



Morphological image matching using deep convolutional neural networks

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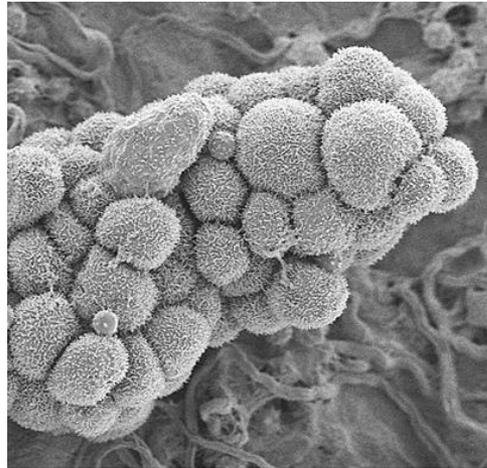


BARCELONA

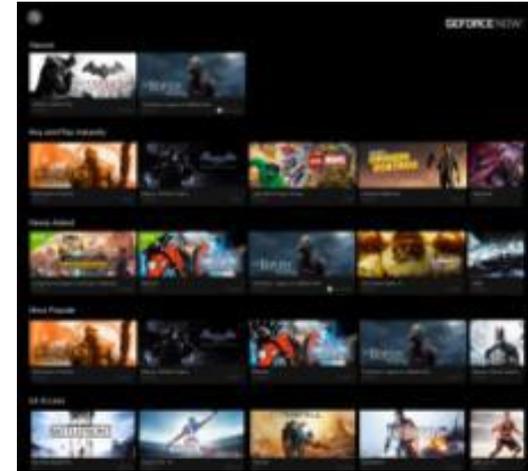
Motivation: Deep Learning everywhere



INTERNET & CLOUD



MEDICINE & BIOLOGY



MEDIA & ENTERTAINMENT



SECURITY & DEFENSE



AUTONOMOUS MACHINES

Image matching problem



Are these images similar?

Lets try to measure similarity using Pytyev morphology*

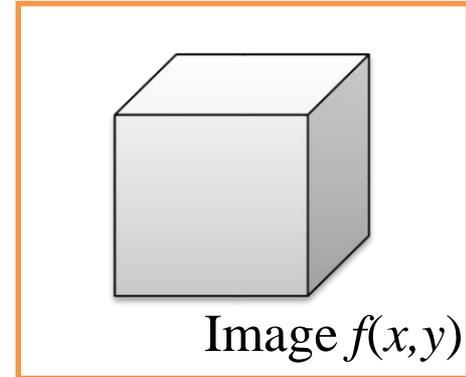
* Pytyev Y. P., Chulichkov A. Methods of Morphological Analysis of Images. 2010. In Russian.

Mathematical definition of “shape”

Let's consider images as elements of a linear space:

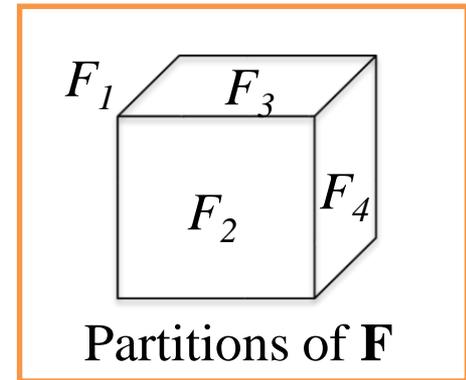
$$f(x, y) = \sum_{i=1}^n f_i \chi_{F_i}(x, y),$$

where n – number of partitions of the image \mathbf{F} ,
 $\mathbf{F} = \{F_1, \dots, F_n\}$; $\mathbf{f} = (f_1, \dots, f_n)$ – the intensity vector of corresponding partitions; $\chi_{F_i}(x, y) \in \{0, 1\}$ – the indicator function of the partition F_i .



Let's consider “shapes” as linear subspaces or as a set of images with similar partitions of \mathbf{F} – $F \subseteq L^2(\Omega)$:

$$F = \left\{ f(x, y) = \sum_{i=1}^n f_i \chi_{F_i}(x, y), \mathbf{f} \in R^n \right\}$$



Shapes as partitions – “mosaic shapes”

* Pytyev Y. P., Chulichkov A. Methods of Morphological Analysis of Images. 2010. In Russian.

Image projection on the shape of the other image

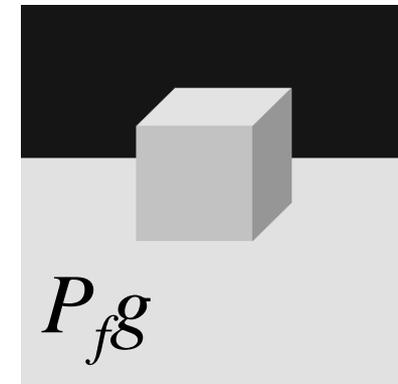
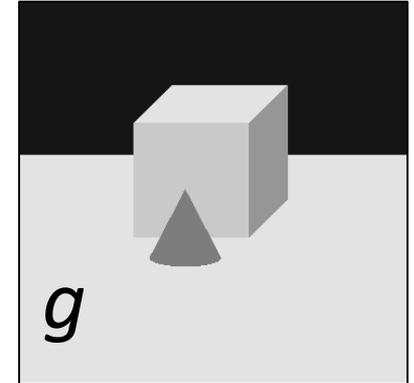
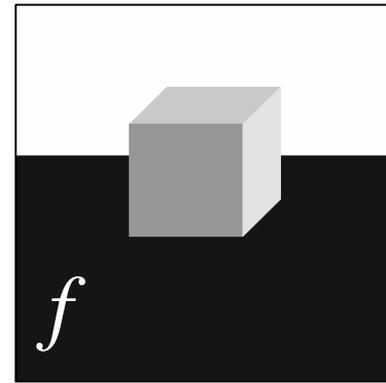
Morphological projection of the image g on the shape of the image f :

