Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

INTERNATIONAL DOCTORATE IN COMPUTER SCIENCE

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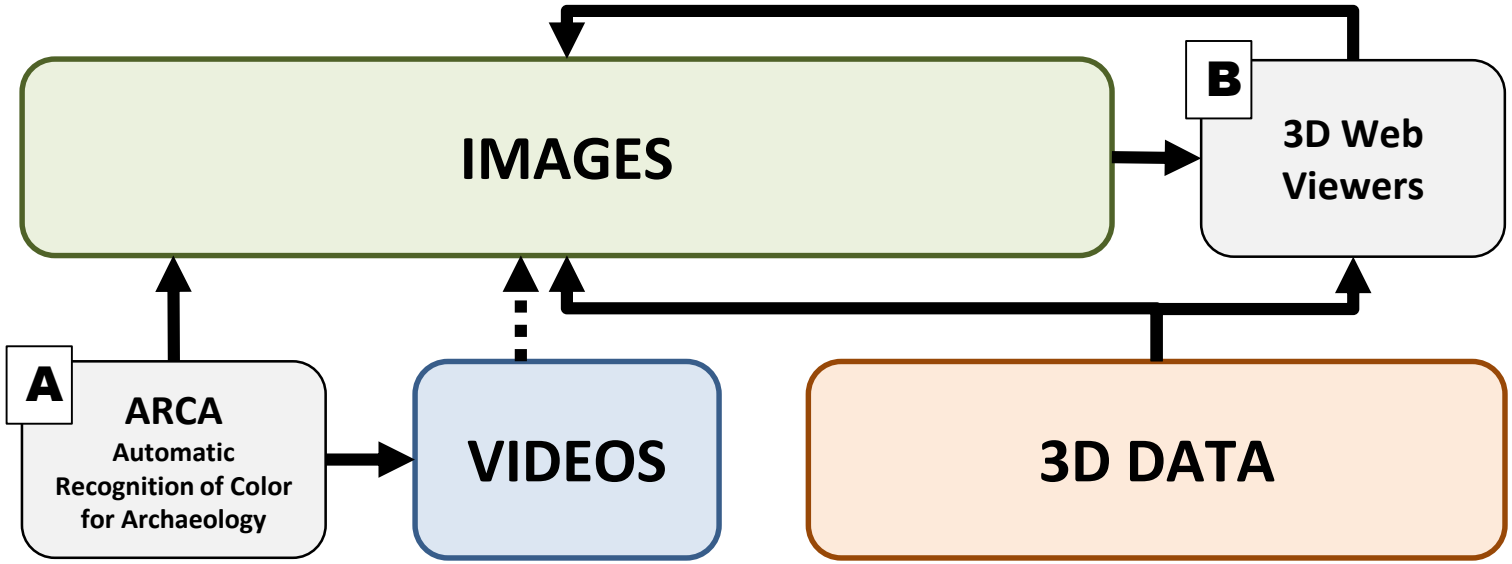
Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

This dissertation collects all the research work done by the PhD candidate in the Joint Open Lab for Wireless Applications in multi-deVice Ecosystems (JOL WAVE CATANIA) of TIM Telecom Italia.

In this lab, novel mobile applications based on versatile software are designed and implemented. The development process is performed employing **highly connectable hardware** and devices like smartphones, tablets, cameras, wearable devices, sensors, actuators, smart objects, and interactive screens.

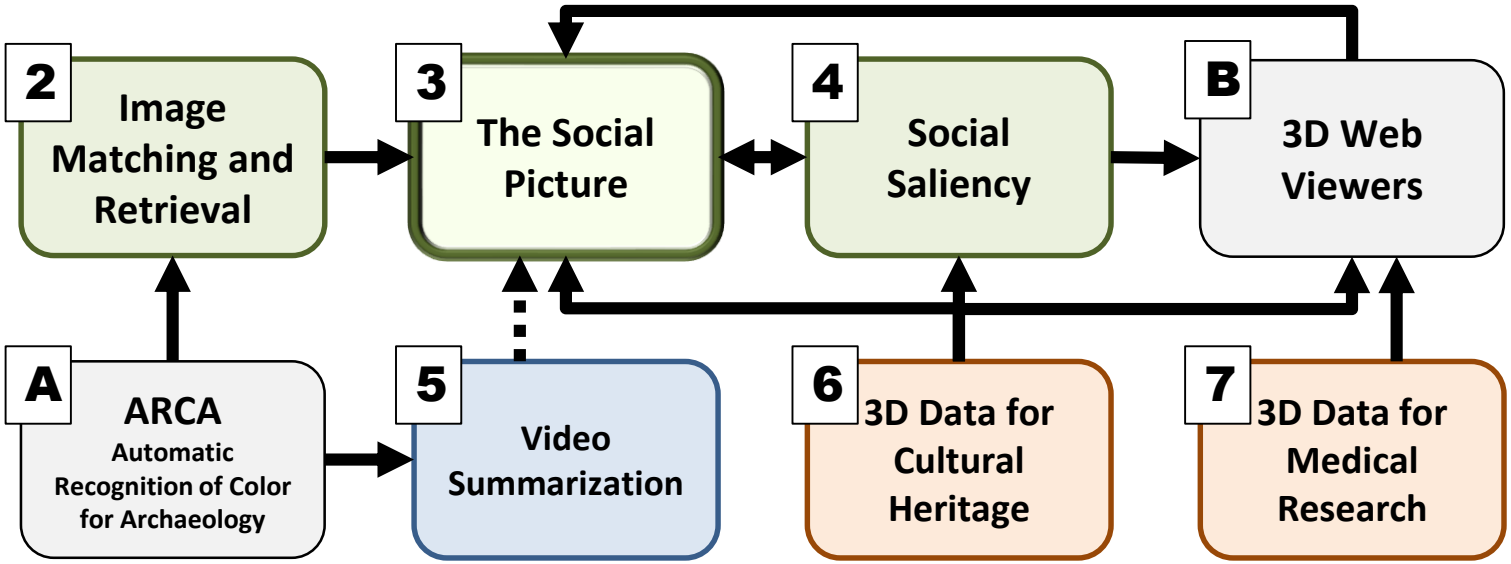
Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

Three main categories of media are treated in this dissertation: images, videos, and 3D data. More in detail, for images and videos we realized two frameworks: The Social Picture and RECfusion, respectively.



Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

Slideshow Structure



PART 1 – IMAGES

Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

Slideshow Structure

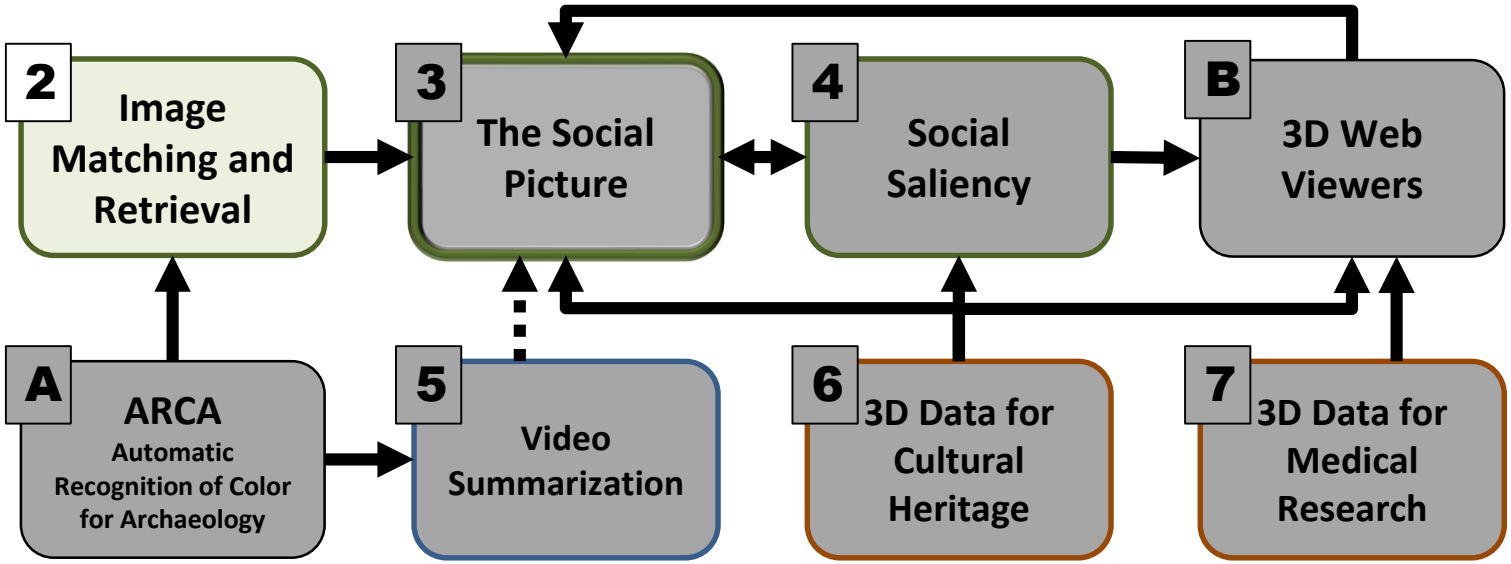


Image Matching and Retrieval

Datasets of images are usually browsed by means of queries based on tags, hash-tags or geodata (where present).

Queries can be even done using other images and looking for the most similar ones in the dataset. This procedure is called "Content Based Image Retrieval" (CBIR) and is based on Image Matching algorithms.

Content Based Image Retrieval (CBIR) has a consolidated workflow:

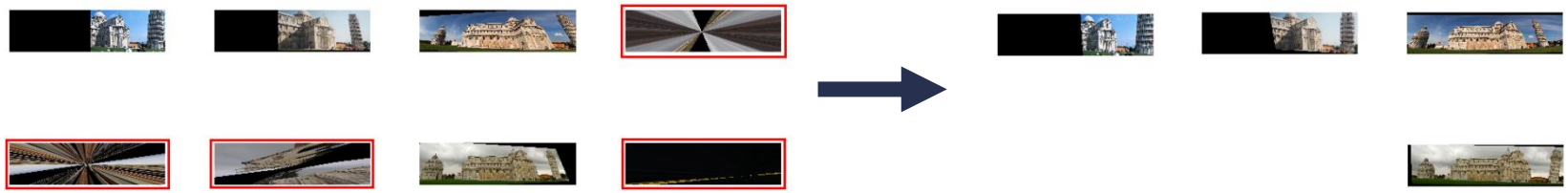
1. Keypoints Detection
2. Features extraction from detected keypoints (Descriptor definition)
3. Features matching
4. Geometric verification
5. Inliers extraction

[23] Rui et al., "Image retrieval: Current techniques, promising directions, and open issues" (1999)
[53] Mikolajczyk et al., "A comparison of affine region detectors" (2005)
[54] Mikolajczyk et al., "A performance evaluation of local descriptors" (2005)

Image Matching and Retrieval

Improvements to CBIR (1/3)

- **Back-Projection Verification**
  - Sometimes, geometric verification step of CBIR may fail to guarantee a good image transformation. Then, noise is introduced.
  - Query image is “warped” (deformed) applying the homography estimated by CBIR. Then, we compute Image matching between warped query image and the original query image. Warped query image is back-projected in the original query image. Using the same tolerance on inliers number chosen we check if back-projection is verified.

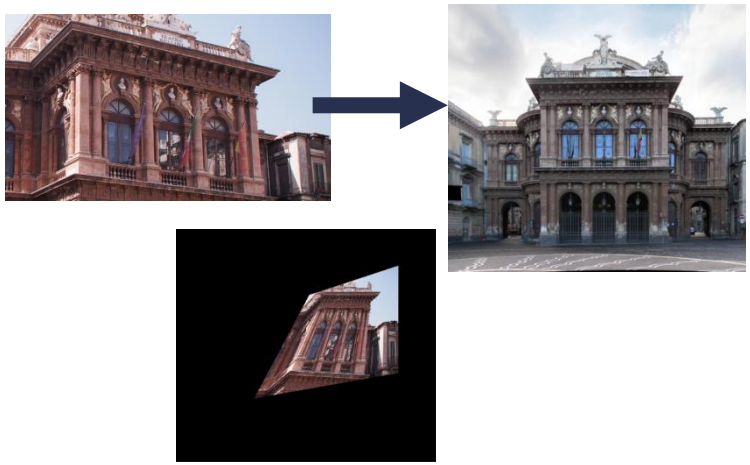


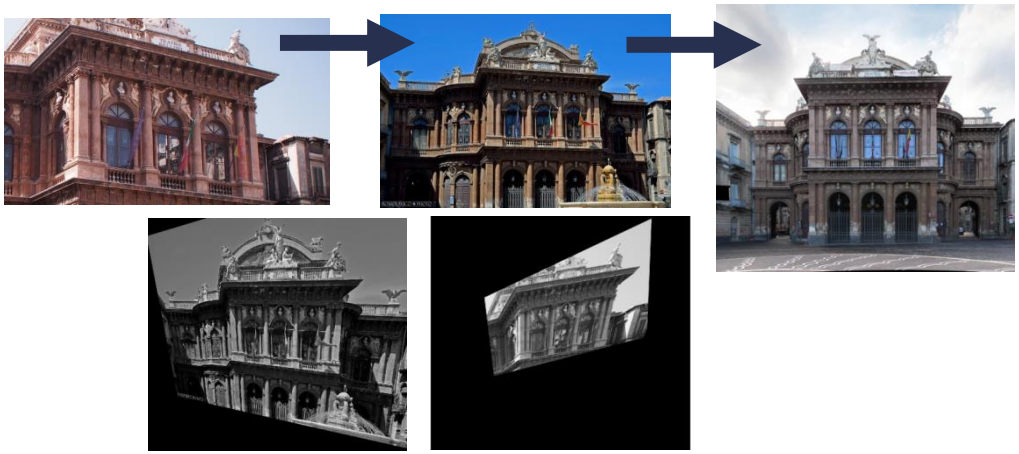
[27] Mikulık et al., “Efficient image detail mining” (2014)

Image Matching and Retrieval

Improvements to CBIR (2/3)

- **Query Expansion (Re-Query)**
  - A single step of Image Matching sometimes is not enough. It is possible to match two query images between themselves and then find the nested relationship for match the query image discarded in the first step of Image Matching.





[27] Mikulık et al., "Efficient image detail mining" (2014)
[69] Chum et al., "Total recall: Automatic query expansion with a generative feature model for object retrieval" (2007)

Image Matching and Retrieval

Improvements to CBIR (3/3)

- **Heatmap Computation**
  - When a reference image is chosen, then a heatmap of matched query images can be computed. The heatmap is updated with relation to query images processed with CBIR workflow and CDVS
  - Heatmap is a **valuable tool for data analysis and summarization** that has been implemented within our framework The Social Picture (TSP)

[69] Mikulık et al., "Image retrieval for online browsing in large image collections" (2013)
[27] Mikulık et al., "Efficient image detail mining" (2014)

Image Matching and Retrieval

Visual comparison between 4 CBIR methods

Reference Image

CDVS_BP-2

SURF-8

MSER-2

VLFeat-1

Image Matching and Retrieval

Visual comparison between 4 CBIR methods

Table 2.7: Heatmap computation performances comparison of tested methods, sorted by True Positive Rate (TPR), computational time and quality (as defined in Section 2.4).

