

# Digital Image

(B4M33DZO, Winter 2024)

## Lecture 9: Image Registration 2

<https://cw.fel.cvut.cz/wiki/courses/b4m33dzo/start>

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**Polar transformation:**

**rotation**     $\implies$     **translation on y-axis**

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$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2}$$

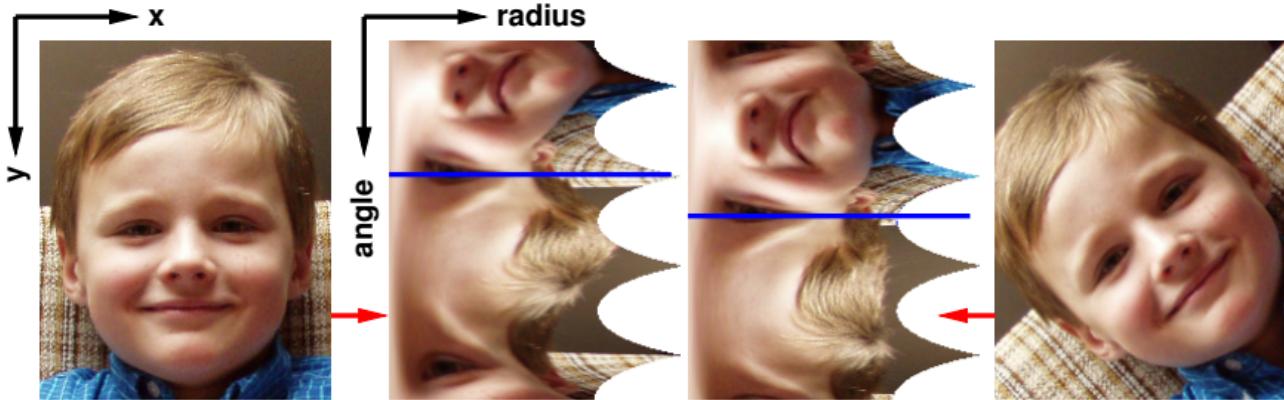
$$\alpha = \arctan \frac{y - y_c}{x - x_c}$$

## Polar transformation:

**rotation**  $\implies$  **translation on y-axis**

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2}$$

$$\alpha = \arctan \frac{y - y_c}{x - x_c}$$



**Log-polar transformation:**

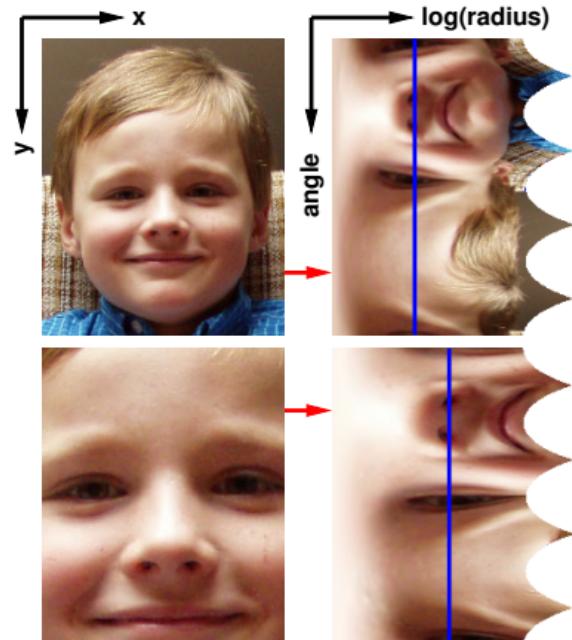
scale     $\implies$    translation on x-axis  
rotation     $\implies$    translation on y-axis

## Log-polar transformation:

scale  $\implies$  translation on x-axis  
rotation  $\implies$  translation on y-axis

$$r = \log \left( 1 + \sqrt{(x - x_c)^2 + (y - y_c)^2} \right)$$

$$\alpha = \arctan \frac{y - y_c}{x - x_c}$$

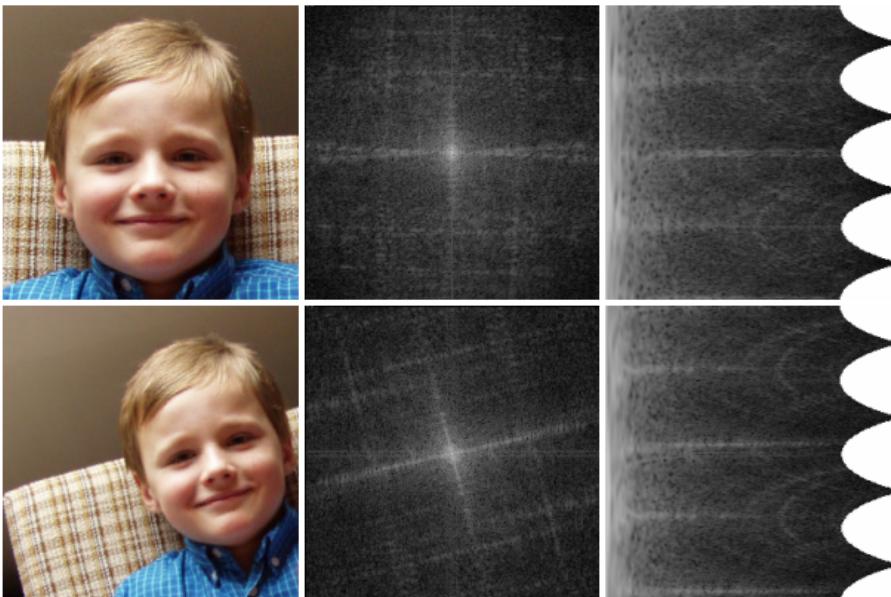


## Fourier-Mellin transformation:

1. Estimate rotation and scale using frequency domain.
2. Resample image to have the same rotation and scale.
3. Use standard phase correlation to estimate translation.

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## Generalized gradient descent:

$$E = \sum_i (\mathbf{A}[\mathbf{W}(\mathbf{x}_i, \mathbf{p})] - \mathbf{B}[\mathbf{x}_i])^2 \approx \sum_i (\mathbf{A}_i + \mathbf{A}'_i \mathbf{J} \mathbf{p} - \mathbf{B}_i)^2$$

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$$\mathbf{A}_i \rightarrow \mathbf{A}[\mathbf{x}_i] \quad \mathbf{B}_i \rightarrow \mathbf{B}[\mathbf{x}_i] \quad \mathbf{A}'_i \rightarrow \frac{\partial}{\partial \mathbf{x}} \mathbf{A}_i$$

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$$E' = 2 \sum_i (\mathbf{A}'_i \mathbf{J})^T (\mathbf{A}_i + \mathbf{A}'_i \mathbf{J} \mathbf{p} - \mathbf{B}_i) = 0$$

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$$\mathbf{p} = \mathbf{H}^{-1} \sum_i (\mathbf{A}'_i \mathbf{J})^T (\mathbf{B}_i - \mathbf{A}_i)$$

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$$\mathbf{p} = \mathbf{H}^{-1} \sum_i (\mathbf{A}'_i \mathbf{J})^T (\mathbf{B}_i - \mathbf{A}_i)$$

$$\mathbf{J} = \underbrace{\begin{pmatrix} \frac{\partial \mathbf{W}_{\mathbf{x}}}{\partial \mathbf{p}_1} & \frac{\partial \mathbf{W}_{\mathbf{x}}}{\partial \mathbf{p}_2} & \dots & \frac{\partial \mathbf{W}_{\mathbf{x}}}{\partial \mathbf{p}_n} \\ \frac{\partial \mathbf{W}_{\mathbf{y}}}{\partial \mathbf{p}_1} & \frac{\partial \mathbf{W}_{\mathbf{y}}}{\partial \mathbf{p}_2} & \dots & \frac{\partial \mathbf{W}_{\mathbf{y}}}{\partial \mathbf{p}_n} \end{pmatrix}}_{\text{Jacobian}} \quad \mathbf{H} = \underbrace{\sum_i (\mathbf{A}'_i \mathbf{J})^T (\mathbf{A}'_i \mathbf{J})}_{\text{Hessian}}$$

## Jacobian

## Jacobian

**Affine transformation:**  $\mathbf{p} = (a_{11}, a_{12}, a_{21}, a_{22}, x_0, y_0)$

$$x' = a_{11}x + a_{12}y + x_0 \quad y' = a_{21}x + a_{22}y + y_0$$

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$$\mathbf{J} = \begin{pmatrix} x & 0 & y & 0 & 1 & 0 \\ 0 & x & 0 & y & 0 & 1 \end{pmatrix}$$

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**Projective transformation:**  $\mathbf{p} = (a_{11}, a_{12}, a_{21}, a_{22}, x_0, y_0, f_1, f_2)$

$$x' = \frac{a_{11}x + a_{12}y + x_0}{f_1x + f_2y + 1} \quad y' = \frac{a_{21}x + a_{22}y + y_0}{f_1x + f_2y + 1}$$

