The TV Workstation project: a research scope

Keynote talk at the LIFAT seminar

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Summary

Introduction

TV video capture

Real-time TV video processing

Conclusions and perspectives

Introduction

- Television (TV) is a huge source of multimedia data[1],
  - $\simeq 27,000$ channels worldwide,
  - $\simeq 55\%$ in Europe, Russia, China, USA,
  - provided with DTT, SaT, Cable TV, IPTV and InternetTV,
  - e.g. France / Vietnam ($\simeq 210$ channels), USA ($\simeq 1,760$ channels),
- Computer Vision and AI could be applied to TV,
  - Social TV, Sync2Ad, Fact-Checking, GenAI for TV, ...,
- A Workstation has to support the scalability / real-time issues, this leads us to develop the TV Workstation since 2017.

[1] audio/video & metadata

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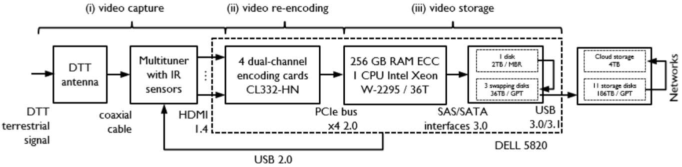
The DELL 5820 computer and tool suite (1/2)

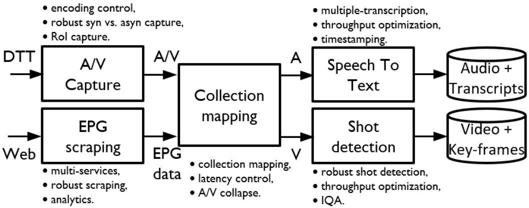
The DELL 5820 **computer** processes 8 channels (HD, 30 FPS, 24h/day), with real-time audio / video (A/V) encoding, control of tuners with IR sensors, internal / external storage of $38 + 190$ TB.



Resolution		Audio/ Video	CPU rate	Video Mbps	TB/ month	Audio Kbps	GB/ month
HD	1280 × 720		20 %	3	7.23	256	621
SD	720 × 576	asyn	12 %	1.6	3.89	160	384
Low	320 × 240		8 %	0.56	1.36	128	308

The DELL 5820 computer and tool suite (2/2)

The DELL 5820 **computer** is offered with a tool suite for adaptive capture, mapping and first analysis of A/V data.



Sources	Area	Length	Size	Ch	BCE	Col	Desc	Words
3	Francophonie	$\simeq$ 2 years	160 GB	310	5 M	120.2 k	1 M	69 M

Ch, **BCE**, **Col**, **Desc** stand for channels, broadcast events, collections and descriptions.

Whisper model	tiny	base	small	medium	large
Throughput	39.8	30.1	6.5	$\simeq$ 4.5	$\simeq$ 2
Audio (h) / week	6,685	5,055	1,090	$\simeq$ 755	$\simeq$ 335
Memory (GB)	22.5	27.5	48	$\simeq$ 115	$\simeq$ 192
CPU rate	$\simeq$ 90 %				

Partial video copy detection (1/4)

Partial video copy detection (PVCD) aims at finding short segment(s) which have transformed in long video(s):

- it is a key topic with application domains (copyright, retrieval),
- existing datasets (VCDB, FIVR-PVCD, VCSL) offer no scalability, control of spatial degradations, null latency and frame-level annotation,
- a TV-based protocol was proposed to design the STVD-PVCD dataset on the task, public available[2,3] [**ORASIS2021**,**ICIAP2022**].

[2] `https://dataset-stvd.univ-tours.fr/pvcd/`

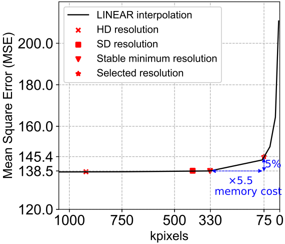
[3] e.g. cove.thecvf.com, datasets.visionbib.com, homepages.inf.ed.ac.uk, kaggle.com, opendatalab.com, paperswithcode.com, . . .

