From Shape to Threat: Exploiting the Convergence Between Visual and Conceptual Organization for Weapon Identification and Threat Assessment

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ABSTRACT

The present work is a part of a larger project on recognizing and identifying weapons from a single image and assessing threats in public places. Methods of populating the weapon ontology have been shown. A clustering-based approach of constructing visual hierarchies on the base of extracted geometric features of weapons has been proposed. The convergence of a sequence of visual hierarchy trees to a conceptual hierarchy tree has been discussed. For illustrative purposes, from the growing conceptual ontology, a conceptual hierarchy tree has been chosen as a point of convergence for a sequence of visual hierarchy trees. A new approach is defined, on the base of the Gonzalez' algorithm, to generate the visual hierarchies. The closest visual hierarchy tree is selected as the search environment for a query weapon. A method of threat assessment is proposed. This method uses the attribute-rich conceptual hierarchy tree to evaluate the results from the visual hierarchy tree search. The two trees are linked at the leaf-level, because the visual hierarchy closest to the conceptual has the same distribution of the leaf nodes. A set of experimental results are reported to validate the theoretical concepts. A portion of the existing weapon ontology is used for this purpose.

Keywords: features extraction, weapon ontology, visual/conceptual hierarchy, convergence, weapon identification, threat assessment

1. INTRODUCTION

The present paper is a part of a larger project whose development is evolving through several papers including.[2,18,19] The project aims to develop a system capable of automatic identification of a firearm/small arm carried by individuals in public areas. The purpose is to assess the threat that may be posed by these individuals to the public.

In this project we assume that a single image is an input. The image may come from different sources like infrared or wave imaging systems[4,17] which does not raise privacy issues. The basics of low-level geometric features extraction were presented in.[18,19] The geometric features subject of extraction are the weapons' shape and convex hull. The methods used to determine a weapon's boundaries are presented in.[2,19] Objects partitioning and weapons' regions matching are discussed in.[18]

The basic concepts of the weapons' ontology semantics are presented in[18] along with a small example of such an ontology. For the purpose of nodes labeling an active contour was applied to extract the convex hull (CH) and the boundary of every weapon.[2,19,20] Finite numerical sequences have been generated from the extracted geometric features and used for nodes labeling. Sequence alignment algorithms were employed to implement the search through a visual hierarchy most close to the conceptual hierarchy. In these experiments, a weapon was retrieved with a 100 percent match to the query weapon in approximately 0.3 seconds.

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In the present work the firearm/small arm ontology was further extended to over 300 nodes. An automatic tool was used to browse the web and other sources to retrieve the information loaded to each node of the ontology. The CHs' generated sequences are used along with clustering algorithms to generate the visual hierarchies which converge to the conceptual hierarchy of the ontology. The new concept of visual hierarchy convergence provides a significant increase of the search speed, because the search is performed in the visual hierarchy most close to the conceptual one, which in turn provides the properties of the firearm on which the threat assessment is based. The links between the leafs of the two hierarchies are used for projection of the weapons, most closely matching the query weapon, from the visual to the conceptual tree. In the latter one the threat assessment is performed following the ancestors of the projection.

The contributions of the present paper consist of:

- significant extension of the first weapon ontology;
- adaptation of Gonzalez'[6] clustering method to develop a visual hierarchy of the weapons;
- use the convergence of this hierarchy to a conceptual hierarchy for swift search to identify the weapon in the query image;
- use of the conceptual hierarchy of the ontology for threat assessment.

The rest of the paper is organized as follows. Section 2 presents the main algorithm employed for quick CH extraction. Section 3 describes the labeling of nodes. The search algorithm is presented in Section 4. Conceptual ontology hierarchy is described in Section 5. Section 6 introduces the algorithm employed for ontology population. The convergence of the visual to the conceptual ontology is developed in Section 7. The threat assessment approach is presented in Section 8, while the experimental results are presented and described in the next one (Section 9) and the paper concludes with discussion and a future work description in Section 10.

2. WEAPON CONVEX HULL DETECTION

The CH is a fundamental notion for the present research, used to label nodes and to cluster the set of weapon images. A number of clusterings are performed and every clustering is presented as a graph called visual hierarchy. A sequence of visual hierarchies (trees) is generated to converge to the conceptual hierarchy of the weapons.

The CH of an object is the convex polygon with the smallest perimeter that circumscribes the object. We consider in the present work that all the weapons in a category will have one and the same CH (see[2,18]). Thus the CHs of the weapons which belong to a certain category have the same CH used to define a finite numerical sequence which labels the node of the weapon's category such as handgun, rifle, machine gun.

The concept of active convex hull model (ACHM) was introduced first in[20] in order to overcome the difficulties experienced by the traditional CH algorithms which will not provide results on large image regions and require modifications to work on color image regions.[20]

ACHM was designed on the approximate solution of the heat partial differential equation (PDE). Thus a stability convergence condition is used there to make the contour converge. To avoid this disadvantage a new parametric active convex hull model (PACHM) was developed on the basis of the exact solution of the heat PDE. PACHM first applies the Shrinking-Active Contour model on the Exact Solution (S-ACES) described in.[2,19] S-ACES extracts the weapon's boundary which is applied to generate a finite numerical sequence used to annotate the node of a single weapon.[2] To evolve the active contour through the image toward the weapon's boundary the S-ACES model uses the following equation:

$$\mathbf{r}(s, t(u)) = e^{as-4a^2(t_0+u\partial t)}[x(s), y(s)], \tag{1}$$

where $x(s) = C_1 \cos(cas)$ and $y(s) = C_2 \sin(cas)$. In Eq. 1 C_1, C_2 and c are real numbers, s is a space parameter, $|ds|/2 = a$, t_0 is the initial time moment, ∂t is the length of the time step, u gives the consecutive time step. S-ACES halts the evolving curve when the following boundary condition (BC) holds:

$$\mathbf{r}(s^*, t) = r(s^*, t + \partial t) \text{ if } \varepsilon_2 > \frac{\partial f(r(s^*, t))}{\partial t} > \varepsilon_1 \tag{2}$$

for a particular $s = s^*$ and for $2.5/a^2 \geq t + \partial t \geq 0.001/a^2$.

Once the active contour is stopped the following function is calculated:

$$d(Q_s(u)) = d(s, u) = |\mathbf{r}(s, t(u)) - \mathbf{r}(s, \frac{0.001}{a^2})|. \tag{3}$$

In Eq.3 $Q_s(u)$ is an active contour point for which the Euclidian distance has been calculated between the initial time $\frac{0.001}{a^2}$ and the time $t(u)$ at which the point stopped evolution.

