Object Oriented Video Retrieval System based on Domain Ontologies

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Abstract - **This paper presents a method for video information retrieval considering the frames extracted from the video sources through the segmentation of each key frame, the tracking of the salient objects and the domain ontologies. Based on disambiguation algorithms are constructed domain ontologies for annotation of the video contents. An object oriented database is used to store all specific data extracted by segmenting, tracking, and annotation of the salient objects. The presented technique combines the visual and semantic descriptors with spatial information for a good indexing of data. The object oriented approach used it was imposed by the complex structure of physical objects you can find in the videos as well as the addition of semantic meanings, which must relate to the objects detected. The annotation based on domain ontologies and the pseudo-natural query language close to human understanding are a proper contribution of this article, which has led to fulfilling the final goal, the extraction of semantics-based syntax and retrieving the frames with relevant information within a pseudo-natural query language close to human understanding. The results obtained for the sport domain validate the research carried out and represents a model for applying this method on videos from multiple domain of activity.**

Keywords: *object oriented system, ontology domain, tracking algorithm, video retrieval system*

I. Introduction

The research on video retrieval systems is an important direction of the computer vision domain. Used in intelligent environments, these systems try to detect and recognize salient objects, actions and activities under video sources. To achieve these goals, a smart video recognition system has two important modules:

- A module for low-level processing of the video sequences, which analyzes frames, detects relevant objects in motion and tracking them in successive frames;

- A high level semantic processing module that allows the annotation of the objects and analyses the movement of objects detected by the lower level to retrieve activities.

The methods used to detect moving objects are mainly based on two techniques: removing the background video sequences [1], or the computation of the differences between two or more successive frames of a sequence [2]. Although the differences between frames is a more robust to changes in illumination than removing the background, the first method is widely used because it is simple and lately developed algorithms were adapted to these changes. Tracking objects in successive frames of a video sequence based on models that simplify objects: lines and segments simplified models [3] or assembling 3D models using geometric forms such as spheres, cones [4].

One of the main problems that arise at the stage of low-level processing of the video sequences consists in the removing of shadows and apparent objects, and objects called "ghost". By segmenting foreground objects, shadows of objects that are inherent due to lighting, objects are detected as distinction; objects "ghost" occurs when switching objects. Although both problems have been proposed methods to eliminate [5], there are no methods to enable their disposal robust.

In the stage of video processing of high-level actions are represented as a series of movements detected in the phase of low-level video processing. In general, the actions detected by intelligent video processing systems fall into three categories [6] primitive actions that are detected directly by process module level below which are the basic elements with which are built other types of actions, actions, or events, which are lots of primitive actions, possibly repetitive and complex sequences of activities that represent a bias between actions.

For the events recognition the proposed methods are divided into two categories: temporal space methods, which recognize actions analyzing successive frames forming spatio-temporal volume and sequentially methods, for which the input is considered a sequence of successive frames. The temporal space approaches differ depending on the attributes of that is analyzed. If the volumes themselves are considered as attributes, actions by measurement recognizing similarities between volumes [7]. If the analyzed attributes are sequences of points 2D or 3D representing the positions of moving objects, these sequences represent trajectories, usually in the space XYZT and recognition shares is performed by measuring similarity between trajectories [8], which allow the recognition of some actions. Another category of attributes used to recognize the actions is represented by the spatio-temporal local attributes extracted from the spatio-temporal volume. In this case, for actions recognition are used different methods such as matching spatio-temporal relations or contextual spaces matching [9]; contextual spaces is n-dimensional spaces contextual attributes. In general, methods using spatio-temporal local attributes recognize same types of actions, as those using trajectories.

In general spatial-temporal methods have good results for repetitive actions because the model for these actions is more robust and can be learned easily. Difficulties arise if there are variations in the movement of objects, as well as their speed of movement. Another problem is to provide an invariant point of view.

The retrieval methods of complex activities are based on the decomposition in a lot of sub-activities, which are in fact actions. For this reason, the retrieval of the activities is based on the retrieval of complex structures of action. As recognition of actions, methods of recognition activities are divided into several categories: models based on the condition that shape state events video in space and time using the knowledge of semantic and semantic models of the events, the activities described by semantic relationships between sub-components events.