## Jacobian

**Affine transformation:**  $\mathbf{p} = (a_{11}, a_{12}, a_{21}, a_{22}, x_0, y_0)$

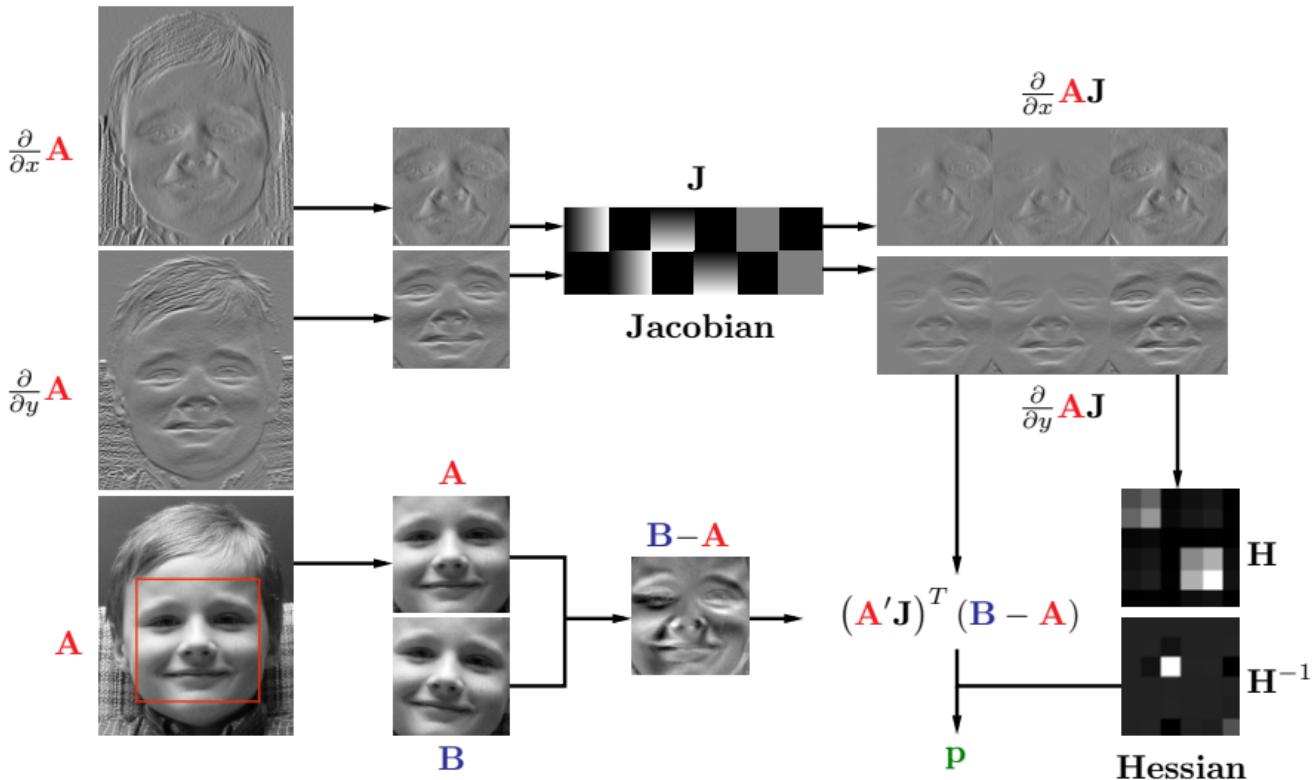
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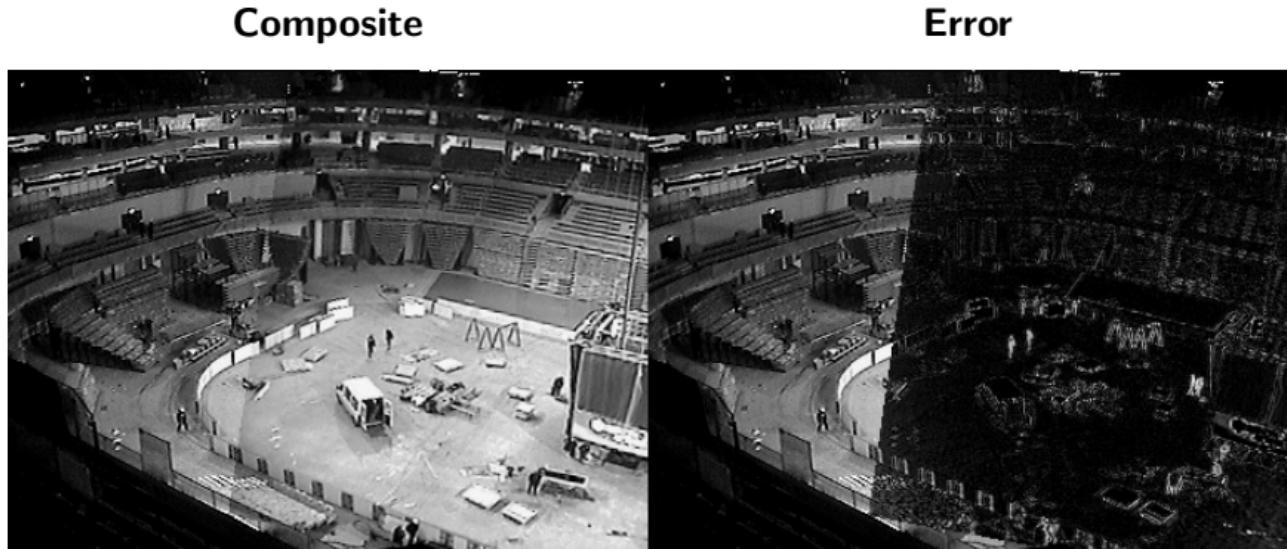
$$x' = \frac{a_{11}x + a_{12}y + x_0}{f_1x + f_2y + 1} \quad y' = \frac{a_{21}x + a_{22}y + y_0}{f_1x + f_2y + 1}$$