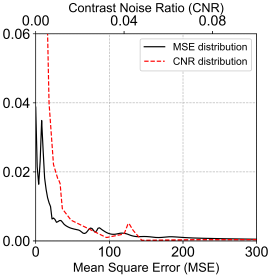
Partial video copy detection (2/4)

STVD-PVCD is the best dataset for scalability and noise control.
It uses a strategy for memory cost optimization[4].

Datasets	**VCDB** 2016	**FIVR-PVCD** 2021	**STVD** 2021	**VCSL** 2022
References	28	100	**243**	122
Positive videos	528	N/A	**19,280**	9,207
Positive pairs	9k	10,8k	**1,688k**	281k
Negative videos	**100,000**	N/A	64,040	N/A
Duration (h)	2,030	N/A	10,660	**17,416**
Noise characterization	real noise	real noise	**noise-free**	real noise
Timestamping (s)	1	1	$\frac{1}{30}$	1

(h): hours, (s): seconds, N/A: not available, k: thousands





[4]75k pixels = 320 × 240 at 560 kbps

Partial video copy detection (3/4)

STVD-PVCD allows a fine characterization for PVCD:

- a root capture plus 5 test sets,
- *video cut* is controlled with a latency model,
- *downscaling*, *compression* depend of correlated parameters,
- *flipping*, *rotating*, *black-border insertion* are standard,
- *video speeding* is done with **[ICAIIC2020]**.

	Video cut	Downscaling	Compression	Flipping	Rotating	Black-border	Video speeding
Root capture	•						
Hello World	•	•	•				
Pixel attacks	•	•	•				
Global transforms	•	•	•	•	•	•	
Video speeding	•	•	•				•
Combination	•	•	•	•	•	•	•

Root capture

Hello world

Pixel attack


Global transforms


Video speeding


Combination

Partial video copy detection (4/4)

STVD-PVCD is suitable to characterize PVCD methods.

- Detection: key-frame based method[5] **[ICPR2016]**
- Features: 10 (BRIEF, 9 CNN features)
- Dataset: STVD sampling[6] without/with training[7]
- Experiments: $>$ 4.4 M vectors and $>$ 445 B matchings
- Metric: F_1

	BRIEF	VGG-16
Hello world	**0.98**	N/A
Pixel attack	0.59	**0.64**

Hello world & Pixel attacks - BRIEF / CNN feature - without training

	Last FC	MAC	R-MAC
ResNet50-v1	**0.926**	0.828	0.823
Inception-v1	0.923	0.738	0.782
VGG-16	0.894	0.922	0.918

Gobal transforms - 9 CNN features - with training

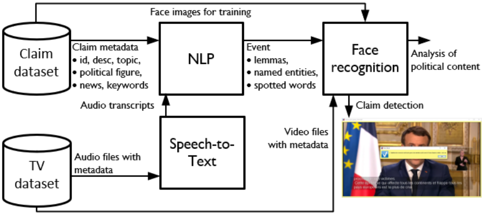
[5] Cosine similarity, at least one key-frame detected

[6] large-scale, balanced positive/negative distribution, accurate timestamping

[7] ratios of $\frac{3}{5}$ for training and $\frac{2}{5}$ for testing

Multimodal audio/video analysis for fact-checking

Fact-checking checks the veracity of claims from various media (print, TV, radio, Web, SN). There is none A/V dataset, we have designed the large-scale french STVD-FC:



- containing 6,730 news / political TV programs (6,540 h) of the French presidential election 2022[8] ($\simeq$ 50 Mwords, $\simeq$ 706 Mimages, 1.96 TB),
- linked to $\simeq$ 10,000 claims ($\simeq$ 10 years / height web services) [**ISS2025**],
- public available[9] [**CBMI2022**] tested a first system [**VISAPP2024**].