The advantage of the models based on states is that they are based on well-formulated mathematical models and models from this category can be created based learning methods examples. That category includes mass-machines Finite State that are simple models and methods that rely on models "Hidden Markov" hierarchical two-level or multi-level [10], allowing the creation of models for recognition of complex activities as discussions between several people.

If the methods are based on semantic models then the semantic knowledge are used to define semantic rules, constraints and relationships that describe an activity. Unlike from the methods that used models based on condition, semantic models are more difficult to learn automatically by example in this case models are constructed manually in most cases. The main methods used ontology based on semantic models that support for building models. When the methods based on ontologies are used, the retrieval of an event or activity boils down to whether a particular video sequence seen as a sequence of terminal symbols, constitutes an instance of an event. An approach based on MPEG-7 [11] standard provides an extensive set of attributes to describe multimedia content. The complexity of the description schemes makes it sometimes difficult to decide how a semantically correct description is given. Through the ontologies the system describes entities and relationships between them in a formal machine representation. An ontology-based knowledge representation is used for content analysis and concept recognition, for reasoning processes and for enabling user-friendly and intelligent multimedia content search and retrieval [12].

In [13] is introduced a novel approach for video annotation. Instead of complete video frames, only the key frames are analyzed to identify the objects present. The object detectors are trained for identification of the object. The annotation is based on ontology which eases the semantic retrieval of videos.

The structure of the paper is as follows. Section II describes the domain ontologies construction and annotation process of the salient objects. The structure of the object oriented retrieval system is defined in Section III. Section IV presents the results of the method for retrieval multimedia information within videos from sport.

II. VIDEO ANNOTATION. DOMAIN ONTOLOGIES

In this section is presented the structure and the construction of the domain ontology for describing the video contents. In the first step of the learning phase is considered a set of key frames from representative videos for a domain. These frames will be integrated in the ontology based on disambiguation algorithms and will result the domain ontology. The goal for designing this ontology is to provide a semantic description for the salient objects. The tracking technique is applied on the set of frames used in the learning phase for realizing interconnection between relevant spatial information. In order to assign to each object a global concept we consider an associated taxonomy based on WordNet [14]. In this phase is designed the domain ontology which will be used also in the query process; the terms used in a query structure corresponds to the entries extracted from WordNet according with the classed presented in Figure 1.

The problem of meaning extracting of a concept corresponds to a Word Sense disambiguation (WSD) domain. In the following subsection are presented the structure graphs exploration approach to determine the most relevant meanings of words in a given context. Most of these approaches are related to the notion of lexical chain. A lexical chain is a sequence of words semantically related $w_1, ..., w_n$ from a source text, so w_i is linked with w_{i+1} via a lexical-semantic relations.

Lexical chains determine the context and contribute to the homogenization of the meanings of words. The algorithms that determine the lexical chains produce most of the time ambiguity prior to produce the sets of words which are semantically related. The first computational model for lexical chains was introduced by [15]. Computational inefficiency of this approach was outdated [16] presented an efficient algorithm, linear time for determining lexical chains.

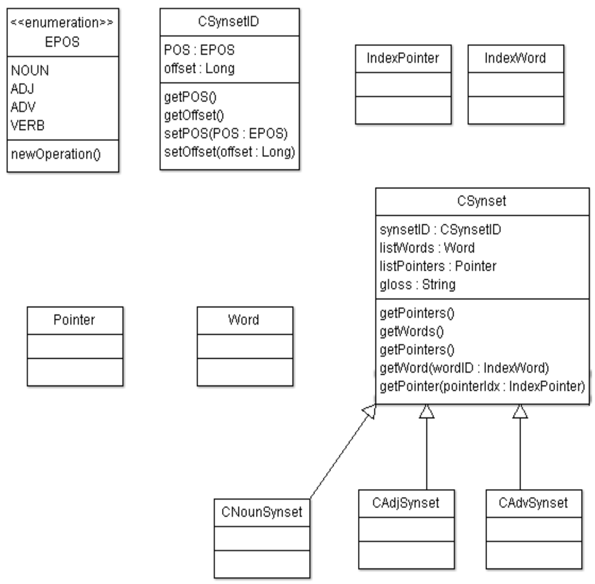

Fig. 1 Wordnet class hierarchy.