$$P_c g(x, y) = \sum_{i=1}^N c_i^* \chi_{A_i}(x, y)$$

$$c_i^* = \frac{\sum_x \sum_y \chi_{A_i}(x, y) g(x, y)}{\sum_x \sum_y \chi_{A_i}(x, y)} = \frac{(\chi_{A_i}, g)}{\|\chi_{A_i}\|^2}$$

$$x, y \in X \quad 0 < c_i < \infty, i = 1..N$$

X – certain image area



* Pytyev Y. P., Chulichkov A. Methods of Morphological Analysis of Images. 2010. In Russian.

Morphological correlation coefficient

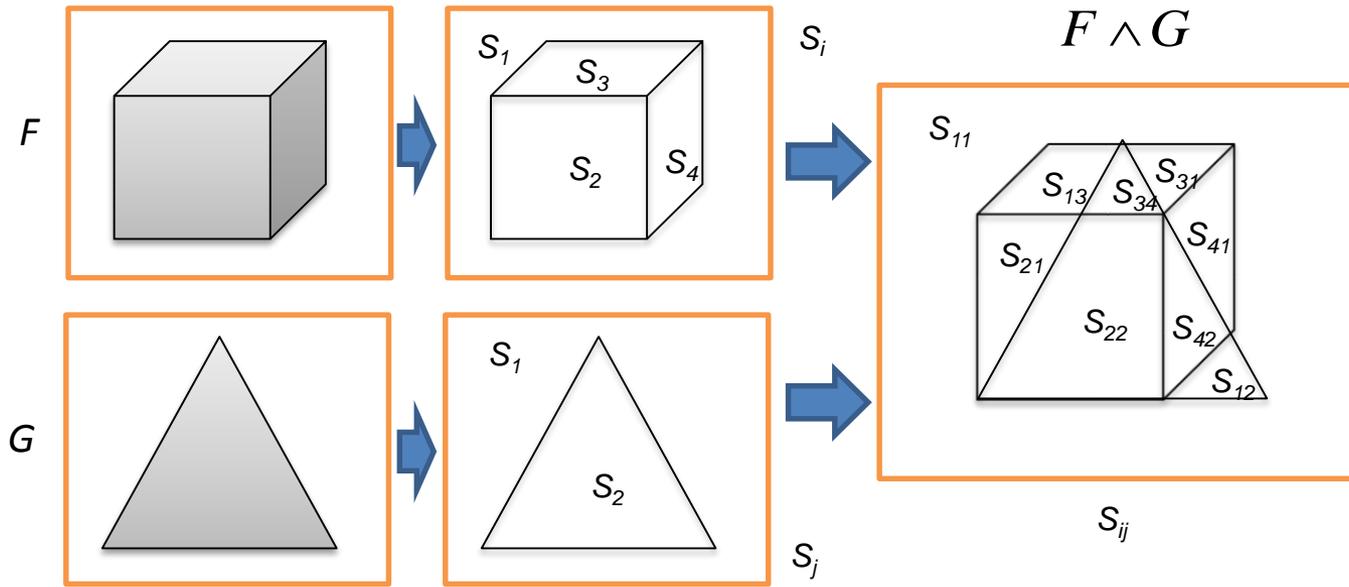
Let's consider a normalized morphological correlation coefficient as a numerical similarity measure of the image g and the shape of the image f :

$$K_M(g, F) = \frac{\|P_F g\|}{\|g\|}, \quad K_M(f, G) = \frac{\|P_G f\|}{\|f\|}$$

In the general case:

$$K_M(g, F) \neq K_M(f, G)$$

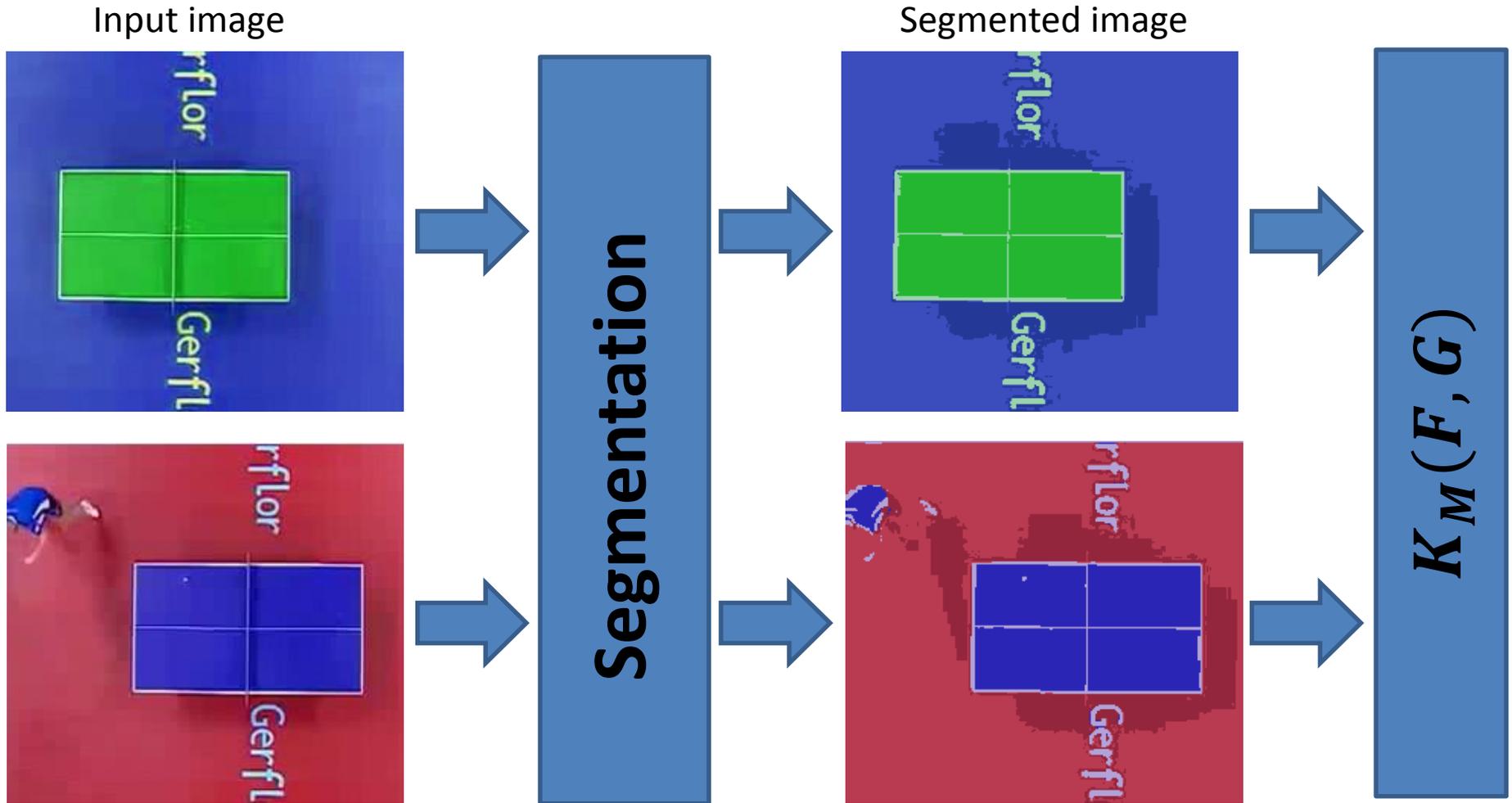
Mean-square effective coefficient of morphological correlation



$$K_M^2(F, G) = \sum_{j=1, \dots, m} \sum_{i=1, \dots, n} \frac{S_{ij}}{S} \frac{S_{ij}}{S_j}$$

* Vizilter Y., Rubis A. Morphological correlation coefficients of the images shapes for the multispectral image fusion tasks, 2012. In Russian.

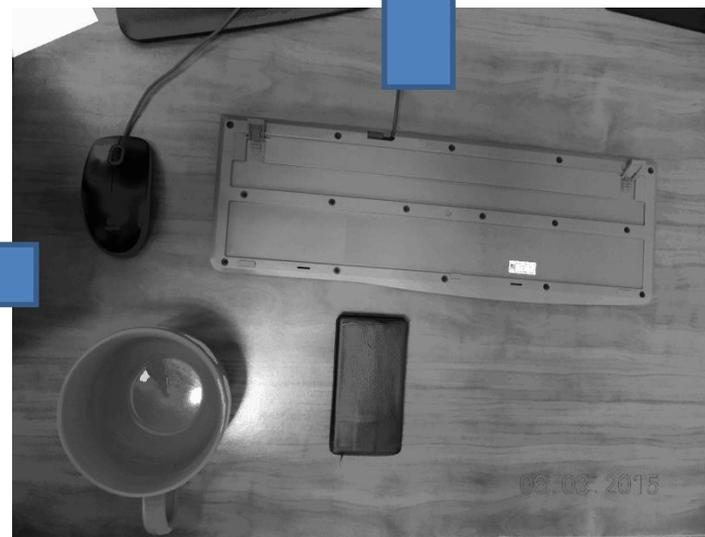
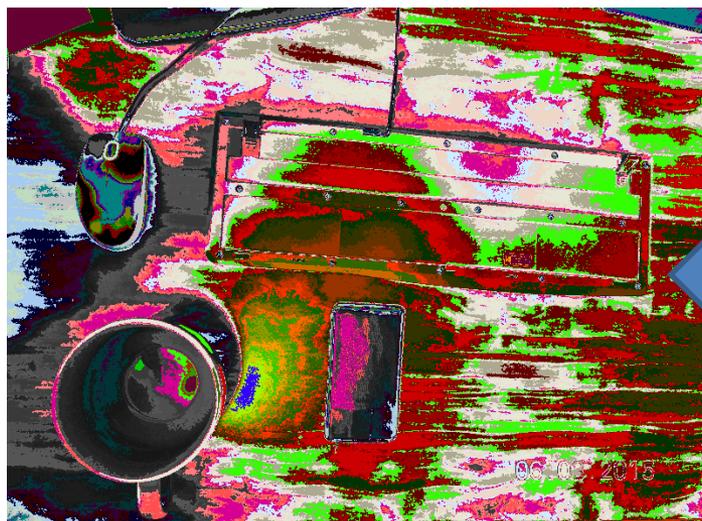
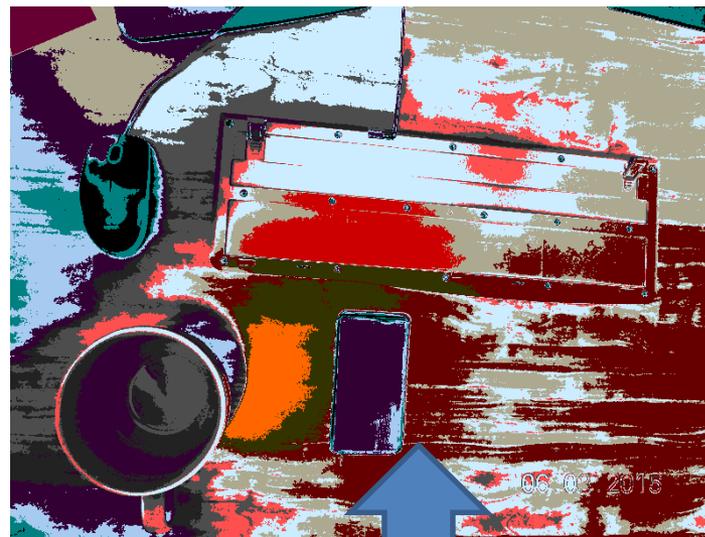
Classical approach



