Segmentation

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Introduction

Segmentation is a challenging problem which consists of two tightly coupled tasks: recognition and delineation.

- Recognition involves detection (object's localization) and result verification (humans $\gg$ computers).
- Delineation consists of defining the precise spatial extent of the object in the image (computers $\gg$ humans).

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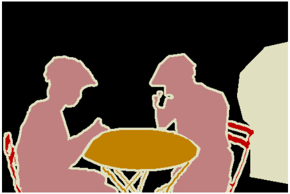

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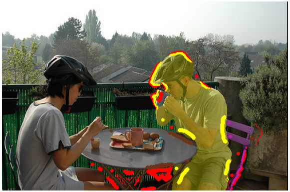

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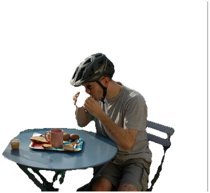

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- Object-based models, which learn object shape and texture (e.g., a pixel classifier) models.
- Hybrid techniques, which combine image- and object-based strategies.

Examples of segmentation approaches are

- pixel-based: thresholding and clustering;
- boundary-based: deformable shape models (e.g., snakes) and contour-tracking methods (e.g., live wire and riverbed);
- region-based: watershed transforms, minimum graph cut, random walks, and level sets.
- object-based: statistical shape models and fully convolutional neural networks.

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- Object-based models usually fail in anomolous cases.

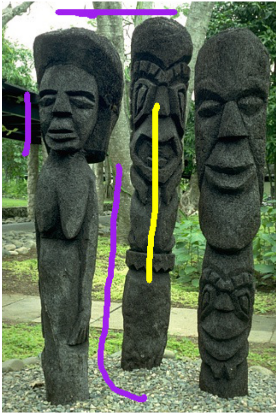
Their combination with minimal user intervention, whenever it is possible, seems to be the most reasonable alternative.

Agenda

- The role of optimum connectivity in image segmentation.
- Interactive object (instance) segmentation using the Image Foresting Transform (IFT) and FLIM [1].
- Hybrid segmentation using IFT and object-based models [2].
- Image segmentation using deep learning.

When do we need connectivity?

One can easily train a pixel classifier from image markers and select the desired object from the label map.



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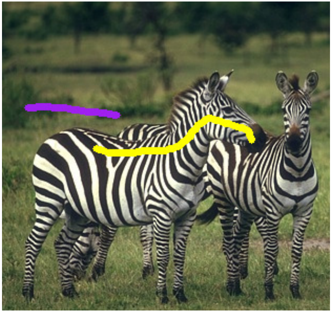
When do we need optimum connectivity?

Optimum connectivity is needed when object and parts of the background with similar properties are connected to each other.



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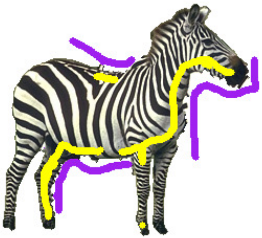

Such a strategy could be used to resume semantic segmentation by an optimum-path forest and correct the results in an interactive fashion [3, 4].

IFT-based object delineation

For a 2D image $\hat{I} = (D_I, \mathbf{I})$, let $(\mathcal{N}, \mathcal{A}, w)$ be such that $\mathcal{N} = D_I$, $\mathcal{A}$ is the 4-neighborhood, and w is an arc-weight function.

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- Let $\mathcal{S}$ be a seed set created by internal and external markers for object delineation.
- A connectivity function suitable for object delineation is

$$
\begin{aligned}
f_{\max}(\langle p \rangle) &= \begin{cases} 0 & \text{if } p \in \mathcal{S} \\ +\infty & \text{otherwise.} \end{cases} \\
f_{\max}(\pi_p \cdot \langle p, q \rangle) &= \max\{f_{\max}(\pi_p), w_i(p, q)\},
\end{aligned}
$$

where $R(p)$ is the root of π_p, and
$w_i(p, q) = \|\mathbf{I}(R(p)) - \mathbf{I}(q)\|$ [5].

IFT-based object delineation with FLIM

For instance, FLIM can be used to compute features from image markers [1] while the object is delineated by Dynamic Trees [5].