$$\mathbf{J} = \frac{1}{f_1x + f_2y + 1} \begin{pmatrix} x & 0 & -xx' & y & 0 & -yx' & 1 & 0 \\ 0 & x & -xy' & 0 & y & -yy' & 0 & 1 \end{pmatrix}$$



## Hierarchical gradient descent (Lucas-Kanade):

1. **Model:** translation  $\Rightarrow$  rigid  $\Rightarrow$  affine  $\Rightarrow$  projective
2. **Scale:**  $32 \times 32 \Rightarrow 64 \times 64 \Rightarrow 128 \times 128 \Rightarrow 256 \times 256$



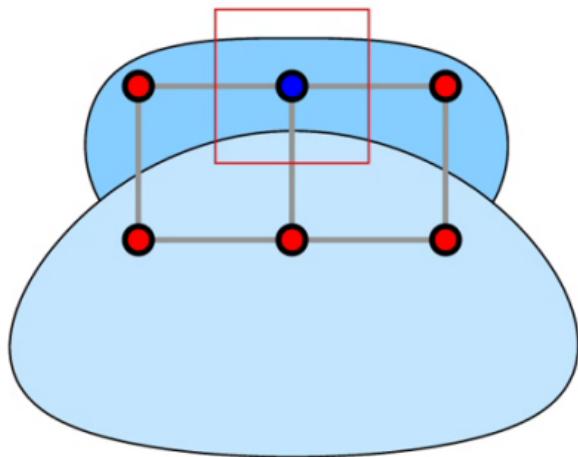
## Algorithm:

repeat

1. **Push:**  
block matching
2. Regularize:  
shape matching

until convergence

Push

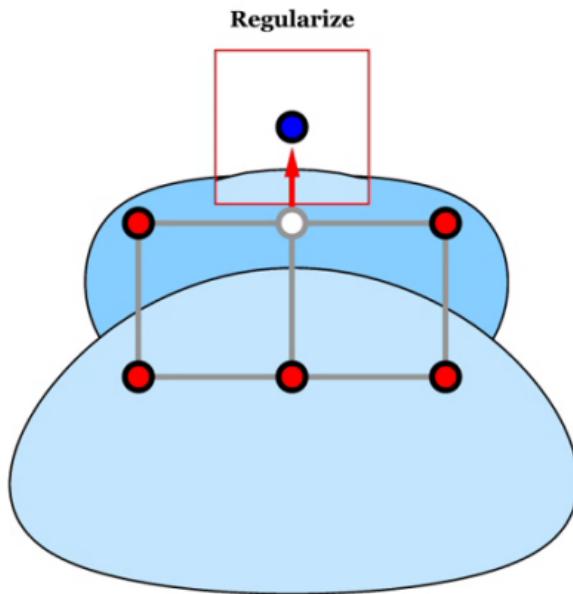


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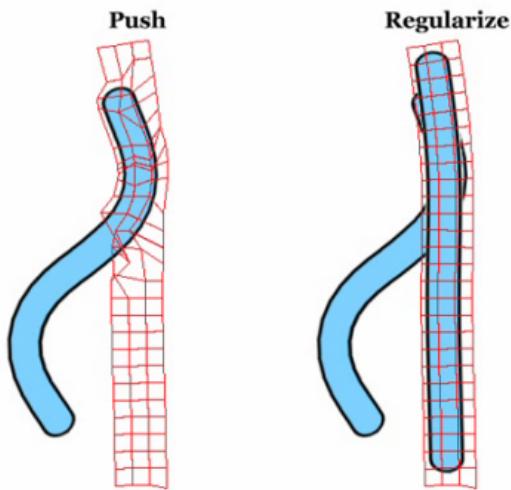


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source frames





**source color frame**