Sorted by TPR (Decreasing order)				Sorted by Time (Increasing order)				Sorted by Quality (Decreasing order)			
TestID	TPR	Time	Quality	TestID	TPR	Time	Quality	TestID	TPR	Time	Quality
CDVS-2	82,19%	~11 h	★☆☆☆☆	*CDVS-6*	3,94%	~15'	★★★☆☆	*CDVS_BP-2*	47,73%	~18 h	★★★★★
CDVS-1	63,11%	~3.5 h	★☆☆☆☆	*CDVS-5*	3,94%	~20'	★★★☆☆	*SURF-8*	38,28%	~11 d	★★★★★
CDVS_BP-2	47,73%	~18 h	★★★★★	*CDVS-7*	3,51%	~20'	★★★☆☆	*SURF-7*	31,19%	~3 d	★★★★☆
CDVS-11	45,12%	~5 h	★☆☆☆☆	*CDVS-12*	1,70%	~20'	★☆☆☆☆	*SURF-6*	26,35%	~2 d	★★★★☆
SURF-8	38,28%	~11 d	★★★★★	*CDVS_BP-3*	2,54%	~20'	★★★★☆	*CDVS-13*	19,26%	~3 h	★★★★☆
SURF-7	31,19%	~3 d	★★★★☆	*CDVS-8*	3,51%	~25 m	★★☆☆☆	*CDVS_BP-3*	2,54%	~20'	★★★★☆
SURF-2	29,50%	~1 d	★★☆☆☆	*CDVS-10*	2,79%	~25'	★★★☆☆	*CDVS_BP-4*	28,47%	~4 h	★★★☆☆
CDVS_BP-4	28,47%	~4 h	★★★☆☆	*CDVS-9*	3,51%	~30'	★★☆☆☆	*SURF-1*	19,26%	~1 d	★★★☆☆
SURF-6	26,35%	~2 d	★★★★☆	*CDVS-3*	23,62%	~3 h	★☆☆☆☆	*SURF-3*	15,87%	~1 d	★★★☆☆
CDVS-4	25,44%	~4.5 h	★☆☆☆☆	*CDVS-13*	19,26%	~3 h	★★★★☆	*CDVS_BP-1*	12,05%	~3.5 h	★★★☆☆
CDVS-3	23,62%	~3 h	★☆☆☆☆	*CDVS_BP-1*	12,05%	~3.5 h	★★★☆☆	*MSER-2*	10,84%	~2 d	★★★☆☆
SURF-1	19,26%	~1 d	★★★☆☆	*CDVS-1*	63,11%	~3.5 h	★☆☆☆☆	*MSER-4*	10,84%	~2 d	★★★☆☆
CDVS-13	19,26%	~3 h	★★★★☆	*CDVS_BP-4*	28,47%	~4 h	★★★☆☆	*MSER-6*	10,72%	~2 d	★★★☆☆
SURF-3	15,87%	~1 d	★★★☆☆	*CDVS-4*	25,44%	~4.5 h	★☆☆☆☆	*SURF-5*	10,66%	~1 d	★★★☆☆
CDVS_BP-1	12,05%	~3.5 h	★★★☆☆	*CDVS-11*	45,12%	~5 h	★☆☆☆☆	*MSER-5*	10,30%	~2 d	★★★☆☆
MSER-1	11,57%	~2 d	★★☆☆☆	*CDVS-2*	82,19%	~11 h	★☆☆☆☆	*CDVS-5*	3,94%	~20'	★★★☆☆
SURF-4	11,51%	~1 d	★☆☆☆☆	*CDVS_BP-2*	47,73%	~18 h	★★★★★	*CDVS-6*	3,94%	~15'	★★★☆☆
VLFeat-1	11,21%	~1 d	★★☆☆☆	*SURF-2*	29,50%	~1 d	★★☆☆☆	*CDVS-7*	3,51%	~20'	★★★☆☆
MSER-2	10,84%	~2 d	★★★☆☆	*SURF-1*	19,26%	~1 d	★★★☆☆	*CDVS-10*	2,79%	~25'	★★★☆☆
MSER-4	10,84%	~2 d	★★★☆☆	*SURF-3*	15,87%	~1 d	★★★☆☆	*SURF-2*	29,50%	~1 d	★★☆☆☆
MSER-6	10,72%	~2 d	★★★☆☆	*SURF-4*	11,51%	~1 d	★☆☆☆☆	*MSER-1*	11,57%	~2 d	★★☆☆☆
SURF-5	10,66%	~1 d	★★★☆☆	*VLFeat-1*	11,21%	~1 d	★★☆☆☆	*VLFeat-1*	11,21%	~1 d	★★☆☆☆
MSER-5	10,30%	~2 d	★★★☆☆	*SURF-5*	10,66%	~1 d	★★★☆☆	*MSER-3*	9,63%	~2 d	★★☆☆☆
MSER-3	9,63%	~2 d	★★☆☆☆	*SURF-6*	26,35%	~2 d	★★★★☆	*CDVS-8*	3,51%	~25'	★★☆☆☆
CDVS-5	3,94%	~20'	★★★☆☆	*MSER-1*	11,57%	~2 d	★★☆☆☆	*CDVS-9*	3,51%	~30'	★★☆☆☆
CDVS-6	3,94%	~15'	★★★☆☆	*MSER-2*	10,84%	~2 d	★★★☆☆	*SURF-4*	11,51%	~1 d	★☆☆☆☆
CDVS-7	3,51%	~20'	★★★☆☆	*MSER-4*	10,84%	~2 d	★★★☆☆	*CDVS-2*	82,19%	~11 h	★☆☆☆☆
CDVS-8	3,51%	~25'	★★☆☆☆	*MSER-6*	10,72%	~2 d	★★★☆☆	*CDVS-1*	63,11%	~3.5 h	★☆☆☆☆
CDVS-9	3,51%	~30'	★★☆☆☆	*MSER-5*	10,30%	~2 d	★★★☆☆	*CDVS-11*	45,12%	~5 h	★☆☆☆☆
CDVS-10	2,79%	~25'	★★★☆☆	*MSER-3*	9,63%	~2 d	★★☆☆☆	*CDVS-4*	25,44%	~4.5 h	★☆☆☆☆
CDVS_BP-3	2,54%	~20'	★★★★☆	*SURF-7*	31,19%	~3 d	★★★★☆	*CDVS-3*	23,62%	~3 h	★☆☆☆☆
CDVS-12	1,70%	~20'	★☆☆☆☆	*SURF-8*	38,28%	~11 d	★★★★★	*CDVS-12*	1,70%	~20'	★☆☆☆☆

Reference Image

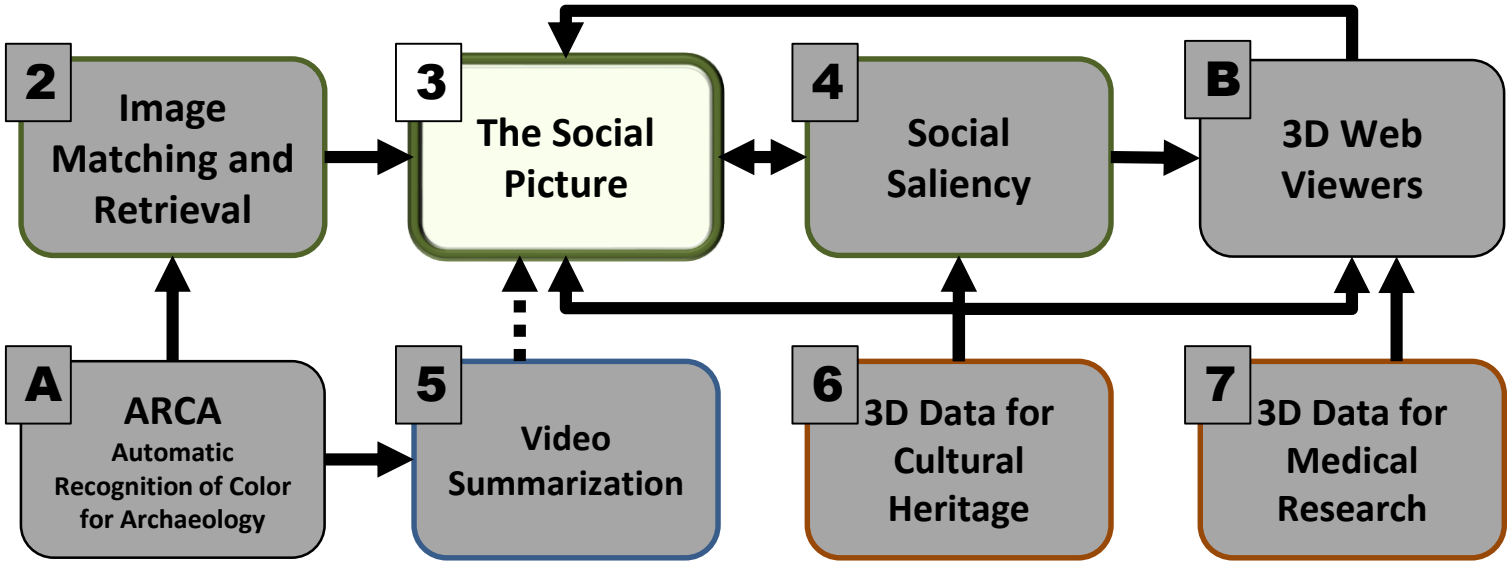
CDVS-2

CDVS-6

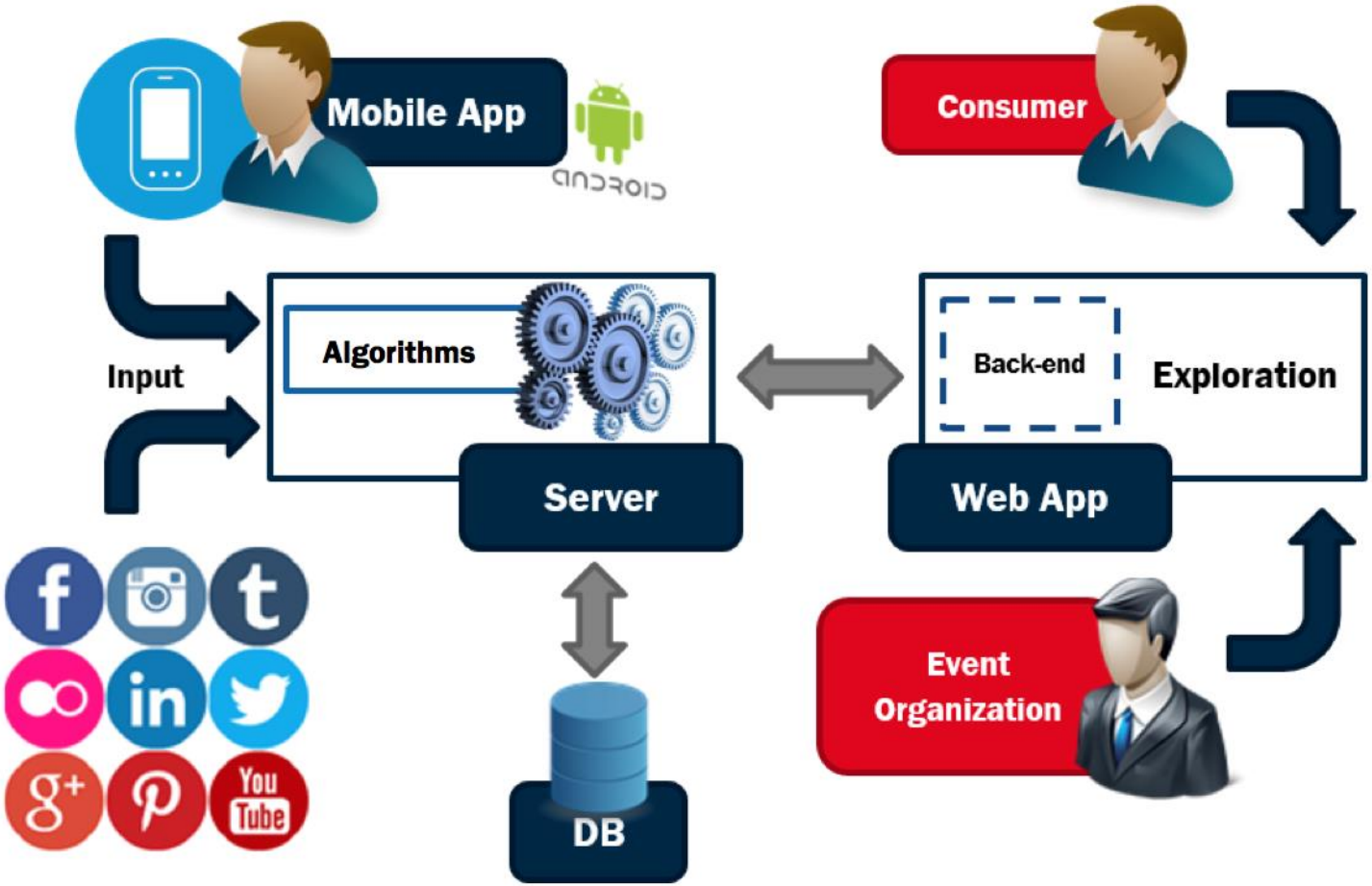
CDVS_BP-2

Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

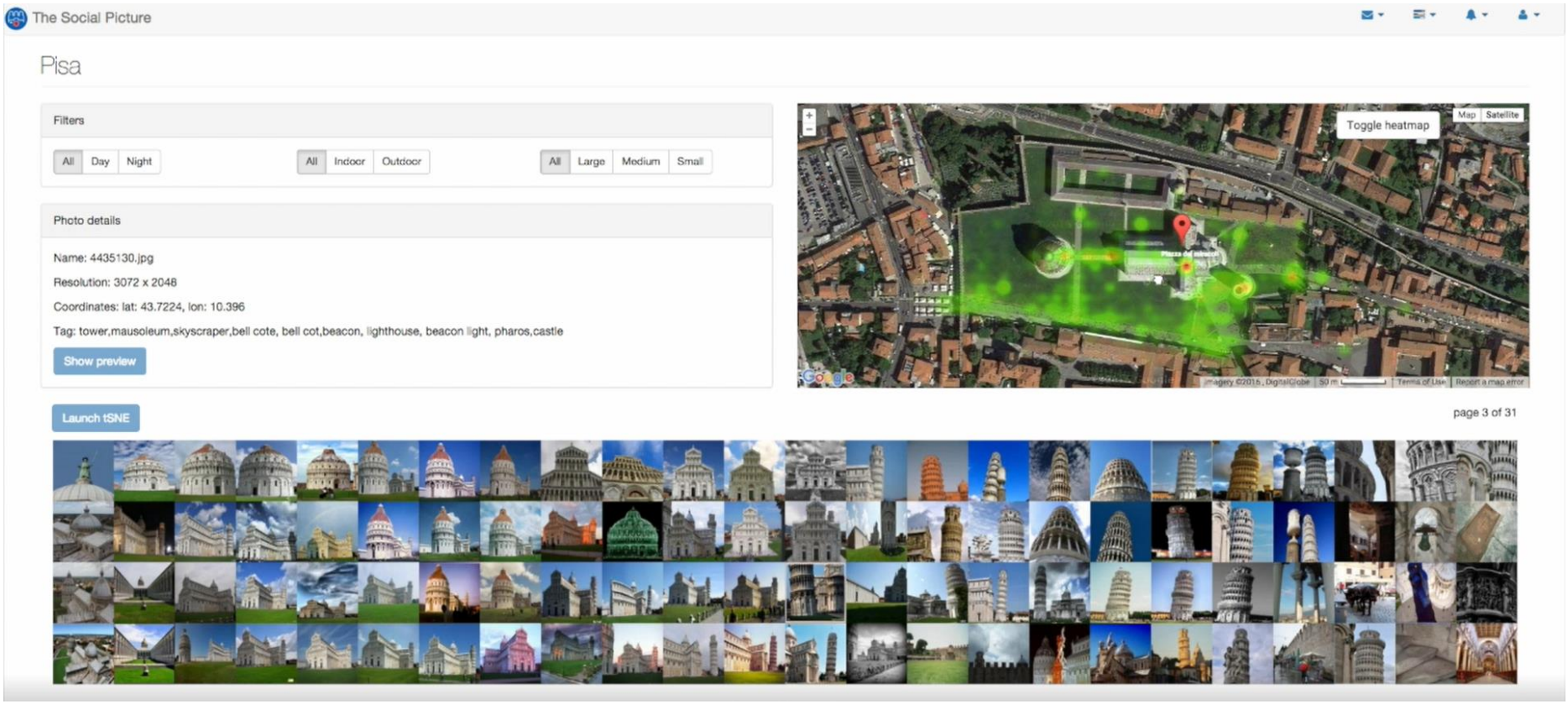
Slideshow Structure



The Social Picture (TSP) Architecture



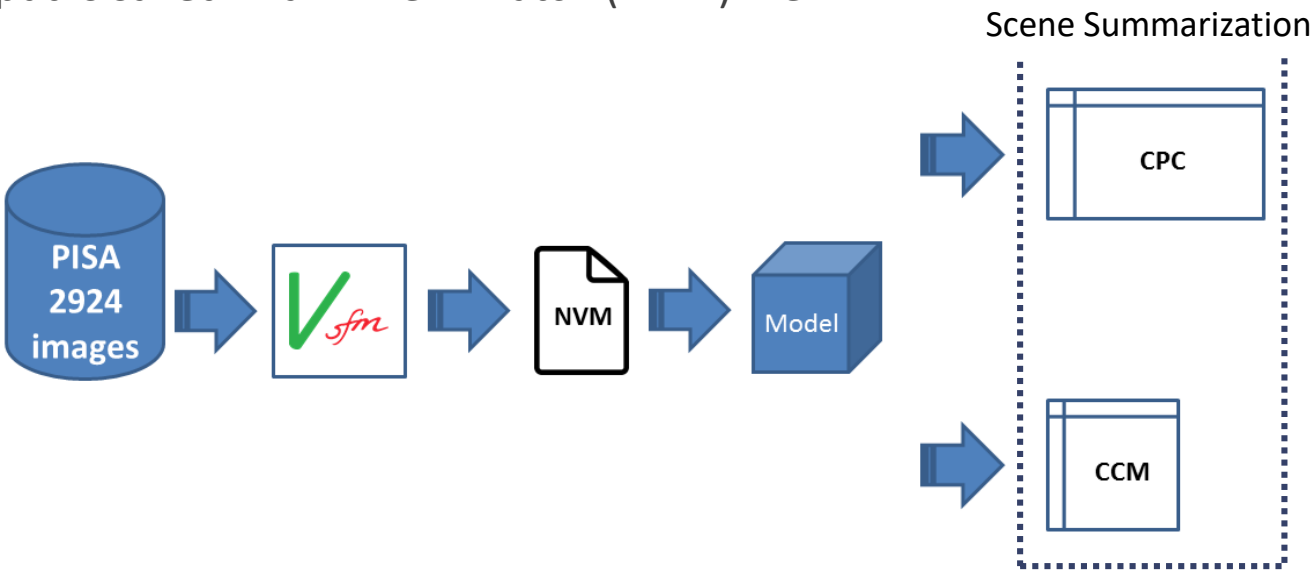
TSP Overview of a Collection



VSFM integration and Model definition

VSFM is a powerful tool of 3D reconstruction from a set of images, exploiting Structure from Motion (SfM)

