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CAMERA POSE ESTIMATION IN AN INDUSTRIAL CONTEXT

Our goal

Feature point-based tracking

Dense camera tracking

Experimental results

Current research

Future developments

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Thank you

for your attention

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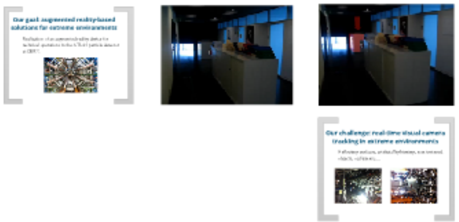

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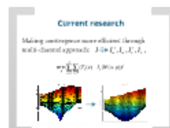

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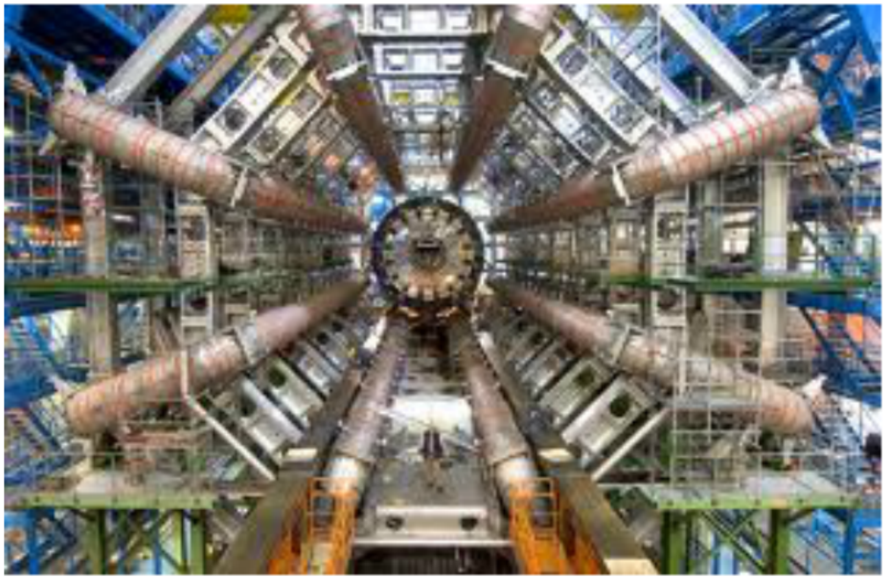
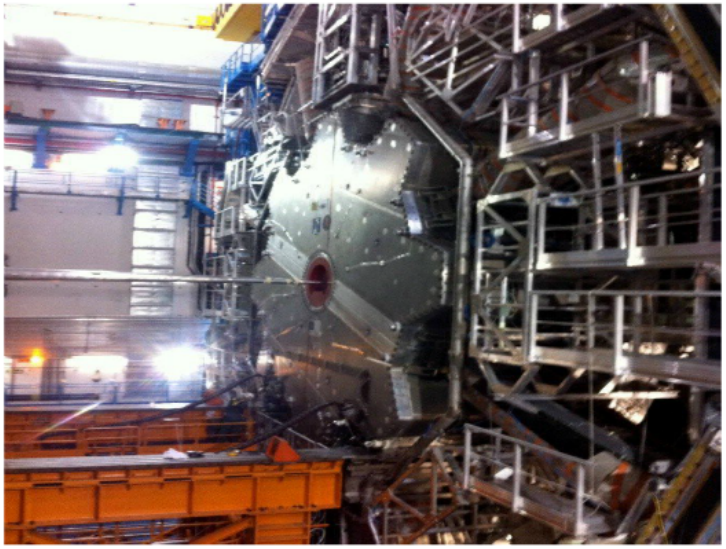
Our goal: augmented reality-based solutions for extreme environments

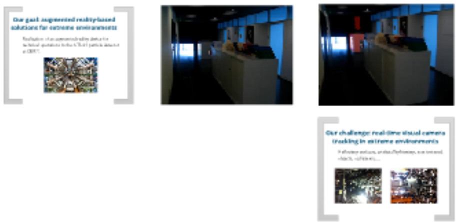
Realization of an augmented reality device for technical operations in the ATLAS particle detector at CERN.



Our challenge: real-time visual camera tracking in extreme environments

Reflecting surfaces, artificial lightening, non textured objects, occlusions, ...