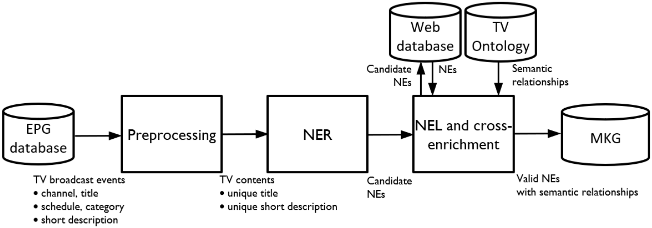
[8] 1^{st} of February to 1^{st} of May 2022

[9] `https://dataset-stvd.univ-tours.fr/fc/`

Multimedia Knowledge Graph (MKG) (1/2)

Multimedia Knowledge Graph (MKG) represents multimedia content (text, image, A/V, etc). There is no large-scale French/MKG, we have designed STVD-KG:

- a preprocessing maps TV broadcast events into contents,
- NEs are detected with NER Spacy/casEN intersection for robustness,
- NEL processes candidate named entities with WebDB and TV ontology,
- STVD-KG is $\times 10$ bigger than state-of-the-art, public available[10].



NER, **NEs**, **NEL**, stand for Named Entity Recognition, Named Entities and Named Entity Linking.

EPG	BCE	CoI	NEs	Triples	Properties
1 year	2.9M	70k	84k / 5.7M	27.6M	21

EPG, **BCE**, **CoI**, **NEs** stand for Electronic Program Guides, broadcast events, collection and named entities.

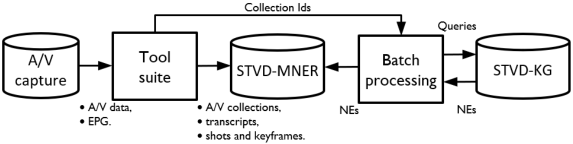
[10] https://zenodo.org/records/15368241

Multimedia Knowledge Graph (MKG) (2/2)

MKG is inherently a Multimodal Knowledge Graph (*M*KG). *M*KG construction is related to the Multimodal Named Entity Recognition (MNER) in A/V data with semi-supervised learning.

LOC: external vs. internal PEO: old vs. young ORG: building vs. object

MNER for A/V is specific, a STVD-MNER$_\beta$ dataset is proposed.



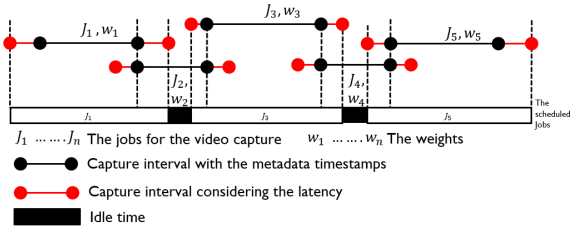
Dur	Col	A/V files	Transcripts	Audio	Video	NEs
819h	284	843 $\times$2	yes	256 kbps	0.56Mbps 320 $\times$ 240	1,231

Dur, **Col**, **NEs** stand for duration, collection and named entities.

Parallel machine scheduling (PMS) for A/V capture

Problem statement: large-scale capture has an hardware / memory cost not needed[11]. A partial capture with PMS:

- is an off-line / no preemptive scheduling using static execution times,
- is a Weighted Interval Selection Problem (WISP) NP-hard having polynomial approximation algorithms (e.g. $GREEDY_\alpha$ [**JA2003**]),
- has a latency $L(t)$ as key parameter of the scheduling problem,
- is delivered with public available dataset STVD-PMS[12] (170 days, 26 channels, 99k jobs, 5,615 hashcodes, offline/online latency).



[11] Frequent, political content, rich EPG data, …

[12] https://dataset-stvd.univ-tours.fr/pms/

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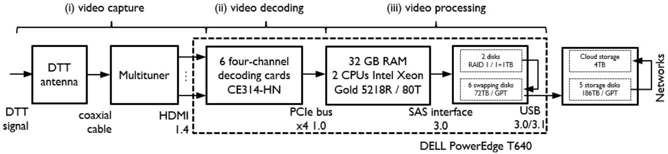
The DELL PowerEdge T640 computer

The DELL PowerEdge T640 **computer** processes 24 channels for real-time video decoding and processing with high-performance CPUs[13] and having an internal / external storage of $72 + 190$ TB.



