ITI-CERTH in TRECVID 2016
Ad-hoc Video Search (AVS)

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Highlights

- AVS’s task objective is to retrieve a list of the 1000 most related test shots for a specific text query
- Our approach: a fully-automatic system
- The system consists of three components
  - Video shot processing
  - Query processing
  - Video shot retrieval
- Both fully-automatic and manually-assisted (with users just specifying additional cues) runs were submitted
System Overview

a) Video shot processing

b) Query processing

Query
“Find shots of a person playing guitar outdoors”

Sub-queries
1) “person playing guitar outdoors”
2) “outdoors”

Selected concepts
outdoors 1.0
acoustic guitar 0.5
electric guitar 0.48
daytime outdoor 0.41

c) Video shot retrieval

Keyframe’s concept vector

Histogram intersection distance

Query’s concept vector

501 Find shots of a person playing guitar outdoors

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MOVING
Video shot processing

- Extract one keyframe from each video-shot and annotate it using a pool of 1345 concepts:
  - ImageNet 1000
  - TRECVID SIN 345
- A temporal re-ranking method is employed to refine the calculated detection scores
- The final keyframe’s concept vector in $\mathbb{R}^{1345}$ represents each video shot
- We find all the synonyms of each concept using WordNet; each concept’s synonyms are considered as equivalent to the original concept
Video shot processing

ImageNet 1000

• Five pre-trained DCCNs for 1000 concepts
  – AlexNet
  – GoogLeNet
  – ResNet
  – VGG Net
  – GoogLeNet trained on 5055 ImageNet concepts (we only considered the subset of 1000 concepts out of the 5055 ones)

• Late fusion (averaging) on the direct output of the networks to obtain a single score per concept
Video shot processing

TRECVID SIN 345

• Three pre-trained ImageNet networks, fine-tuned (FT; three FT strategies with different parameter instantiations from [1]; in total 51 FT networks) for these concepts
  – AlexNet (1000 ImageNet concepts)
  – GoogLeNet (1000 ImageNet concepts)
  – GoogLeNet originally trained on 5055 ImageNet concepts
• The best performing FT network (as evaluated on the TRECVID SIN 2013 test dataset) is selected
• Examined two approaches for using this for shot annotation
  – Using the direct output of the FT network
  – Linear SVM training with DCNN-based features

Query processing

• Each query is represented as a vector of related concepts
  – We select concepts which are most closely related to the query
  – These concepts form the query’s concept vector
  – Each element of this vector indicates the degree that the corresponding concept is related to the query

• A five-step procedure is used
  – Each step selects concepts, from the concept pool, related to the query
Query processing: Step 1

Motivation: Some concepts are semantically close to input query and they can describe it extremely well

Approach:

– Compare every concept in our pool with the entire input query, using the Explicit Semantic Analysis (ESA) measure

– If the score between the query and a concept is higher than a threshold (0.8) then the concept is selected

– If at least one concept is selected in this way, we assume that the query is very well described and the query processing stops; otherwise the query processing continues in step 2

Example: the query *Find shots of a sewing machine* and the concept *sewing machine* are semantically extremely close
Query processing: Step 1

The processing stopped in step 1 for 3 out of the 30 queries:

- For **Find shots of a sewing machine** the concept **sewing machine** was selected.
- For **Find shots of a policeman where a police car is visible** the concept **police car** was selected.
- For **Find shots of people shopping** the concept **tobacco shop** was selected.
Query processing: Step 2

**Motivation:** Some (complex) concepts may describe the query quite well, but appear in a way that subsequent linguistic analysis to break down the query to sub-queries can make their detection difficult.

**Approach:**
- We search if any of the concepts appear in any part of the query, by string matching.
- Any concepts that appear in the query are selected and the query processing continues in **step 3**.

**Example:** For the query *Find shots of a man with beard and wearing white robe speaking and gesturing to camera* the concept *speaking to camera* was found.
Query processing: Step 2

For 5 out of 30 queries concepts were selected through string matching

- For *Find shots of a man with beard and wearing white robe speaking and gesturing to camera*, the concept *speaking to camera* was selected
- For *Find shots of one or more people opening a door and exiting through it*, the concept *door opening* was selected
- For *Find shots of the 43rd president George W. Bush sitting down talking with people indoors*, the concept *sitting down* was selected
- For *Find shots of military personnel interacting with protesters*, the concept *military personnel* was selected
- For *Find shots of a person sitting down with a laptop visible*, the concept *sitting down* was selected
Query processing: Step 3

Motivation: Queries are complex sentences; we decompose queries to understand and process better their parts.

