The TV Workstation project: a research scope

Keynote talk at the VNU-ITI

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Summary

CV in short

Introduction

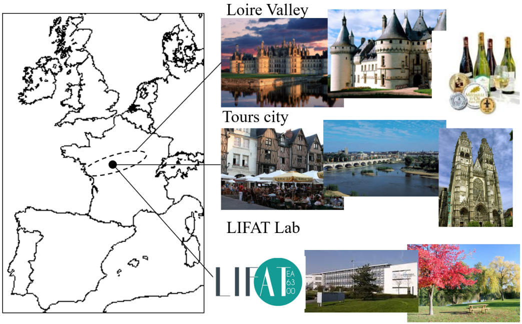
TV video capture

Real-time TV video processing

Conclusions and perspectives

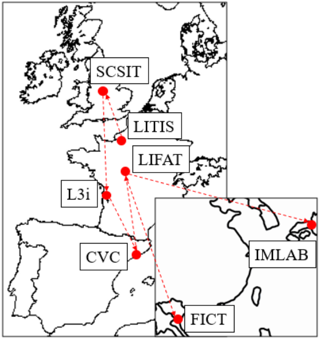
CV in short - Mathieu Delalandre (1/2)

- PhD in computer science with > 20 years of experience,
- Associate Professor at the LIFAT Lab - UT (Tours, France),
- fields of image processing and machine learning,
  - local detectors, processing in the transform domain, template matching,
- application domains,
  - video copy detection, scene text detection, document image networking, manga copyright protection, symbol/logo detection and recognition,
- journals and conferences/workshops,
  - JRTIP, TIP, PR, PRL, IJDAR,
  - CBMI, ICIAP, VISAPP, CAIP, ICPR, ICDAR, DAS, GREC.



CV in short - Mathieu Delalandre (2/2)

- international experience as ($<$ 2009) research fellows in Europe ($>$ 2013) visiting positions in Asia,
- PhD supervisor of T.A. Pham, C. Nguyen, V.H. Le and G. Vu
- head of international LIFAT-RFAI, TV Workstation project
- teacher at the Polytech school,
  - operating systems, real-time systems, distributed systems & computing,
  - head of international exchanges, networking and systems program
- more about myself: http://mathieu.delalandre.free.fr/ .



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Introduction

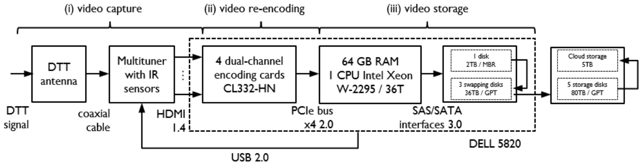
- Television (TV) is a huge source of multimedia data[1],
  - $\simeq 27,000$ channels worldwide,
  - $\simeq 55\%$ in Europe, Russia, China, USA,
  - provided with DTT, SaT, Cable TV, IPTV and InternetTV,
  - e.g. France / Vietnam ($\simeq 210$ channels), USA ($\simeq 1,760$ channels),
- Computer Vision and AI could be applied to TV,
  - Social TV, Sync2Ad, SmartZapping, fact-cheking, catchup 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

Summary

The DELL 5820 computer

The DELL 5820 **computer** processes 8 channels (HD, 30 FPS, 24h/day), with real-time audio / video encoding, control of tuners with IR sensors, internal / external storage of 38 + 80 TB.



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

Partial video copy detection (1/2)

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, VCSL) offer no scalability, control of degradation, frame-level annotation, concistency,
- a TV-based protocol was proposed to design the STVD-PVCD dataset on the task, public available[2] with an agreement, published at [**ORASIS2021**,**ICIAP2022**] referred in the main research portails[3].

[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 (2/2)

The STVD-PVCD is compared to the state-of-the-art.

Datasets	**VCDB** 2016	**STVD** 2021	**VCSL** 2022
References	28	**243**	122
Positive videos	528	**19,280**	9,207
Positive pairs	9K	**1,688K**	281K
Negative videos	100,000	64,040	N/A
Duration (h)	2,030	10,660	17,416
Noise characterization	real noise	**noise-free**	real noise
Consistency	yes	**yes**	no
Annotation cost (m-h)	700	**105**	20,000
Timestamping	1s	$\frac{1}{30}$ **s**	1s

(h): hours, (s): seconds, (m-h): man-hours and N/A: not available

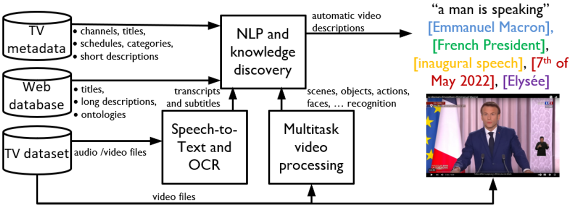
Set A Set B Set C Set D Set E Set F

STVD-PVCD allows deeper characterization tasks e.g. characterization of 2D CNN features [**CAIP2023**].

Automatic video description with knowledge representation

Automatic video description aims to tell a story about events happening in a video:

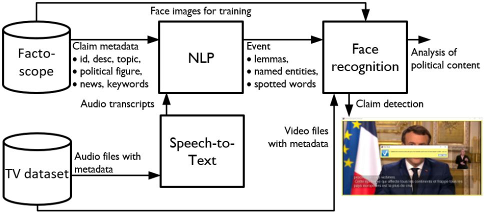
- it is a key problem in the computer vision field [**IEEE2021**],
- datasets[4] suffer from heterogeneity, scalability, lack of context and multimodal information, timing accuracy, black-box characterization,
- a TV protocol could offer a video normalization, a scalability, a knowledge representation [**PT2016**] for a robust and contextual video description.