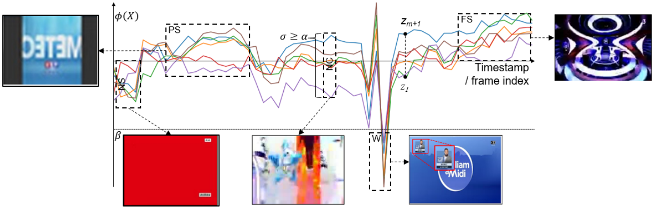
Ch	BPP	Res	FPS	Images	Bandwidth		
24	32	SD	$600 = 24 \times 25$	51.8 M/day	0.69 GB/s	57.9 TB/day	34%
		HD	$528 = 24 \times 22$	45.6 M/day	1.81 GB/s	152.9 TB/day	91%
		Full HD	$240 = 24 \times 10$	20.7 M/day	1.85 GB/s	156.4 TB/day	93%

[13] 2×40 threads with AVX 512 Vector Neural Network Instructions

Real-time PVCD

Real-time PVCD processes with a deadline Δ (e.g., 1-3s) and can be applied to multiple video streams [**CBMI2021**,**CAIP2023**]:

- with real-time video decoding using hardware on the Workstation,
- with rigid (ZNCC) and no-rigid (2D CNN) features for matching,
- with key-frame selection methods using goodness criteria.



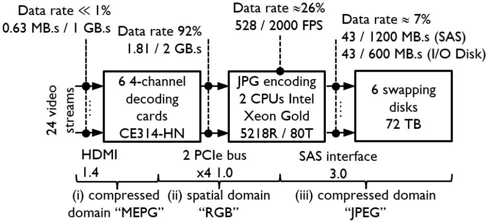
Time optimization for real-time deep learning to investigate:

- acceleration [14] with INT8 and VNNI [**CCIS2020**],
- soft real-time with adaptive inference [**PR2020**].

[14] $\simeq \times 15$ acceleration on *ResNet-50* (OpenVino vs. TensorFlow).

Real-time frame capture and IQA (1/2)

Real-time frame capture decodes videos into frames re-encoded as image files (e.g. jpeg). The workstation can process 24 streams (22 FPS / HD) in real-time and offers a large storage (72 TB).



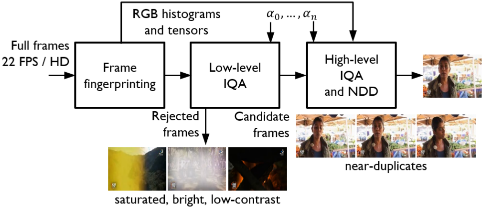
No bottleneck, the problem is the storage cost (3 weeks max).

	Day	Month	Year	Disks
data	3.4 TB	103.2 TB	1.22 PB	72 TB
image	45.6 M	1.4 B	16.7 B	0.96 B

M, B, TB, PB stand for Millions, Billions, Terabyte, Petabyte

Real-time frame capture and IQA (2/2)

Image Quality Assesment (IQA) filters high quality frames into a two steps pipeline.



- low-level IQA filters out low quality frames with standard processing,
- high-level IQA requires time-efficient blur detection methods [**CIS2023**],
- Near-Duplicate Detection (NDD) filters out duplicate frames for storage,
- parameters $\alpha_0, \ldots, \alpha_n$ are set for storage requirements (e.g. $\simeq 12$ FPM).

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- project launched in 2017, specific / ready-to-use platform,
- cross-disciplinary project (CV, NLP, OR),
- 9 researchers working on, $\simeq$ 44.7 k€ of investment,
- 3 PhD (V.H. Le, H.G. Vu, L. Nguyen),
- 7 publications[15] and 4 public datasets STVD[16],
- research perspectives (*M*KG, MNER, RT CV, ...),
- project submission (Fact-Checking, Social TV, TV GenAI).

15 **[AI4TV2019**, **CBMI2021**, **ORASIS2021**, **ICIAP2022**, **CBMI2022**, **CAIP2023**, **VISAPP2024]**

16 `https://dataset-stvd.univ-tours.fr/`

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