In [17] is proposed an algorithm for determining semantic interconnection structure (Semantic Structure Interconnections - SSI), a development of semantic-based chains encoding a context-free grammars the semantic interconnection templates available. For a given word w, SSI algorithm assumes the construction of a sub-graph based on dictionary WordNet that includes all the meanings of words from WordNet and intermediate concepts that appear in at least one valid lexical chain that connects a pair of meanings in WordNet. In the second stage, the algorithm selects those meanings to words in context that maximizes connectivity of the sub-graph for the semantic dictionary WordNet. A characteristic feature of the algorithm is that it produces justification for the semantic meaning in terms of graphs that can be used to support manual and automatic validation annotations meaning.

The steps of the algorithm to construct domain ontologies are:

1. Choose a core ontology for focused domain; if don't exist the core ontology is built based on key concepts provided by the user.

2. Apply SSI algorithm to link sub-hierarchies of concepts previously determined core ontology concepts, thus extending the domain ontology.

3. Determine and remove recurrent links within the domain ontology extended.

4. Check if there are singular concept in the ontology and if there are, they are removed.

Step 5: Determine the ontology schema in RDF format and save the ontology in the object-oriented database.

The need for implementation of ontologies for analyzing and annotating salient objects from key frames, prioritized this area on two levels are closely correlated. On the one hand, the low level containing specific properties of the objects (color, texture, form) and that the second level, the content consists of information that can be perceived by the human user. An ontology management system should model the data layer low-level extraction and inference to support their content level.

A scenario of using such a system could be as follows: a user uploads all ontologies in a particular field, and allows selection of different objects from key frames and their correlation with concepts from domain ontology. The system extracts the visual descriptors for these concepts and stores them in the object-oriented databases.

To represent a visual feature associated with low-level descriptors are used different visual properties. The visual characteristics of domain concepts cannot be described using a single instance of visual descriptors concerned. This conceptualization requirement means more descriptions in terms of scope and involves support for multiple visual descriptors. The spatial relationships between salient objects are represented as simple model concepts. The result of annotation (content analysis) is integrated with the structure of the key frames and with the output of the tracking algorithm.

For automatic annotation of the objects was used learning algorithms based on decision trees. Using the advantage of robust decision trees for situations where low-level features extracted from key frames are incomplete or have values changed due to the presence of noise. To avoid problems caused by meshing characteristics of the key frames, the algorithm DT-ST [18] was used. This involves defining the semantic templates for each domain ontology concept.

The building of the semantic templates is made based on local characteristics of training frames. For each useful concept and each low-level feature is defined a semantic template (ST) as low level centroid characteristic values for all key frames which have been assigned the same concept.

For each concept we have a vector of five components [*color perimeter area compactness eccentricity*]; the normalized values of these components are used and results a lot of semantic templates $ST = \{ST_i\}$ $i = 1..$ no_concepts with $ST_i = \{C_i, S_i\}$, $C_i=\{color_i\}$ and $S_i=\{$ perimeter$_i$, area$_i$, compactness$_i$, eccentricity$_i$ $\}$.

For an object detected and un-annotated with known characteristics vector is calculated Euclidean distance between each partition and corresponding partition vector component vector determined semantic characteristics of each template.

Based on semantic templates determined for each concept, it generates a lot of decision rules allowing automatic annotation of a salient object with a high level concept based on the low characteristics. The input attributes for decision tree are the color and the shape of the each salient object. The induction of the decision tree algorithm is described in the following:

1. Compare the values of feature for the current objects with the highest probability of correct annotation corresponding to the similar objects that were already annotated.

2. If the shortest distance calculated is less than a threshold value, the current object is annotated with the corresponding concept of the minimum distance, otherwise go to step 3.

3. Compare the value of characteristic with each similar component from semantic templates of each concept and determine the feature that has the highest probability of correct annotation and the step 2 is restarted.

The algorithm ends either in step 2 if annotation is done (successfully) or in step 3, if no characteristics are not involved in determining the rules of annotation (with failure).

For the second situation, the object will be marked by setting a field that will specify the un-annotation object. This marking is important validation step of the algorithm of automatic annotation.

III. OBJECT ORIENTED VIDEO RETRIEVAL SYSTEM

The proposed structure of semantic content retrieval system represented in Figure 2 has three distinct components video:

- The module that processing frames within which are highly relevant objects and attributes required different interpretation operations;

- The intermediate level of interpretation, in which the spatial analysis of the elements that allow tracking salient objects in multiple successive frames;

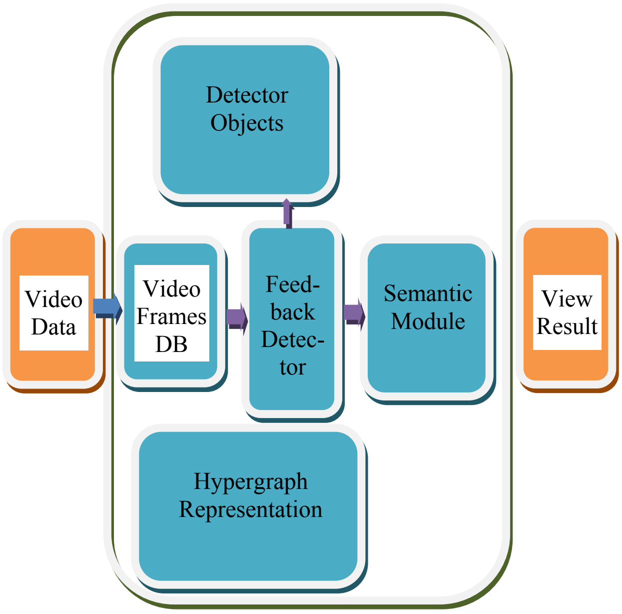

Fig. 2 General architecture of system.

- The module for the semantic interpretation that combined the elements of taxonomy (the concepts of knowledge areas) with visual concepts (objects related) determined in the intermediate level.

The SQL language was the starting point for querying databases and involves a set of restriction on the data set according to a certain set of criteria to get a result set. Object-oriented databases using query language data object oriented - Object Query Language (OQL) - which has been standardized by ODMG 3.0 [19] and used for formulating queries ODL scheme. Stored data contain both data and executable code (through methods) so OQL queries can refer to these methods to get a lot of complete and accurate results; the set of methods forms library functions interface (API - Application Programming Interface) that allows the application to control the data.

Hypergraph Object Query Language (HGOQL) is an extension of graph object query language (GOQL) [20] and it based also on OQL. The schema for the object oriented database that uses language HGOQL is defined as a set of classes {$class_i$ | i = 1 .. n}. A class is defined using the triplet: class:= <state, behavior, inheritance> with class.state::={ attributes, relations}:

- class.state.attribute:= {<$attribute_i$, $type_i$> | i = 1 .. a, where a is the number of the attributes};

- class.state.relations:= {<$relation_i$, $object\_type_i$> | i = 1 .. r, where r is the number of the relations}.

The component behavior is defined as {$method_i$ | i = 1 .. m, where m is the number of the methods}:

- class.behavior.method:= {<parameters_list, type>} with class.behaviour.method. parameters_list ::= {<$parameter_i$, $type_i$>, | i = 1..p, where p is the number of the parameters for the method. The component class.inheritance:= { $class_i$ | i = 1..c, c is the number for the base classes for the current class}.