Further, the local minima of the function $d(s, u)$ are determined. Next, all consecutive triplets of the local minima that define convex arc are detected. Linking these local minima defines the convex hull of the weapon under consideration. Both S-ACES and PACHM were applied to extract the boundary and the CH of about fifty weapons. Fig. 1 Part a) shows a Howell Automatic Rifle along with its boundary and CH.

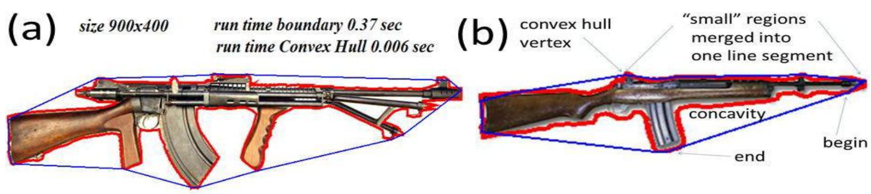

Figure 1. a) Image of a Howell Automatic Rifle along with its boundary (in red) extracted by S-ACES and CH (blue) defined by PACHM; b) CH and boundary of an AC-556 assault rifle. A CH vertex, and a concavity with its start and end are marked by arrows. Concave and convex regions on the boundary with a small area are all merged into a line segment.

3. NODE LABELING

Cyclic sequences of fixed-precision angles generated from CH and boundaries of 2D-images of firearms are used to label nodes as described in.[2] A *convex hull sequence* is a cyclic sequence of angles, where an angle at a vertex is defined by the two intersecting sides. A *boundary sequence* is a cyclic sequence of segments, where each segment is a sequence of angles defined by boundary points and segment start and end points. Each segment has a sign indicating if it is a line, a concave, or convex segment. Fig. 1 Part b) illustrates the CH and boundary of an AC-556 assault rifle. One boundary segment is indicated by its begin and end points in the figure. The boundary sequence for this weapon contains a concave segment that corresponds to this boundary segment. There may be many segments with small area (a small fraction to the entire area) on the boundary of any shape. Such consecutive segments are merged into one line segment. An example boundary part, where this may be the case, is shown on the top right part of the weapon boundary in Fig. 1 Part b).

Arslan et al.[2] label intermediate nodes by CH sequences. Experts choose which intermediate nodes and which CH sequences are to be used. The motivation is to implement the class-subclass relation for a visual hierarchy of the ontology within the ontology itself. The present paper proposes defining the subclass relation using clustering of CHs of firearm extracted from images. This yields a separate visual hierarchy tree on which weapon queries are performed. The conceptual hierarchy tree will be used to interpret the search results and compute the threat assessment. The leaves of the visual hierarchy tree are labeled with boundary sequences. Each subtree corresponds to a cluster. For each cluster there is a designated member weapon called cluster representative. Each intermediate node is labeled with the convex hull sequence of the weapon which is the representative of the cluster that corresponds to the subtree rooted at this intermediate node. *Diameters* of clusters visited on any path from the root to a leaf are monotonically non-increasing, where the diameter of a cluster is defined as the maximum distance between any of its members. This labeling facilitates fast search on the visual hierarchy tree.

4. SEARCH

Arslan et al.[2] define the weapon identification problem as the following search problem:

Given an input image object, find in an ontology, a weapon or a group of weapons with significant similarity to the input.

Arslan et al.[2] present a method that is based on traversing the conceptual hierarchy tree. This method compares the CH of the query image with the CH at an intermediate node using cyclic sequence alignment, and explores the subtree rooted at this node only if there is "significant" similarity between the two CHs. This method relies on experts' distributing CHs over intermediate nodes. The present paper relaxes this requirement by using an additional tree (visual hierarchy tree) which is constructed by clustering the CHs of weapon shapes.

We assume that the firearm ontology is complete, and its conceptual hierarchy (T_c) is available. Another assumption is that a visual hierarchy (T_v) that is "close" to T_c has been generated. We also assume that there are additional links from T_v to T_c such that for every leaf u, in T_v u is linked to a unique leaf v in T_c if u and v have the same label (i.e. they correspond to the same weapon). We call these links *leaf-connectors.* These leaf connectors can easily be created by processing T_c and T_v.

Once weapons are found as a result of a visual search, the interpretation of the results occurs in the conceptual hierarchy tree. This is because the query may match multiple weapons with different probabilities, and relevant attributes of matching weapons may be needed to evaluate results and determine the corresponding level of threat. We propose the following algorithm for this problem:

`Algorithm IdentifyAndReport`

`Step 1. Generate convex hull and boundary sequences from the image of the query object.`

`Step 2. Perform a visual search on the visual hierarchy tree` T_v `by using cyclic sequence alignment between the query object and labels (sequences) of the nodes in` T_v`. Let` M `be the set of leaves in` T_v `that matches the query (i.e. whose sequence similarity is higher than a given threshold).`

`Step 3. Locate leaves in` T_c `by following the leaf connectors from` T_v `. Find all lowest common ancestors of arrived nodes by tracing ancestors bottom up. Generate a summary report. Determine and output the threat level.`

Figure 2. Algorithm that identifies a weapon and generates a report

Step 1 of the algorithm uses CH and boundary extraction, and processes them to generate sequences as described in Arslan et al.[2]

For Step 2, Arslan et al.[2] perform a branch-and-bound type of search by comparing node labels with the query sequence at each node, and exploring only those sub-trees that may yield a match. Thus the search is narrowed down to a few clusters. In the present paper we propose a similar approach. Once matching clusters are identified, a more rigorous match can be done at the leaf level. For each leaf, in an explored cluster *cyclic sequence alignment*[10] is performed between the CH sequences first. If the resulting similarity score is larger than or equal to a given threshold, boundary sequences are also aligned cyclically by using an efficient method developed in.[2] A leaf in T_v is identified as a match if (in addition to the convex hull similarity) the boundary similarity to the query is also larger than or equal to a given threshold.

In Step 3, leaf connectors from matching leaves in T_v are followed to the leaves in T_c. After these leaves are located in T_c, their common ancestors are found, and reported. We note that each ancestor can have a different probability calculated from the degree of shape similarity for their descendants to the query. This yields the following problem: Given n leaf nodes with their probabilities in T_v, find most likely ancestor(s) of arrived leaves in T_c. This problem is addressed in Section 8.

We note that the search in our method goes beyond a similar shape search because all potential matches in the conceptual hierarchy are located and threat levels are calculated by using a rich set of attributes applying these matches.

Cyclic sequence alignment of two sequences of length $\Theta(n)$ takes $O(n^3)$ time if we follow a naive algorithm. There exists a $O(n^2 \log n)$-time algorithm[10] for the problem. Arslan et al.[2] define a variation of cyclic sequence alignment for boundary sequences, and present a fast algorithm for the resulting problem. Their algorithm runs in $O(c^3 + g^3 + n^2)$ time if each of the two input shapes have c convex hull vertices, g segments of the boundary, and if their boundary sequences are of length $O(n)$. In practical settings $c < g << n$, therefore we develop and use algorithms based on cyclic sequence alignment algorithms proposed by Arslan et al.[2] Search in the visual tree T_v examines only a fraction of nodes in the tree because CH matches are used as a filter before exploring subtrees whose roots are labeled with cluster representatives (see Fig.7). The query is compared to cluster representatives and if there is no significant match the entire subtree is excluded from the search.

5. CONCEPTUAL ONTOLOGY HIERARCHY

The conceptual ontological hierarchy of firearms was developed within the framework of Ontological Semantic Technology (OST). OST was intended for natural language processing[8,12,15] and thus includes a combination of dynamic and static knowledge resources discussed in,[8,12,15] but which are not relevant in this context.

An ontology is language-independent and contains information about the general world as it may be referred to in any text, as well as information from all relevant subdomains for a given application (e.g., medicine, law). Additional knowledge can come from previously processed information as stored in the InfoBase, as well as language-independent common-sense rules. Simplistically, it can be conceptualized as what the system knows about the world.

For the current application, we developed an ontology of firearm concepts, which represents the relevant information about firearms. Ontologies are typically represented as acyclical connected graphs (trees). The firearms ontology is a branch of a general ontology, attached as a child under the ARTIFACT concept. The ontology will be broadened to include all weapons in future iterations of this project. For the current application, we leverage this knowledge with a focus on threat assessment. The ontology is formatted in XML, compatible with OWL (RDF), and is handled by an editing tool developed in Java.

Each node in the ontology is a concept: either a terminal node (a leaf) in the tree, corresponding to a specific firearm (e.g., AK_47, Colt_45), or an intermediate class of weapons (e.g., personal_weapon, assault_rifle). Each concept has a unique name and a set of properties. Each concept inherits the properties of its superordinates and all the descendants of a concept inherit its properties e.g., all the descendants of REVOLVER inherit the property has_object_as_part(firearm_cylinder). Descendant concepts have unique properties not inherited from their parent concepts. If a property inherited from a parent concept conflicts with a more specific one, the more specific property overwrites the inherited one.

For the current stage of our research, we do not require a separate natural language lexicon that is mapped into this branch of our ontology. But for future extensions that are envisaged to integrate visual and textual input for threat assessment, all terminal concepts will receive complementary lexicon entries with a special rule base for common abbreviations of the names of makers and types of guns. Furthermore, the lexicon will be completed with generic terms for firearms and firearm types that are mapped onto the lowest possible branch in the ontology. As usual in OST, in processing the lexical items are understood to refer to the concept they are mapped onto, as well as any of its children. We anticipate very interesting research questions to be posed, once we integrate visual and natural language input, including heuristics for identifying as the same firearm and specifying its type for a firearm that was initially referred to only as "gun," but, for example, later called a "shotgun" and brought in connection with a certain caliber and/or number of shells to be reloaded: "Hand me more of the 12-gauge!"

The overall hierarchical structure of the current firearm ontology as part of the OST ontology is that of a directed graph (see Fig. 3), a class of objects that is mathematically well understood and for the handling of which a large variety of algorithms is available. Our current proof-of-concept ontology has about 300 actual weapons (terminal vertices), as discussed above.

In order to decide which properties of the guns to capture we determined which of them are commonly assumed to differentiate the different levels of threat the firearms pose (see section 8 below). To illustrate the choices, Fig. 4 shows the properties of an example. In that figure, the terminal concept for an assault rifle, the AK 74, a development of the notorious AK 47, shows the properties we currently chose to capture (see section on population) with special relevance for the threat assessment of the firearms. We also populated other properties, if available, in anticipation of further refinements of our algorithms from future research.

As an initial operationalization of an overall metric for a gun's threat level, we plan to sum up the varying fillers of the properties with factors to reflect the general importance of the property in relation to the environment.

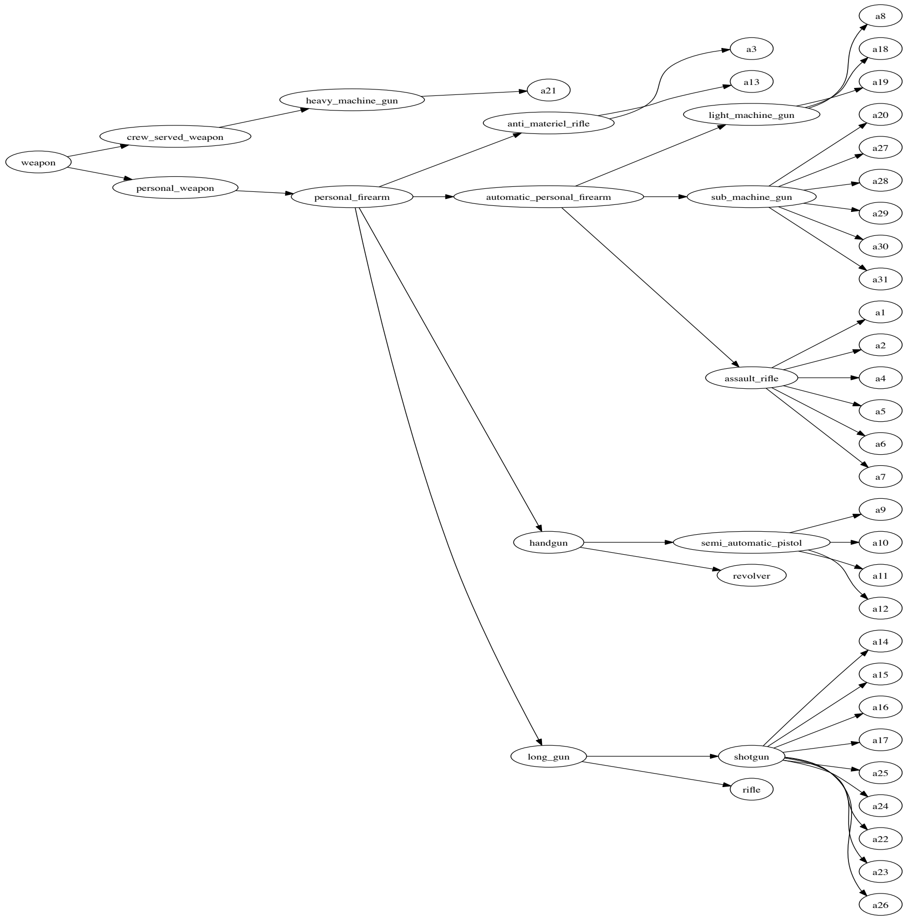

Figure 3. WEAPON branch of the conceptual ontology with firearm leaf nodes marked with short names for convenience

```
AK_74
    is_a assault_rifle
       discharge_type     automatic semi_automatic single_shot
    weight >3.2 3.4<
    length 943 >490 943<
    cyclic_rate 700 >650 700<
    muzzle_vel 900 >735 900<
    effective_range 625
       has_object_as_part
       firearm_barrel
          caliber_mm 5.45
          length 415 >210 415<

       firearm_magazine
          magazine_type detachable external
          magazine_size 30 45
       firearm_stock foldable
```

Figure 4. Partial terminal concept properties for the AK 74 assault rifle (a6 in 3)

In addition, the structure of the conceptual ontology reflects the main assumptions of gun laws in the United States , reflecting mainly the handling qualities of longer and shorter guns and the orthogonal property of type of discharge, and the results of the few studies on the topic that we identified (see section 8). This generated a conceptual ontology structure, in which the guns are already grouped according the threat-relevant types.

6. ONTOLOGY POPULATION

Since our system requires the organization of the information in more than one hierarchical structure, we keep the unstructured information separated from the hierarchical structures. In order to edit and insert information we developed a content management system, in which the unstructured information is stored in a database and the data in the database is then linked to the particular nodes of the ontologies, according to particular attributes. The content management system provides two main ways to edit the informations: manual insertion of the data through an interface to the database and a semi-automatic system that allows us to acquire and edit a large amount of information with minimal user interaction.

The manual insertion of data is supported by an interface which performs consistency checks on the data format. The automatic population of the ontology allows the user to import data from HTML pages or other databases.

Since we use different sources to populate the ontology we expect that some of those sources contains information that may already exist in our database and may also conflict with other information in the database. Because some sources may be more reliable than others, we allow the user to specify a trustworthiness value for each source, so that information that already exist in the database will be overwritten only if the actual source has a rank greater or equal to the one associated to the information in the database. This method allow us to keep our data updated avoiding reduplication and ensuring reliability.

What follows is a brief description of the process for the automatic population of the ontology.

Step 1. The user inserts the URI of an HTML page and a trustworthiness value. The trustworthiness value can be: "Low" the lowest value associated usually when the source is not well known, "Medium" is a medium value used when the source is reliable end edited by professionals, "High" is the maximum value usually used only when the source is the manufacturer or a government organization. After the user input, the system performs a parsing of the HTML code in order to extract tables and lists. This is because,in HTML pages, usually the data are organized using such structures. The extraction of tables and lists is meant to make easier the subsequent information extraction operation. However we expect to deal also with data structured in different ways, thus we allow for this feature to be switched off, allowing the user to fully control the filtering criteria.

Step 2. The output of the previous filtering operation is presented to the user. At this time, the user defines new filters using regular expressions. For each expression, the system defines a number of capturing groups and each one of these group is linked, by the user, with the corresponding attribute of the database. The information is thus extracted and inserted in the database. The insertion of the information in the database will result in an insertion and update operation throughout the database. However the update operation will be performed only if the data to be inserted is associated with a trustworthiness value greater or equal to the one of the record in the database that has to be updated.

The data is then inserted in the ontology's hierarchy according to relations defined on the attributes of the database. Thus the objects are updated or added to the hierarchy automatically. With this system of automatic population we added more than 3000 skeleton entries to our ontology, by extracting information from "Wikipedia." By processing in the same way manufacturer web pages and databases built by professionals, we were able to both add new data to our system and validate the data inserted from other sources. These skeleton entries currently contain only the name of the weapon and its position within the hierarchy; these entries will be filled with attributes, like images, and meta information.

Usually in web pages that contain huge amounts of information, the data are wrapped in HTML code that is automatically generated and therefore characterized by patterns. Hence it is possible to extract data from those pages by identifying those patterns. The problem is that the patterns from one web page to another may be completely different. To ensure reliable data extraction, we first filter standard patterns that are in almost any web page: tables and lists. After this operation, we use user interaction to identify particular patterns. There are also automated methods that allow for the identification of particular patterns in different web pages. Those techniques usually use similarity and statistical calculation to identify the patterns and extract data. However the data extracted using fully automated methods is sometime characterized by noise and sometimes those methods lead to a loss of data. The update and/or population of the ontology is an operation performed offline and with a very low frequency, which is the reason we chose to use a non fully automatic method which allows for a more precise and reliable extraction of information.

Currently, within the 3000 concepts we have acquired, about 385 have images associated with them, and 31 are complete with all the attributes needed for the application of the algorithms described in the paper. All studies presented in this paper were performed on this subset of the ontology.

7. VISUAL AND CONCEPTUAL HIERARCHIES

Our hypothesis is that there exists a clustering algorithm that yields a visual hierarchy tree that is "close enough" to the conceptual hierarchy tree such that a visual search for a given image can be done on the visual hierarchy tree and the evaluation of the search can be carried out in the conceptual hierarchy tree for identifying the threat posed by the weapon from the query image.

A number of hierarchical clustering algorithms could be applied for generating sequence of visual hierarchies. For the present illustration of the new approach we use two clustering algorithms to create visual hierarchy trees. The first one is the UPGMA program. For the conceptual hierarchy tree shown in Fig. 5, the UPGMA program[5] creates a visual hierarchy tree shown in Fig. 5 for part of the weapon ontology whose conceptual hierarchy is shown in Fig. 3. The *convex hull similarity score* between two weapons is the optimum alignment score between their convex hull sequences divided by the average length of these convex hull sequences. This yields a number in $[0, 1]$. By subtracting this value from 1, we obtain the *convex hull distance* between two weapons, which is also in $[0, 1]$. We define the *boundary similarity score* and *boundary distance* between two weapons similarly and use sequence similarity score (for both CHs and boundaries) normalized in $[0, 1]$ as the *degree of similarity*, and also for *match probability.* In generating the tree in Fig. 5, convex hull distances of weapons are used with the UPGMA program.