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The arc weight may also be defined as

$$w(p,q) = K\left[\gamma w_o(p,q) + (1-\gamma) w_i(p,q)\right],$$

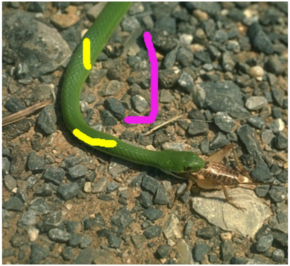
where

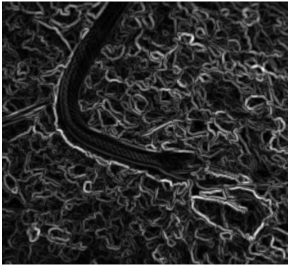
- $w_o(p,q) = |O(p) - O(q)| \in [0,1]$ is the absolute difference in object membership between p and q, according to an object map O and
- $\gamma \in [0,1]$ and $K > 1$.

IFT-based object delineation

The user can select markers and visualize the resulting arc weights as an image $\hat{D} = (D_I, D)$,

$$D(p) \quad = \quad \max_{\forall q \in \mathcal{A}(p)} \{w(p,q)\}.$$





with $w_i(p,q) = \|\mathbf{I}(p) - \mathbf{I}(q)\|$ only.

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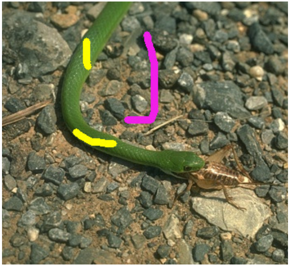
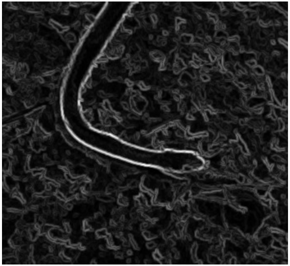
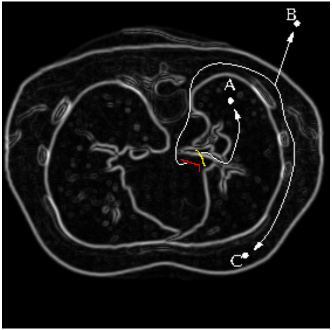
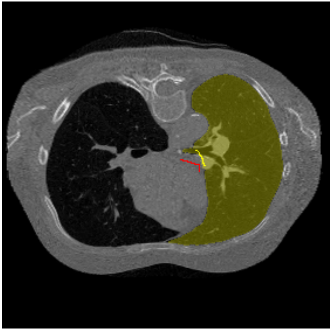




with $w_o(p,q)$ and $w_i(p,q)$, for $\gamma = 0.8$.

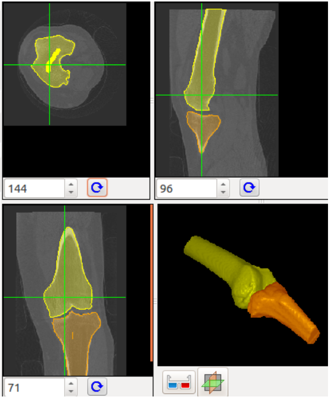
Seeds must be selected around low-contrast parts of the object's boundary.

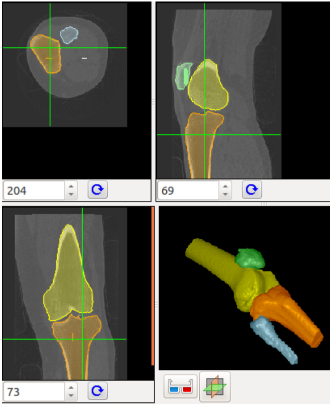




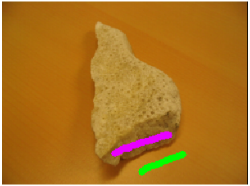
Seed addition/removal for delineation

The segmentation can be edited by adding and/or removing seeds, such that the forest is reconstructed in a differential way [6].