- VSFM performs a linear-time incremental SfM method
- VSFM extracts visual features and computes 3D reconstruction
- Output is saved in a N-View Match (NVM) file

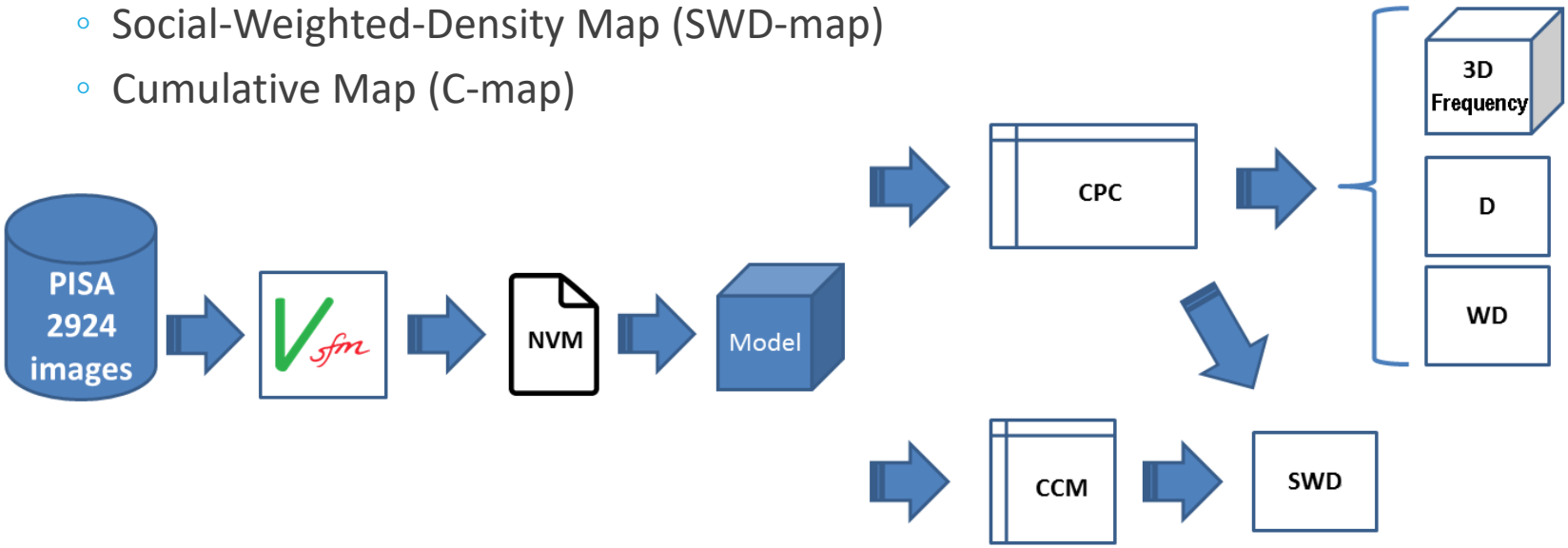


[4] Wu, "Towards linear-time incremental structure from motion" (2013)
[82] Simon et al., "Scene summarization for online image collections" (2007)

Feature Density Maps

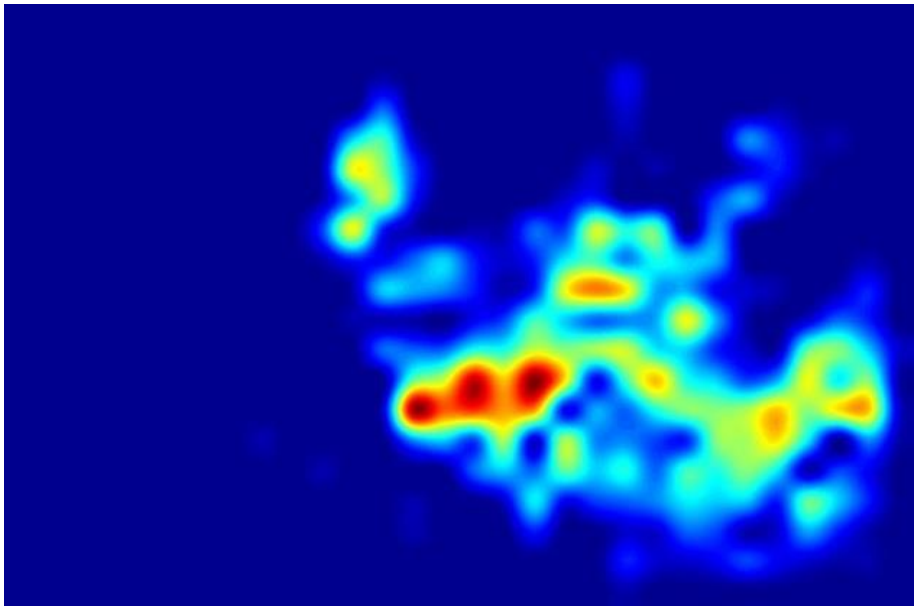
Exploiting *CPC* matrix we can select all the points used as features by a given camera. Through theModel, which is parsed from NVM file, we also know the position of features in the image. Given the positions of visual features, we can define several kinds of maps

- Density Map (D-map)
- Weighted-Density Map (WD-map)
- Social-Weighted-Density Map (SWD-map)
- Cumulative Map (C-map)



Density Map (D-map)

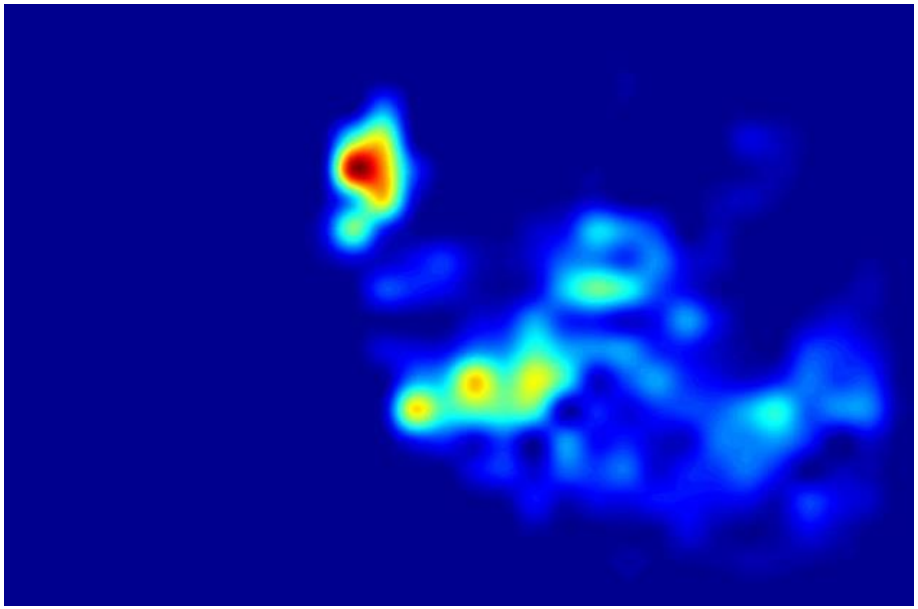
Visual feature density is obtained quantizing the 2D space of the image and counting how many features are contained in each quantized interval



Weigthed-Density Map (WD-map)

D-maps can be further refined taking into account a weight for each visual feature.

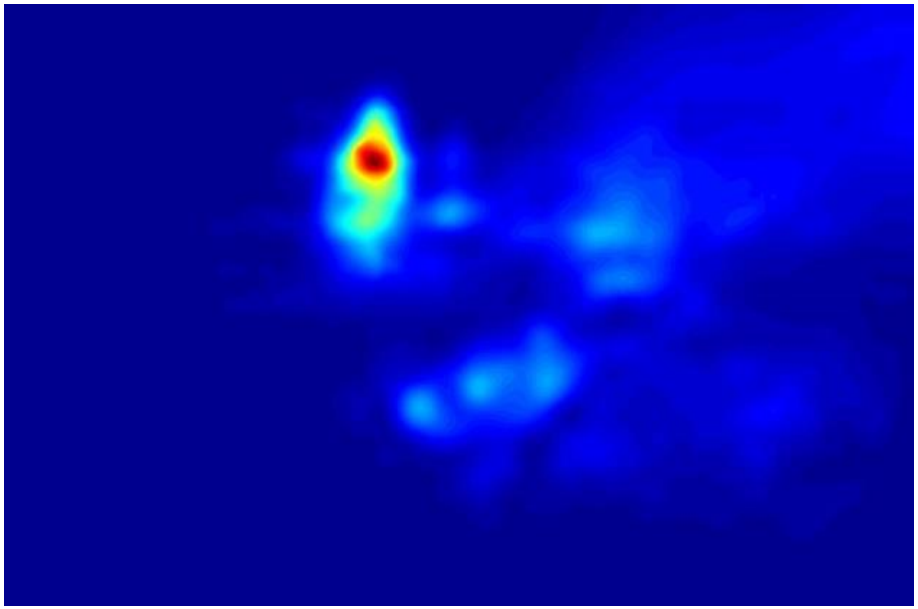
Weight is equal to the feature-frequency, as computed through the column-wise sum from *CPC* matrix.



Social-Weigthed-Density Map (SWD-map)

We estimate the perspective transformation *T* between matching images. All the WD-maps of matching images, transformed with their own *T*, are summed to the WD-map of the reference image

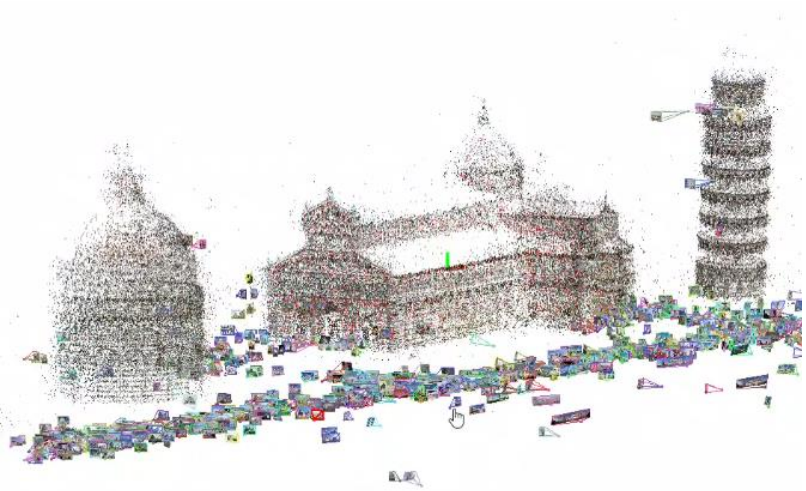
The rationale behind the computation of SWD-maps is that images similar to a reference one might contain information that is not present in the reference image



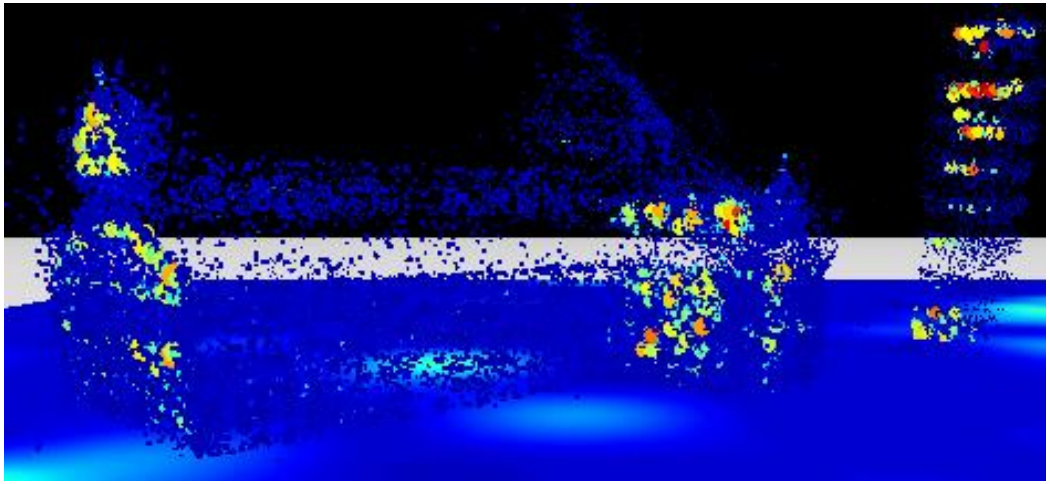
3D-points Frequency Representation

The column-wise sum of *CPC* gives as result how many times each point has been viewed by cameras

This “frequency of been viewed by a camera” can be used in place of the *color vertex* in the 3D representation

