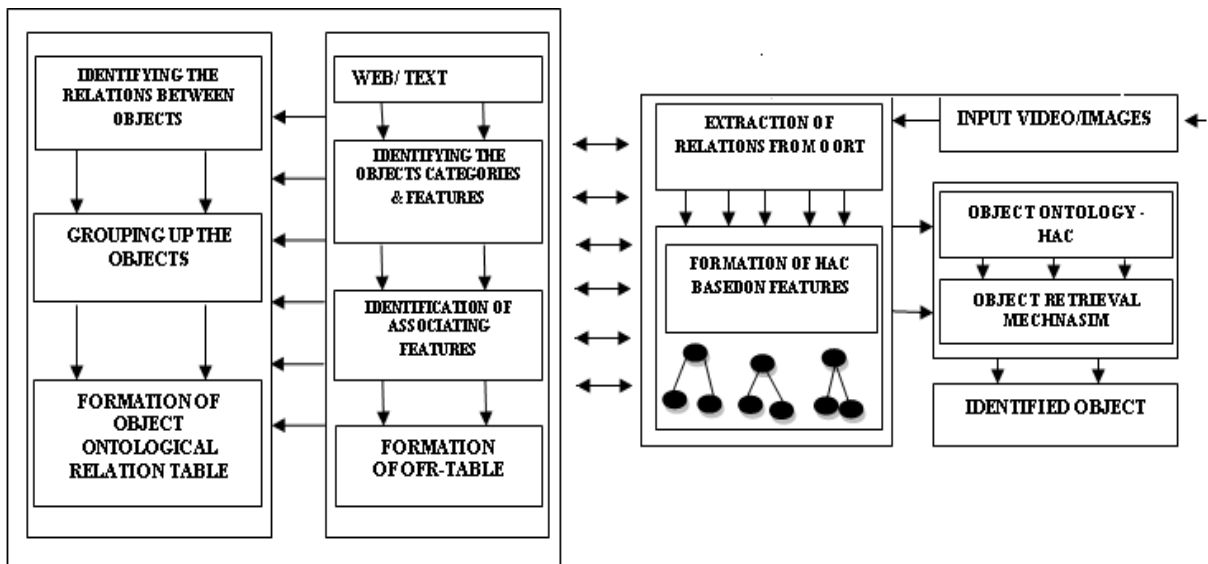


Fig. 5 Architecture of Automatic Retrieval of Target using HAC based object recognition ontology

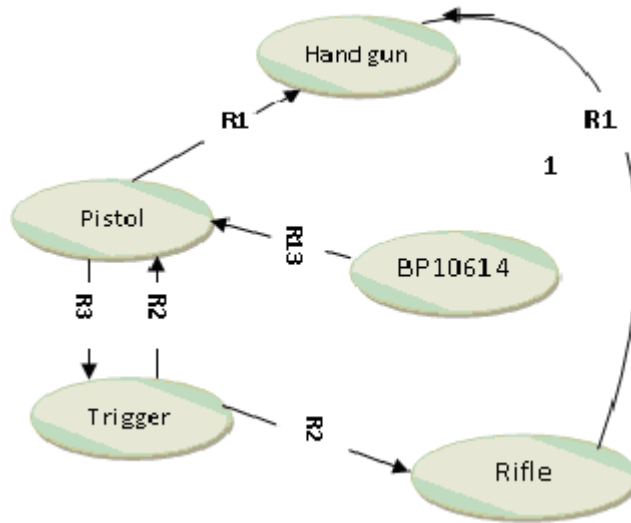


Fig. 6 Part of the firearms ontology from OORT to illustrate relations.

subset of the OORT based upon the features extracted by the sensors; this is called an HAC. We can generate ‘N’ number of HAC’s based upon the different combinations of the features. As we extract the HAC from the OORT based upon the features from the sensors (Nicolas, et al., 2007; Dasiopoulou, et al., 2001; Sang, et al, 2006) this results in more efficiency by eliminating all unnecessary relations. We have a predefined matching and a traversing method which is a property-oriented approach. It corresponds to verifying the validity of property values of the object according to the properties and the constraints defined in the concepts and retrieving the target object as shown in Fig. 5.

6. Image Segmentation

We assume that an image is given from a source. Also, ontology is available and linked to the recognition ONTO-SEE system (software). The ontology provides knowledge about the objects subject of interest, as described in section “Ontological Semantics”.

In the present section we introduce an image segmentation and geometric features extraction by using an active contour presented by Sirakov and Ushkala (2009). The extracted low level geometric features are used by HAC and by the weapons ontology in order to discover objects relations and meta information which is not seen from the image.

The very first task to be performed before low level features extraction is image segmentation. To sharpen the image and facilitate the work of the boundary detection algorithms a high bust filter (Gonzales et al. 2008) is applied on the base of the following equation:

$$f_N(x, y) = Af(x, y) - Df(x, y) - \nabla^2 f(x, y). \quad (1)$$

In Eq. 1 A denotes an integer, $Df(x, y)$ represents the sum of the directional derivatives in the directions of 45^0 , 135^0 , 225^0 , and 315^0 from the pixel with coordinates (x, y) (the central pixel in Fig.7), $f(x, y)$ denotes the image function, whereas $\nabla^2 f(x, y)$ shows the Laplacian, and $f_N(x, y)$ denotes the new filtered value of the image function.

Approximating the derivatives, in Eq.(1), on two consecutive nodes leads to the sharpening mask shown in Fig. 7. Such a mask may be used to smooth the background, erase noise and small details if the sum of the mask entries is positive.

To obtain the image of the pistol shown in Fig.8 a mask with value $A=1$ was used. Comparing the images of the pistol in Fig. 8 (a) with those on Fig. 8 (c) shows that the area around the boundary is sharper and clearer.

- 1	- 1	- 1
- 1	A+ 8	- 1
- 1	- 1	- 1

Fig. 7 A high boost mask generated by Eq. 1.



Fig. 8 a) noisy image of a pistol; b) CH; c) the image of the pistol filtered with the mask from Fig.1, and $A=1$; d) its boundary extracted with the active contour.

Another sharpening mask may be constructed if the negative signs in Eq.1 are switched to positive. In this case the positive sign will switch as well, and this will make the mask “stronger”. In other words the new mask will delete details that could be important for the phase of identification. Thus for the sake of the present study the mask shown in Fig. 7 will be used.

To automatically extract geometric information from the image objects, subject of interest, the integral active contour model (IACM) presented in (Sirakov et al. 2009) is applied. The model uses the following vector form of the exact solution of a modification of the geometric heat differential equation (Sirakov et al. 2009):

$$r(s,t) = e^{\frac{|ds| - |ds|^2 t}{2}} \{C_1 \cos(c \frac{s}{2} |ds| \sqrt{3}), C_2 \sin(c \frac{s}{2} |ds| \sqrt{3})\}, \quad (2)$$

of the so called Active Convex Hull Model (ACHM) published in (Sirakov 2006). In addition to Eq.2 an initial and boundary conditions are applied (Sirakov et al. 2009):

$$r(s,t) \Big|_{|ds|^2 t=0.001, C_1=C_2=R, c=1000} = e^{\frac{|ds| - 0.001}{2}} R \{ \cos(s |ds| 500\sqrt{3}), C_2 \sin(s |ds| 500\sqrt{3}) \} \quad (3)$$

$$\text{if } \frac{\partial f}{\partial t}(r(s^*, t)) > \varepsilon \text{ for } t > 0.001, s = s^* \text{ then } r(s^*, t + \Delta t) = r(s^*, t), \text{ otherwise } r(s^*, t + \Delta t) \neq r(s^*, t) \quad (4)$$

Eqs.2, 3 and 4 define an active contour model. To make it capable of progressing into concavities a re-parameterization approach is used (Sirakov 2006) (see Figs. 8 (c), 9 (b) and 10). To determine the convex hull (CH) of the object a distance function is minimized and linked to the IACM model (Sirakov et al. 2009).