In the current paper the queries are specified through the extension of the query language for graph data structures (GOQL) to the hypergraph structures (HGOQL). It defines a set of data structures for object model: the values scheme defines attributes that contain a class of objects. Items can be atomic or multi-value; the instance: defines a set of objects according to the scheme. An object is a pair O = <id, v>, where id is the identifier's object and v is the value of the object (properties); the dependencies for the functional values are used in the scheme to check the value of a set of attributes that uniquely determines the value of another attribute. The object schema is a triplet <N, F, S> with N - value scheme, F - a set of dependencies of functional values for N and S – a set of subsets from N. This structure is defined using hypergraphs by establishing a one-to-one correspondence between schema object <N, F, S> and interpretation in which N is a hypernodes, F represents its oriented hyperedges and S unoriented hyperedges.

An hypergraph manipulation language (HML - Hypergraph Manipulation Language) for querying and updating them has two operators to query identifier or based on value, and eight insertion and deletion operators for hyperedges and hypernodes. In the developed language (HGOQL) have implemented only refers to query operators.

Using hypergraphs structures involves several advantages: using a unique formalism for the representation of classes and inheritance; avoiding data redundancy (inherited values for sub-objects are taken from the super-objects); definition of complex objects (using unoriented hyperedges) and functional dependencies (using oriented hyperedges); allows the unique identification technique trough Object Identifier and provides the mechanisms for multiple inheritance specifying.

Given all this was done an interpreter that enables the translation of the semantic queries based on pseudo-natural language into queries that respect the syntax specific to HGOQL.

To define the symbolic language was used as lexical atoms, on the one hand the concepts form the ontologies used in the annotation, and on the other the elements corresponding to the visual concepts.

In the proposed system through graphical query interface it is allows to load in tree structure visualization, the ontology corresponding visual concepts and the domain ontology. The user can choose any domain concept and any elements of visual ontology. Based on chosen concepts a query is specified in pseudo-natural language with as first element a domain concept and has the syntax given in the form of productions:

<query> → <domain_concept><visual_concept_list>

<visual_concept_list> → | <visual_concept>|

<visual_concept_list><visual_concept>

In the first stage of the transformation process of a query is used both object-oriented hypergraph grammar for disambiguation and semantic query processing and the synsets from WordNet dictionary stored in the database. According to the grammar is generated a lexical analyzer and a parser. The semantic actions attached to the production under syntactic analysis function that is found at the entrance take a terminal value and returns the corresponding the identifier of the synset (unique synset ID). Based on each ID whose basic word is part of the symbolic query is determined the IDs for the synsets that are synonymy relationship and it form an hyperedge. The hyperedge corresponding to the domain concept is unified with each corresponding visual concepts hyperedges through "attribute-of" edges.

IV. EXPERIMENTS

In this chapter are described the developed system for the study of methods and perform specific experiments specific to the video sequences flow processing: segmentation and object tracking, annotating, storing data and interpretation of semantic queries.

The developed prototype is organized according to the following architecture:

- The segmentation module for frames;
- The module for tracking salient objects;
- The module for translating semantic queries;
- The graphical user interface.

The first two modules generate syntactical and semantic information corresponding to the processed video sequences and structures in which they are stored in the database. Through graphical user interface performs semantic queries using symbolic language. The simplified representation of architecture of the system is specified in Figure 3.

Two types of queries are allowed: query by example and semantic query based on symbolic language. For the first forms of interrogation, the module has a graphical interface that allows loading frames of video sequences that are intended to be used in the query, and by processing it choose a key frame considered relevant to the content of the neighbor frames that are intended to be retrieved. The syntactic characteristics of salient objects chosen are given by: perimeter, area, center of gravity, compactness and the signature of the shape object. Positioning the center of gravity of an object is determined by the arithmetic mean of the coordinate's pseudo-focal points of the hexagons that are on the outline of the object.

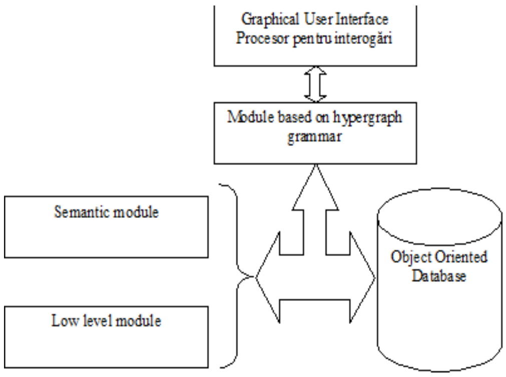

Fig. 3 System architecture.