For the search algorithm in Fig. 2, a cluster representative is needed at each intermediate node. This can be done for each intermediate node p by arbitrarily selecting a leaf from the subtree rooted at p.

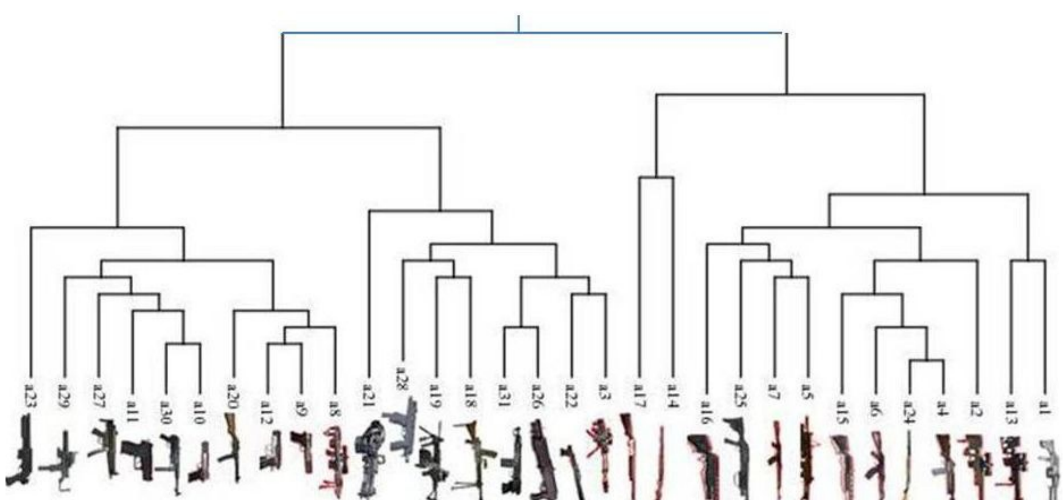

Figure 5. *Clustering of 31 weapons and their visual hierarchy tree generated by using the UPGMA program*[5]

We also develop a new algorithm for creating a visual hierarchy tree based on Gonzalez' clustering algorithm.[6] Given an integer k, this algorithm creates k clusters with the objective that the maximum diameter over all

```
Algorithm Gonzalez((G,E,W),k)
Graph G has vertices V = {v_1, v_2, ..., v_|V|}, edges E with weights W (add a new parameter t)
precondition:  G is a complete graph, and k < |V|
Set B_1 = V (initialize T with vertex u_1)
Pick one vertex in B_1 and label it head_1 (make the vertex v_t the head head_1)
for j = 2 to k do
   Let v_i be a vertex in B_r where r in [1, j-1]
   whose distance to the head of the cluster B_r is maximum
   Move v_i to B_j (create and connect a new node in T that corresponds to cluster j) and label it head_j
   For all v_l in {B_1, B_2, ..., B_{j-1}}, move v_l to B_j if its distance to v_i is not larger than the distance
   to the head of the cluster it belongs (add edges from source and destination nodes in T)
```

Figure 6. Gonzalez' clustering algorithm[6] which approximates k-clustering to minimize maximum cluster diameter with modifications given in parentheses for creating a hierarchy tree T

k clusters is minimized. This optimization problem is NP-hard.[6] Unless $P = NP$, there does not exist a polynomial time algorithm for this problem. However, Gonzalez' algorithm guarantees k clusters with maximum cluster diameter within a factor of two of the minimum possible. This algorithm is shown in Fig. 6.

We modify it to create a tree T, which will be a visual hierarchy tree for the clusters (visual hierarchy tree T_v for the ontology): The distances between vertices are the convex hull distances between the convex hull sequence-labels in these vertices. The head of cluster B_1 is chosen as vertex v_t using added parameter t (this parameter allows creating hierarchy trees with different root). T is initialized with a single vertex u_1. Whenever the algorithm creates a new cluster B_j with an element moved from cluster B_r we create a new vertex u_j with a directed edge from u_r to u_j in T. Whenever the algorithm moves elements from cluster B_p to cluster B_q, we add a directed edge from u_p to u_q . After the algorithm terminates, we postprocess the created graph as follows: if there are multiple paths between two nodes x to y we then delete the last edges coming into y on these paths, and add a directed edge from x to y. By this construction and postprocessing, we always obtain a tree.

Gonzalez' algorithm aims to minimize the diameter (the longest pairwise distance) within clusters. This is a desired feature for search because placing similar objects in the same cluster narrows down the search to relevant subtrees pruning out other unfruitful ones for a given query.

When we use Gonzalez' algorithm, we specify a representative (parameter t) for the first cluster (the root cluster), and the number of clusters (parameter k). With our modification, the resulting tree has k nodes excluding the leaf nodes. Based on these parameters a number of trees are possible. In Fig. 7, we show two visual hierarchy trees obtained with parameters weapon $a25$ and number of clusters 4 (Part (a)), as well as weapon $a11$ and number of clusters 5 (Part (b)). The second parameter should not be smaller than the number of subtrees in the conceptual tree. Our experience is that increasing this parameter does not necessarily increase the height of the tree because of the postprocessing rule that creates direct edges when there are multiple paths between two nodes.

The search is done in the visual hierarchy most close to the conceptual one, but results are finalized in the conceptual hierarchy tree. The leaves found in the virtual hierarchy identify the leaves in the conceptual hierarchy, then, following the edges bottom up, common ancestors are located and also reported in the summary. For effective and efficient results through our approach the visual hierarchy tree that is used and the conceptual hierarchy tree for the weapon ontology should be close. The *tree edit distance*[3] is applied for measuring the distance between the trees. Fig. 8 shows the edit operations on a tree that can be used to transfer one tree to another. Minimum possible total weight of a sequence of such weighted operations is the tree edit distance between two trees. The search space for finding a closest visual hierarchy tree to the conceptual hierarchy tree is very large. For example, the two parameters for our modified Gonzalez' clustering algorithm define a very large set. The trees can be systematically generated and compared with the conceptual hierarchy tree one at a time. In the present paper, for illustrative purposes, we only consider the three trees in Fig.s. 5, and 7. We compare each of these trees with the conceptual hierarchy tree shown in Fig. 3. We use the tree edit distance program in.[13] The closest of the three trees is the one in Fig. 7 Part (b).