Both, the filtering and IACM have a calculation complexity in the order of $O(N^2)$, where N is the size of the image. Experiments were performed to validate the expectations of a high speed of performance and non user interaction. The image in Fig. 8 (a) is of size 128x128. The filtering is taking approximately 0.016 sec, and the filtered pistol is shown in Figs. 8 (c). The boundaries given in Fig. 8 (d) are extracted in approximately 0.235 sec. In Fig.9 is shown an image of the pistol SIG P220. The image is of size 760x509. Its boundary was extracted (see Fig.9 (b)) in 1.4 sec, whereas the CH (see Fig. 9 (c)) was determined in less than 0.016 sec. The image in Fig. 10 (a) is of size 509x156 and the boundary of the object was determined in 0.432 sec. To run the experiments a PC with Core Duo CPU 2.16GHz was used.

The experimental results given above show that CH is a geometric property with a very low runtime of extraction. This property along with its geometric features makes it desirable for ontology search.

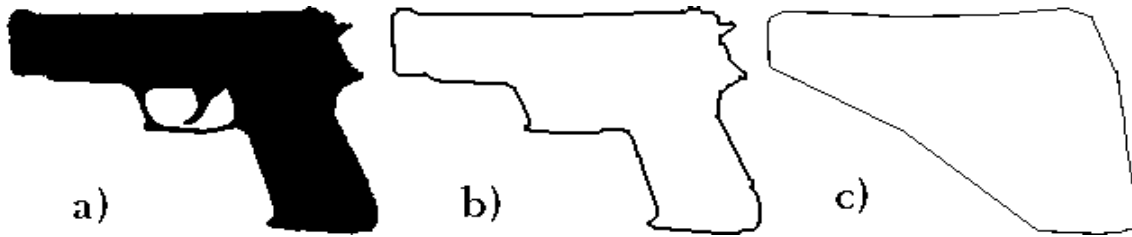


Fig. 9 a) Image of SIG P220; b) its boundary extracted with IACM; c) the CH.

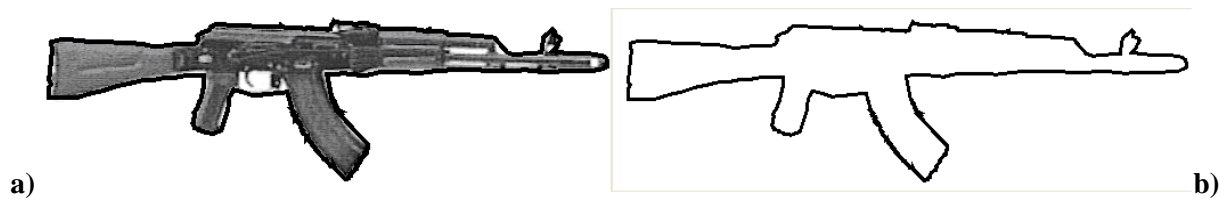


Fig. 10 a) AK-47 and its boundary determined by IACM; b) the extracted boundary.

7. Semantics Detection with the Help of Ontology

The image semantic we are interested in regards the relationship between a human and a weapon. In other words, we are interested whether the weapon is in a closed proximity of a person. To answer this question the system will use a knowledge derived from weapons ontology. In particular the information needed is about the real maximal length and width axis (Gonzales et al. 2008) of human and a weapon. This information will be obtained after ontology search using the extracted low level boundary and CH features.

Denote by $O(H_l)$, $O(H_w)$ the maximal length and width axis of the human body obtained from ontology, and by $O(W_l)$, $O(W_w)$ the same information regarding the corresponding weapon.