Approach:
- We define a *sub-query* as a meaningful smaller phrase or term that is included in the original query, and we automatically decompose the query to subqueries.
  - NLP procedures (e.g. PoS tagging, stop-word removal) and task-specific NLP rules are used.
  - For example the triad **Noun-Verb-Noun** forms a *sub-query*.
- The ESA distance is evaluated for every *sub-query* – concept pair.
- If the score is higher than our step-1 threshold (0.8), then the concept is selected.
Example: the query *Find shots of a diver wearing diving suit and swimming under water* is split into the following four sub-queries: *diver wearing diving suit*, *swimming*, *water*

- If for every sub-query at least one concept is selected we consider the query completely analyzed and we proceed to *video shot retrieval* component
- If for a subset of the sub-queries no concepts have been selected we continue to **step 4**
- If for all of the sub-queries no concepts have been selected we continue to **step 5**
Query processing: Step 3

- On average, a query was broken down to 3.7 sub-queries
- For none of the test queries there was at least one concept from our pool matched to each sub-query
- For 17 out of 27 queries, concepts were matched to a subset of the sub-queries, thus the processing continued to step 4
- For the remaining 10 queries, no concept was matched to any of their sub-queries, thus the processing continued to step 5
Query processing: Step 4

**Motivation:** For a subset of the *sub-queries* no concepts were selected due to their small semantic relatedness (i.e., in terms of ESA measure their relatedness is lower than the 0.8 threshold)

**Approach:**
- For these *sub-queries* the concept with the higher value of ESA measure is selected, and we proceed to *video shot retrieval*

**Example:**

<table>
<thead>
<tr>
<th>Query: Find shots of one or more people walking or bicycling on a bridge during daytime</th>
<th>Sub-queries</th>
<th>Selected concepts (ESA score)</th>
</tr>
</thead>
</table>
| Steps 2,3 | • people walking  
• bicycling  
• bridge | • walking (1.0)  
• bicycle-built-for-two (1.0)  
• suspension bridge (1.0)  
• bicycles (0.85)  
• bridges (0.84)  
• bicycling (0.84) |
| Step 4 | • daytime | • daytime outdoor (0.74) |
Query processing: Step 5

**Motivation:** For some queries none of the above steps is able to select concepts

**Approach:**

- Our MED16 000Ex framework is used
- The query title and its sub-queries form an Event Language Model
- A Concept Language Model is formed for every concept using retrieved articles from Wikipedia
- A ranked list of the most relevant concepts and the corresponding scores (semantic correlation between each query-concept pair) is returned
- We proceed to *video shot retrieval* component
Query processing: Step 5

Example: For the query **Find shots of a person playing guitar outdoors** the framework returns the following concepts: **outdoor, acoustic guitar, electric guitar** and **daytime outdoor**
Video shot retrieval

• The query’s concept vector is formed by the corresponding scores of the selected concepts

• If a concept has been selected in steps 1, 3, 4 or 5 the corresponding vector’s element is assigned with the relatedness score (calculated using the ESA measure) and if it has been selected in step 2 it is set equal to 1

• Histogram intersection calculates the distance between query’s concept vector and keyframe’s concept vector for each of the test keyframes

• The 1000 keyframes with the smallest distance from query’s concept vector are retrieved
Submitted Runs

• We submitted both fully-automatic and manually-assisted runs

• For the manually-assisted ones
  – We used the same fully-automatic system, but
  – A member of our team that was not involved in the development of our AVS system took a look at each query and manually suggested sub-queries for it, without knowledge of the automatically-generated ones
  – The manually defined sub-queries were added to the automatically-generated ones, and our automatic AVS system was applied
Submitted Runs

**ITI-CERTH 1:**
- Late fusion of the direct output from 5 DCNNs for ImageNet 1000 concepts
- SVM-based concepts detectors for 345 TRECVID SIN concepts

**ITI-CERTH 2:**
- Late fusion of the direct output from 5 DCNNs for ImageNet 1000 concepts
- The direct output of the FT network for 345 TRECVID SIN concepts

**ITI-CERTH 3:** ITI-CERTH 1 run without step 4

**ITI-CERTH 4:** ITI-CERTH 1 run without step 2

<table>
<thead>
<tr>
<th>Submitted run:</th>
<th>ITI-CERTH 1</th>
<th>ITI-CERTH 2</th>
<th>ITI-CERTH 3</th>
<th>ITI-CERTH 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>MXinfAP (fully-automatic)</td>
<td>0.051</td>
<td>0.042</td>
<td>0.051</td>
<td>0.051</td>
</tr>
<tr>
<td>MXinfAP (manually-assisted)</td>
<td>0.043</td>
<td>0.037</td>
<td>0.037</td>
<td>0.043</td>
</tr>
</tbody>
</table>
Results (fully-automatic runs)
Results and conclusions

• Training SVMs on DCNN-based features instead of using the direct output of the DCNNs, for the 345 TRECVID SIN concepts, improves the accuracy (i.e., run ITI-CERTH 1 outperforms ITI-CERTH 2)

• In the AVS 2016 dataset
  – Step 4 could be omitted for the fully-automatic runs
    • Sub-queries without high semantic relatedness can be ignored; ITI-CERTH 1 & ITI-CERTH 3 achieve the same results
  – Step 2 could be omitted
    • String matching between the test query and concepts does not improve the accuracy; semantic relatedness makes the difference

• Fully-automatic runs outperformed the manually-assisted ones

• Our best fully-automatic run was ranked 2nd-best in the fully-automatic run category; it also outperformed the runs of all but one participant in the manually-assisted run category
Questions?

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TRECVID 2016 paper: