Medical Image Analysis Project Presentation

Reformulating Level Sets as Deep Recurrent Neural Network Approach to Semantic Segmentation

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Idea of the segmentation

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How to describe the boundery C mathematically?

By *Level set*!

Level-set method

We find a magic function φ so that

$$C = \{(x, y) : \varphi(x, y) = 0\}$$
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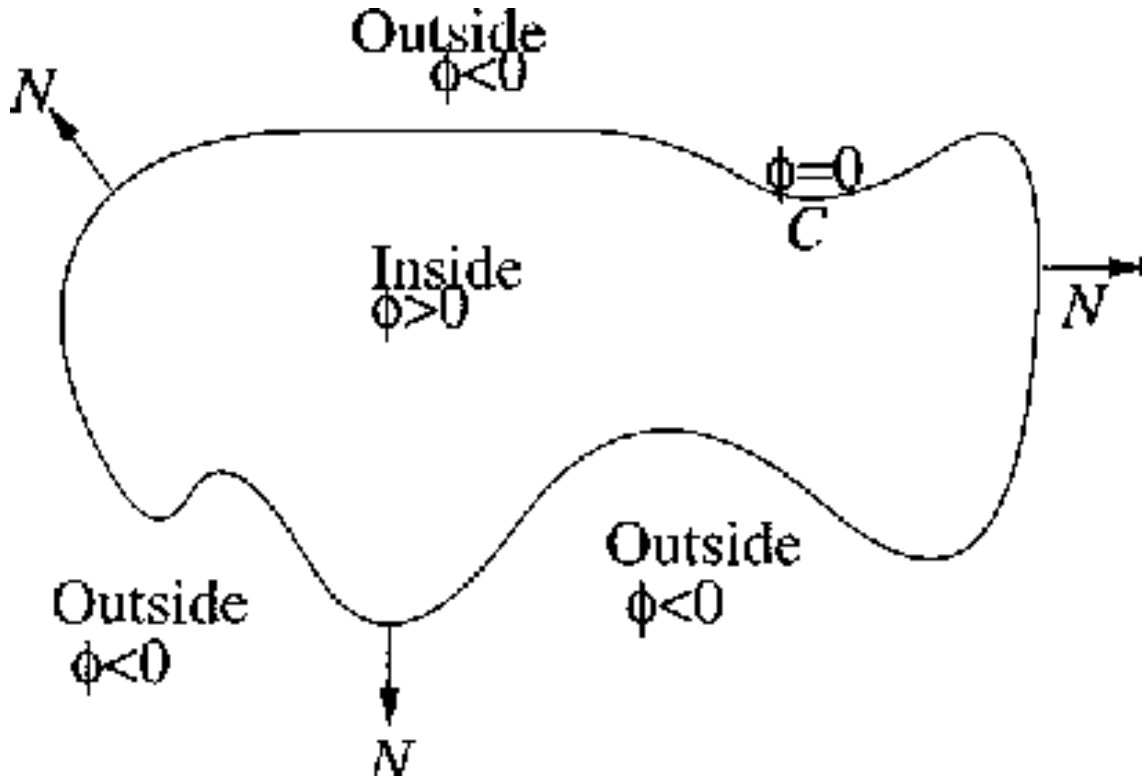

Example

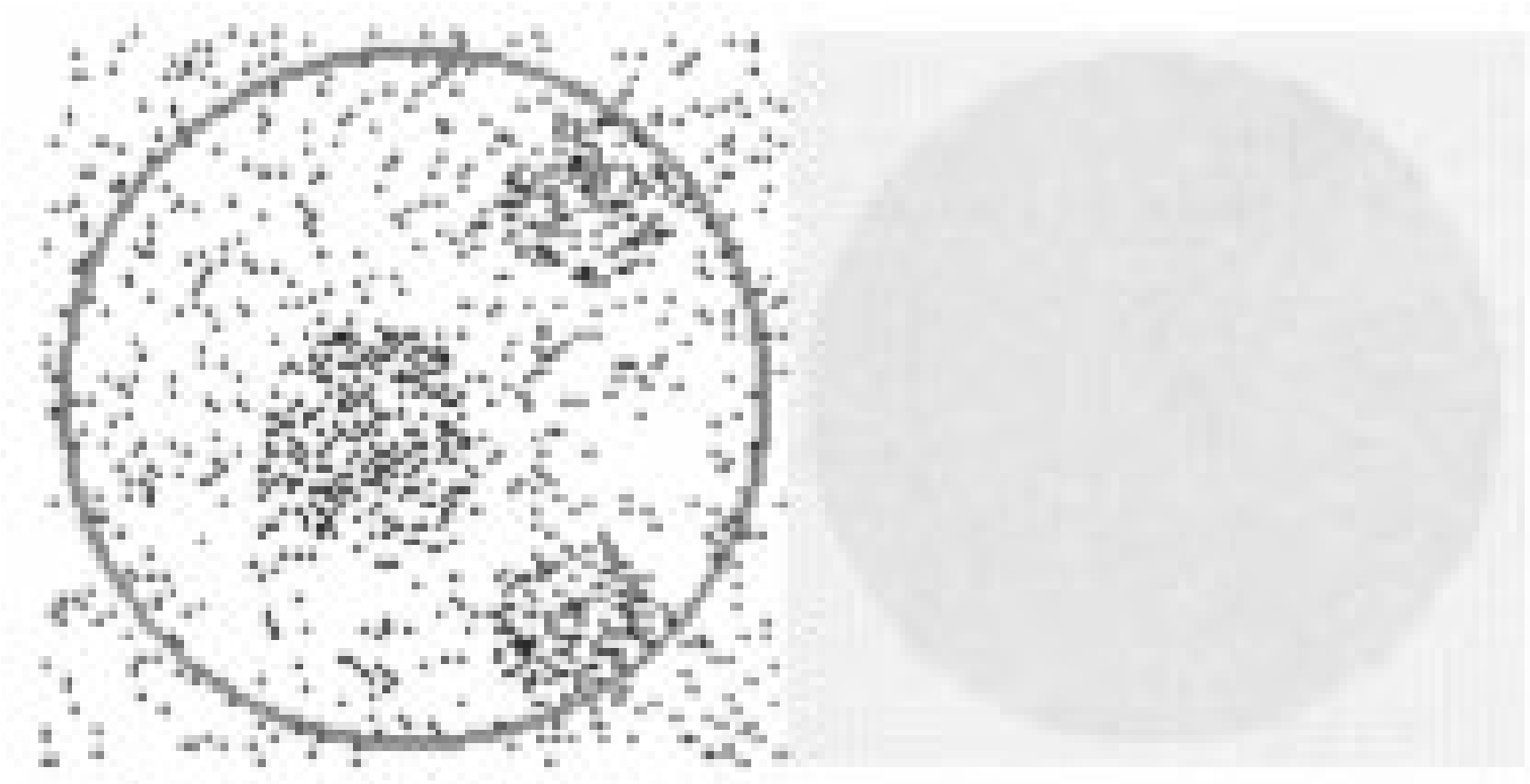

Figure: Detection of a simulated minefield, with contour without gradient.

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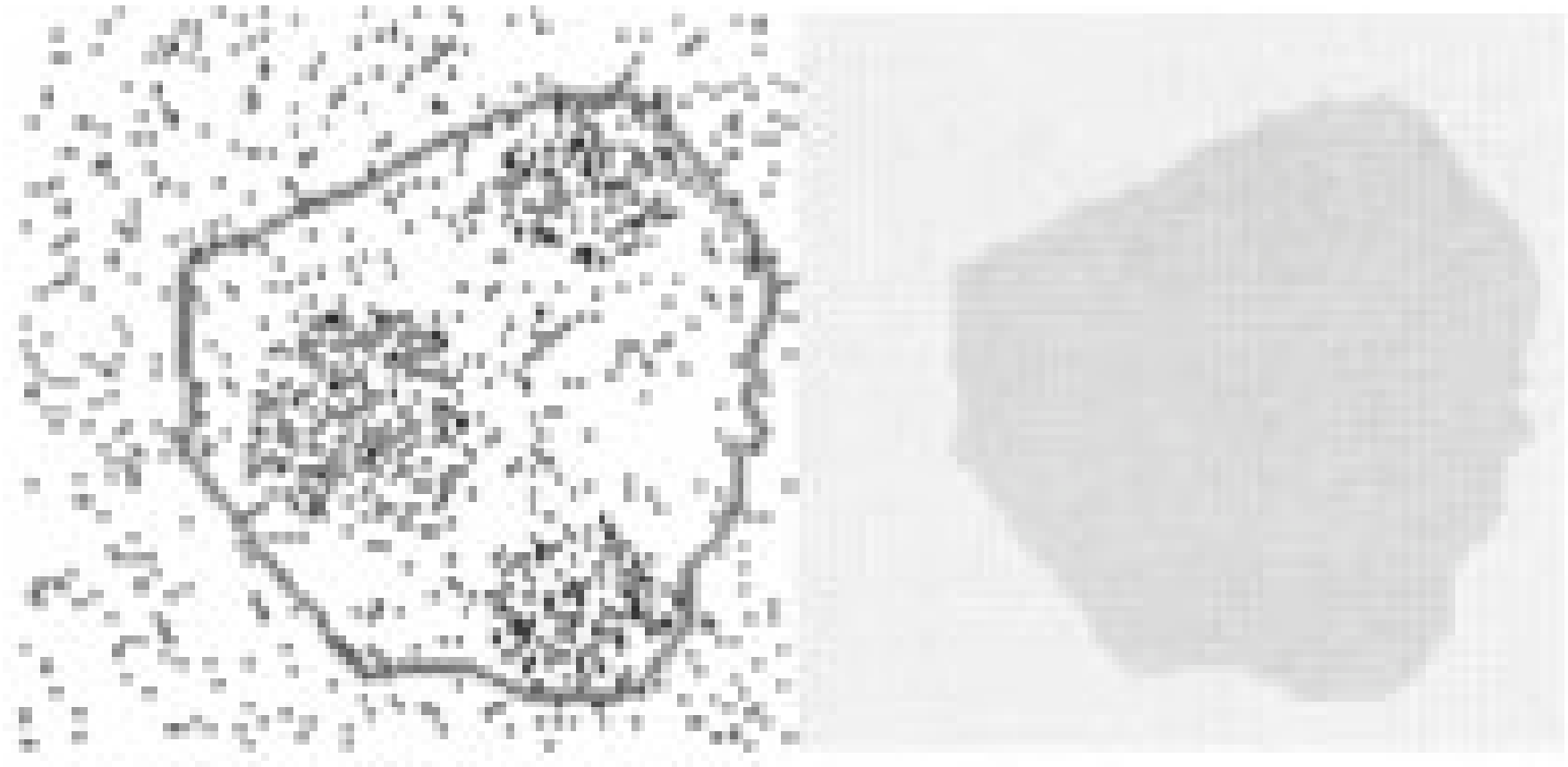

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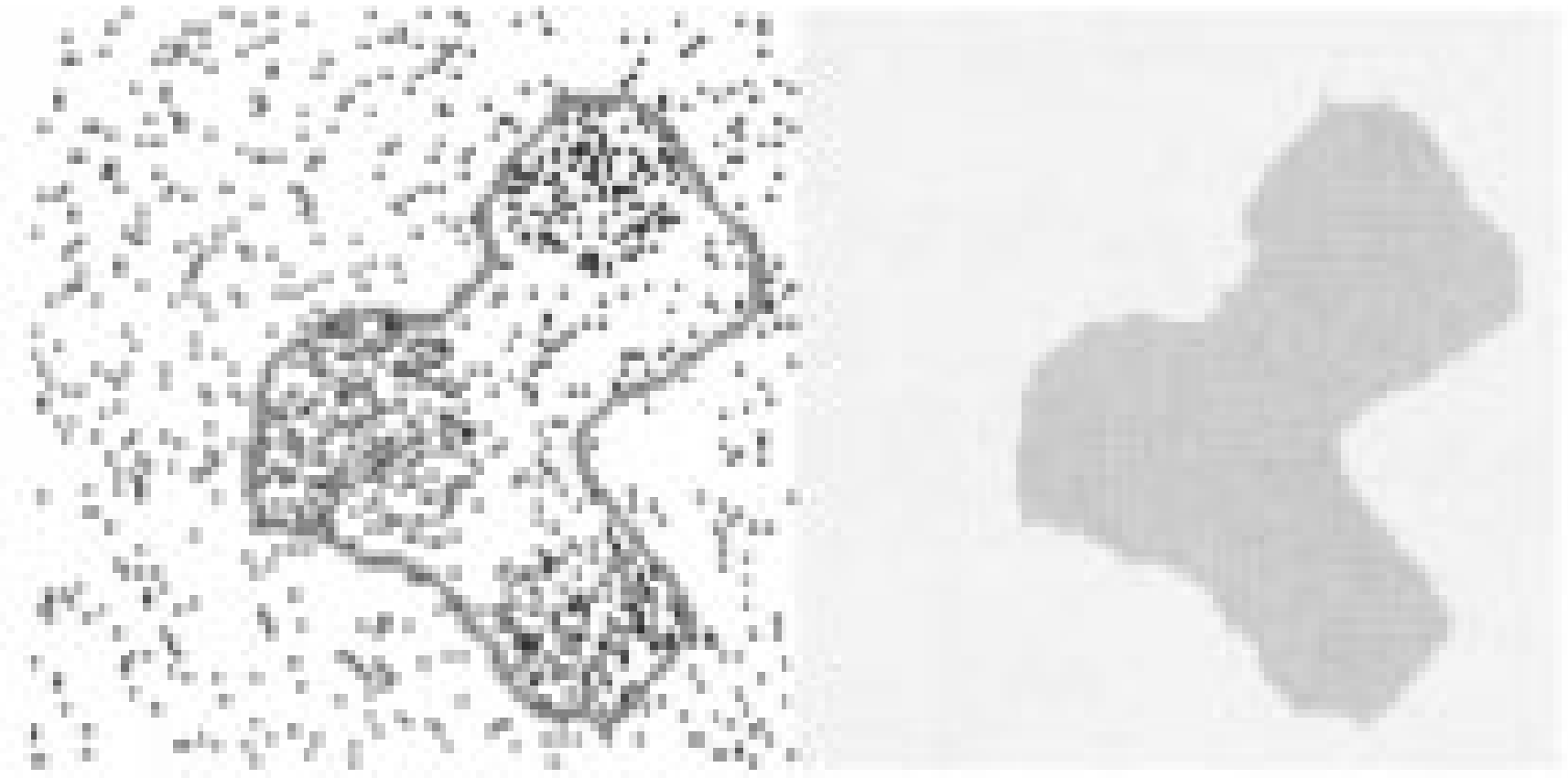

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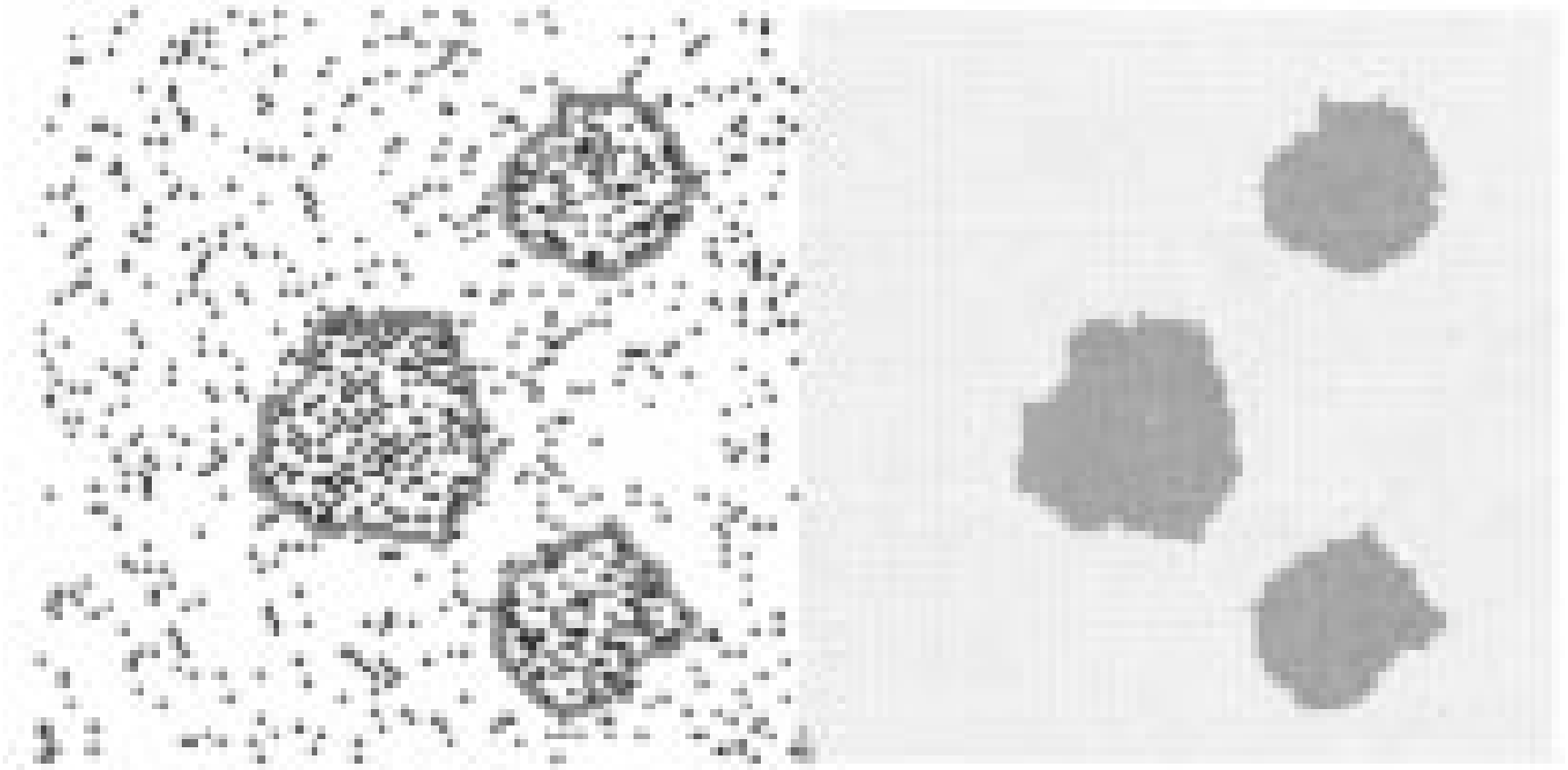

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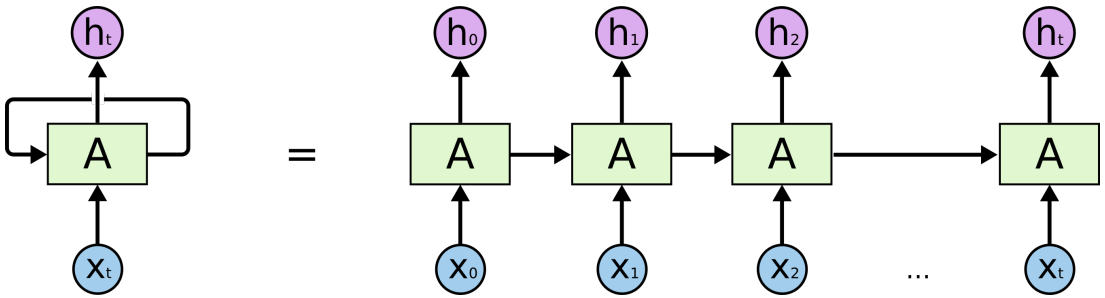
Recurent Neural Network

- Class of artificial neural network where connections between units form a directed graph along a sequence;
- Recurrent Neural Network comes into the picture when any model needs context to be able to provide the output based on the input, RNN remembers everything;

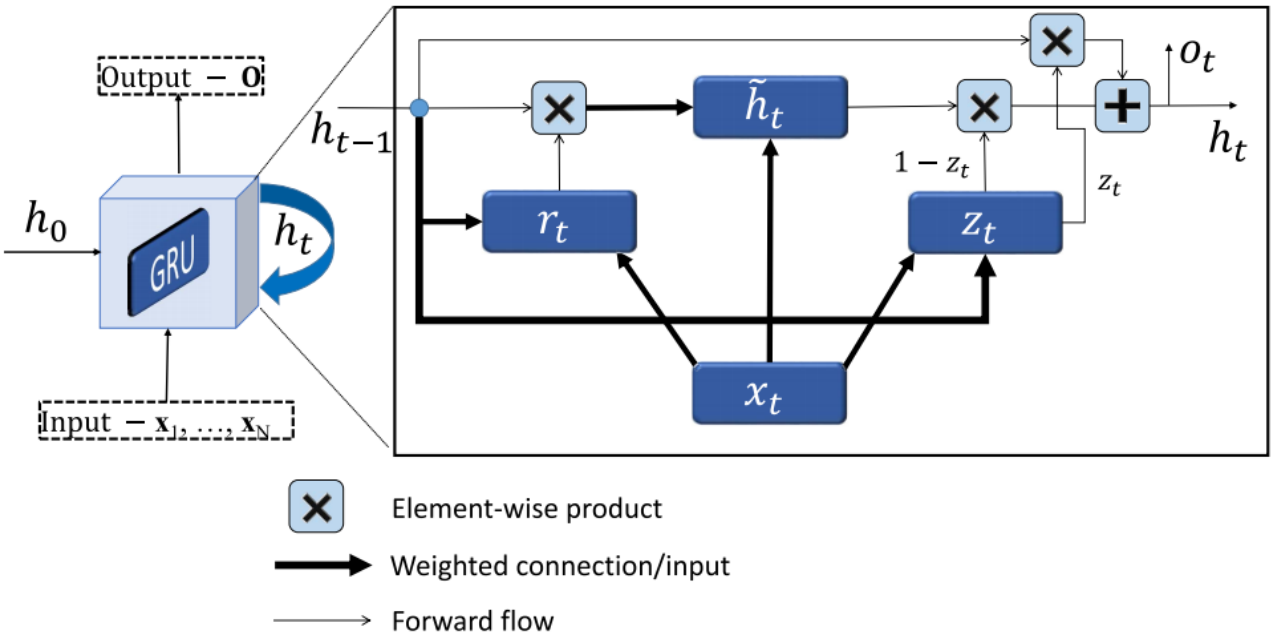


Gate Recurrent Unit

- GRU fully exposes its memory content each timestep and balances between the previous memory content and the new memory content ;
- Each GRU has a reset gate r_t, an update gate z_t, an activation state h_t and a new candidate memory content o_t given by the following equations

GRU

- An input sequence $x_1, x_2, \ldots, x_N$ and an initial state hidden h_0



Problems occuring when we reformulate the problem

- The difficult part of reformulating CLS as recurrent network is data configuration. Recurrent network works on sequence data while both the input and the output of the CLS approach are single images $\Longrightarrow$ How to generate sequence data from a single image ?

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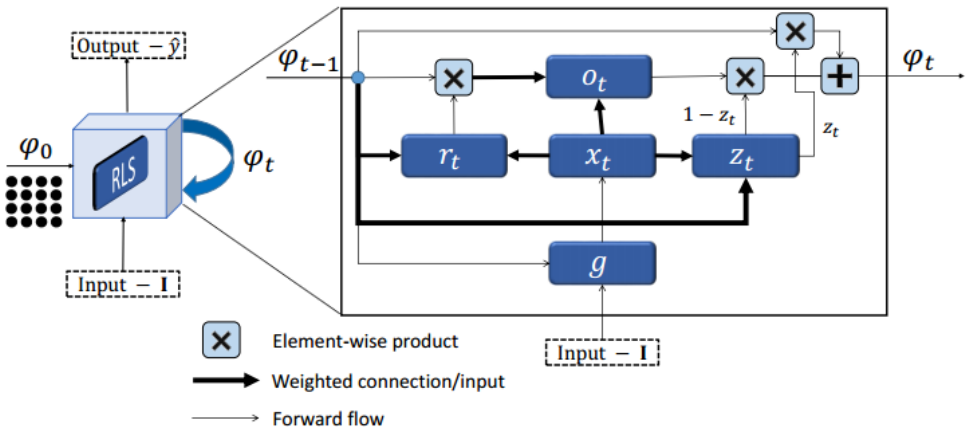
- The difficult part of reformulating CLS as recurrent network is data configuration. Recurrent network works on sequence data while both the input and the output of the CLS approach are single images $\Longrightarrow$ How to generate sequence data from a single image ?
- Solution $\Longrightarrow$ compute x_t, which would be considered as an input sequence, as a function of φ introduce in the CLS ; Here φ will be seen as the hidden state

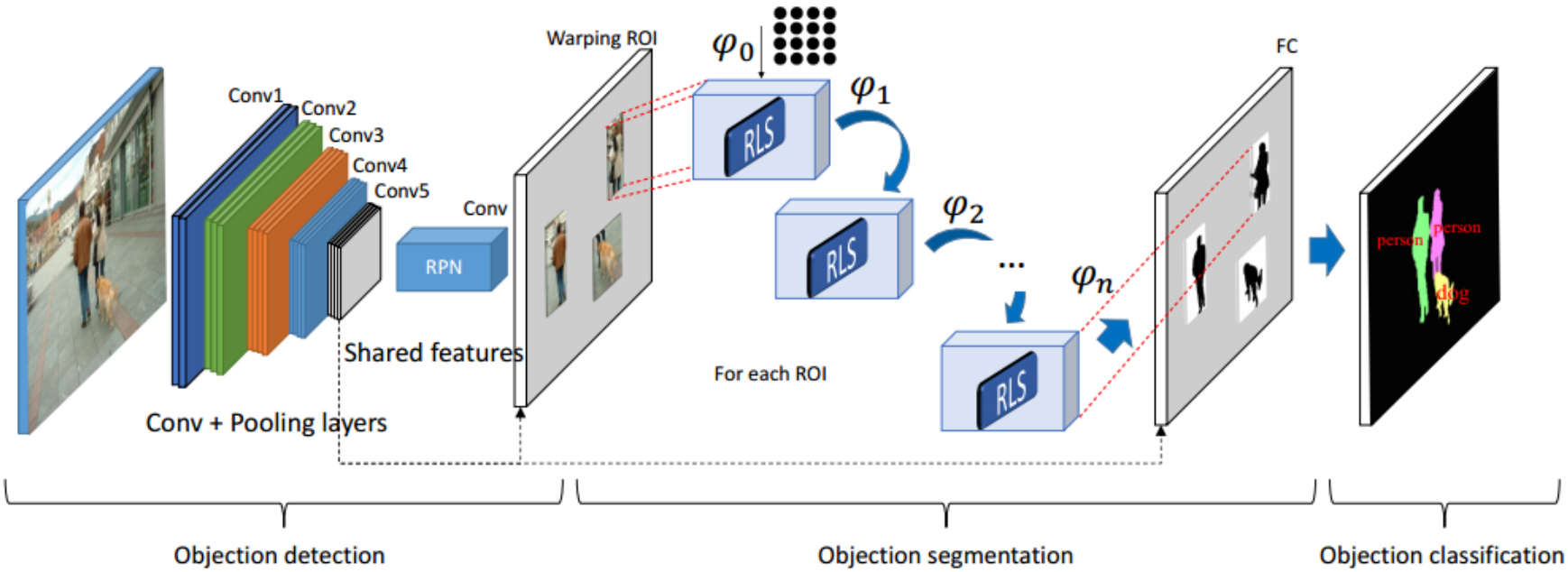
Solutions and reformulation

	CLS	GRU	RLS
Input	Image $\mathbf{I}$ Initial LS function φ_0	Sequence $x_1, x_2, ..., x_N$ Initial state hidden h_0	Image $\mathbf{I}$ Initial LS function φ_0
Update	$\varphi_{t+1} = \varphi_t + \eta \frac{\partial \varphi_t}{\partial t}$ $\frac{\partial \varphi}{\partial t} = \delta_\epsilon(\varphi[\nu\kappa(\varphi - \mu)\lambda_1(\mathbf{I}-c_1)^2+\lambda_2(\mathbf{I}-c_2)^2])$	$z_t = f(U_z x_t + W_z h_{t-1})$ $r_t = f(U_r x_t + W_r h_{t-1})$ $o_t = tanh(U_h x_t + W_h(h_{t-1} \circ r_t))$ $h_t = (1 - z_t)h_{t-1} + z_t o_t$	$x_t = \kappa(\varphi_{t-1}) - U_g((\mathbf{I} - c_1))^2 + W_g((\mathbf{I} - c_2))^2$ $z_t = \sigma(U_z x_t + W_z \varphi_{t-1} + b_z)$ $r_t = \sigma(U_r x_t + W_r \varphi_{t-1} + b_r)$ $o_t = tanh(U_o x_t + W_o(\varphi_{t-1} \circ r_t) + b_o)$ $\varphi_t = z_t \circ \varphi_{t-1} + (1 - z_t) \circ o_t$
Output	φ_N	$softmax(V h_N)$	$softmax(V \varphi_N + b_V)$