Denote also by $I(H_l)$, $I(H_w)$ and $I(W_l)$, $I(W_w)$ the maximal length and width axis of the two subjects, obtained from the image. To determine the relation between the human and the weapon the following expressions are used:

$$\frac{O(H_l)}{O(W_l)} \neq \frac{I(H_l)}{I(W_l)} \quad \text{and} \quad \frac{O(H_w)}{O(W_w)} \neq \frac{I(H_w)}{I(W_w)} \quad (5)$$

Criterion: If Eq.5 is satisfied, both objects in the image are not in a close proximity to each other. In other words: most likely the human in the image does not carry the weapon.

If Eq.5 is not satisfied both objects are in a close proximity in the image, and most likely the human does carry the weapon.

Now the question which needs an answer is how does the system determine the length and width axis of an image object? There are number of algorithms to do so (Gonzales et al. 2008), but in this study we will present a new one based on the CH of the image objects.

As we showed above the IACM (Sirakov et al. 2009, Sirakov 2006) extracts the CH of an object (see Figs. 7 (b), 8 (c)). It follows from the CH definition that the maximal length axis equals the maximal distance between the CH vertices. To determine the width all straight segments perpendicular to the maximal length are determined and the longest one is selected among them.

The number of operations needed to find all distances between n points is $n(n-1)/2$. Follows that the complexity of this process is in the order of $O(n^2)$. Extracting the maximum value between n^2 numbers has the same complexity. Therefore the calculation complexity of defining the maximal length and width axis of an image object by using its CH vertices is in the order of $O(n^2)$, where n is the number of CH vertices. Taking into account that the number of vertices on the CH is usually relatively small (smaller than 100 vertices) the run time on the above mentioned machine (CPU 2.16GHz) will not exceed 20 milliseconds as one may tell from the experimental results given above.

Ontology provides semantic information about the objects in the image received from a source. Such information is: relation between objects; practical usage; creation of a new object on the base of multiple others; real sizes. This knowledge would be difficult to extract from images. Also, the domain oriented ontological information may help the recognition system identify an object on the base of a determined neighbor.

8. Conclusions

The general problems of extracting semantic (meaningful) information from low-level visual information remains daunting, but by integrating various geometrical and visual analytical techniques with ontological semantics and the HAC approach to data-clustering, we believe we have pointed to a fruitful path of research.

While the advantages of the system we are building are obvious, its disadvantages may be less so: for one the system is domain specific and will not scale or be portable outside of the domain of weapons. The theoretical basis, however, is generalizable to any domain. Another problem is that the domain-specific information needs to be acquired largely by hand (although HAC techniques can help automate part of the acquisition). Other problems, tied to the visual detection component, are that the algorithms do not currently handle automatically holes and require human intervention.

A contribution of this paper is in the use of automatically extracted low level geometric features to retrieve high level meta data and knowledge from ontology, in this particular case weapons ontology. Another contribution is in the hierarchical grouping of the low level features to facilitate and accelerate the ontology search.

As stated in the introduction, the primary application of the ONTO-SEE system is to automatically identify a weapon from single image in real time. Another possible application is to the field of image authentication if the ONTO-SEE system is combined with a low level system such as the one presented by U. Govindaswamy, A. Shanmugam (2005).

The realization of ONTO-SEE is still in its preliminary phases. We are building the basic components of the system, and some have already been acquired, as described in the paper. We have already built a small sample ontology that allow us to run a series of experiments for automatic identification of weapon extracted from a single image.

This work continues with the design of an algorithm to fuse knowledge derived from image analysis and ontology clustered by HAC on the base of non-ordered features. Some software components of the algorithm are already in use, but other are under development. The team is: building up a larger

example of weapon ontology; developing and coding algorithms for quick features extraction from noisy images; working on ontology clustering on the base of the extracted features; and finally, working on integrating visual low level features with meta data and semantic within the ontology. Efficient indexing algorithms using low level features to accelerate the ontology search are under development as well.

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