

Advanced Image Processing and Image Segmentation Techniques

– Segmentation



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Fuzzy Connectedness Analysis

I. Introduction:

- 1 Fuzzy relation
- 2 Fuzzy digital space and paths
- 3 Fuzzy adjacency and affinity
- 4 Fuzzy connectedness

II. Fuzzy connectedness-based image segmentation:

- 1 Fuzzy objects
- 2 Starting points
- 3 Fuzzy connectedness scene
- 4 Multi-objects fuzzy connectedness

III. Implementation:

- ① Graph searching using dynamic programming
- ② Graph searching using Dijkstra algorithm
- ③ Matrix transformation-based graph analysis

- The fuzzy connectedness (FC) theory is a branch of science using fuzzy logic, sets and relations.
- Authors: Jayaram Udupa and Supun Samarasekera (1996), Azriel Rosenfeld (1979) - Digital topology



Azriel Rosenfeld



Jayaram Udupa

Articles:

- ① A. Rosenfeld, Digital Topology, American Mathematical Monthly, (86):621–630, 1979.
- ② A. Rosenfeld, Fuzzy Digital Topology, Information and Control, 40(1): 76–87, 1979.
- ③ J. Udupa, S. Samarasekera, Fuzzy Connectedness and Object Definition: Theory, Algorithms, and Applications in Image Segmentation, Graphical Models and Image Processing, 58(3): 246–261, 1996.
- ④ P. Saha, J. Udupa, D. Odhner, Scale-Based Fuzzy Connected Image Segmentation: Theory, Algorithms, and Validation, Computer Vision and Image Understanding, 77(9): 145–174, 2000.
- ⑤ J. Udupa, P. Saha, Fuzzy Connectedness and Image Segmentation, Proceedings of the IEEE, 91: 1649–1669, 2003.

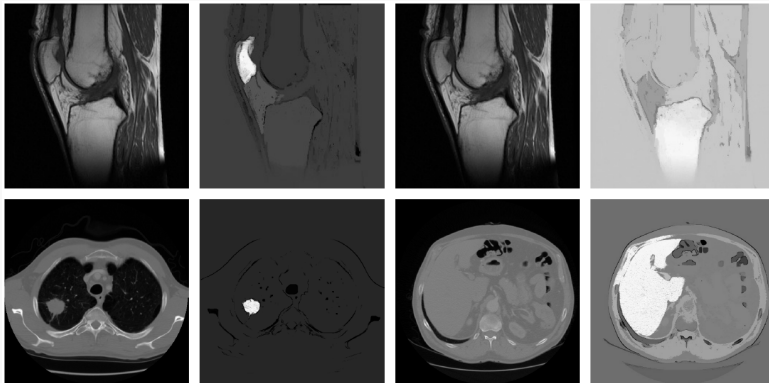
Motivation

- heterogeneity of intensity analysis
- heterogeneous object segmentation
- the analysis of ordered and connected data
- natural grouping of voxels

Applications

- image processing - image segmentation

Motivation - to segment the objects / create the fuzzy connectedness scene



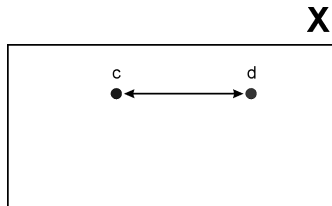
Methodology

- operating on multidimensional and multifeature sets of ordered data
- points classified into single objects are strongly connected to each other by some more or less abstract relations
- their relations to points constituting other objects have relatively lower values

Fuzzy connectedness = some fuzzy relation

Fuzzy relation ρ binds a pair of spels (spacial elements) c, d of some set \mathbb{X} using the function $\mu_\rho(c, d) \in \langle 0, 1 \rangle$:

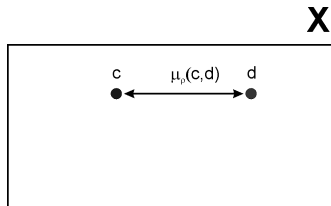
$$\rho = \{(c, d), \mu_\rho(c, d), \quad c, d \in \mathbb{X} \times \mathbb{X}\}$$



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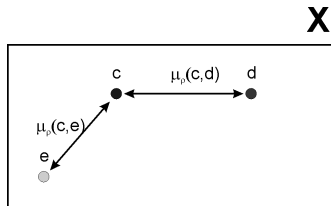
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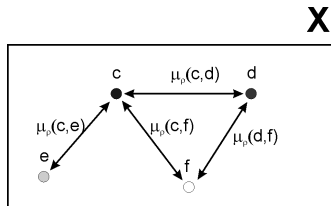
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If \mathbb{X} is n -dimensional image of field \mathbb{X}^n , then \mathbf{c}, \mathbf{d} are points (pixels, voxels), being vectors of n coordinates:

$$\rho = \{(\mathbf{c}, \mathbf{d}), \mu_\rho(\mathbf{c}, \mathbf{d}), \quad \mathbf{c}, \mathbf{d} \in \mathbb{X}^n \times \mathbb{X}^n\}$$



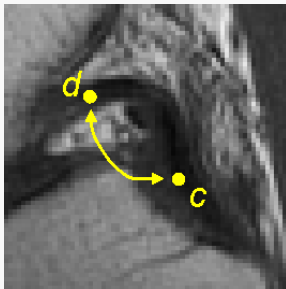
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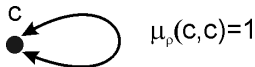
$$\rho = \{(\mathbf{c}, \mathbf{d}), \mu_\rho(\mathbf{c}, \mathbf{d}), \quad \mathbf{c}, \mathbf{d} \in \mathbb{X}^n \times \mathbb{X}^n\}$$



Properties of fuzzy relations (this corresponds to the equivalence relation in hard sets) – similitude relation

- Reflexivity:

$$\forall (c, c) \in \mathbb{X} \times \mathbb{X} : \quad \mu_{\rho}(c, c) = 1.$$



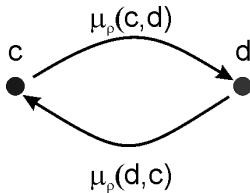
Note:

Each element is connected with itself with maximal value of μ_{ρ}

Properties of fuzzy relations

- Symmetry:

$$\forall (c, d) \in \mathbb{X} \times \mathbb{X}: \quad \mu_\rho(c, d) = \mu_\rho(d, c).$$



Note:

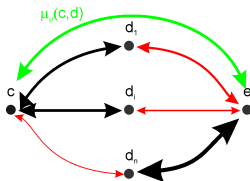
Each two elements are connected with the same relation in both sides

Properties of fuzzy relations

- Transitivity:

$$\forall (c, d), (d, e), (c, e) \in \mathbb{X} \times \mathbb{X} :$$

$$\mu_{\rho}(c, e) = \max_d \{ \min \{ \mu_{\rho}(c, d), \mu_{\rho}(d, e) \} \} .$$



Note:

The relation of two elements may consist of their relations with third element, according to above rule

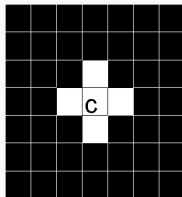
Crisp adjacency

An image - a **topological ordered set**: the spacial relations between its elements (points) are defined.

Crisp adjacency relations α are e.g. 4-, 8-adjacency for 2D images or 6-, 18- and 26-adjacency for 3D image series. Exemplary 4-adjacency:

$$\forall \mathbf{c} = (c_x, c_y), \mathbf{d} = (d_x, d_y) \in \mathbb{X}^2 \times \mathbb{X}^2 :$$

$$\mu_{\alpha}(\mathbf{c}, \mathbf{d}) = \begin{cases} 1 & \Leftrightarrow \sum_{i=x,y} (|c_i - d_i|) \leq 1, \\ 0 & \text{otherwise.} \end{cases}$$

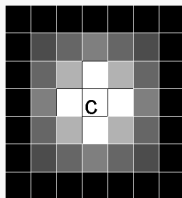


Fuzzy adjacency relation

Fuzzy spel adjacency is a reflexive and symmetric fuzzy relation $\mu_\alpha \in \langle 0, 1 \rangle$ in \mathbb{X}^2 and assigns a value to a pair of spels (c, d) based on how close they are spatially, eg.:

$$\forall \mathbf{c} = (c_x, c_y), \mathbf{d} = (d_x, d_y) \in \mathbb{X}^2 \times \mathbb{X}^2 :$$

$$\mu_\alpha(\mathbf{c}, \mathbf{d}) = \begin{cases} \frac{1}{\|\mathbf{c} - \mathbf{d}\|} & \Leftrightarrow \|\mathbf{c} - \mathbf{d}\| < 3, \\ 0 & \text{otherwise.} \end{cases}$$



Fuzzy affinity κ - the primary fuzzy relation in FC theory

Fuzzy affinity membership function $\mu_{\kappa} \in [0, 1]$ takes non-zero values for adjacent (fuzzy adjacent) elements only.