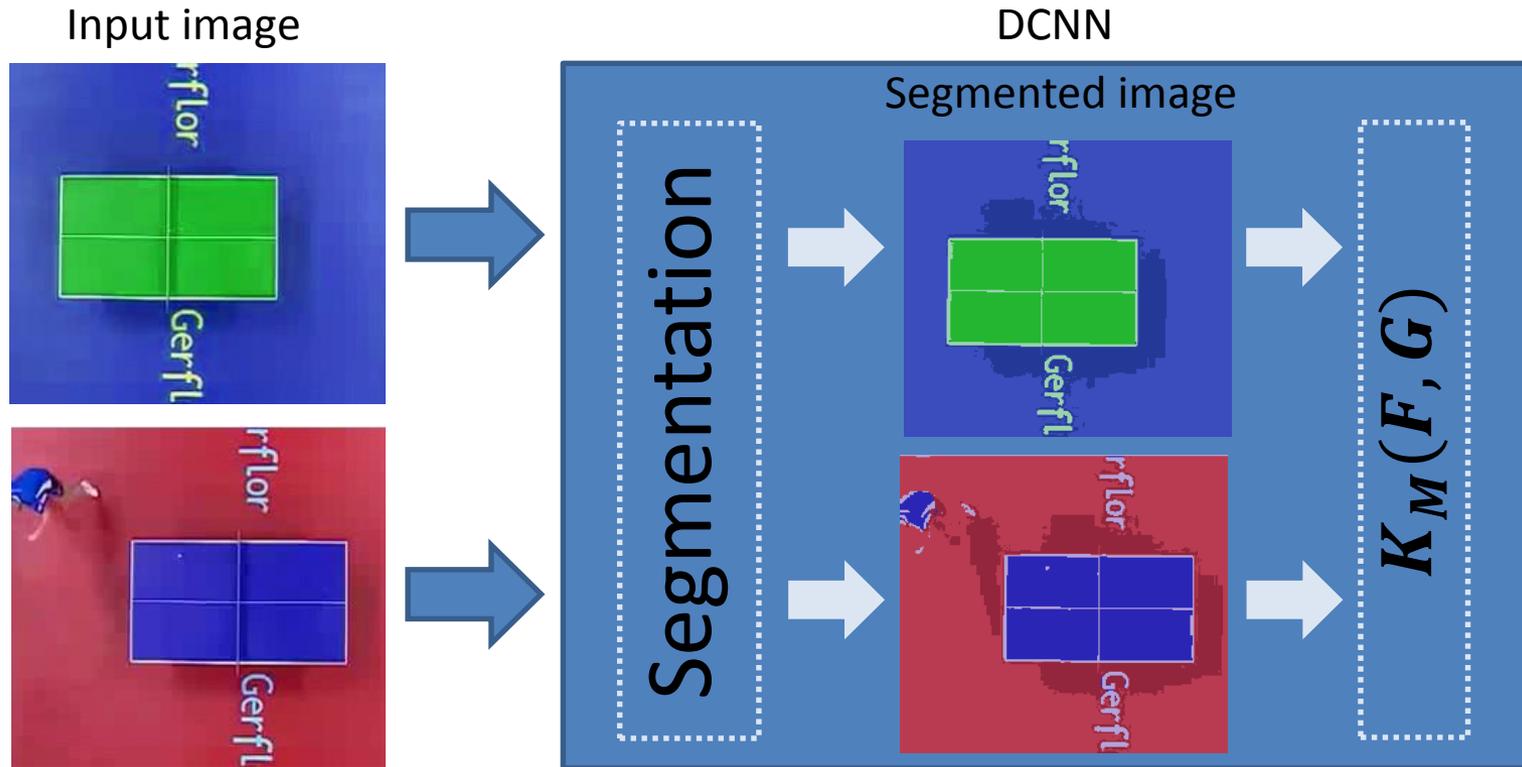
Classical approach drawbacks

Result strongly depends on:

- Stability and quality of segmentation
- Image noise
- Geometric distortion



Proposed approach

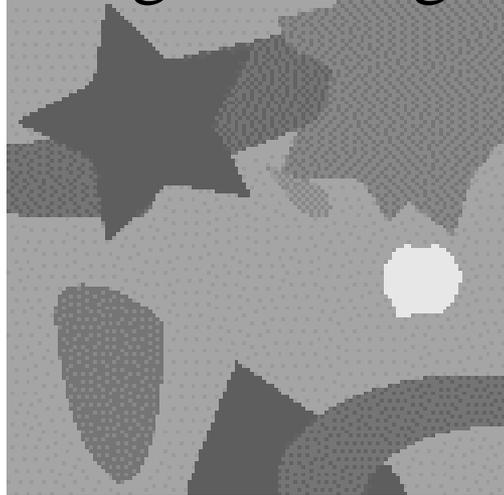


Our approach advantages:

- No explicit segmentation
- Robustness to image noise through machine learning
- Robustness to geometric distortions through machine learning

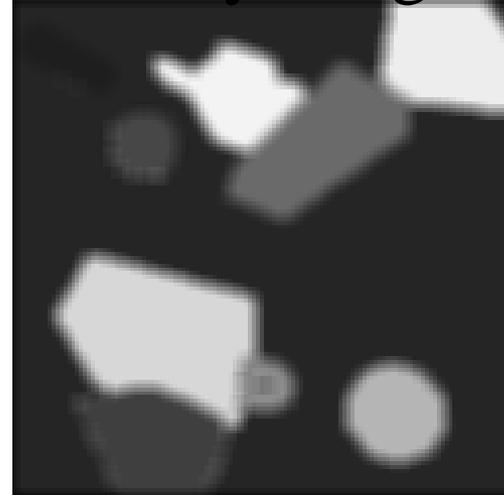
Image dataset

Original image



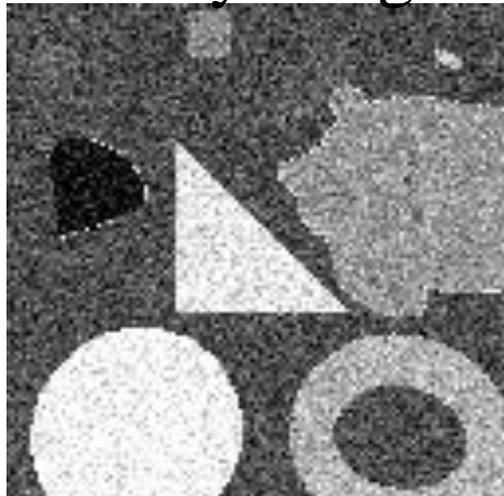
a)

Blurry image



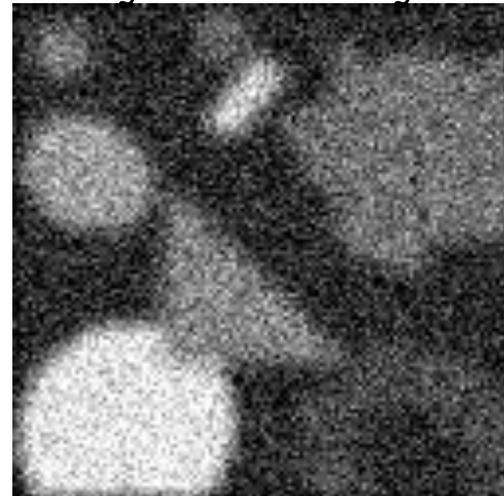
b)