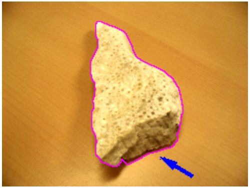




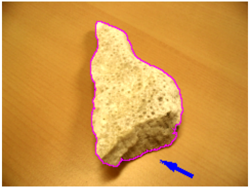
Region-based delineation using border orientation



original



non-oriented



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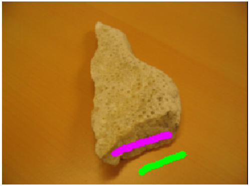

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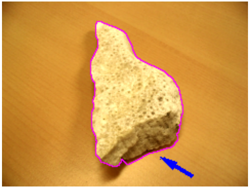

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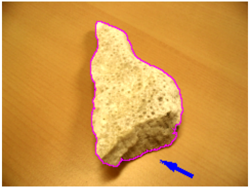


oriented

$$
\begin{aligned}
f_{omx}(\langle p \rangle) &= \begin{cases} 0 & \text{if } p \in \mathcal{S}_i \cup \mathcal{S}_e \\ +\infty & \text{otherwise,} \end{cases} \\
f_{omx}(\pi_p \cdot \langle p, q \rangle) &= \max\{f_{omx}(\pi_p), w(p,q)\} \\
w(p,q) &= \begin{cases} w_i^{1.5}(p,q) & \text{if } O(p) > O(q) \text{ and } R(p) \in \mathcal{S}_i, \\ w_i^{1.5}(p,q) & \text{if } O(p) < O(q) \text{ and } R(p) \in \mathcal{S}_e, \\ w_i(p,q) & \text{otherwise,} \end{cases}
\end{aligned}
$$

where $\mathcal{S}_i$ and $\mathcal{S}_e$ are internal and external seeds, and $R(p)$ is the root of p [7].

The IFT algorithm with f_{omx} can be described as follows.

Input: Arc-weighted graph $(D_I, \mathcal{A}, w_i')$ and seed set $\mathcal{S}_i \cup \mathcal{S}_e$ labeled by function λ: $\mathcal{S}_i \rightarrow \{1\}$ and $\mathcal{S}_e \rightarrow \{0\}$.

Output: Label image $\hat{L} = (D_I, L)$.

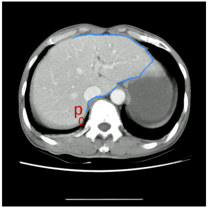
Auxiliary: Priority queue $\mathcal{Q}$, connectivity map V, root map R, and var

Instead of using $R(p) \in \mathcal{S}_i$ and $R(p) \in \mathcal{S}_e$, one may use $L(p) = 1$ and $L(p) = 0$, respectively, when computing $w(p, q)$.

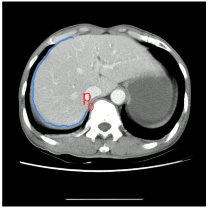
Region-based delineation using border orientation

1. For each $p \in D_I$, do.
2. If $p \in \mathcal{S}_i \cup \mathcal{S}_e$ then.
3. Set $L(p) \leftarrow \lambda(p)$, $R(p) \leftarrow p$ and $V(p) \leftarrow 0$.
4. Else, set $V(p) \leftarrow +\infty$.
5. Insert p in $\mathcal{Q}$.
6. While $\mathcal{Q} \neq \emptyset$, do.
7. Remove p from $\mathcal{Q}$ such that $p = \arg\min_{\forall q \in \mathcal{Q}}\{V(q)\}$.
8. For each $q \in \mathcal{A}(p) \mid q \in \mathcal{Q}$, do.
9. Set $tmp \leftarrow \max\{V(p), w(p,q)\}$.
10. If $tmp < V(q)$, then.
11. Set $V(q) \leftarrow tmp$, $R(q) \leftarrow R(p)$ and $L(q) \leftarrow L(p)$.
12. Return $\hat{L} = (D_I, L)$.

Oriented boundary delineation

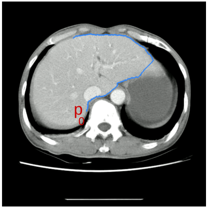


non-oriented



clockwise oriented

Oriented boundary delineation



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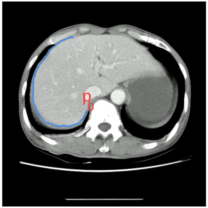

clockwise oriented

$$
\begin{aligned}
f_{lwr}(\langle p \rangle) &= \begin{cases} 0 & \text{if } p = p_0 \\ +\infty & \text{otherwise,} \end{cases} \\
f_{lwr}(\pi_p \cdot \langle p, q \rangle) &= f_{lwr}(\pi_p) + w(p,q) \\
w(p,q) &= \begin{cases} [K - w_i(r,l)]^{1.5} & \text{if } O(l) > O(r), \\ K - w_i(r,l) & \text{otherwise,} \end{cases}
\end{aligned}
$$

where p_0 is an initial point on the boundary, r and l are the right (interior) and left (exterior) pixels of (p, q) [8].

Oriented boundary delineation from p_0 to p_1

The IFT algorithm with f_{lwr} can be described as follows.

Input: Arc-weighted graph $(D_I, \mathcal{A}, w_i')$, seed pixel p_0, and target pixel p_1.

Output: Predecessor image $\hat{P} = (D_I, P)$.

Auxiliary: Priority queue $\mathcal{Q}$, connectivity map V, and variable tmp.

Oriented boundary delineation from p_0 to p_1

1. For each $p \in D_I$, do.
2. If $p = p_0$ then.
3. Set $P(p) \leftarrow nil$ and $V(p) \leftarrow 0$.
4. Else, set $V(p) \leftarrow +\infty$.
5. Insert p in $\mathcal{Q}$.
6. While $\mathcal{Q} \neq \emptyset$, do.
7. Remove p from $\mathcal{Q}$ such that $p = \arg\min_{\forall q \in \mathcal{Q}}\{V(q)\}$.
8. If $p = p_1$ then return $\hat{P} = (D_I, P)$.
9. For each $q \in \mathcal{A}(p) \mid V(q) > V(p)$, do.
10. Set $tmp \leftarrow V(p) + w(p, q)$.
11. If $tmp < V(q)$, then.
12. Set $V(q) \leftarrow tmp$ and $P(q) \leftarrow p$.

- The path $\pi = \pi_{p_0 \rightarrow p_1}$ is obtained by calling $Path(P, \pi, p_0, p_1)$ for π initially empty.

  $Path(P, \pi, p_0, p)$:
  1. If $(p = p_0)$ then.
  2. Return $\pi \leftarrow \langle p_0 \rangle$.
  3. Else
  4. Return $\pi \leftarrow Path(P, \pi, p_0, P(p)) \cdot \langle P(p), p \rangle$.

- Now suppose p_1 is the cursor position and it moves to p_2, the predecessor map P can be updated by the following incremental algorithm.

Oriented boundary delineation from p_0 to p_2

1. If $p_2 \notin \mathcal{Q}$ then return $\hat{P} = (D_I, P)$.
2. While $\mathcal{Q} \neq \emptyset$, do.
3. Remove p from $\mathcal{Q}$ such that $p = \arg\min_{\forall q \in \mathcal{Q}} \{V(q)\}$.
4. If $p = p_2$ then return $\hat{P} = (D_I, P)$.
5. For each $q \in \mathcal{A}(p) \mid V(q) > V(p)$, do.
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How can texture and shape models substitute a human in object localization?

Hybrid segmentation using IFT and object models

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- A shape model estimates markers, while it translates and imposes shape constraints for object delineation.

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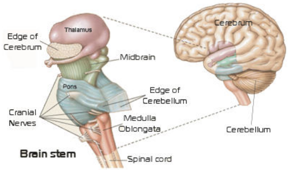
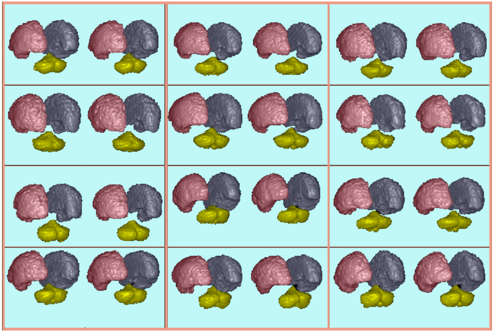
A voxel classifier can reduce candidate locations and avoid wrong marker selection.

Result of model-based segmentation of the brain hemispheres and cerebellum without the brain stem.