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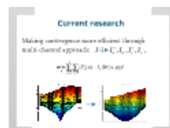

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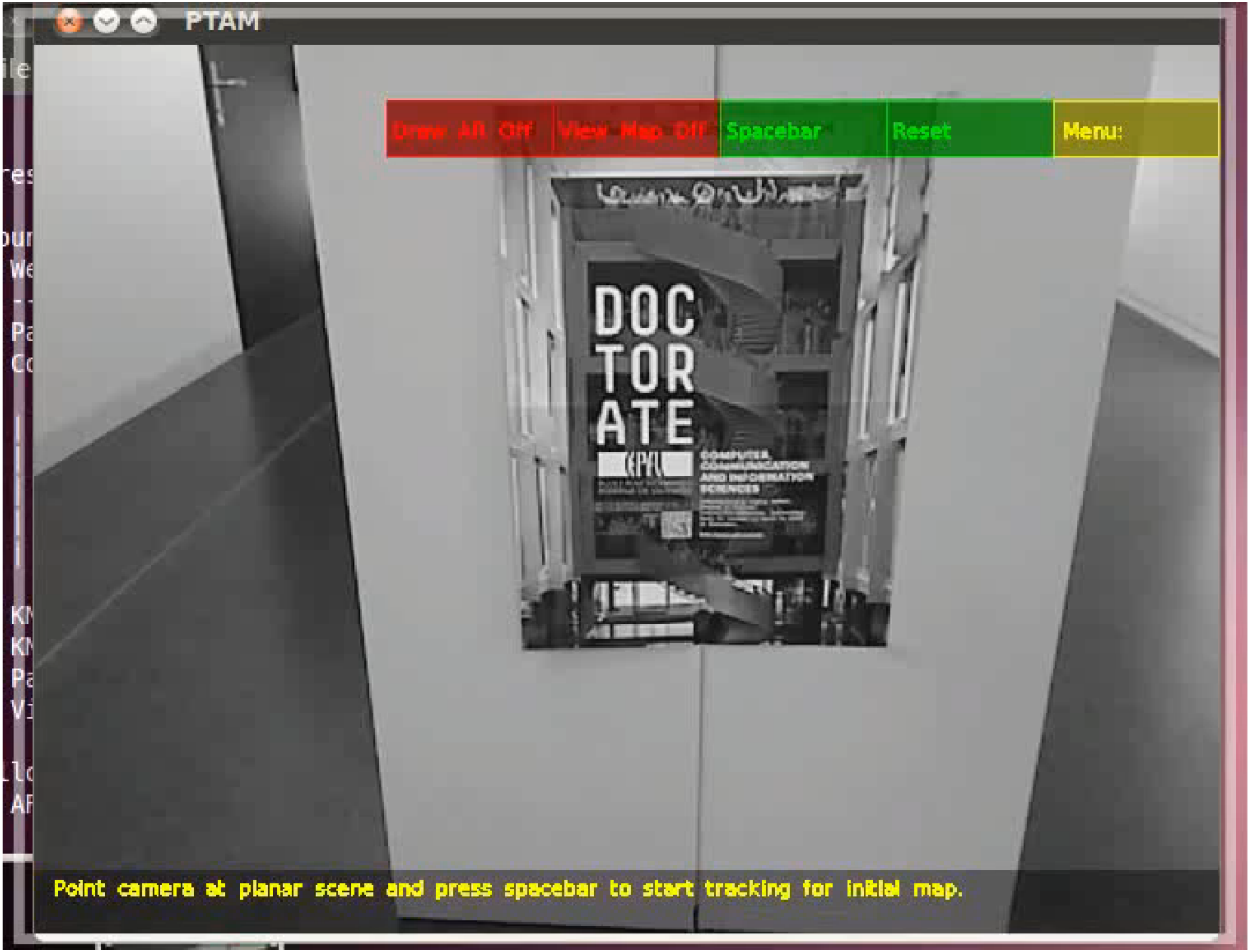
Feature-based tracking workflow

Given a set of calibrated key-frames and a 3D model of the scene, for each query frame I:

1. Find conspicuous visual features in I (interest points).
2. Employ a suitable descriptor for each feature.
3. Match each descriptor with those of the key-frames.
4. Estimate pose from correspondences with robust methods

Interest points can be edges, corners, blobs, or any easily recognizable spot on a frame.

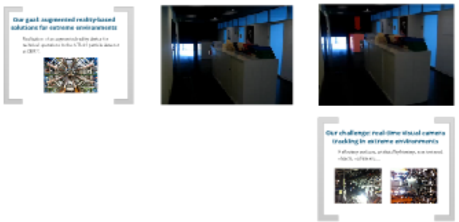

PTAM
Draw AR Off
View Map Off
Spacebar
Reset
Menu:
DOC
TOR
ATE
Point camera at planar scene and press spacebar to start tracking for initial map.

Feature-based tracking

Allows for synthetic description of images: only descriptors of interest points are retained.

Features matching is a noisy, ill-conditioned task in the considered environments.

We opted for a **dense approach** for pose estimation.