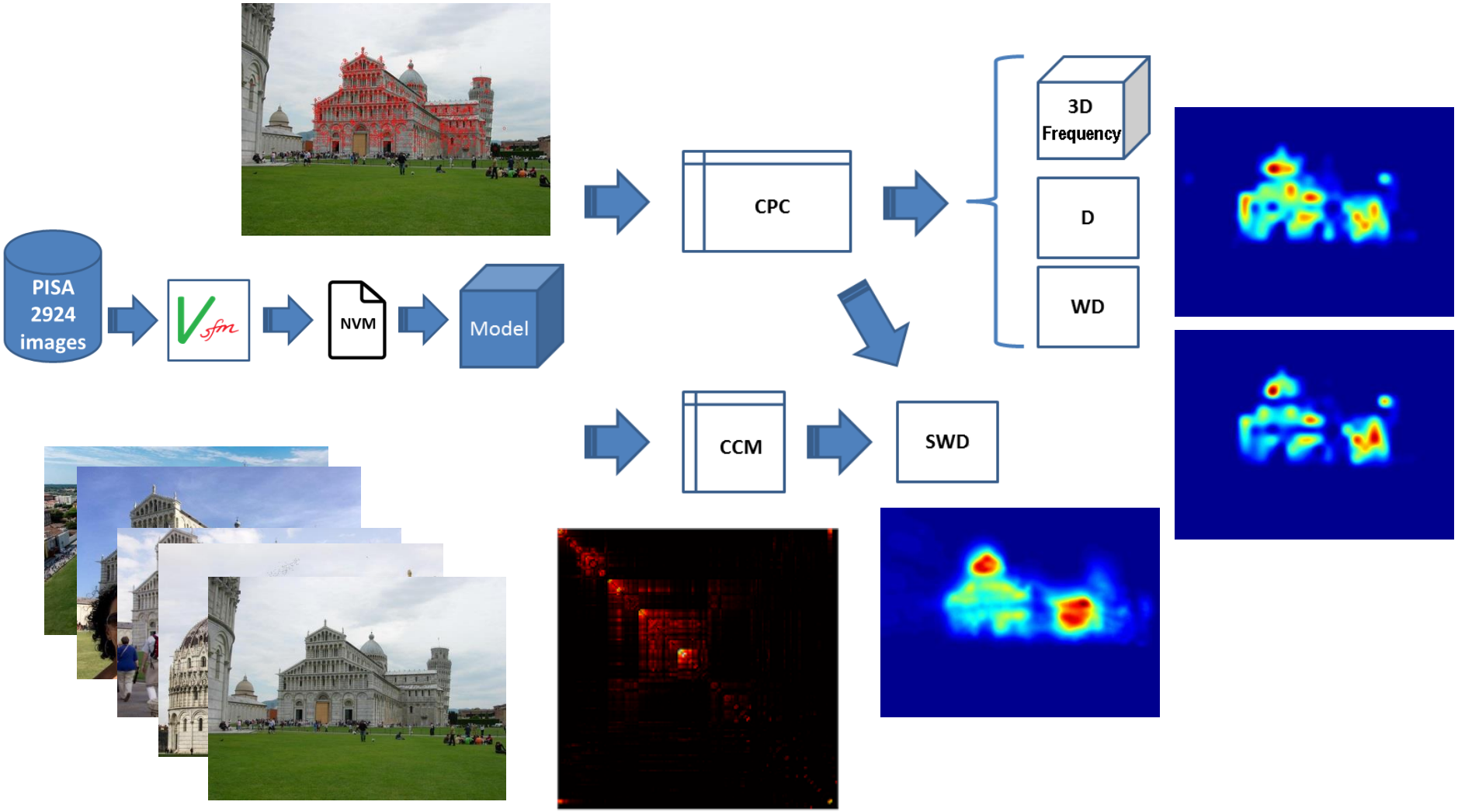


3D Reconstruction with VSFM

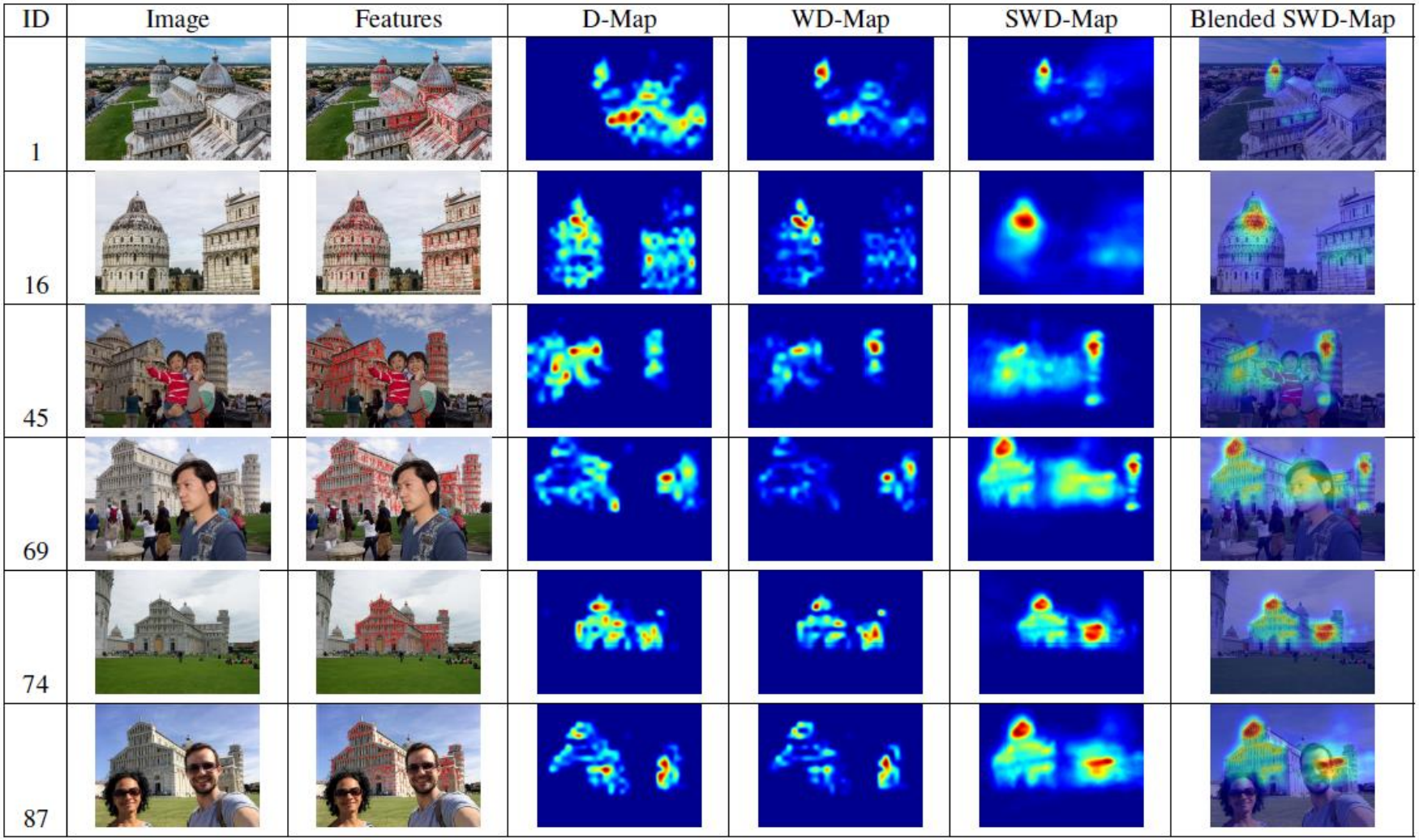


3D Reconstruction + Features weights

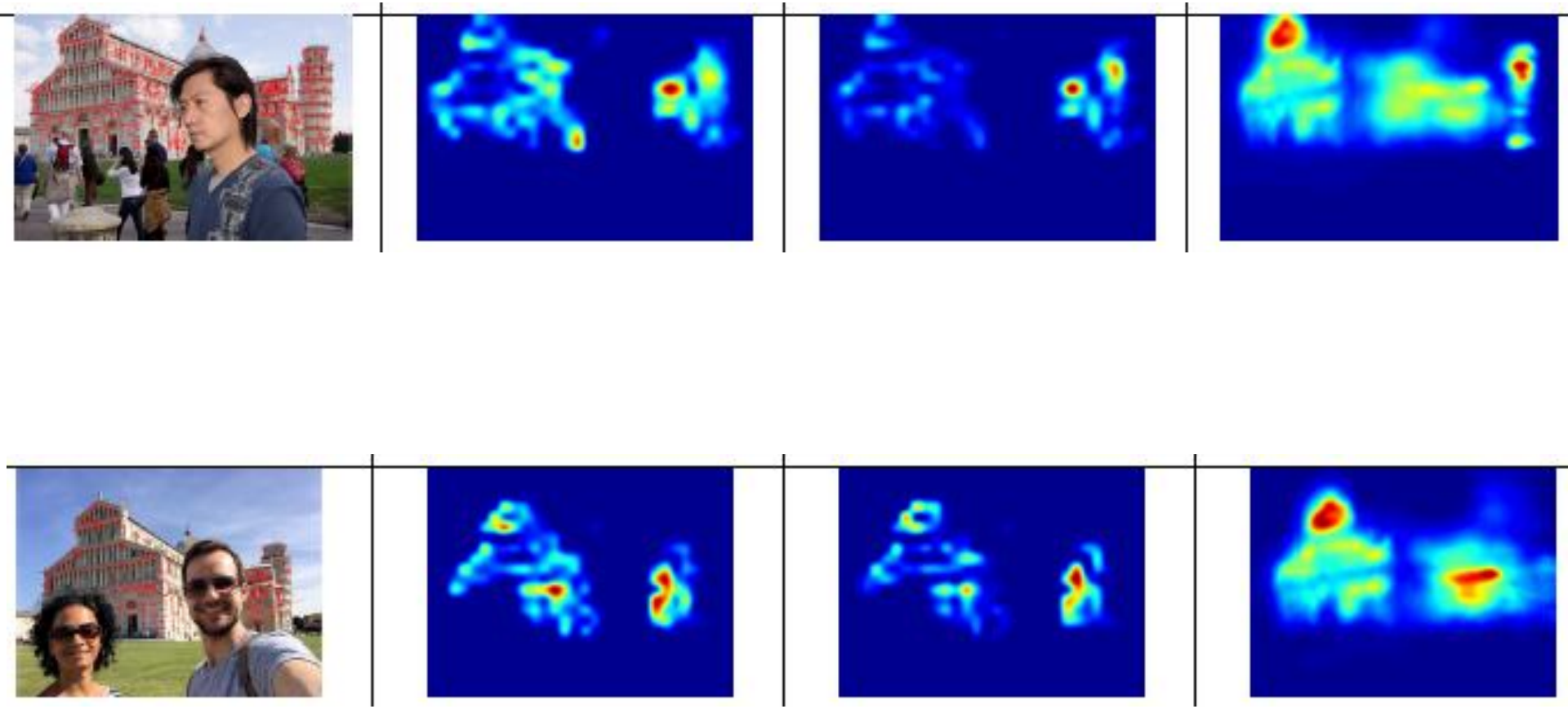
Recap



Feature Density Maps – Examples



Feature Density Maps – Occlusion

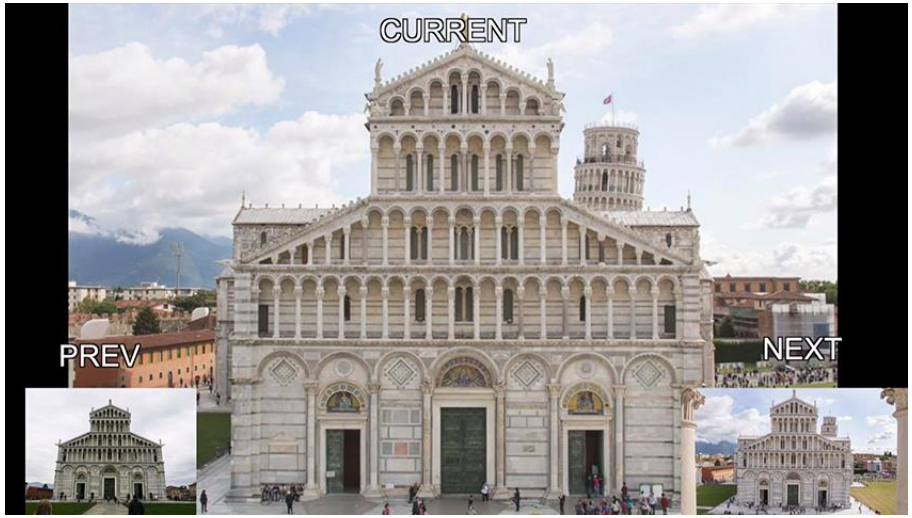


Scene Summarization

We compute a **score** for each node (camera) in *MST*

- Score = sum of adjacent edge-weights
  - Row-wise sum of *CCM*

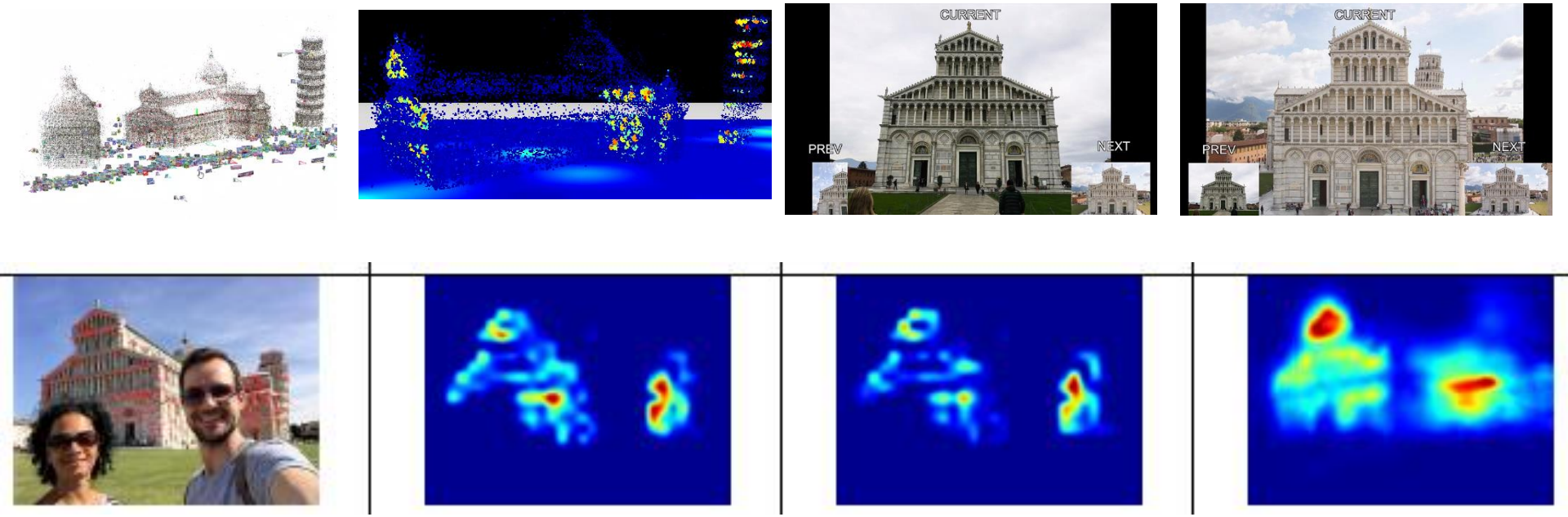
We performed a DFS graph traversal on MST, using the node with the highest score as starting node



[82] Simon et al., "Scene summarization for online image collections" (2007)
[83] Kim et al., "Joint summarization of large-scale collections of web images and videos for storyline reconstruction" (2014)

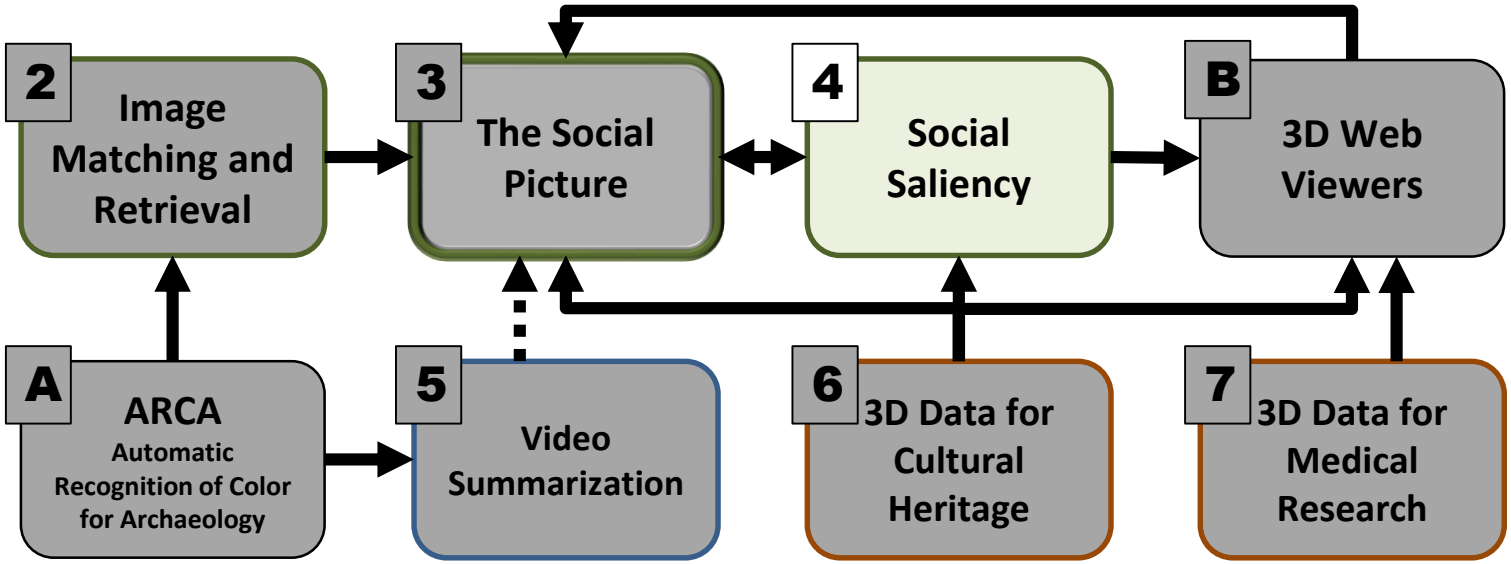
TSP – Conclusion

Using VSFM and its 3D reconstruction, we defined new features added to TSP, such as the **3D-points frequency**, and presented two advanced Image Analysis applications: **Scene Summarization (SS)** and **Feature density-maps**

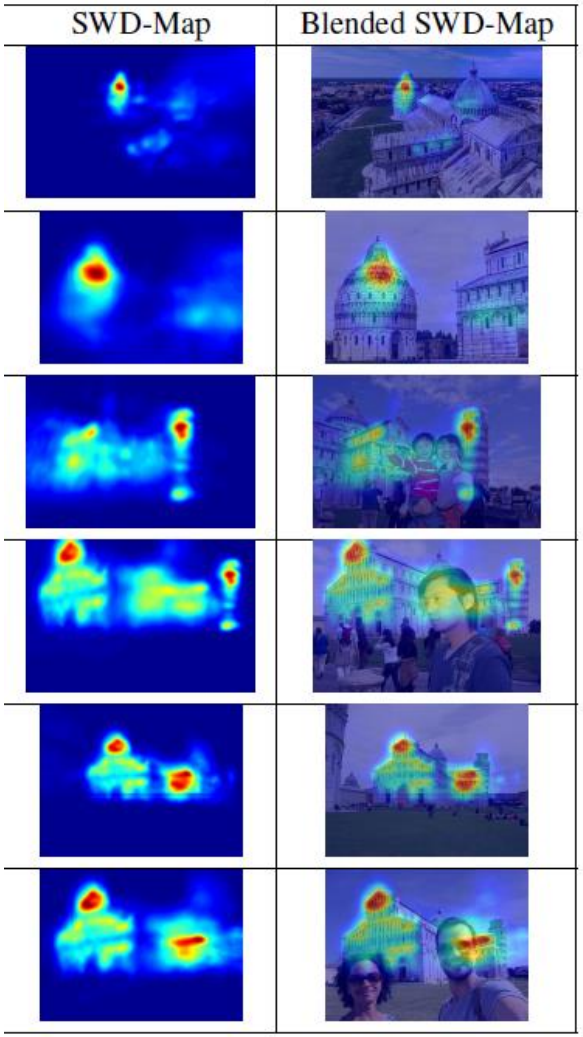


Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

Slideshow Structure



Social Saliency



Definition of saliency:

spatial regions in the visual field that attract attention

Social saliency, intended as a saliency estimated from a social point-of-view, represents a novel definition of saliency.