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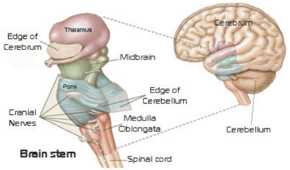
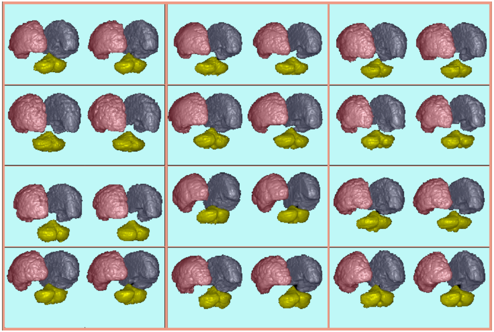
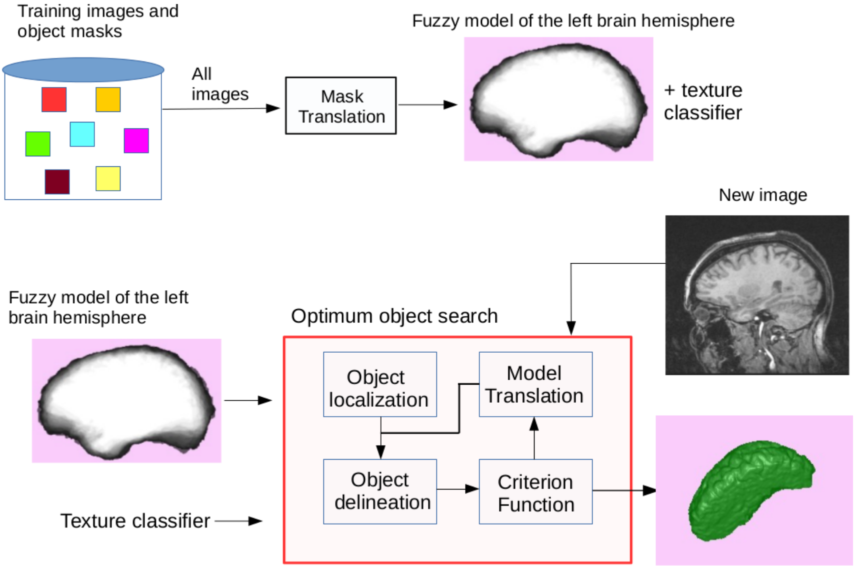


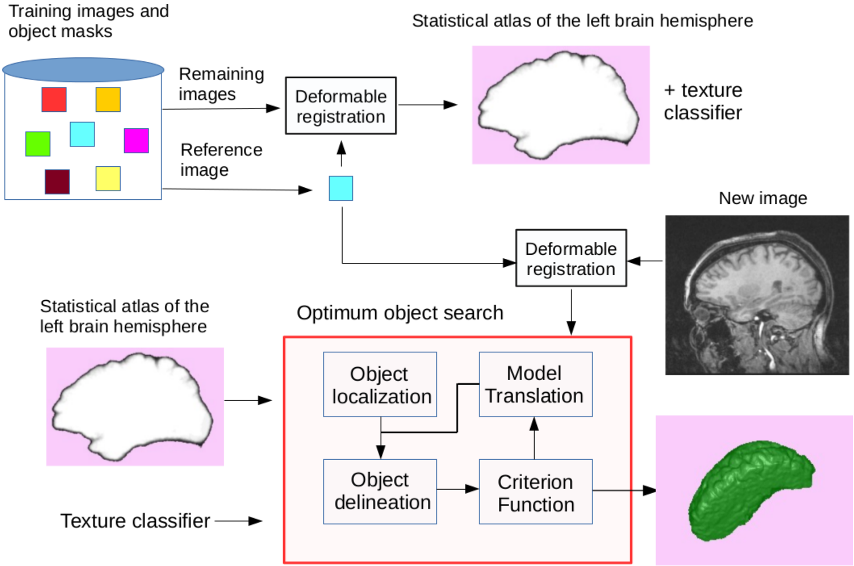


We have developed two types of shape models under this segmentation paradigm, fuzzy models [9] and statistical atlases [10, 11, 2].

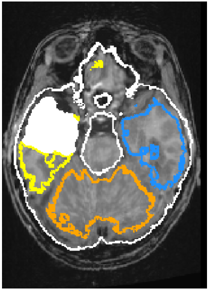
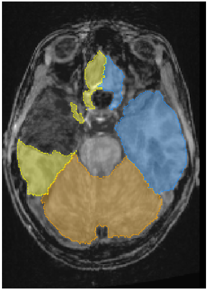
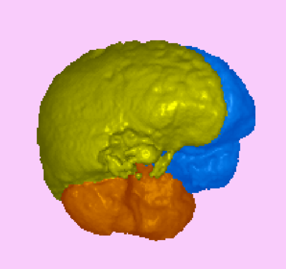
Fuzzy object shape models: construction and use



Statistical atlases: construction and use



Abnormal brain: the voxel classifier avoids internal markers in surgically removed regions of the brain.