It assigns a value to a pair of spels (c, d) based on how close they are spatially and intensity-based-property-wise (local hanging-togetherness).

The value of μ_{κ} is based on the c and d features, like **coordinate adjacency**, **image intensities** $I(c)$, $I(d)$ or **local intensity gradients**.

Fuzzy spel affinity

The most popular formula using in image processing:

$$\mu_{\kappa}(\mathbf{c}, \mathbf{d}) = \mu_{\alpha}(\mathbf{c}, \mathbf{d}) \cdot g(\mu_{\phi}(\mathbf{c}, \mathbf{d}), \mu_{\psi}(\mathbf{c}, \mathbf{d})),$$

where:

- μ_{ϕ} – intensity component, describing expected mean intensity of connected points,
- μ_{ψ} – gradient component, describing expected difference of intensities of connected points.

Fuzzy spel affinity

The most popular formula using in image processing:

$$\mu_{\kappa}(\mathbf{c}, \mathbf{d}) = \mu_{\alpha}(\mathbf{c}, \mathbf{d}) \cdot g(\mu_{\phi}(\mathbf{c}, \mathbf{d}), \mu_{\psi}(\mathbf{c}, \mathbf{d})),$$

Expected properties of g :

- range within $[0,1]$
- monotonically non-decreasing in both arguments

Examples:

$$\mu_{\kappa}(\mathbf{c}, \mathbf{d}) = \frac{1}{2} \mu_{\alpha}(\mathbf{c}, \mathbf{d}) (\mu_{\phi}(\mathbf{c}, \mathbf{d}) + \mu_{\psi}(\mathbf{c}, \mathbf{d}))$$

$$\mu_{\kappa}(\mathbf{c}, \mathbf{d}) = \mu_{\alpha}(\mathbf{c}, \mathbf{d}) \sqrt{(\mu_{\phi}(\mathbf{c}, \mathbf{d}) + \mu_{\psi}(\mathbf{c}, \mathbf{d}))}$$

Fuzzy spel affinity:

$$\kappa = \{((\underline{e}, \underline{d}), \mu_\kappa(\underline{e}, \underline{d})) : (\underline{e}, \underline{d}) \in C \times C\},$$
$$\mu_\kappa(\underline{e}, \underline{d}) = \mu_\alpha \cdot (w_1 \textcolor{red}{H}_1(\underline{e}, \underline{d}) + w_2 \textcolor{blue}{H}_2(\underline{e}, \underline{d})),$$

with parameters w_1 and w_2 denoting such positive constants that

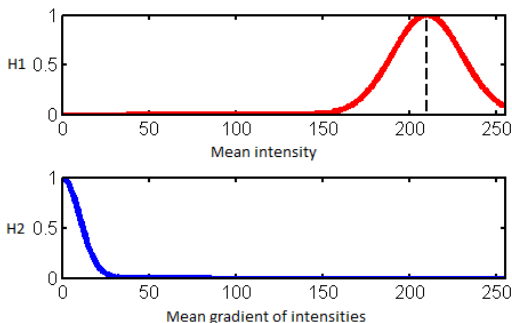
$$w_1 + w_2 = 1.$$

Components H_1 and H_2 are defined as:

$$\textcolor{red}{H}_1(\underline{e}, \underline{d}) = \exp \left(-\frac{1}{2\sigma_1^2} \left(\frac{I(\underline{e}) + I(\underline{d})}{2} - \lambda_1 \right)^2 \right),$$
$$\textcolor{blue}{H}_2(\underline{e}, \underline{d}) = \exp \left(-\frac{1}{2\sigma_2^2} (|I(\underline{e}) - I(\underline{d})| - \lambda_2)^2 \right).$$