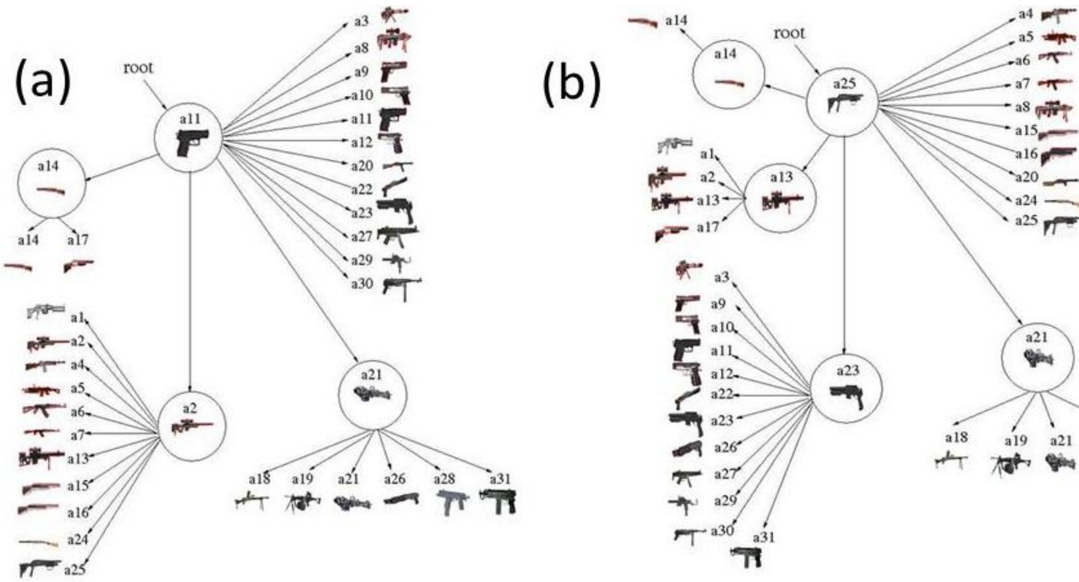

Figure 7. Visual hierarchy tress obtained by using modified-Gonzalez clustering algorithm with parameters: a) weapon $a11$ is the representative of the first cluster, and $k = 4$ is the number of intermediate cluster nodes, and b) weapon $a25$ is the representative of the first cluster, and $k = 5$ is the number of intermediate cluster nodes

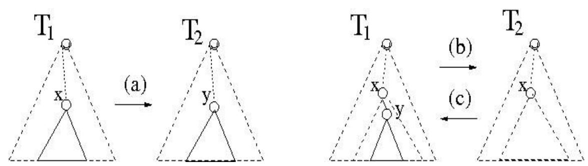

Figure 8. Edit operations on a tree: (a) Changing node label x in T_1 to y yields T_2; (b) Deleting subtree with root label y in T_1 yields T_2; (c) Inserting subtree with root label y in T_2 yields T_1

8. THREAT ASSESSMENT

Recall that Step 3 of Algorithm `IdentifyAndReport` in Fig 2 solves the following problem: Given n leaf nodes with their probabilities in T_v, find most likely ancestor(s) of arrived leaves in T_c. Solving this problem efficiently can be a topic for future research. When a weapon is detected, a naive solution to this problem assumes reverse links in the conceptual hierarchy tree and that these links are followed starting with the matching leaves arrived at from the result of a visual match, and all common ancestors are located bottom up. During this process, the rich set of attributes of these common ancestors, in the conceptual hierarchy tree, provides information for a possible weapon and its potential for causing harm to the public. The details of the threat assessment as part of this step based on weapons' attributes are being developed along with the ontology. Section 9 shows sample outcomes of this step on several queries.

All things being equal, in particular independently of the handling capabilities of their bearer, any firearm type poses a threat that is inherently different from the other types. We also propose that each ontological firearm class has such an inherent threat level that differs from those of others. This section sketches a first operationalization of these differences in threat as another goal for our system.

Because the experience in handling of any given gun by the perpetrators is unknown, currently the only factor beyond the inherent threat of a given type (or class of types) of firearm is the environment in which the firearms are handled. To provide extreme examples, in unobstructed outdoor surroundings a single-shot pistol can cause significantly less harm than a heavy machine gun, while an unwieldy semi-automatic assault rifle with extended stock is less of a threat than a semi-automatic pistol in a small crowded room.

Different levels of perceived threat are an important basis for state and federal gun regulations, which reflect some basic assumptions about inherent threat levels of firearms form one basis of our initial metric. The main gun control laws of the United States, enforced by the Bureau of Alcohol, Tobacco, Firearms, and Explosives, are Title II (26 U.S.C. ch. 53; National Firearms Act of 1934, revised 1968, 1986), on banned weapons, mainly machine guns and short-barreled rifles and shotguns), Title I (18 U.S.C. ch. 44; Gun Control Act of 1968), and the Federal Assault Weapons Ban of 1994 (H.E. 3355, 103rd Congress; expired 2004).

Beyond legislation, there is scant literature on the inherent threat of firearms. One study found that in Milwaukee, WI, over a 4-year period in the 1990s, the 524 firearms used in homicides fell into the following classes:[7] handguns 89%, shotguns 5%, rifles 3%, unspecified 3%. The caliber of the handguns was predominantly medium (.32 to 9mm: 69%), followed by small (.22 and .25: 25%), and large (.40 and larger: 7%). Interestingly, the inexpensive, small-caliber Raven Arms MP-25 semi-automatic pistol accounted for 10% of the firearms used and belongs to the class of "Saturday Night Specials" that were also targeted by Title I (see above). This frequency with which certain gun classes were used in homicides is of limited relevance for our purposes though, because few of these occurred in public spaces.

Another, more central, study focuses on a *weapons instrumentality effect*, very similar to our focus, namely, "the impact of firearms on lethality while controlling for the effects of other situational, contextual, and demographic variables". In contrast to one of the main assumptions of older gun legislation and in line with more recent demands, this study, based on,[21] found that automatic weapons are not significantly more lethal than their semi-automatic counterparts".[9] An important caveat for this result is that the data this study is based on did not allow for an assessment of number of victims per incident. It must be assumed that an attack involving an automatic weapon can be lethal to more victims than one with a single-shot firearm. Other useful results from this study rank shotguns above, but closely followed by, handguns, and above rifles in lethality. It needs to be noted, though, that lethality is not our concept of threat, as we mean more generally the ability to cause harm, including non-lethal injury.