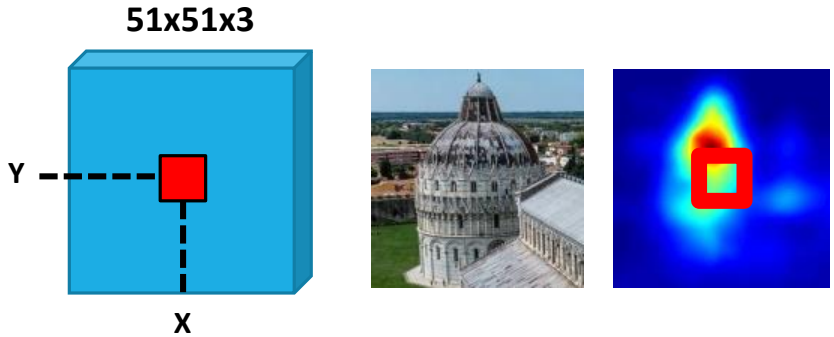
Similar concept of saliency are defined as ***co-saliency***, ***multi-camera saliency*** or ***likelihood of joint attention***.

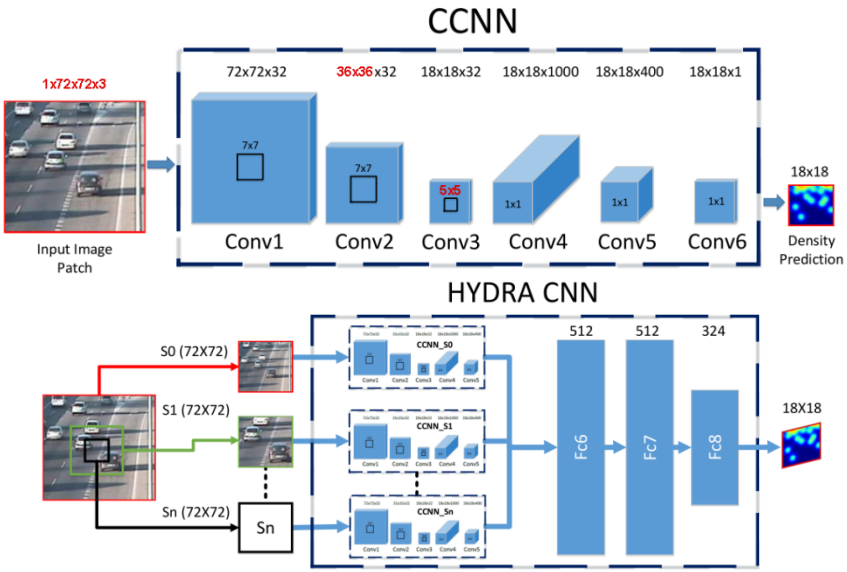
[14] K. Duncan and S. Sarkar, "Saliency in images and video: a brief survey". In: IET Computer Vision 6.6 (2012), pp. 514-523
[86] Zhang et al., "Co-saliency detection via looking deep and wide" (2015)
[87] Zhang et al., "A self-paced multiple-instance learning framework for co-saliency detection" (2015)
[88] Luo et al., "Multi-camera saliency" (2015)
[90] Soo Park et al., "Social saliency prediction" (2015)

Social Saliency

We tested two methods to learn saliency models: one is based on **Support Vector Regression (*SVR*)** and the other one on a **Counting Convolutional Neural Network (*C-CNN*)** named ***Hydra C-CNN***. We compared results of linear and non-linear SVR with the ones obtained by Hydra.

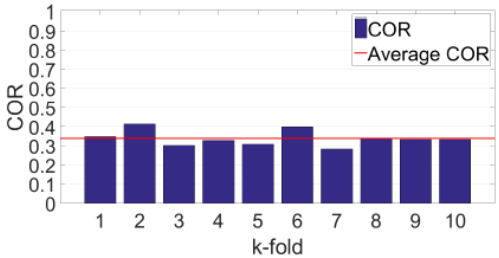
SVR



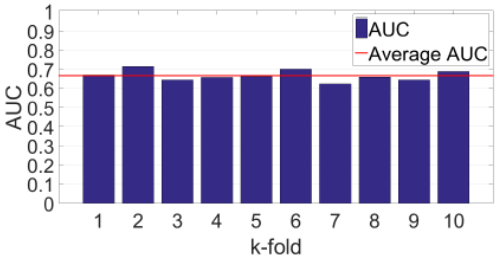


[92] Onoro-Rubio et al., "Towards perspective-free object counting with deep learning" (2007)

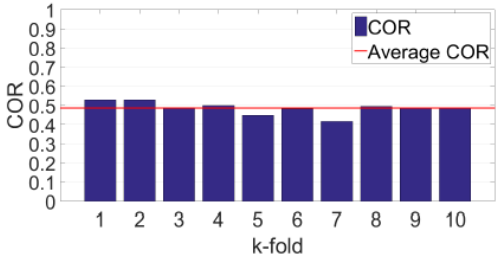
Social Saliency – Experimental Results



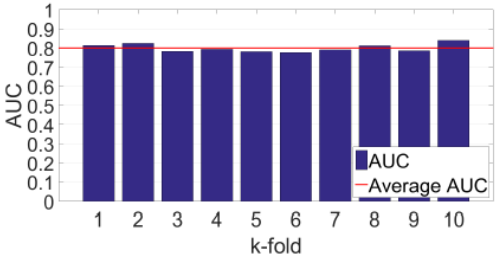
(a) COR - SVR Linear



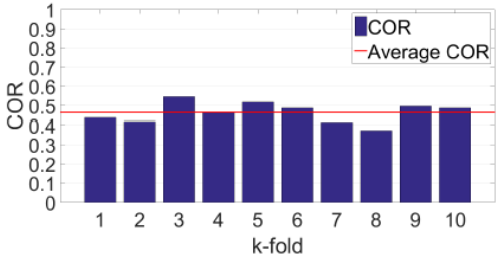
(b) AUC - SVR Linear



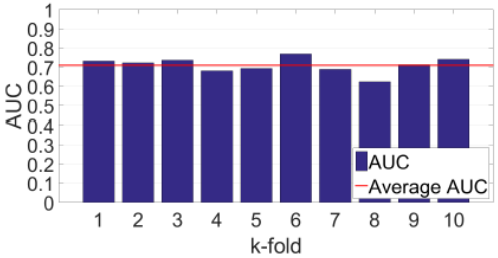
(c) COR - SVR Gaussian



(d) AUC - SVR Gaussian



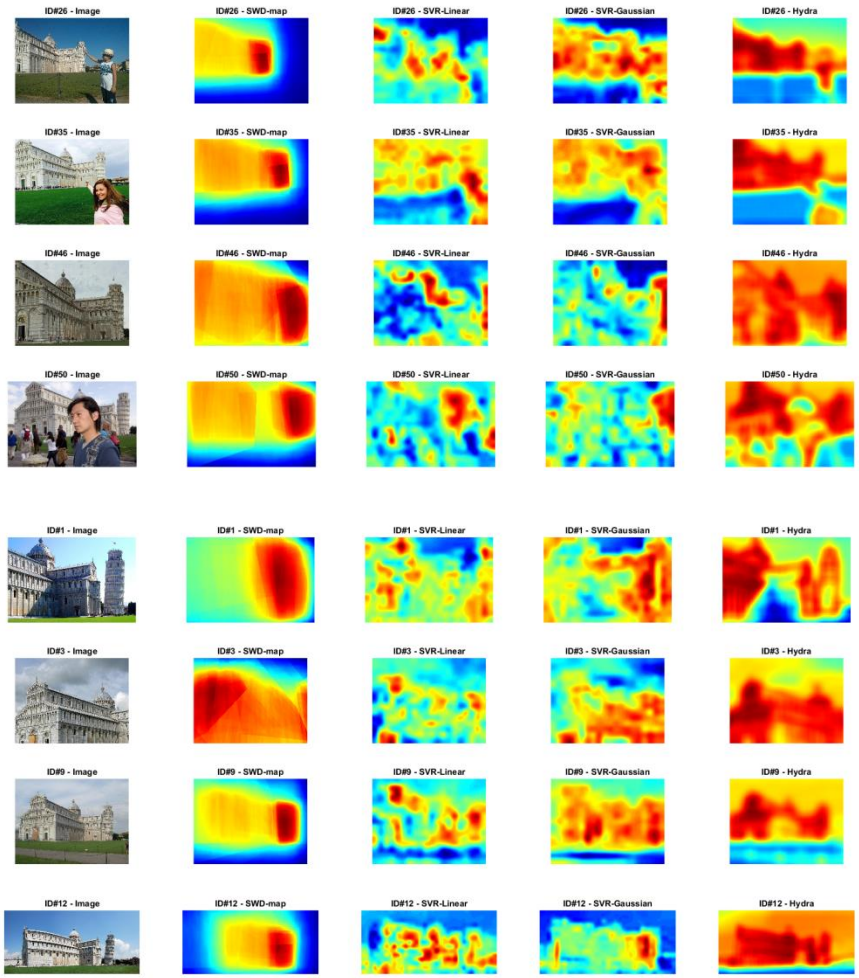
(e) COR - Hydra

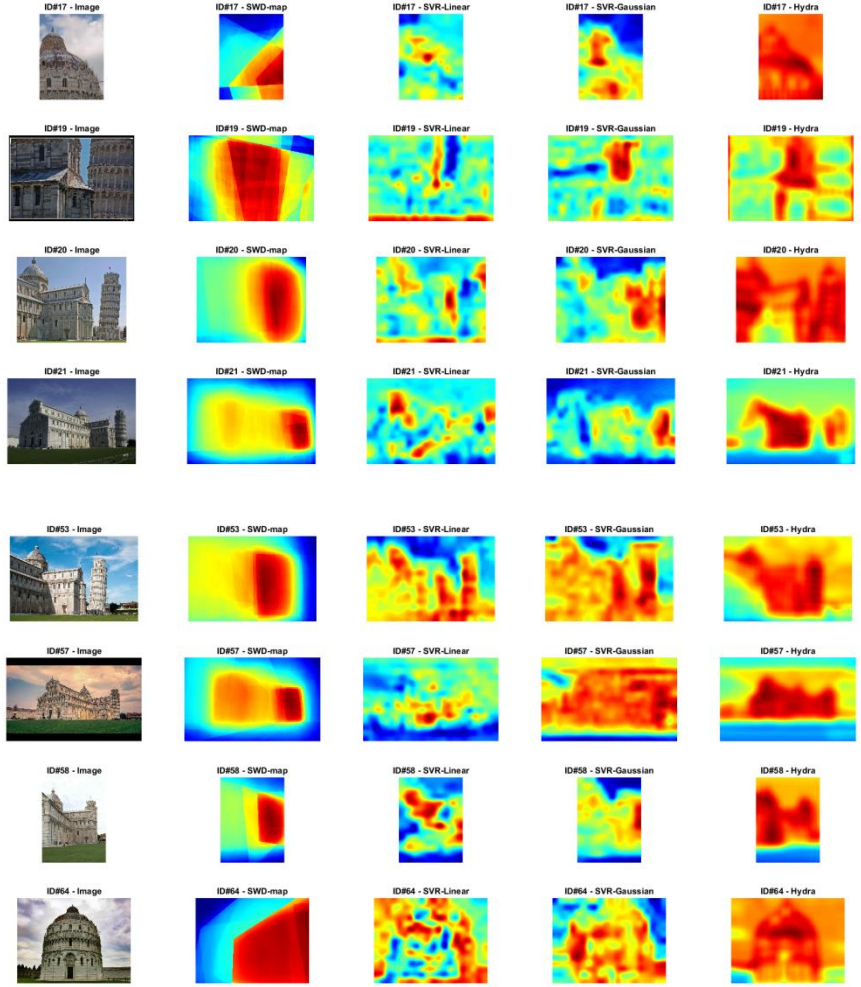


(f) AUC - Hydra

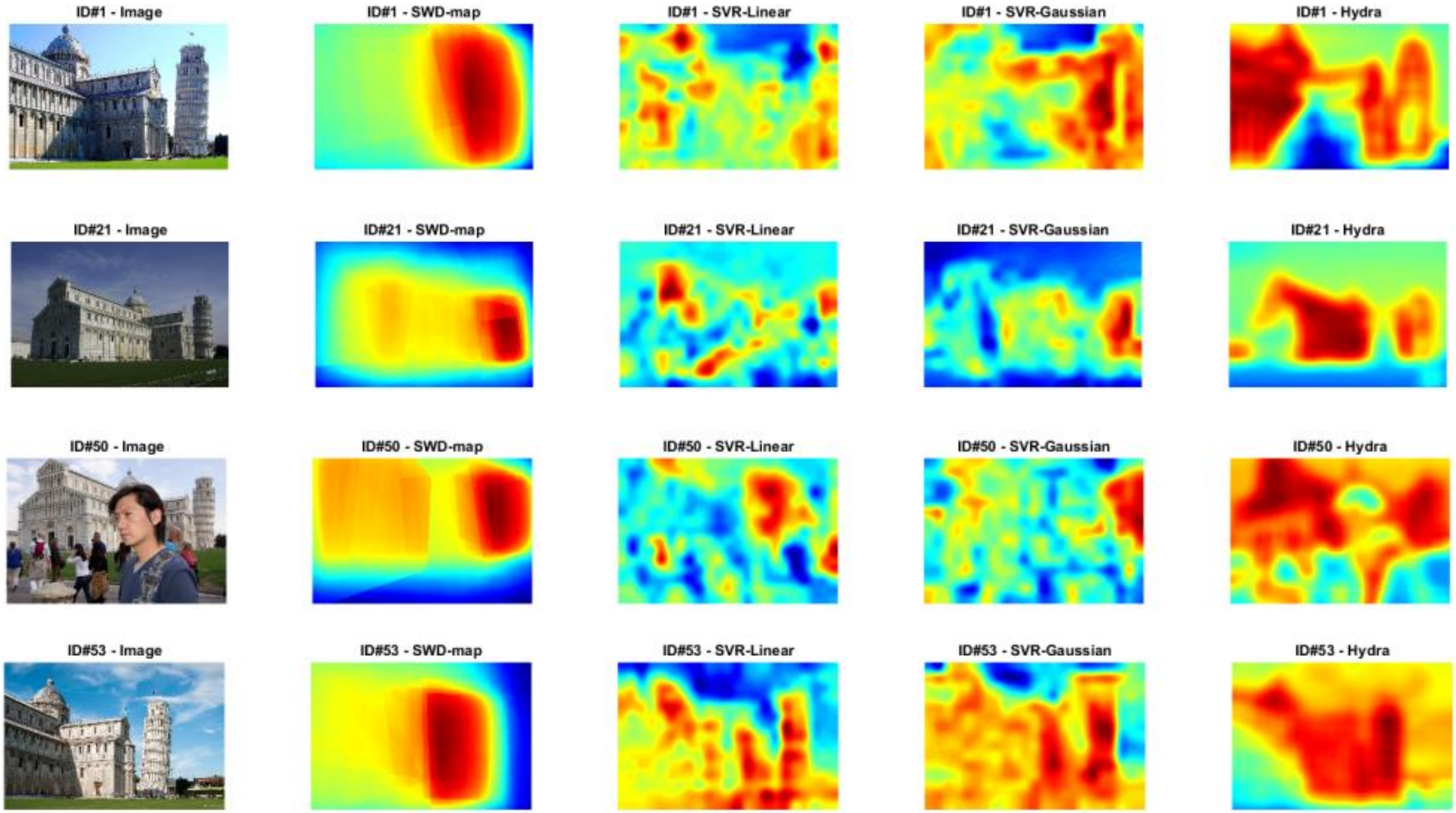
[121] Website: mit saliency benchmark. ***http://saliency.mit.edu/home.html***