Noisy image



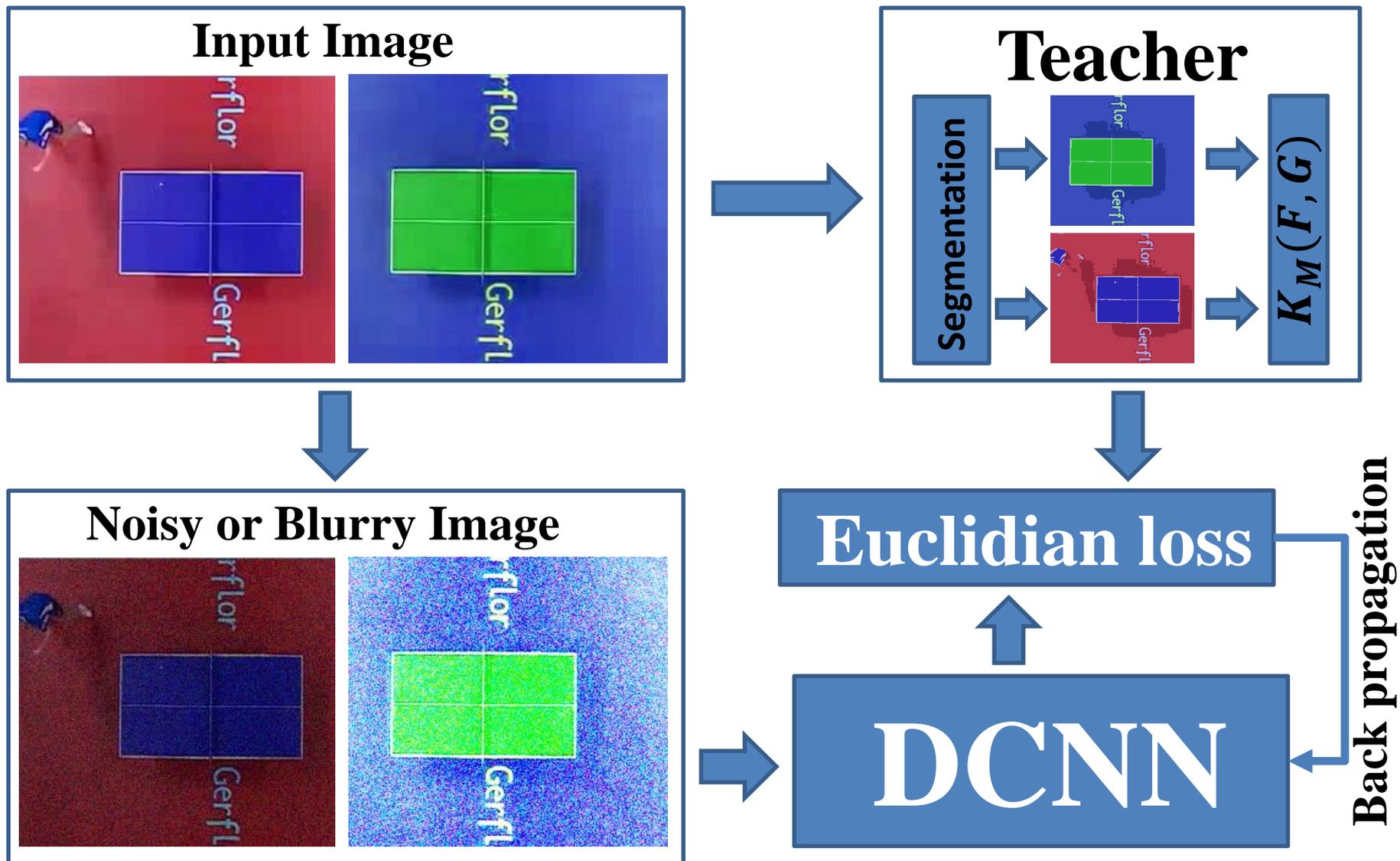
c)