The full model using RLS in order to do semantic segmantation (CRLS)

- Model construct in 3 parts: Detection,segmentation and classification;



Experimental results : RLS object segmentation

Performance measure

- Synthetic dataset made of black and white images
- F-measure :

$$2\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

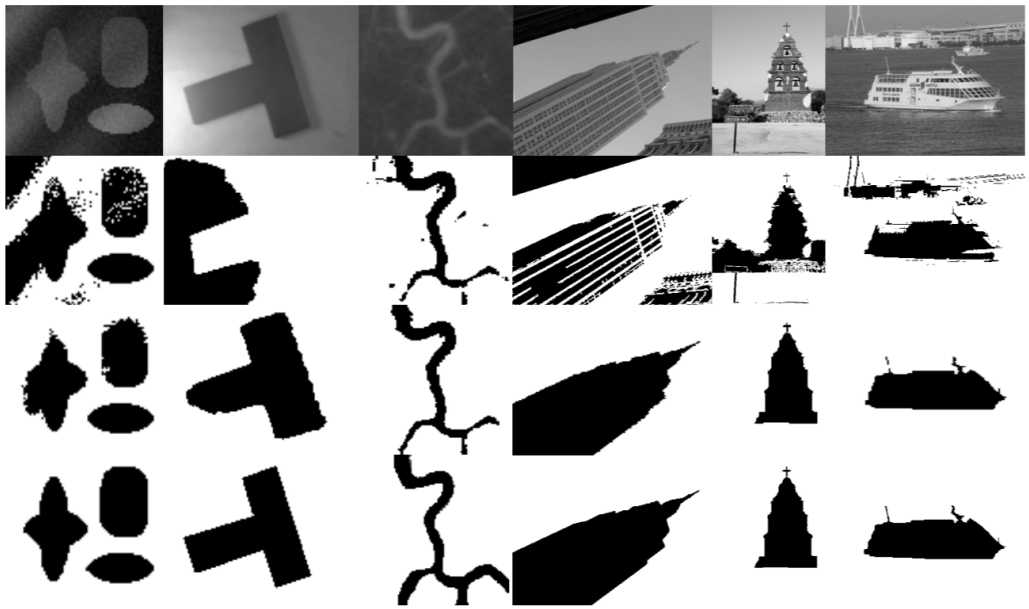
Compared methods

- Classical level-set approach
- Simple neural network
- Recurrent level-set (RLS)

Experimental results : RLS object segmentation

Results

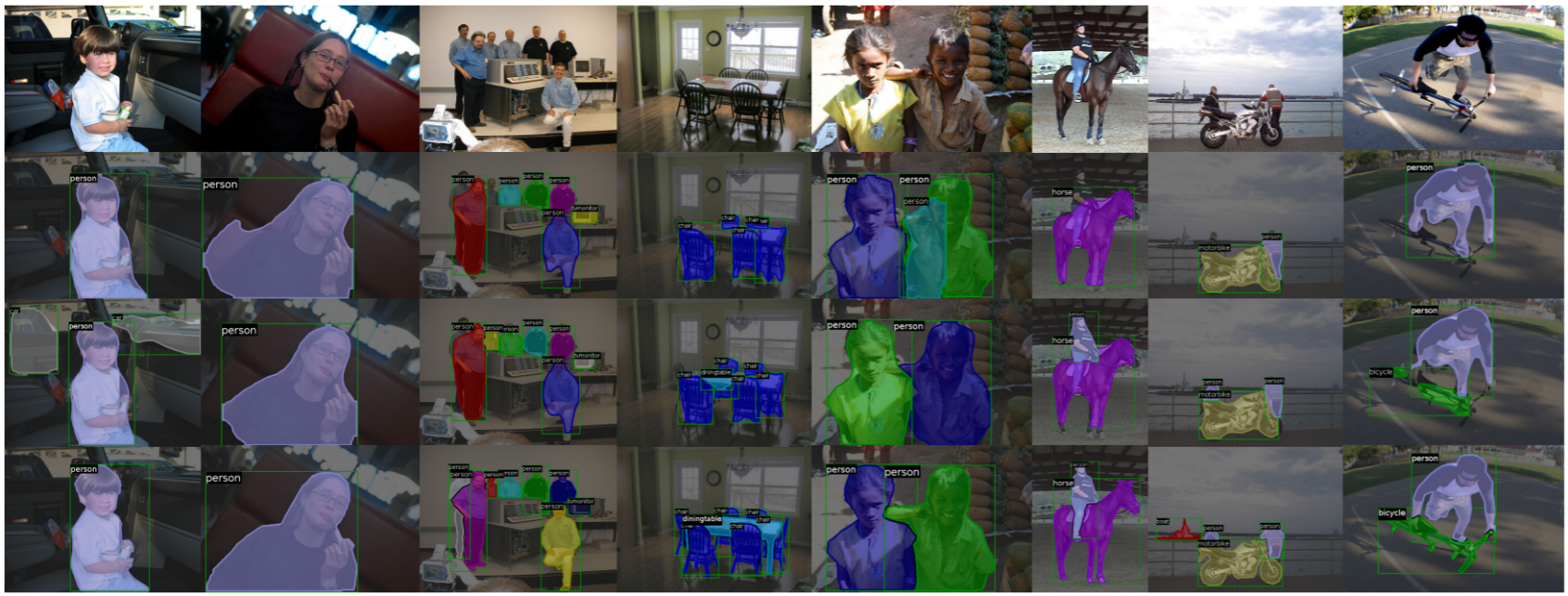
Methods	GT1	GT2	Test Time (s)
CV	88.51	87.51	13.5
FCN	93.3	93.26	0.001
RLS	99.16	99.17	0.008