- Semantic segmentation has been addressed with no user intervention.

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- Successful methods start by using fully convolutional neural networks – i.e., rather than applying CNNs to patches around pixels, convolutional layers extract image features and a pixel classifier predicts their labels [12].

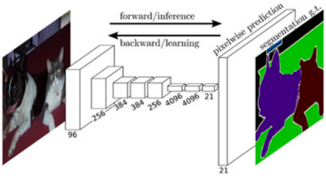

Figure from [12].

- Subsequenty, the predictor was substituted by deconvolutional layers (convolution with upsampling) forming an encoder-decoder architecture, with skip connections [13].

Image segmentation with deep learning

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- However, as downsampling used by pooling is crucial for object detection, accurate boundary delineation becomes compromised.

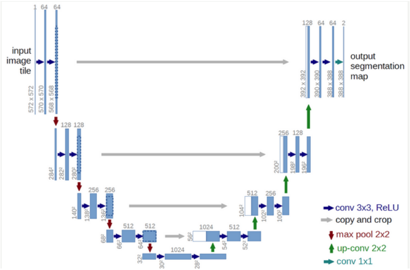

Figure from [13].

Atrous (dilated) convolution and spatial pyramidal pooling have been introduced and combined to alleviate the downsizing problem and capture multiscale information [14].

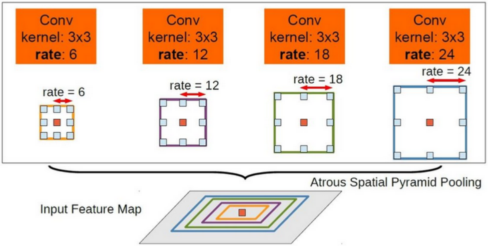

Figure from [14].

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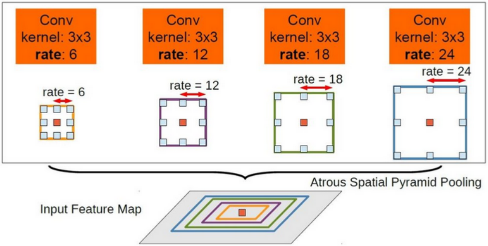

Figure from [14].

However, boundary delineation is still compromised since the backbone comes from CNNs (VGG-16 or ResNet-101) used for image classification.

Image segmentation with deep learning

A compromise between detection and delineation is still subject of investigation by combining large kernels for localization (Global Convolutional Blocks), boundary refinement blocks [15, 16], and kernel-sharing atrous convolution (when dilated kernels are combined into a single one) [17].

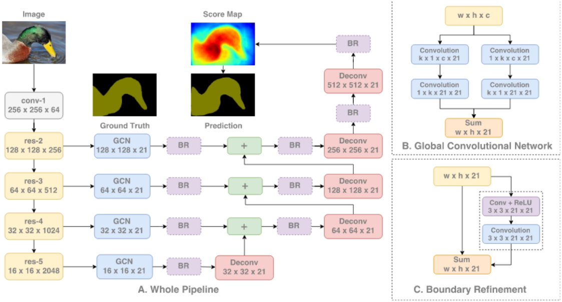

Figure from [15].

Still, user interaction is needed to improve prediction, especially for instance segmentation, and with no guarantee that the classified pixels are connected to the user clicks [18].

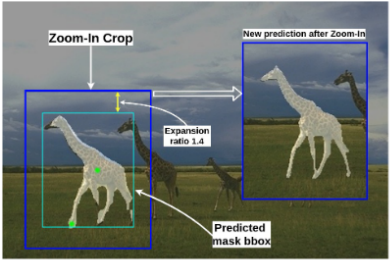

Figure from [18].

Image segmentation with deep learning

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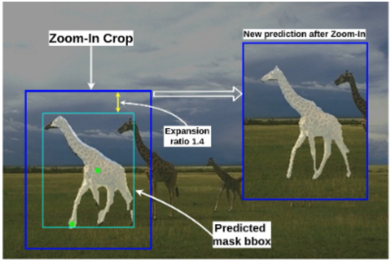

Figure from [18].

Could we use the IFT to add connectivity information and improve object delineation in deep learning?

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