Blurry & Noisy image

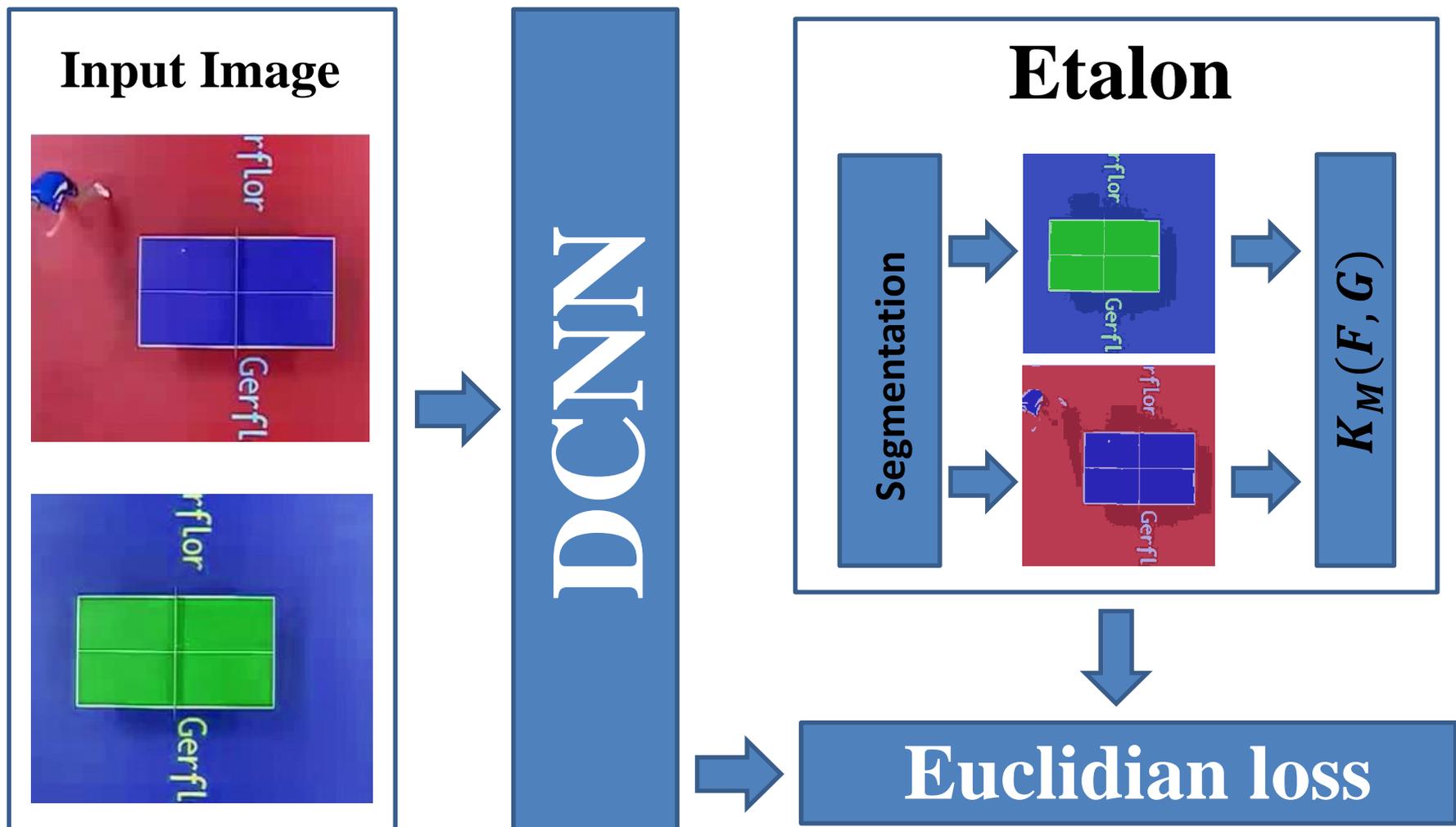


d)