Experimental results : CRLS object segmentation

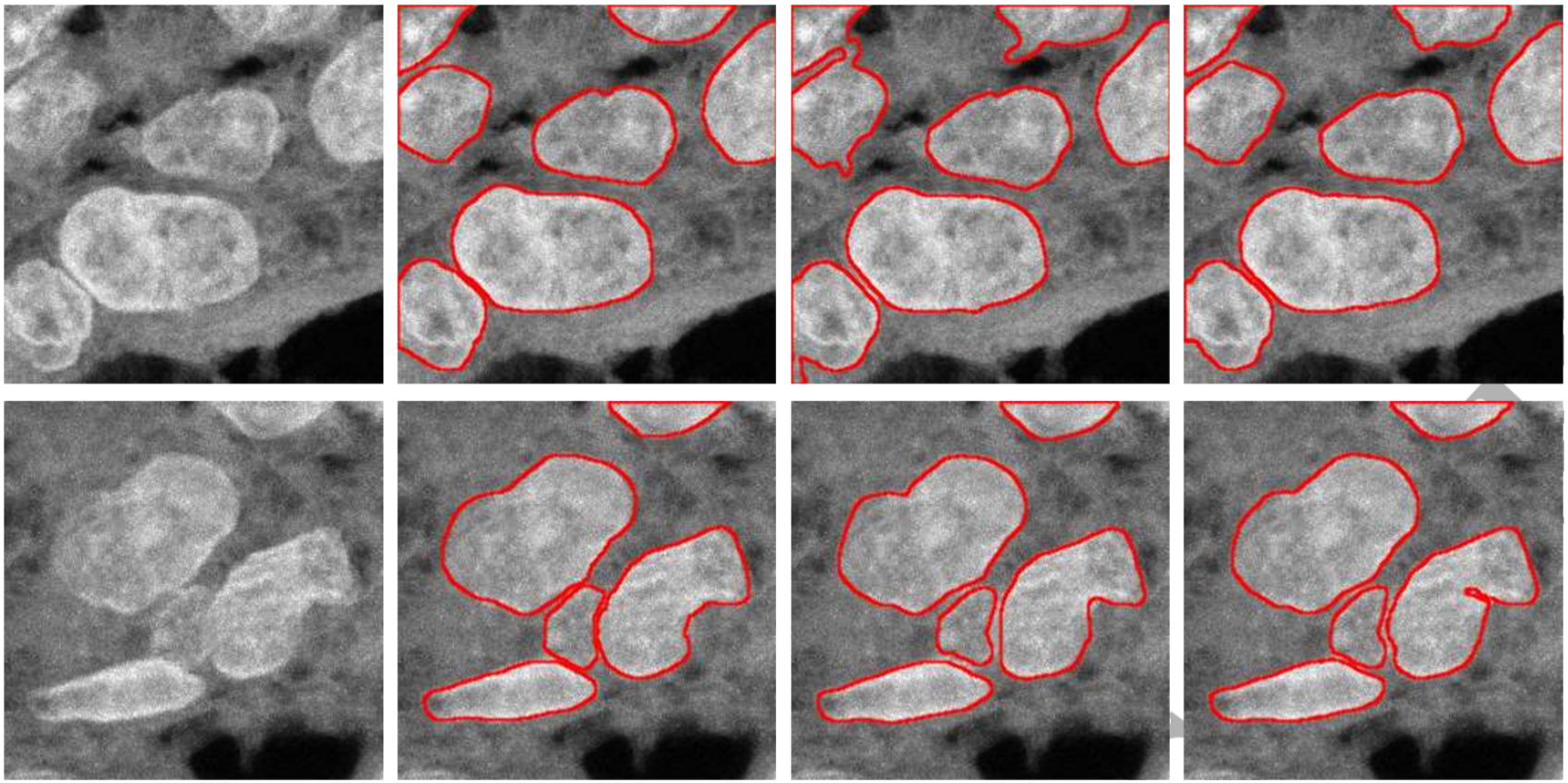
Performance measure

- Pascal VOC image semantic segmentation challenge
- Intersection over Union (mIoU)
- Threshold at 0.5



Application to medical images

- Missing point of the article
- GRUU-Net: Integrated convolutional and gated recurrent neural network for cell segmentation, Medical Image Analysis, 2019, T. Wollmann, M. Gunkel, I. Chung, H. Erfle, K. Rippe, K. Rohr



Improve the level set approach

Classical method

- Combine region-based and edge-based object segmentation technics
- Hybrid level set models by maximising an hybrid energy