Social Saliency – Experimental Results





Social Saliency – Experimental Results



Part 1 – Images

Publications

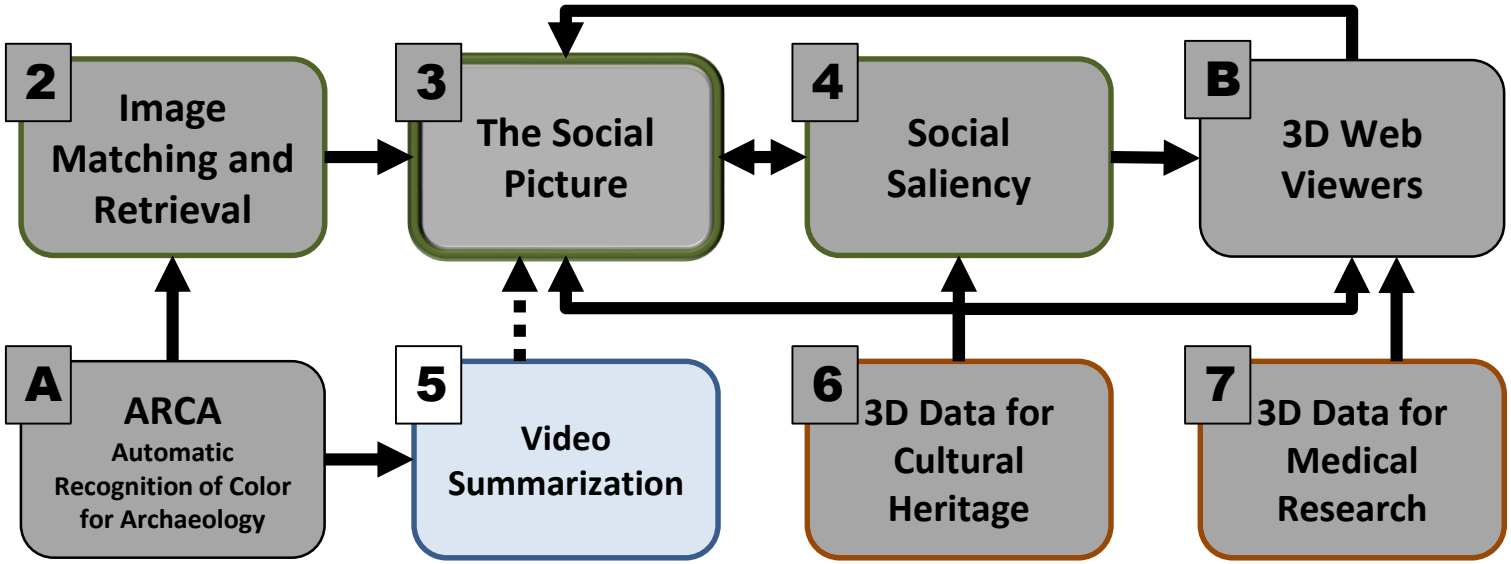
- S. Battiato, G.M. Farinella, F.L.M. Milotta, A. Ortis, L. Addesso, A. Casella, V. D'Amico, and G. Torrisi. "The Social Picture". In: **Proceedings of the 2016 ACM on International Conference on Multimedia Retrieval. ACM**. 2016, pp. 397–400.

- F.L.M. Milotta, M. Bellocchi, and S. Battiato. "The Social Picture: Advanced Image Analysis Applications". In: **STAG: Smart Tools and Applications in Graphics (2017)**.

PART 2 – VIDEOS

Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

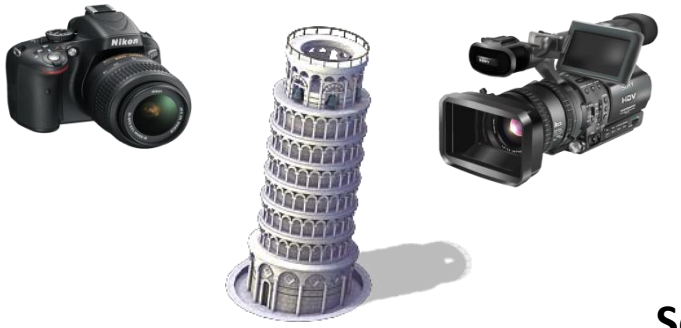
Slideshow Structure



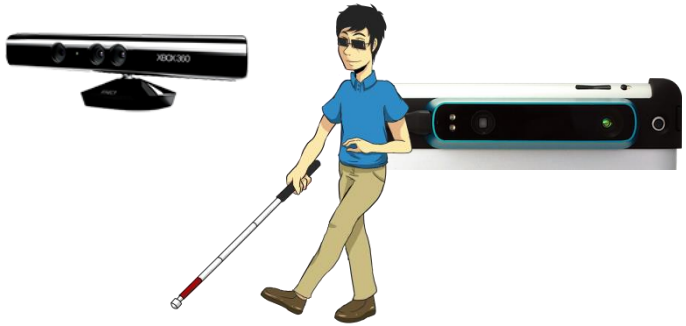
Motivations

The automatic processing of video data from many devices, as smartphones, tablets, webcams, surveillance cameras, etc., in the real-time context is not a trivial issue

Cultural Heritage



Assistive Technology



Social Media

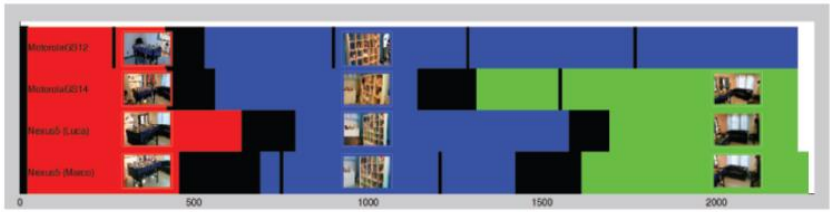
Main Aims and Challenges

- Analysis of video streams from multi-source multi-device context
  - **Different acquisition formats**

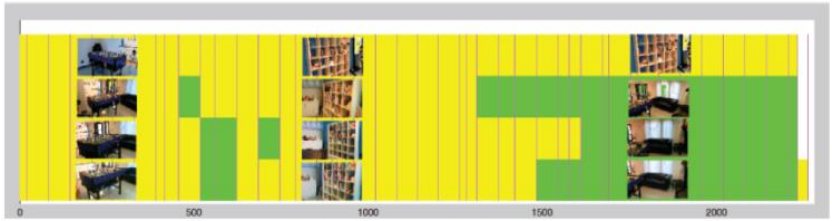
- Identification of the **scenes of interest** through clustering of video sequences
  - **Different point-of-views from the many users**

- Time tracking of the computed scenes clusters
  - **Synchronization is needed**

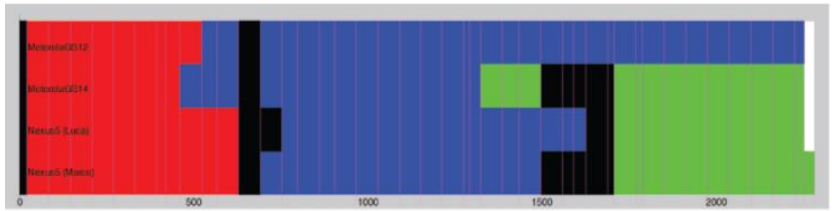
Three kinds of classification



(a) Intraflow Analysis



(b) Interflow Analysis



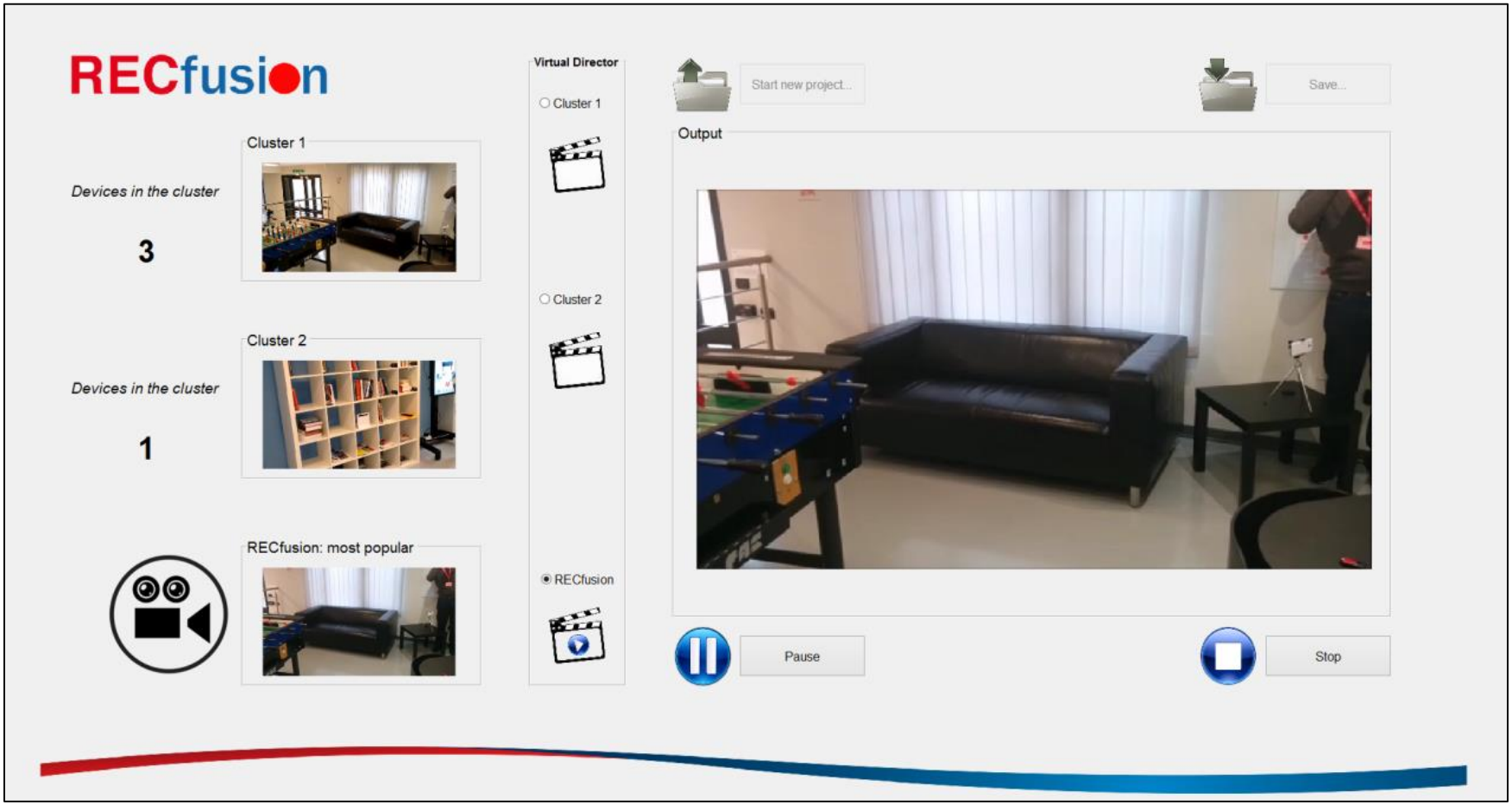
(c) Cluster Tracking

Table 5.2: Validation Results of Popularity Estimation.

Scenario	Devices	Models	P_a/P_r	P_g/P_r
Foosball	4	2	1.02	1
Meeting	2	2	1.01	0.99
Meeting	4	4	0.99	0.95
Meeting	5	5	0.89	0.76
SAgata	7	6	1.05	1
Magician	6	6	0.73	0.73
Concert [150]	3	1	1.06	1
Lecture [150]	3	1	1.05	0.86
Seminar [150]	3	1	0.62	0.62

[150] Hoshen et al., "Wisdom of the crowd in egocentric video curation" (2014)

RECfusion – Conclusion



Part 2 – Videos

Publications

- F.L.M. Milotta, S. Battiato, F. Stanco, V. D'Amico, G. Torrisi, and L. Addesso. "RECfusion: Automatic Scene Clustering and Tracking in Video from Multiple Sources". **In: EI – Mobile Devices and Multimedia: Enabling Technologies, Algorithms, and Applications.** 2016.

- S. Battiato, G.M. Farinella, F.L.M. Milotta, A. Ortis, F. Stanco, V. D'Amico, L. Addesso, and G. Torrisi. "Organizing Videos Streams for Clustering and Estimation of Popular Scense". **In: 19th International Conference on Image Analysis and Processing (ICIAP 2017)**.

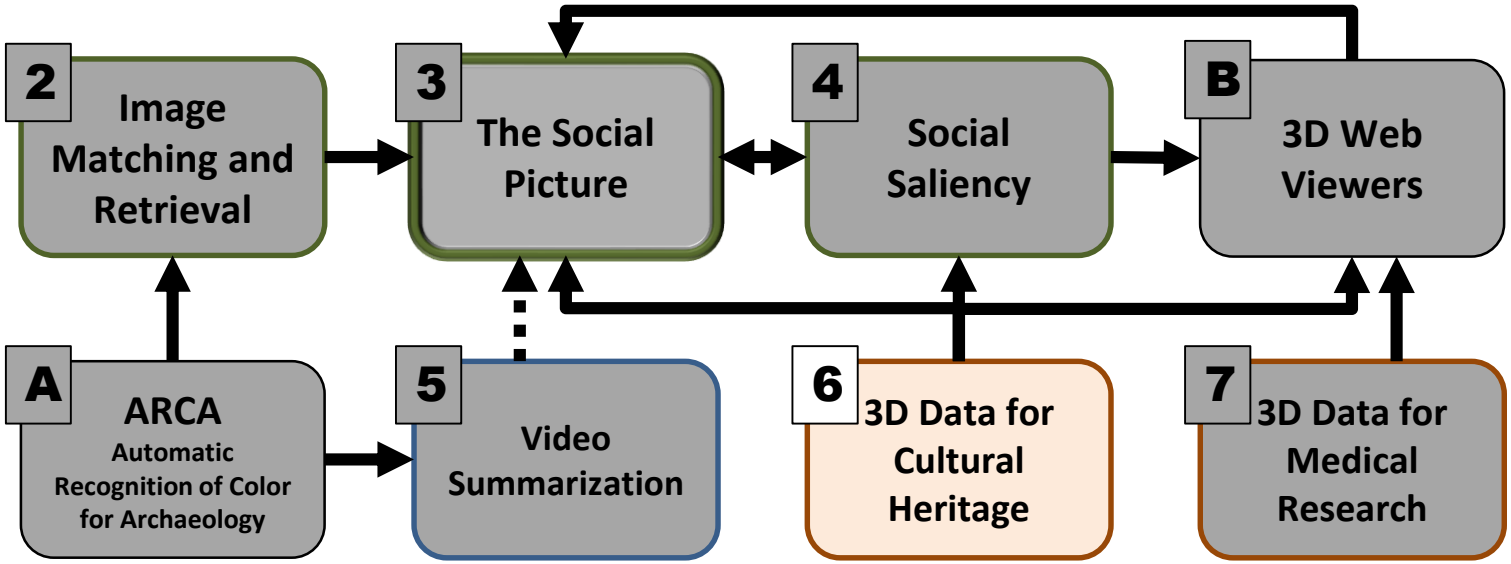
PART 3 – 3D DATA

Case Studies:

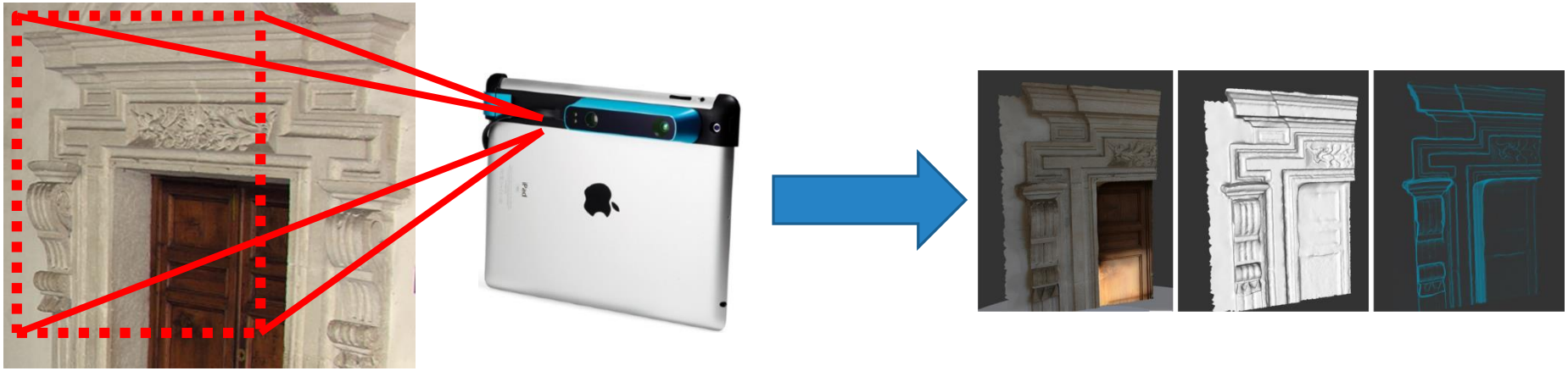
1. Doorway of the Monastery of Benedettini in Catania
2. Morgantina Silver Treasure
3. Kourous of Leontinoi

Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

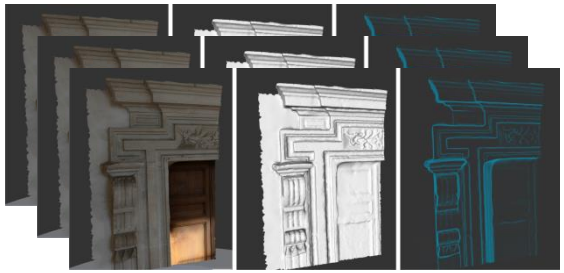
Slideshow Structure



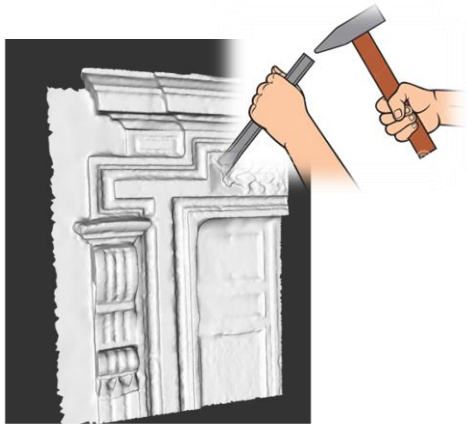
Motivation: Cultural Heritage Preservation



Multiple Digital Copies

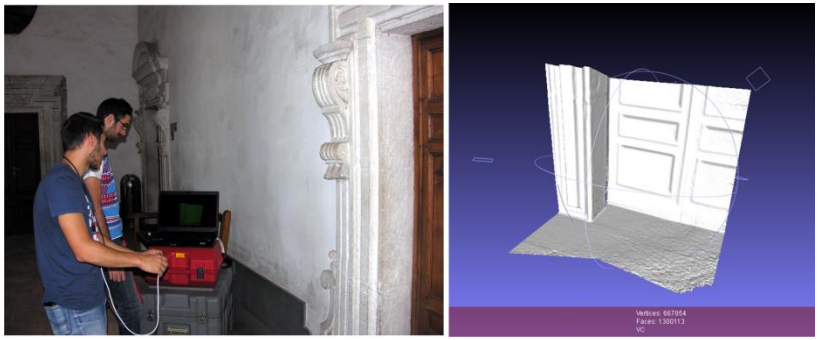


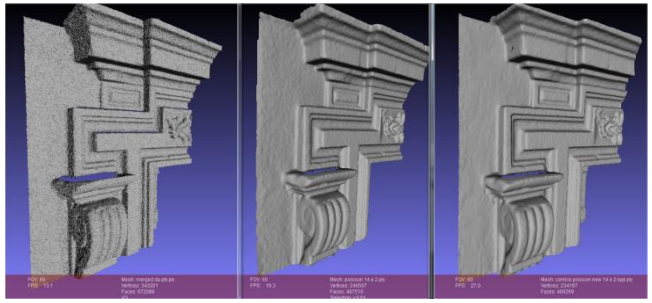
Digital Restoration

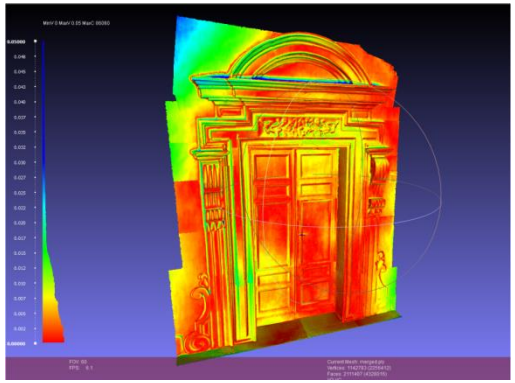


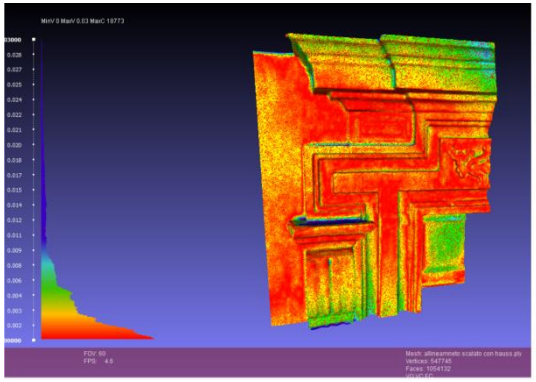
Catalogue and Archive
(monitoring purposes, …)

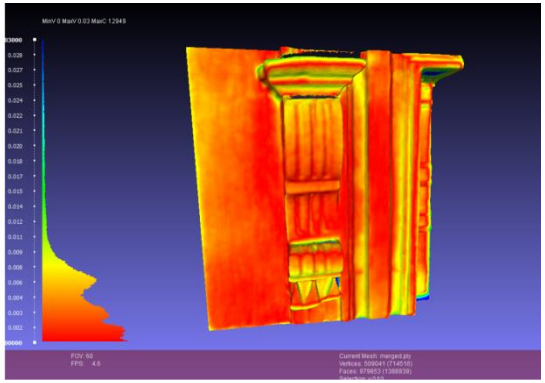
3D Scan of CH – Benedettini's Door



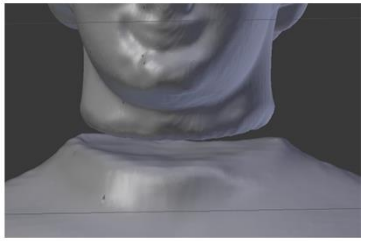


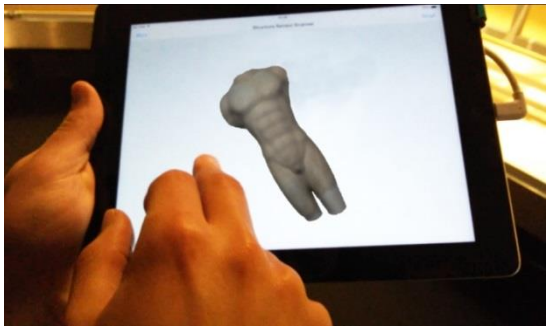




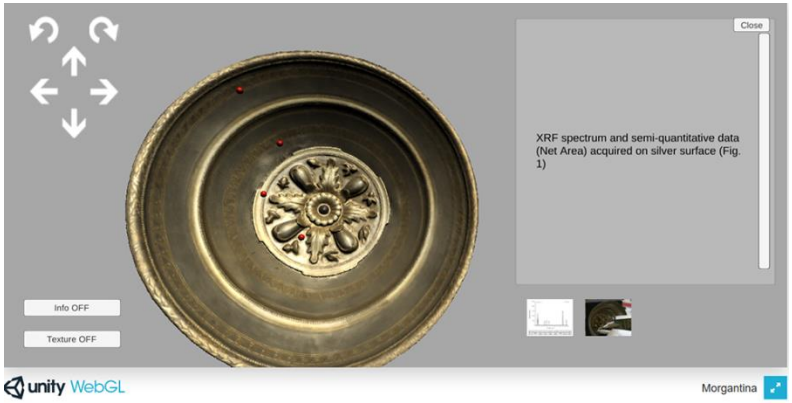


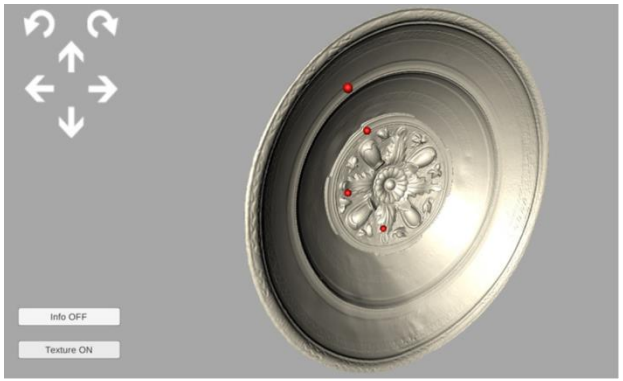
3D Scan of CH - Kouros





Morgantina silver treasure





Part 3 – 3D Data

Cultural Heritage – Publications

- M.F. Alberghina, F. Alberghina, D. Allegra, F. Di Paola, L. Maniscalco, F.L.M. Milotta, S. Schiavone, and F. Stanco. "Archaeometric characterization and 3D survey: new perspectives for monitoring and valorization of Morgantina silver Treasure (Sicily)". **In: 1st International Conference on Metrology for Archaeology** (2015).
- D. Allegra, E. Ciliberto, P. Ciliberto, F.L.M. Milotta, G. Petrillo, F. Stanco, and C. Trombatore. "Virtual unrolling using x-ray computed tomography". **In: Signal Processing Conference (EUSIPCO), 2015.** 23rd European. IEEE. 2015, pp. 2864–2868.
- D. Allegra, G. Gallo, L. Inzerillo, M. Lombardo, F.L.M. Milotta, C. Santagati, and F. Stanco. "Low cost handheld 3D scanning for architectural elements acquisition". **In: Proceedings of the Conference on Smart Tools and Applications in Computer Graphics**. Eurographics Association. 2016, pp. 127–131.
- F. Stanco, D. Tanasi, D. Allegra, and F.L.M. Milotta. "3D digital imaging for knowledge dissemination of Greek archaic statuary". **In: Proceedings of the Conference on Smart Tools and Applications in Computer Graphics.** Eurographics Association. 2016, pp. 133–141.

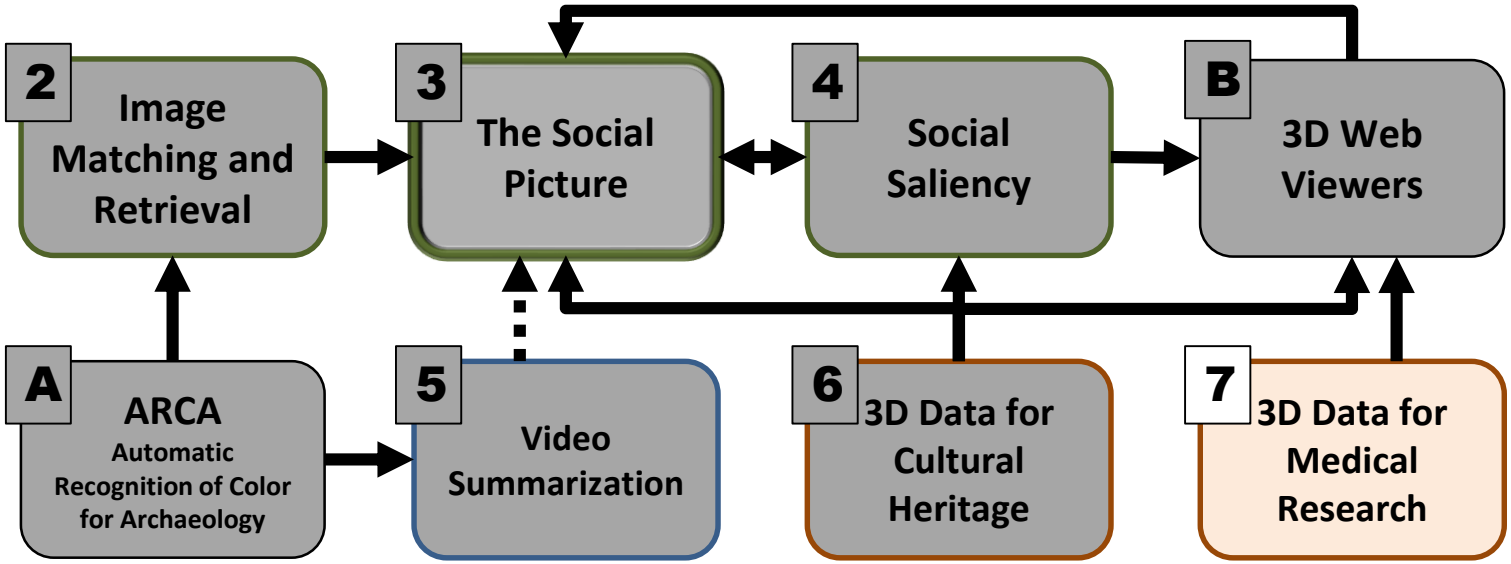
Part 3 – 3D Data

Cultural Heritage – Publications

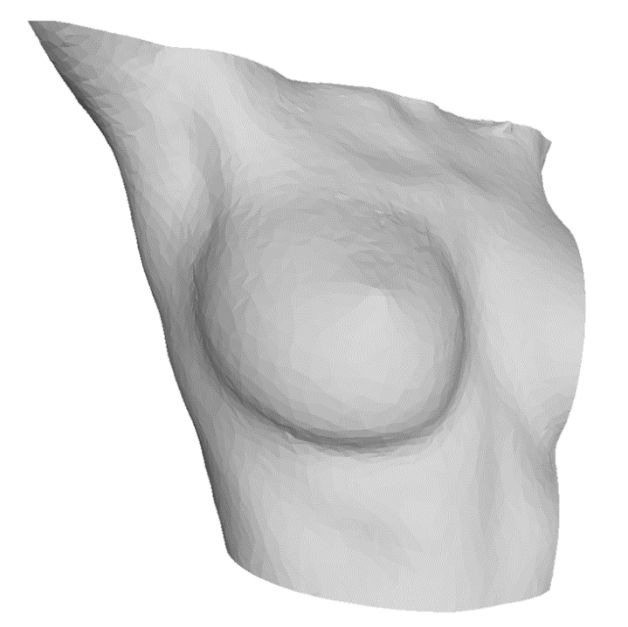
- F. Stanco, D. Tanasi, D. Allegra, F.L.M. Milotta, G. Lamagna, and G. Monterosso. "Virtual anastylosis of Greek sculpture as museum policy for public outreach and cognitive accessibility". **In: Journal of Electronic Imaging 26.1 (2017), pp. 011025–011025**.
- D. Allegra, G. Gallo, L. Inzerillo, M. Lombardo, F.L.M. Milotta, C. Santagati, and F. Stanco. "Hand Held 3D Scanning for Cultural Heritage: Experimenting Low Cost Structure Sensor Scan". **In: Handbook of Research on Emerging Technologies for Architectural and Archaeological Heritage**. IGI Global, 2017, pp. 475–499.
- M. F. Alberghina, F. Alberghina, D. Allegra, F. Di Paola, L. Maniscalco, G. Milazzo, F.L.M. Milotta, L. Pellegrino, S. Schiavone, and F. Stanco. "Integrated three-dimensional models for noninvasive monitoring and valorization of the Morgantina silver treasure (Sicily)". **In: Journal of Electronic Imaging 26.1 (2017), pp. 011015–011015.**