[4] MSVD, MSR-VTT, ...

Multimodal audio/video analysis for fact-checking

Fact-checking is the process that check the veracity of claims from various media (print, TV, SNS). There is none multimodal / scalable dataset. We have designed the largest dataset STVD-FC:



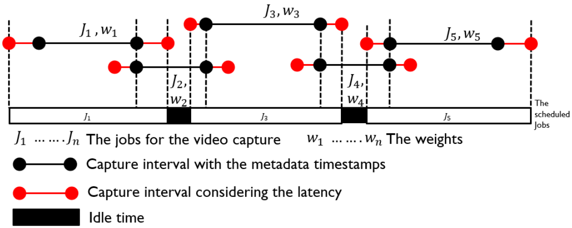
- containing $6,730$ news / political TV programs ($6,540$ h) of the French presidential election 2022[5] ($\simeq 50$ Mwords, $\simeq 706$ Mimages, 1.96 TB),
- linked to $1,300$ claims collected over 6 years (200 political figures, 241K words, 24K named entities) scraped from the Factoscope[6],
- public available[7] with an UT agreement, published at [**CBMI2022**].

[5] 1^{st} of February to 1^{st} of May 2022
[6] `https://rattrapages-actu.epjt.fr/factoscope`
[7] `https://dataset-stvd.univ-tours.fr/fc/`

Parallel machine scheduling (PMS) for video capture

Problem statement: a largest capture (e.g. 32 channels) has an important cost (32k€ + 5k€ a year for storage[8]) not needed for the applications[9]. A partial capture with PMS can be handled:

- as an off-line / no preemptive scheduling using static execution times,
- it is Weighted Interval Selection Problem (WISP) NP-hard having polynomial approximation algorithms (e.g. $GREEDY_\alpha$ [**JA2003**]),
- the latency $L(t)$ is a key parameter of the scheduling problem,
- a public available dataset STVD-PMS[10] published with an UT agreement (170 days, 26 channels, 99k jobs, 5,615 hashcodes, offline/online latency).



[8] Desktop version without maintenance and hosting / 186 TB a year (SD)

[9] Not repeated / idle, political, entertainment TV programs, . . .

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

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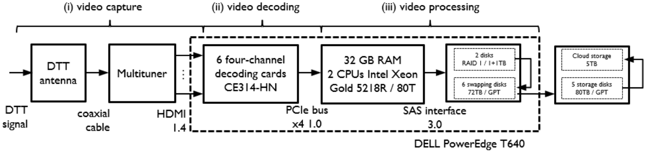
The DELL PowerEdge T640 computer

The DELL PowerEdge T640 **computer** processes 24 channels for real-time video decoding and processing with high-performance CPUs[11] and having an internal / external storage of $72 + 80$ TB.



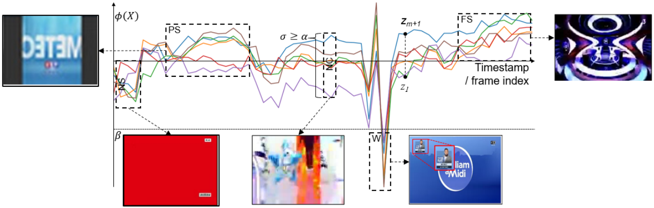
Ch	BPP	Res	FPS	Images	Bandwidth		
24	32	SD	$600 = 24 \times 25$	51.8 M/day	0.69 GB/s	57.9 TB/day	34%
		HD	$528 = 24 \times 22$	45.6 M/day	1.81 GB/s	152.9 TB/day	91%
		Full HD	$240 = 24 \times 10$	20.7 M/day	1.85 GB/s	156.4 TB/day	93%

[11] 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.



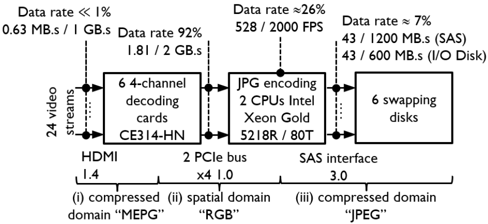
Time optimization for real-time deep learning to investigate:

- acceleration [12] with INT8 and VNNI [**CCIS2020**],
- soft real-time with adaptive inference [**PR2020**].

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

Real-time frame capture, IQA and NDD (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 with its hardware architecture.



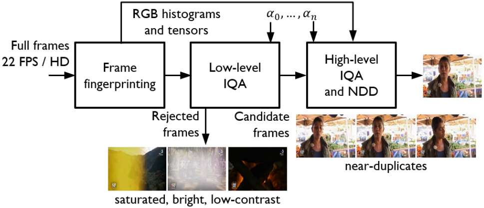
No bottleneck appears, the problem comes from the storage cost.

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

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

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

Image Quality Assesment (IQA) and Near-Duplicate Detection (NDD) filter out low quality and duplicate images.



- standard video processing supports low-level IQA and NDD, high-level IQA requires time-efficient blur detection methods [**CIS2023**],
- 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,
- 2 PhD grants in progress (V.H. Le, J. Vu), applications to other grants (VIED 89, French Embassy),
- $\simeq$ 40 k€ of investment, 8 researchers working on,
- 6 publications[13] and 3 public available datasets STVD[14],
- cross-disciplinary project (CV, NLP, OR),
- perspectives with key research topics (video description, real-time deep learning, ...),
- projects in the queue (social TV, Fact-Checking).

[13] **[AI4TV2019, CBMI2021, ORASIS2021, ICIAP2022, CBMI2022, CAIP2023]**

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

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