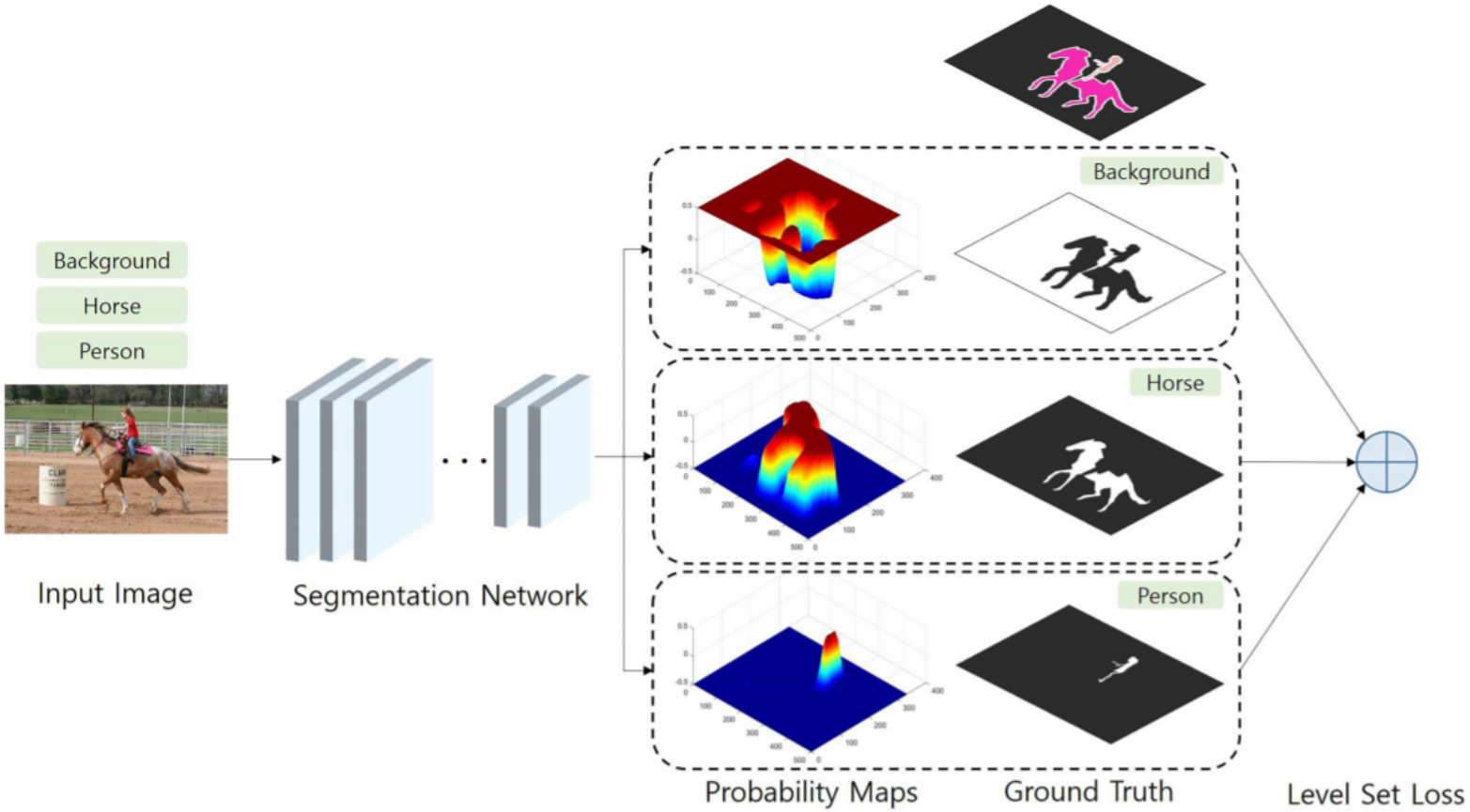
$$E_{hybryde} = E_{edge} + \lambda E_{region}$$

- ResIs: Region and edges energetic level set framework for image segmentation, IEEE Transactions on Image Processing, 2019, W. Zhang, X. Wang, W. You, J. Chen, P. Dai, and P. Zhang

Improve the level set approach

Deep learning method

- End-to-end standard deep learning procedure
- Loss functions inspired by level-sets



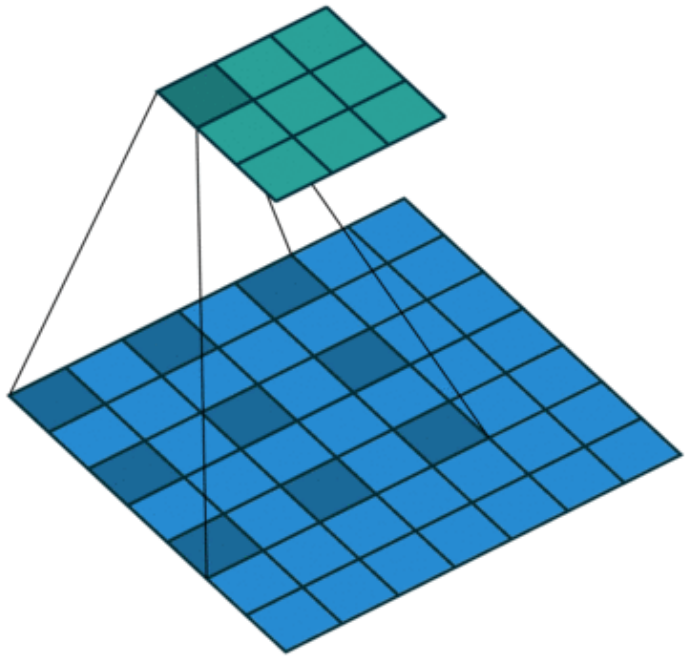
- Cnn-based semantic segmentation using level set loss, 2019, Y. Kim, S. Kim, T. Kim, and C. Kim

Limitation of sequential modeling with RNN and level-sets approaches

- Quite involved
- Computationally expensive
- Designed for object segmentation and not semantic segmentation
- Does not yield state-of-the-art performance

State-of-the-art model for semantic segmentation

- Atrous convolution : deal with multi scale structures



- Semantic image segmentation with deep convolutional nets and fully connected, 2014, L. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. Yuille

Conclusion

- Classical level-set approaches
- RNN based approaches for sequential modeling
- CNN based approaches using level-set inspired loss functions
- State-of-the-art : CNN with atrous convolutions