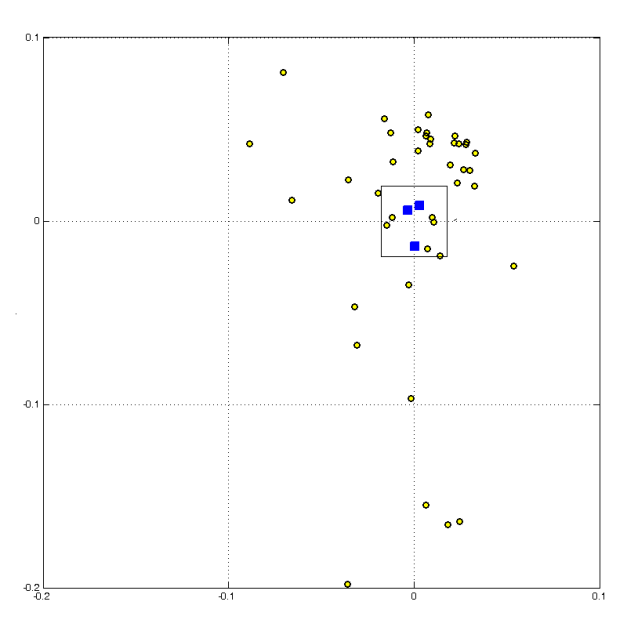
Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

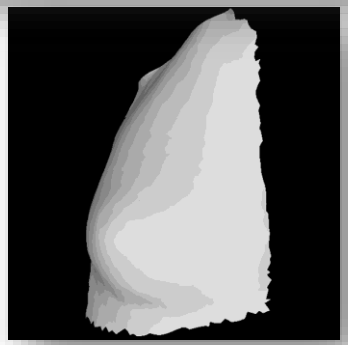
Slideshow Structure

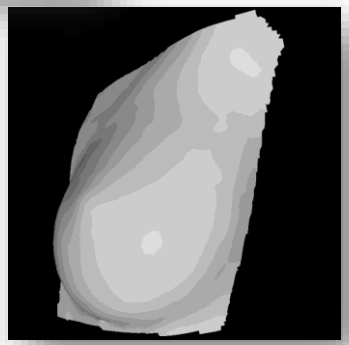


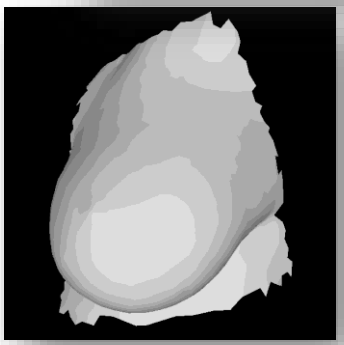
3D Scanning for medical imaging



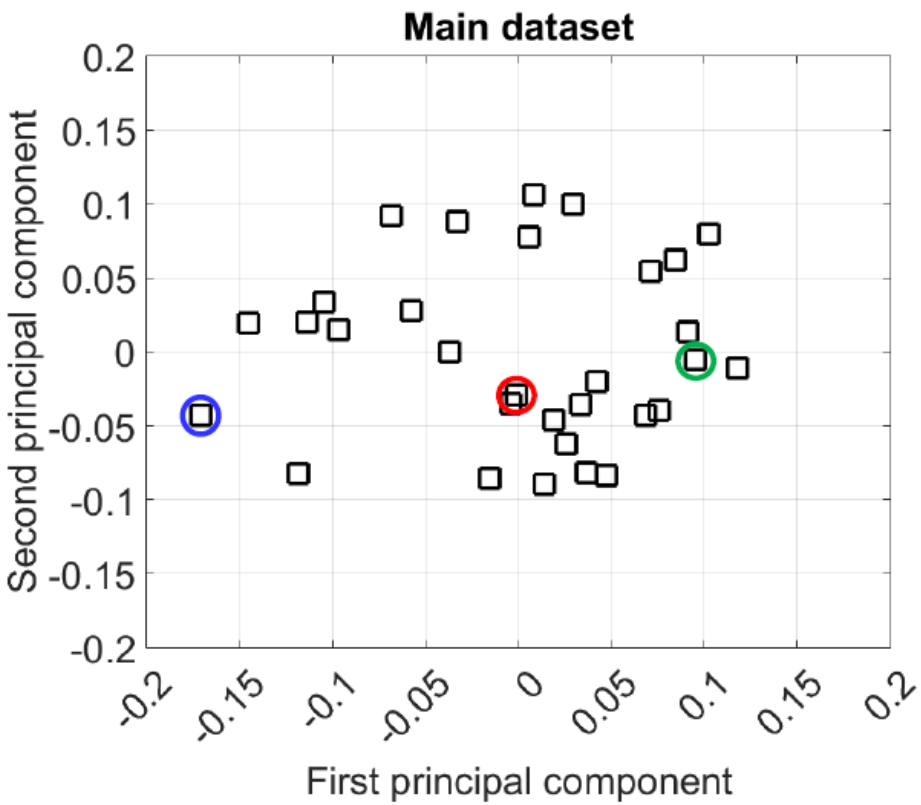


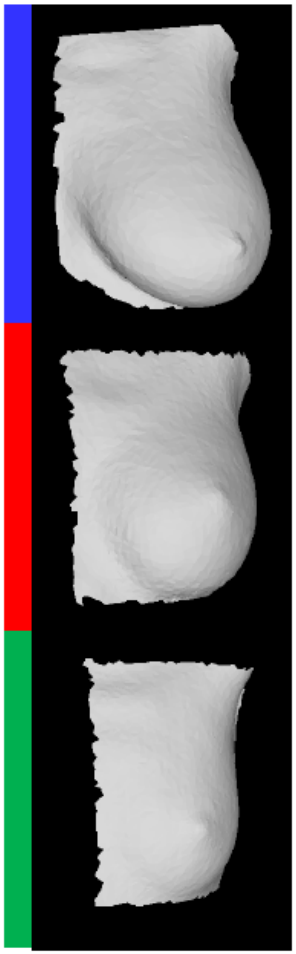




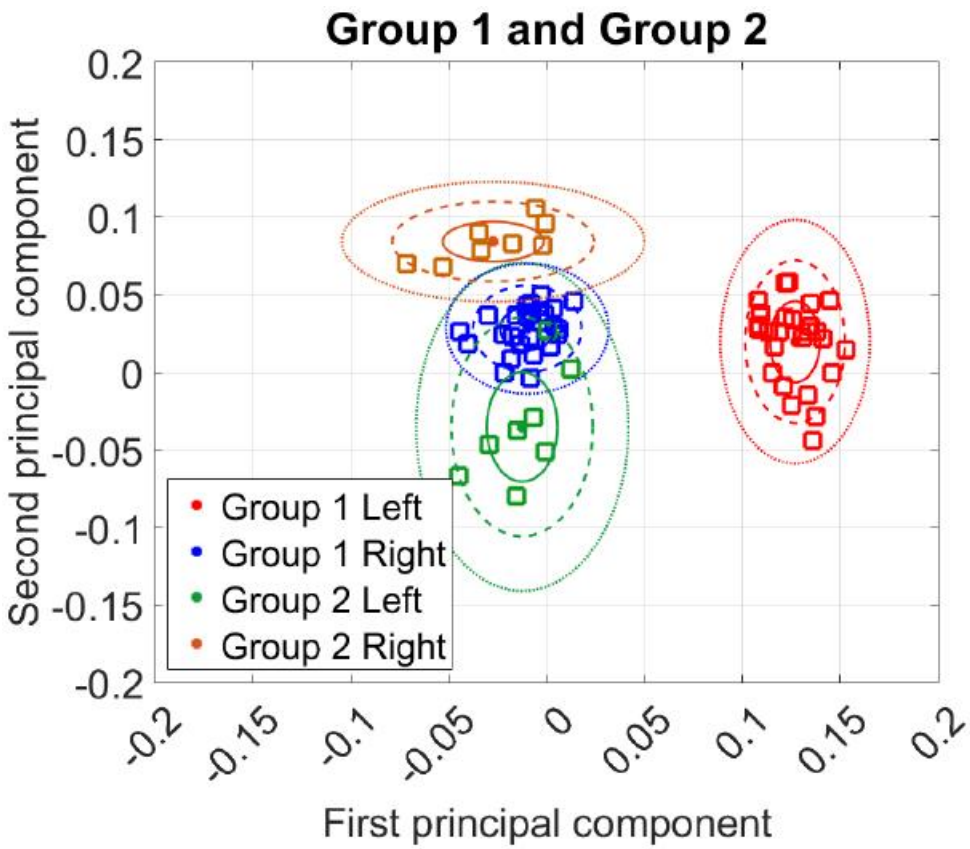


3D Scanning for medical imaging

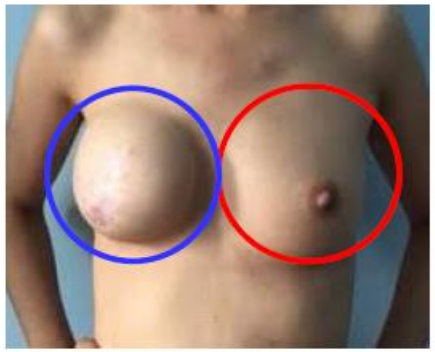




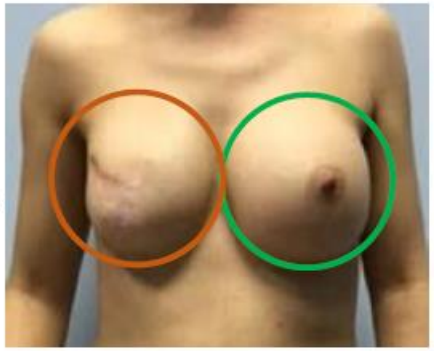
3D Scanning for medical imaging



Pre-operation



Post-operation



Part 3 – 3D Data

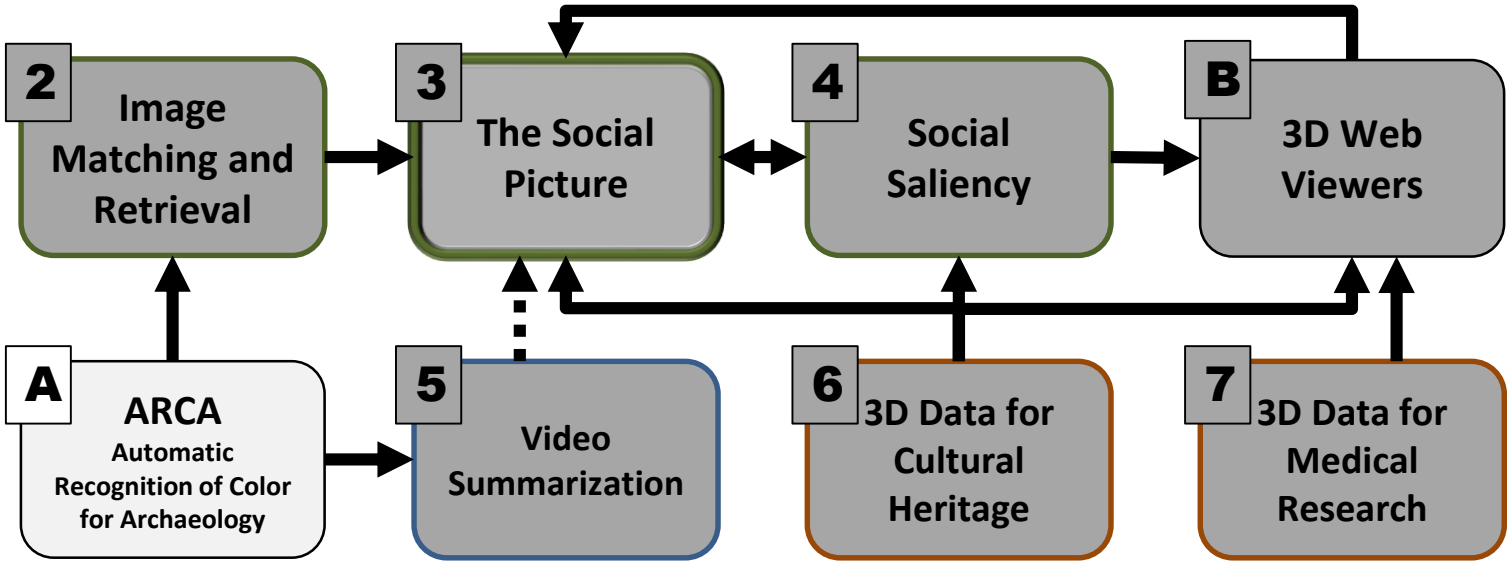
Medical Research – Publications

- G. Gallo, D. Allegra, Y.G. Atani, F.L.M. Milotta, F. Stanco, and G. Catanuto. "Breast Shape Parametrization Through Planar Projections". **In: International Conference on Advanced Concepts for Intelligent Vision Systems.** Springer. 2016, pp. 135–146.
- D. Allegra, F.L.M. Milotta, D. Sinitò, F. Stanco, G. Gallo, T. Wafa, and G. Catanuto. "Description of Breast Morphology through Bag of Normals Representation". **In: 19th International Conference on Image Analysis and Processing (ICIAP 2017)**. Springer.
- G. Catanuto, W. Taher, N. Rocco, F. Catalano, D. Allegra, F.L.M. Milotta, F. Stanco, G. Gallo, M.B. Nava. "Breast Shape Analysis With Curvature Estimates and Principal Component Analysis for Cosmetic and Reconstructive Breast Surgery". **In: Aesthetic Surgery Journal**, 2018.

APPENDICES

Multi-Device Media Analysis and Summarization for High Bandwidth Connected Environment

Slideshow Structure



ARCA

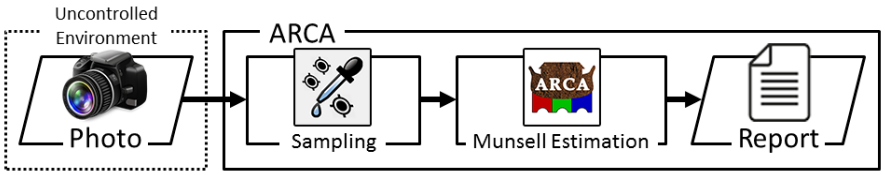
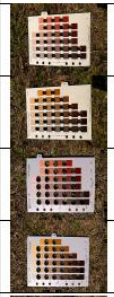
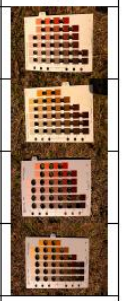


Image Dataset: ARCA328
328 Images (56,160 samples)

Set	Name	RAC	RSC	RCC	SAC	SSC	SCC
1	10R						
1	7.5YR						
2	10R						
2	7.5YR						
3	Test Case #1			N\A	N\A		N\A
3	Test Case #9			N\A	N\A		N\A

Set	Name	RAM	RSM	RCM	SAM	SSM	SCM
1	10R						
1	7.5YR						
2	10R						
2	7.5YR						
3	Test Case #1	N\A	N\A	N\A	N\A	N\A	
3	Test Case #9	N\A	N\A	N\A	N\A	N\A	

ARCA

Publications

- F.L.M. Milotta, F. Stanco, and D. Tanasi. "ARCA (Automatic Recognition of Color for Archaeology): a Desktop Application for Munsell Estimation". **In: 19th International Conference on Image Analysis and Processing (ICIAP 2017)**. 2017.
- F.L.M. Milotta, F. Stanco, D. Tanasi, and A.M. Gueli. "Munsell Color Specification using ARCA (Automatic Recognition of Color for Archaeology)". **In: Journal of Computing and Cultural Heritage.** 2018. (accepted)

- **PROVISIONAL PATENT** Automatic Digital Method for Classification of Colors in Munsell Color System United States Patent and Trademark Office on April 19, 2017, and assigned Serial No. 62/487,178
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FINAL DISCUSSION, REMARKS AND FUTURE WORKS

Conclusion

- Image
  - Improvements to CBIR: Telecom-CDVS descriptor, Back-Projection Verification, Query Expansion, and **Heatmap**.
  - In **The Social Picture (TSP)** an huge amount of crowdsourced social images can be collected and explored. It represents a **well suited enabling technology for LTE networks**.
  - **Social-Weigthed-Density (SWD)** maps have been used for reach a novel definition of a saliency model we that we named ***Social Saliency***.
- Video
  - **RECfusion** is a framework designed for automatic video curation driven by the popularity of the scenes acquired by multiple devices.
- 3D Data
  - **Digital Archaeology:** we shown how **3D scanning** and **web sharing** can contribute to the improvement of museum policies in the field of public outreach
  - **Medical Context:** we were able to **represent 3D data with just 2 parameters**, gaining a **compact descriptor** easier to be transfered and browsed through hospital networks

THANKS FOR THE ATTENTION… QUESTIONS?

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