In sum, gun laws specify certain properties of firearms that determine whether they are outright banned or must be controlled, with the implicit assumption that these properties make the firearms pose higher threats than other firearms. These properties are also emphasized in the studies cited. Thus, the threat posed by a weapon as such is determined by a number of partially interrelated factors. In overall descending order of importance, in this initial sketch we assume these to be:

- [t] type of discharge: single-shot/semi-automatic/automatic
- [r] (effective) rate of fire
- [c] caliber (diameter of ammunition)
- [ms] magazine size
- [mt] magazine type: fixed/detachable
- [ma] magazine attachment (external/internal)

This leads to our initial formula for the inherent, environment-independent, threat (T) of a firearm (f): $T_f = t * f + r/2 + c * 10 + ms * (mt + ma)$ where f is 2.5 for automatic, 2 for semi-automatic, and 1 for single shot, mt is 1 for detachable and 0.5 for fixed, and ml is 1 for external and 0.5 for internal.

The following properties also have a strong influence on the threat of the firearm in relation to the environment in which it is used and their contribution is operationalized differently in the current work:

- [v] muzzle velocity/effective range
- [l] overall length (handling and ease to conceal)
- [w] overall weight
- [p] projectile: bullet/shot/etc.
- [s] stock: folding/telescopic/etc.

As mentioned, we are aware of the differentiating dimension of enclosed (small room) vs. open handling environment (very large room, outdoors; an environment significantly more dangerous than an indoors one,[9]), mainly reflecting differences in overall size of the firearms and effective range. This, of course, intersects with discharge type and lock type, a lock firing from an open bolt, resulting in lower accuracy, which is a difference that is again mostly relevant for crew-served heavy machine guns and ignored here.

Our conceptual ontology hierarchy agrees with most firearm taxonomies. But in addition it ranks its classes as per the environment-dependent hierarchy below and distinguishes personal and crew-served firearms. The latter have much higher firepower but handling qualities that make them largely irrelevant in the type of scenario our system is currently envisioned for. Among personal firearms we distinguish long guns, handguns, automatic personal firearms, and anti-materiel rifles, the latter again considered marginal for our application, but with very high threats at very long ranges. Among long guns, we distinguish rifles and shotguns, with crucially different threat levels depending on the environment, the shotgun being most useful at intermediate range and rifles at long range. Among handguns we distinguish revolvers and semi-automatic pistols with equally high threat in enclosed environments and a higher threat from semi-automatic pistols because of type of discharge (slightly counterbalanced by ease of maintenance and handling of revolvers).

Among the class of automatics, important for our system as also reflected by their ban in the United States, we distinguish assault rifles, light machine guns, and sub-machine guns, with assault rifles generally carrying the highest threat because of their combination of high rate of fire and ease of handling in enclosed and medium-open environments. Submachine guns are a somewhat obsolete category, while light machine guns are hard to handle but carry a high threat in open environments and where accuracy is important.

With these intersecting properties, we propose the following hierarchies of threat in descending order for open environments and, conversely, in ascending order for closed environments. In other words, the higher in the list a firearm class, the more dangerous it is indoors; the lower a firearm class in the list, the more dangerous it is outdoors. Given in parentheses after each class is first the factor for indoor threat and then for outdoor threat. This factor will be multiplied with the outcome of the initial formula:

semi-automatic pistol (10/2)/revolver (9/2)/shotgun (8/4)/sub-machine gun (6/5)/rifle (4/7)/assault rifle (4/7)/ light machine gun (3/9)/heavy machine gun (2/10)/anti-materiel rifle (1/10)

Another threat factor we are not addressing at the present stage of our research, the ballistic threat of the individual shot, depends on more than just the round itself. Variables include its composition, shape, caliber, mass, angle of impact, and impact velocity.

To assign threat values to intermediate classes, as well as to firearms that are not uniquely identified, two methods are feasible: We can assume the worst case and assign a class the threat of its most dangerous member and an unidentified firearm the threat of its most dangerous possible type. The other method would be to average the threat of the firearms for the classes and through inverse inheritance[14,16] give the ancestor class this average threat. Similarly for unidentified guns, we would average the threats of the possible firearms that it could be, factor in the probabilities, and give the firearm this assumed threat. The choice between these two methods should be given to the user.

Given our initial threat algorithm and our factor for the environment in relation to firearm classes, the following are threat values for selected gun classes in relation to environments and populated through inverse inheritance of the threat values of the guns in these classes by the class itself. The first pair of figures gives the average and worst-case threat of the class, the second pair average indoor/outdoor threat:

assault rifle: 357.13/513.10, 1429/2500
shotgun: 527.37/648.20, 3164/3692
semi-automatic pistol: 124.50 / 192.00, 1245/124.50

The above threat values are calculated by applying the formula for T_f. The values used by the variables in this formula are taken from several online sources including Wikipedia. Examples, for three of our weapons are given below.

	t	r	c	ms	mt	ma	T_f
AK 74 (assault rifle)	2.5	700	5.45	30	1	1	**467**
Benelli Legacy (shotgun)	1	30	18.3	3	0.5	0.5	**202**
Arsenal P M02 (semi-automatic pistol)	2	45	9	15	1	0.5	**137**

The formula for T_f as quoted above is an initial approximation based on the literature cited above and in relation to the properties of the firearms in our sample. Its refinement is subject of further research. The lower and the upper bounds for the indoor and outdoor threats depend on the sample space and the formula for T_f . Currently the upper bound is estimated at 6415.

9. EXPERIMENTAL RESULTS

The parametric active convex hull model (PACHM) and the Shrinking-Active Contour model on the Exact Solution (S-ACES), presented in Section 2, are coded in Java and employed to extract the CHs and the boundaries of about 50 weapons.

We use the tree edit distance program described in Pawlik and Augsten[13] with equal weight 1 for each edit operation. We converted our trees to the required input format (the {root{}{}...{}} representation). In doing so, if two subtrees from the compared trees are isomorphic and they have identical leaves, we generate, and use the same names; otherwise, different names are generated. We order the children of each parent by alphabetical order. This results in many different names in intermediate nodes within each tree thus increasing the tree edit distances. The tree in Fig. 5 is very far from the conceptual hierarchy tree because it has many internal nodes. The tree edit distances from the conceptual tree is 35 for the tree in Fig. 7 Part (a), and 33 for the tree in Fig. 7 Part (b), which is the closest one and is used for search of the query object.