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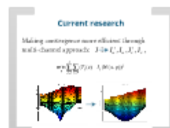

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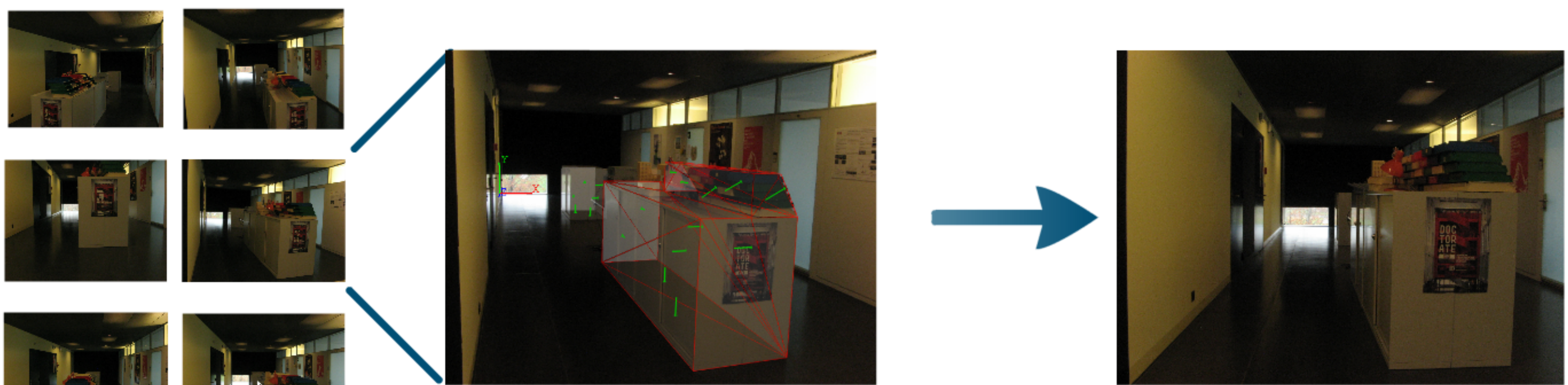
Dense camera tracking workflow

Given a 3D model of the scene and a set of calibrated key-frames, for each query frame I :

- Find the key-frame T that is most similar to I
- Parametrize the warp that maps each pixel x of T into I: $x_I = W(x, p)$
- Find an estimates of the parameters p by solving a minimization problem: $\min_{p} \sum_{x \in T} (T(x) - I(W(x,p))^2$



T I

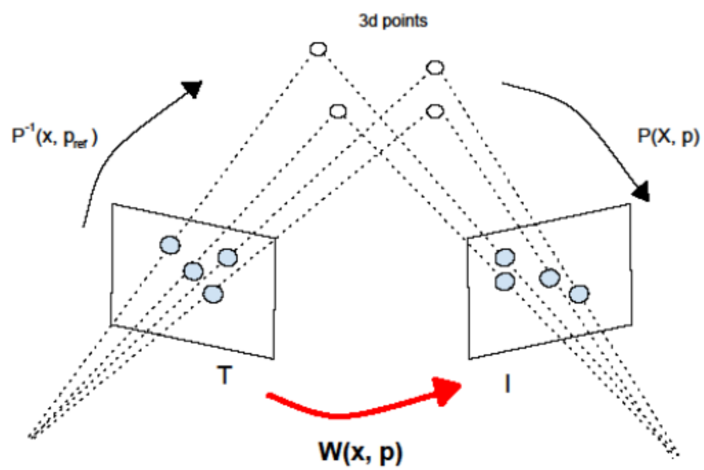
Find T in the key-frames database

Maximization of the normalized cross correlation :

$$NCC(T, I) = \frac{\sum_x (T(x) - \bar{T})(I(x) - \bar{I})}{\sqrt{\sum_x (T(x) - \bar{T})^2} \sqrt{\sum_x (I(x) - \bar{I})^2}}$$

Warp parametrization

The warp depends on the pose of I: we parametrize it with 6 parameters that determine the position and orientation of I in the 3D space



Solving the minimization problem

Lucas-Kanade algorithm

Given an initial estimate p, iterate:

$$\delta p = \arg\min \sum_{x \in T} (T(x) - I(W(x, p + \delta p)))^2$$

$$SD_p(x) = \left[\nabla I \frac{\partial W(x,p)}{\partial p} \right]$$

$$H_p = SD_p(x)^T \cdot SD_p(x)$$

$$\delta p = H_p^{-1} \cdot (SD_p(x)^T \cdot (T(x) - I(W(x,p)))$$

$$p \leftarrow p + \delta p$$

Until $\|\delta p\| < \varepsilon_{tol}$

IC algorithm

Given an initial estimate p0,

compute:

$$SD_0(x) = \left[\nabla T \frac{\partial W(x, p_0)}{\partial p} \right]$$

$$H = SD_0(x)^T \cdot SD_0(x)$$

Then, iterate:

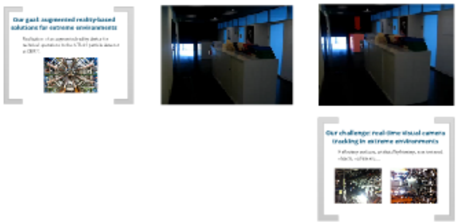
$$\delta p = \arg\min \sum_{x \in T} (T(x, \delta p) - I(W(x, p)))^2$$

$$err(x) = (I(W(x,p)) - T(x))$$

$$\delta p = H^{-1} \cdot (SD_0(x)^T \cdot err(x)$$

$$W(x,p) \leftarrow W(x,p) \circ W^{-1}(x, \delta p)$$

Until $\|\delta p\| < \varepsilon_{tol}$



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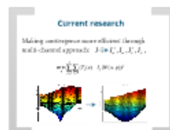

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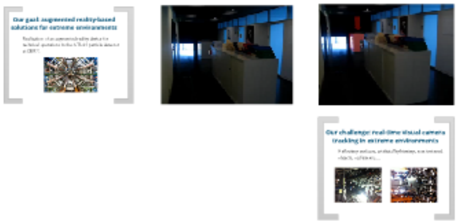

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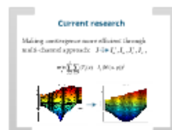

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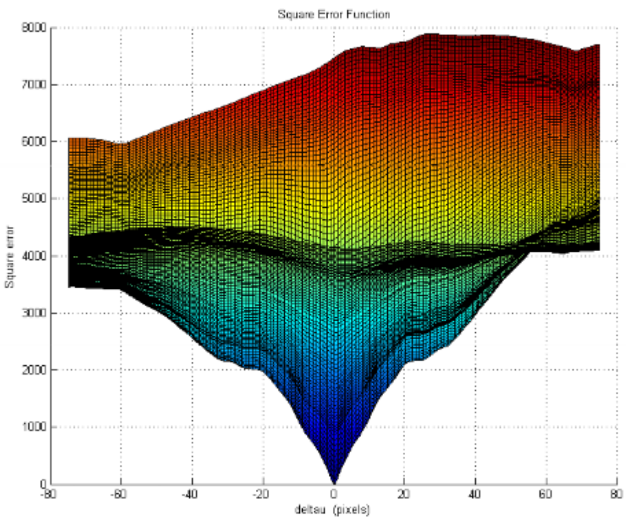
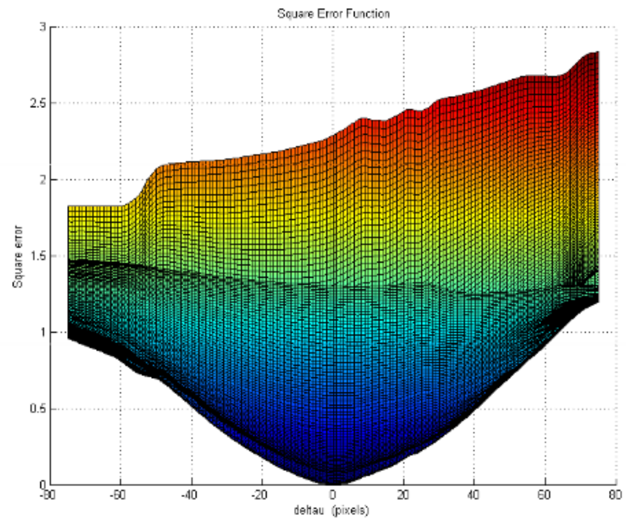
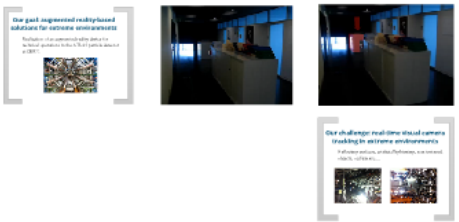
Current research

Making convergence more efficient through multi-channel approach: $I \rightarrow I_u^+, I_u^-, I_v^+, I_v^-,$

$$\min_p \sum_{j=1}^{J} \sum_{x \in T} (T_j(x) - I_j(W(x,p))^2$$







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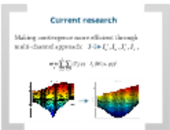

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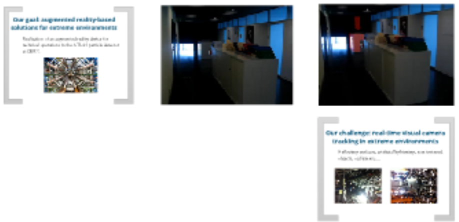
Future developments

- Find more effective sparse channels learning optimal filters;
- Improve robustness wrt occlusions and illumination changes;
- Effective real time implementation (in collaboration with University of Rome);
- Large key-frames sets handling;



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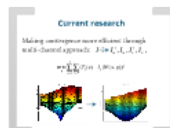

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ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

CERN

MARIE CURIE ACTIONS