Machine learning workflow

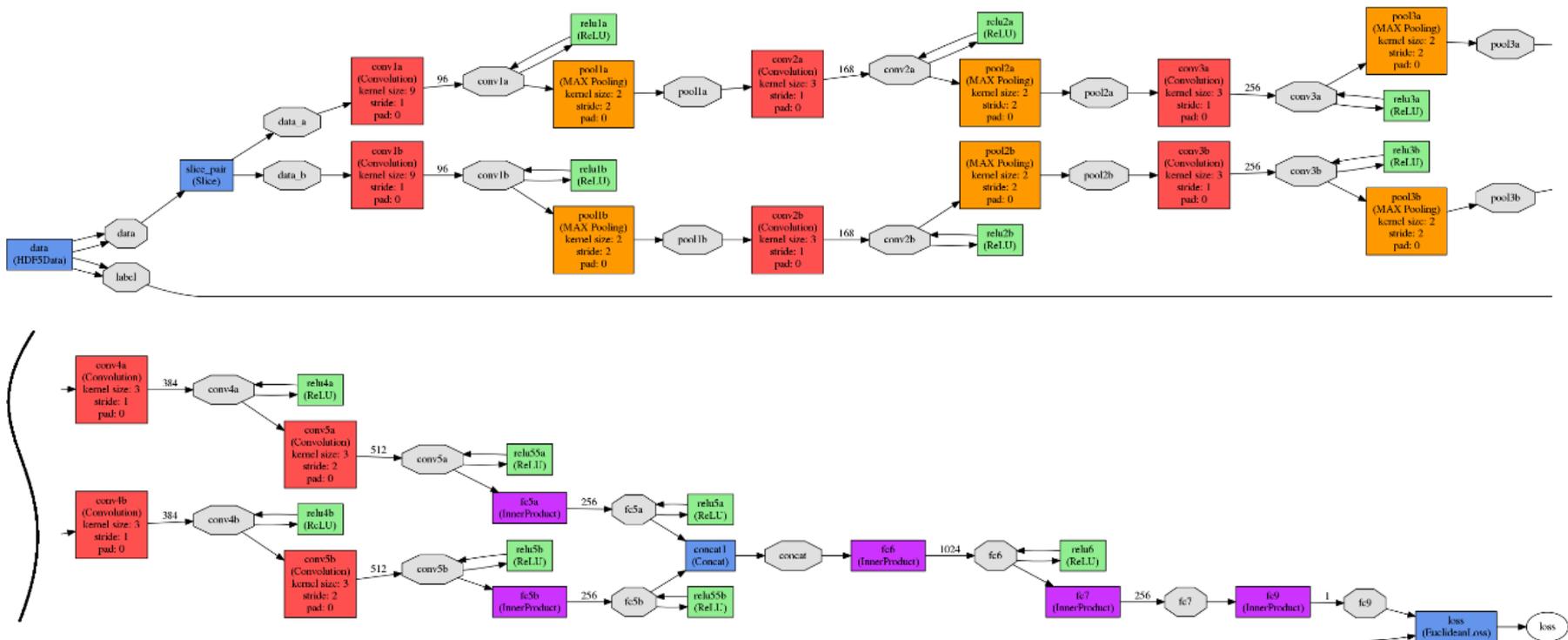


Quality estimation (testing) workflow



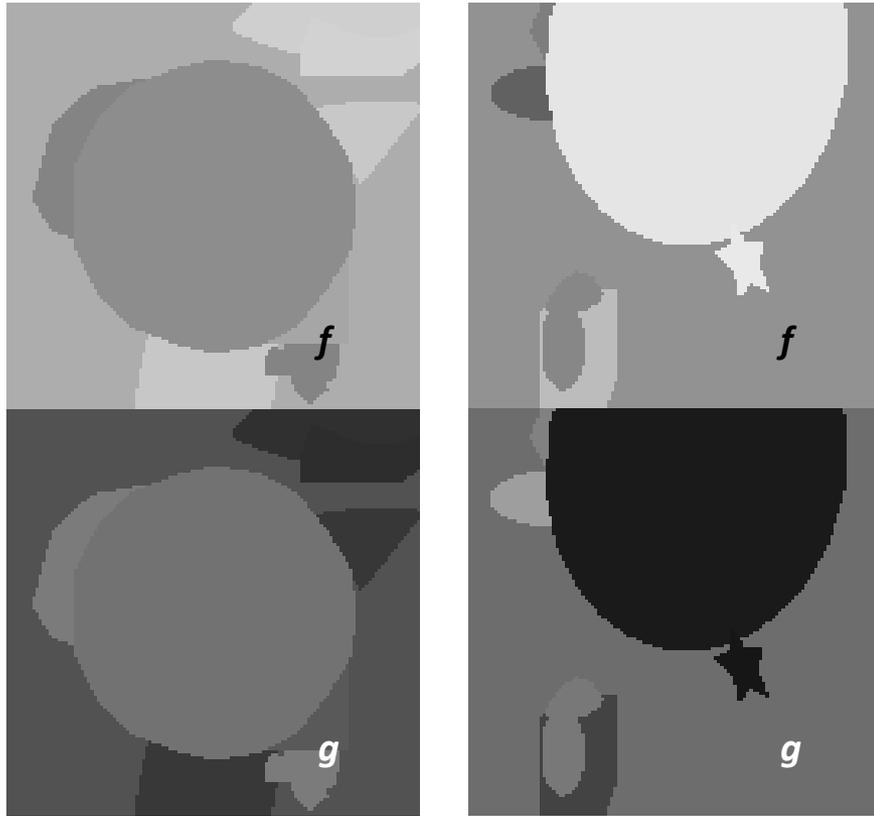
Network topology

Our network is based on a Siamese neural network that contains 5 convolutional layers (3x3), 3 full meshed layers (256x2, 1024, 256) and a ReLU function as an activation function. Also we used the quadratic function as a loss function.

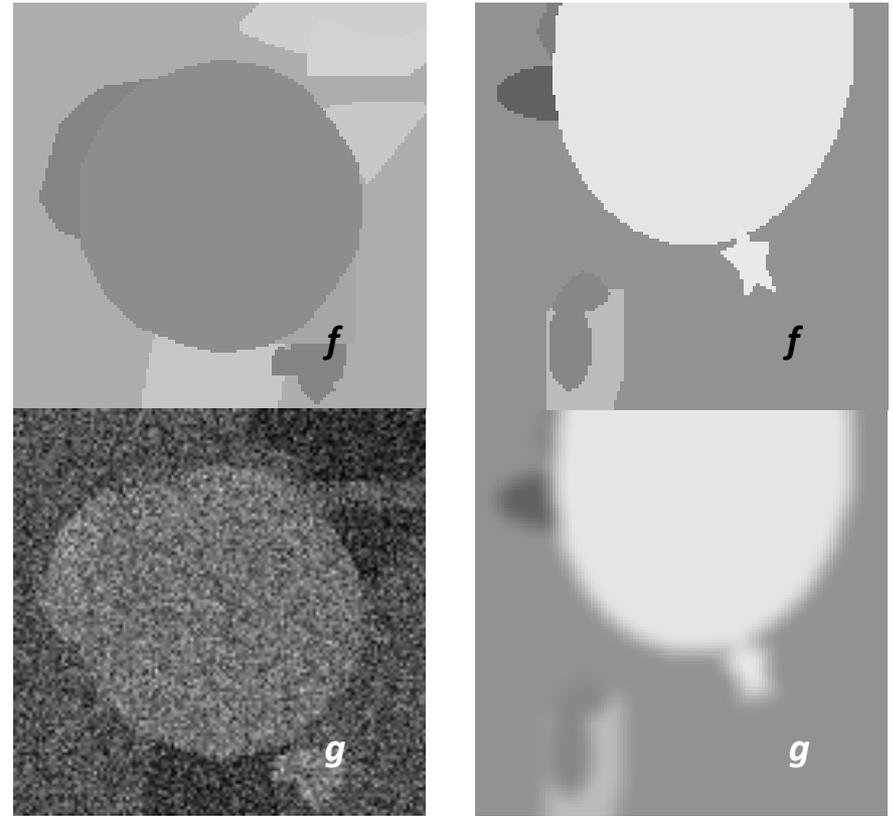


Results

Our approach preserves the properties of the morphological correlation coefficients



Our approach is robust to image noise



$K_M(G,f) = 1.0$	$K_M(G,f) = 1.0$	$K_M(G,f) = 0.34$	$K_M(G,f) = 0.93$
$K_{dl}(G,f) = 1.0$	$K_{dl}(G,f) = 0.973$	$K_{dl}(G,f) = 0.92$	$K_{dl}(G,f) = 0.916$
Mean-square error is about 3%		Mean-square error is about 7%	

Conclusions

We propose the new approach of morphological image matching using the deep convolutional neural networks for calculation of the morphological correlation coefficients with the following properties:

- No explicit image segmentation
- Highly precise values in cases of image distortions, when classical morphological correlation coefficients don't work

Experiments on the synthetic images proves the efficiency of the proposed approach.

Future research

Future research will include:

- Extra training and optimization of the neural network parameters
- Adding more samples to the training sets, including the images with the distorted or overlapped models

THANK YOU!

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