The circular list of the distances between the center of gravity of the object and the pseudo-focal points of the boundary of the hexagons (centroid distances) determines the unique signature related to the shape of a non-deformable object.

Based on these distances are determined the polar coordinates of super-pixel contained in hexagons border. In the experiments conducted, we tested the retrieval by example for a set of video sequences; for each category there are 25 frames have been processed priori and processing the results were stored in an object-oriented database. I used queries on the same type of video (equivalence class) obtained by operation type translation, rotation with a number of degrees and scaling by a factor given objects seen in a video sequence will be considered as the query sequence . To generate the types of frames considered were implemented specific operations of each frame.

The second type of query supposes a simple graphical interface for allowing the symbolic language query and visualization of the obtained frames ranked by value metric that determines the distance between query and response; the metric value involves the computation of the distance between each query-frame and obtained frame.

Unlike the graphical interface, the passing from the semantic query to a syntax recognized by database system management, it involves a complex transformation. The first part of the query processing ensures the transition from symbolic language into HGOQL format.

In the second part, HGOQL query is converted into a SPARQL ((Protocol and RDF Query Language) [21] query that allows the implementation of matching algorithm for the hypergraph structure. As example an SPARQL query that corresponding to the initial query "player red square" finds all frames in which appears a player with red equipment. A subset of frames obtained is shown in Figure 4. The result set must be included only the frames containing only one player dressed in red and are in the box.

The SPARQL query has three components: SELECT clause corresponds to the selected operator specific databases; WHERE clause specifying the criteria for selecting the hypergraphs objects in the database and FILTER allows the restriction on search results. The good results obtained using simple queries demonstrate that this approach is promising.

The relationships between the concepts of domain ontology attached to the objects in annotation stage and low level attributes extracted in the process of segmentation allowed formalizing queries using native language which is based on syntactic characteristics. Such queries are part of the query by example. We used standard format native object-oriented query that allows formalizing queries as instances of a class.

Fig. 4 Key frames result.

After the execution of a query the result has a lot of objects that correspond with the similar frames, this type of query is useful only for queries by example. The consistency of the native queries is given by the flexibility of object-oriented languages and the possibility of their parameterization and application of such dynamic query is easily achieved based on properties such languages. In this way, productivity for object-oriented programming is not affected by using another query language that is based on the standard SQL.

The query expressions written in symbolic language are analyzed and converted through the double translation in a specific format SPARQL query language. All the elements present in a query is looking for the correspondence with WordNet synsets and these synsets are marked. If a synset for a word it was not marked as used in the process of annotating, searching based on WordNet corresponding relations (hyperonymy or hyponymy) a first synset marked as used. If not found any such synset, the corresponding element of the query is returned to the user as irrelevant to the semantic query and automatically extracted from the expression. After this stage, for the list of words from the original query is obtained a synsets ID list.

Following the execution of such queries is obtained a list of objects that match the semantic content frames that include elements of the query expression. For the prototype system it was used and object oriented database - HyperGraphDB [22] that allows formulating the queries.

V. CONCLUSIONS

This paper presents an object oriented video retrieval system considering the frames extracted from the video, domain ontologies and the tracking the salient objects. An object oriented database is used to store in a uniform mode all specific data extracted by segmenting, tracking, and annotation of the salient objects.

The object oriented approach used it was imposed by the complex structure of physical objects you can find in the videos as well as the addition of semantic meanings, which must relate to the objects detected. The algorithms for domain ontologies construction and frames annotation are a proper contribution of this article, which has led to fulfilling the final goal, the extraction of semantics-based syntax and retrieving the frames with relevant information within a pseudo-natural query language close to human understanding. The integration of the methods which refer to different stages of processing machine in the prototype of the system described in chapter IV and the results obtained for the sport domain validate the research carried out and represents a model for applying this method on videos from multiple domain of activity.

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