We perform tests on several queries to illustrate and verify the ideas experimentally. We take an existing weapon as a query object. Since the visual hierarchy in Fig. 7 Part (b) is the closest to the conceptual hierarchy tree, we used this tree in our tests. Fig. 9 summarizes the results. Our search algorithm compares the query with the cluster representatives. Only those clusters whose representatives are similar enough to the query are explored; others are pruned. The comparisons are done between the CH sequences, and a threshold percent similarity (we used 75%) determines if the weapons are visually similar enough. This requirement translates to convex hull similarity score 0.75 or more. For clusters that are explored every leaf is compared with the query. This comparison involves both CH sequences and boundary sequences. For a leaf to be reported as a match to the query, the CH sequence similarity must be at least 75%, and the boundary sequence similarity must be at least 65% (the latter requirement translates to boundary sequence similarity score 0.65 or more). Fig. 9 summarizes the results.

When the query weapon is $a7$, only the cluster with representative $a25$ has a CH similarity with $a7$ meeting the similarity threshold 75%. In this cluster, every leaf's CH is compared with that of $a7$. Leafs $a5$, $a6$, $a7$, $a8$, $a16$, $a20$, $a25$ have convex hull similarity with the query meeting this threshold. Among these only $a7$, $a5$ and $a20$ have boundary similarity with the query meeting the 65% similarity threshold. We combine CH and boundary similarity percentages with equal weight, and report combined percent similarity to the query. The results are listed in the last column in the table in Fig. 9. According to these results, the query weapon was recognised as $a7$ with 100% of confidence. However, if we would like to consider all possibilities, following the links in reverse in the conceptual hierarchy tree in Fig. 3 starting with $a7$, $a20$, and $a5$, the conclusion would be that the weapon is either a sub machine gun or an assault rifle, and following further up in the hierarchy that it can only be an automatic personal firearm, which posses a significant threat, which can now be quantified in terms of the algorithm and factors outlined at the end of Section 8. Similarly, when the query is $a11$, only the cluster with representative $a23$ is similar enough in CHs with the query. Weapons $a9$, $a10$, $a11$, $a12$, $a23$, $a26$, $a27$, $a29$, $a30$ are all found to have close enough CH similarity with the query. However, comparing also boundaries only $a11$ and $a12$ have the required boundary similarity. The combined percent matches are reported for this case, too, in the last column of the table in Fig. 9. The query was correctly recognized as $a11$ with 100% of confidence. However, if we would like to consider all possibilities, following the links in Fig. 3 starting with $a11$ and $a12$ the conclusion would be that it is a semi-automatic pistol, which poses a low level of threat, according to the values at the end of Section 8. The third query is a broom (an object with a long "neck" which

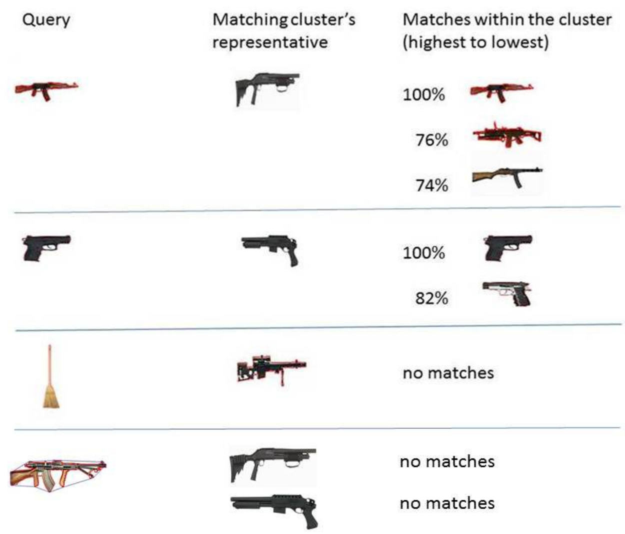

Figure 9. Four illustrative queries and results

could conceivably be confused with the barrel of a gun). It has convex hull match (above the threshold) with the cluster whose representative is $a13$. The leaves in this cluster have been compared with the query, and none of these comparisons generated a combined (CH and boundary) match meeting the threshold percent score. Hence our system would not mistake a broom for a gun. The last query in Fig. 9 is a Howell Automatic Rifle. This weapon is not in the experimented part of the current ontology. The search finds that it has convex hull similarity beyond the threshold with the cluster representatives shown in the figure. All weapons in the two clusters have all been compared with this weapon. However, no matches have been found when boundary sequences are compared although 15 of them ($a5, a6, a7, a8, a16, a20, a25, a9, a10, a11, a12, a23, a27, a29, a30$) have high enough convex hull sequence similarity with the query.

The searches performed on the crossest visual tree are very fast. On a 1.6GHz laptop computer the search times are 16ms for the first query, and 46 ms for the second query. The search takes 31 ms for the third, and 46 ms for the fourth query. These times exclude CH and boundary extraction, and sequence generation times for the query (900x400 pixels), which take approximately 0.353s on a 2.3GHz machine.

10. CONTRIBUTIONS AND FUTURE WORK

The major contribution of this paper is the development of the concept for generating visual hierarchies from set of objects (weapons in the present case) extracted from images. The idea extends further to presenting the visual hierarchies as a sequence converging to a conceptual hierarchy. The next new idea is the use of the visual hierarchy most close to the conceptual as an environment to search for a query object. Such retrieved objects most close to the query are projected to the conceptual tree, where the threat assessment is calculated with a newly developed formula. This is done by finding the ancestors of the projection. Another theoretical advancement is the adaptation of the Gonzalez' algorithm[6] for visual hierarchy generation. The practical contributions are in the use of software engine for automatic ontology population, which led to enrichment and extension of the ontology reported in[2] to 300 nodes with names and images and 3000 with names only.

The theoretical concepts were validated by performing experiments with a portion of the ontology containing 31 nodes shown in the figures throughout the paper. The experimental results shown in Section 9 are obtained from the visual hierarchy tree most close to the conceptual one. The same experiments were done on the remaining visual hierarchy trees. Comparing all of the results, it was observed that the closest visual tree offers the best results when both accuracy and speed are important.

The future work will continue with the further enrichment and expansion of the first weapon ontology through including visual and meta data about the munitions used and the inherent particles characterizing every weapon.

Optimization of the visual hierarchy construction is the next goal, which implies the following one regarding the fastens convergence of the sequence of visual hierarchies in an effort to further decrease the speed of search preserving the high accuracy of retrieval and threat assessment.

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