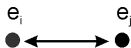
Fuzzy spel affinity

$$\mu_{\kappa}(\mathbf{c}, \mathbf{d}) = \mu_{\alpha}(\mathbf{c}, \mathbf{d}) \left(w_1 e^{\frac{\left(\frac{I(\mathbf{c})+I(\mathbf{d})}{2} - \lambda_1\right)^2}{2\sigma_1^2}} + w_2 e^{\frac{(|I(\mathbf{c})-I(\mathbf{d})| - \lambda_2)^2}{2\sigma_2^2}} \right) :$$



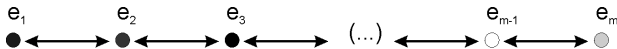
Path

A single pair of points $\langle \mathbf{e}_i, \mathbf{e}_j \rangle$ with non-zero affinity is called **link** and the value of $\mu_\kappa(\mathbf{e}_i, \mathbf{e}_j)$ – its strength.



Path

A path is any sequence of $m \geq 2$ spels $\langle \mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_m \rangle$ such that for any $i \in [1, m-1]$ a pair $\langle \mathbf{e}_i, \mathbf{e}_{i+1} \rangle$ is a link. It is noted p_{cd} if $\mathbf{c} = \mathbf{e}_1$ and $\mathbf{d} = \mathbf{e}_m$.



Let P_{cd} denotes the set of all possible paths p_{cd} from \mathbf{c} to \mathbf{d} .

Then the set of all possible paths in \mathbb{X}^2 is

$$P = \bigcup_{\mathbf{c}, \mathbf{d} \in \mathbb{X}^2} P_{cd}$$

Strength of path

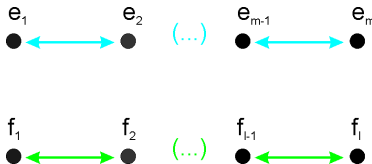
Fuzzy membership function $\mu_{\mathcal{N}}(p_{cd})$ describing any path $p_{cd} \in P_{cd}$ is said to be its **strength** and is the smallest spel affinity along p_{cd}



$$\mu_{\mathcal{N}}(p_{cd}) = \begin{cases} \min_{i=1..m-1} \{\mu_{\kappa}(\mathbf{e}_i, \mathbf{e}_{i+1})\} & \Leftrightarrow p_{cd} = \langle \mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_m \rangle \\ 0 & \Leftrightarrow p_{cd} = \langle \rangle. \end{cases}$$

Path – join to path operation

A binary *join to* operation denoted "+" is defined as follows

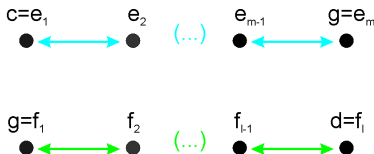


$$\langle e_1, e_2, \dots, e_m \rangle,$$

$$\langle f_1, f_2, \dots, f_l \rangle.$$

Path – join to path operation

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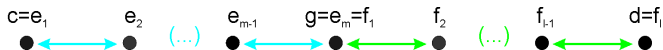


$$p_{cg} = \langle \mathbf{c}, \mathbf{e}_2, \dots, \mathbf{g} \rangle,$$

$$p_{gd} = \langle \mathbf{g}, \mathbf{f}_2, \dots, \mathbf{d} \rangle.$$

Path – join to path operation

A binary *join to* operation denoted "+" is defined as follows



$$p_{cg} + p_{gd} = \langle \mathbf{c}, \mathbf{e}_2, \dots, \mathbf{g}, \mathbf{f}_2, \dots, \mathbf{d} \rangle.$$

Path – join to path operation

For empty paths:

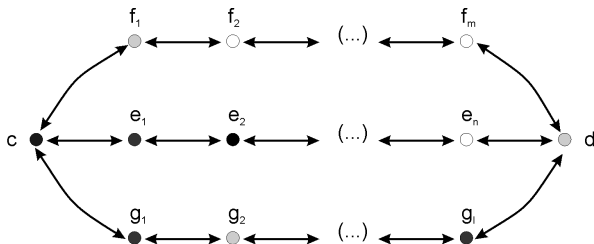
$$p_{cd} + \langle \rangle = p_{cd},$$

$$\langle \rangle + p_{cd} = p_{cd},$$

$$\langle \rangle + \langle \rangle = \langle \rangle.$$

Fuzzy connectedness

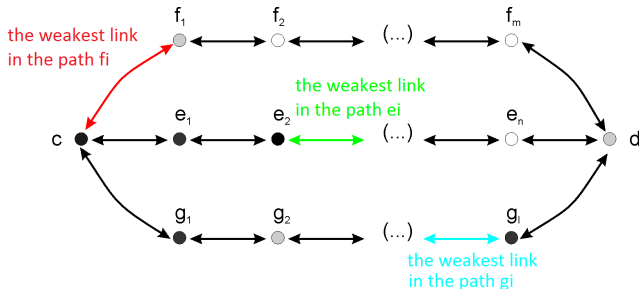
There exist many different paths p_{cd} constituting a set P_{cd} .



Fuzzy connectedness

Fuzzy connectedness

Each path p_{cd} has a defined strength μ_N .



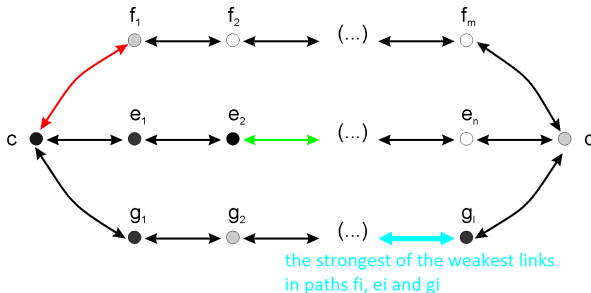
$$\mu_N(p_{cd}) = \begin{cases} \min_{i=1..m-1} \{\mu_\kappa(\mathbf{e}_i, \mathbf{e}_{i+1})\} & \Leftrightarrow p_{cd} = \langle \mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_m \rangle \\ 0 & \Leftrightarrow p_{cd} = \langle \rangle. \end{cases}$$

Fuzzy connectedness

Fuzzy connectedness

Any image spels **c** and **d** are fuzzy connected according to relation K .

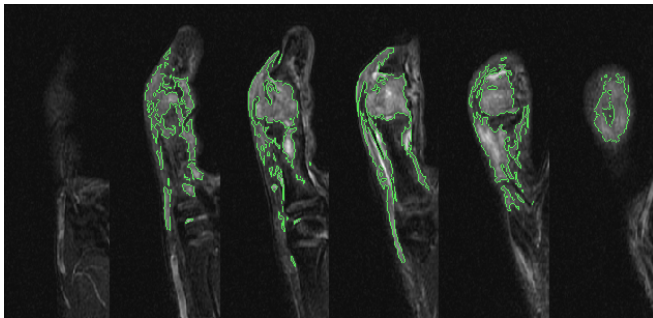
The membership function of fuzzy connectedness $\mu_K(\mathbf{c}, \mathbf{d})$ is the strength of the strongest path p_{cd} of all the paths between **c** and **d**, forming a set P_{cd} (global hanging-togetherness):



Fuzzy connectedness vs image segmentation

If the set \mathbb{X} is an image, then the information concerning fuzzy relation between its points (pixels) makes it possible to group them into semantically interpretable regions - **to segment them**.

The theorems were given in (Udupa&Samarasekera, 1996).



Fuzzy connected object

Fuzzy κ_{θ_x} object – $\mathcal{O}_{\theta_x}(\mathbf{o})$ containing a seed spel \mathbf{o} is a fuzzy subset of \mathbb{X} whose membership function is:

$$\mu_{\mathcal{O}_{\theta_x}(\mathbf{o})}(\mathbf{c}) = \begin{cases} \eta(\mathbf{c}) & \Leftrightarrow \mathbf{c} \in \mathcal{O}_{\theta_x}(\mathbf{o}) \\ 0 & \text{otherwise} \end{cases}$$

where η assigns an objectness value to each spel perhaps based on $f(\mathbf{c})$ and $\mu_{\kappa}(\mathbf{o}, \mathbf{c})$.

Fuzzy digital space

$$(\mathbb{X}^n, \alpha)$$

Scene (over a fuzzy digital space)

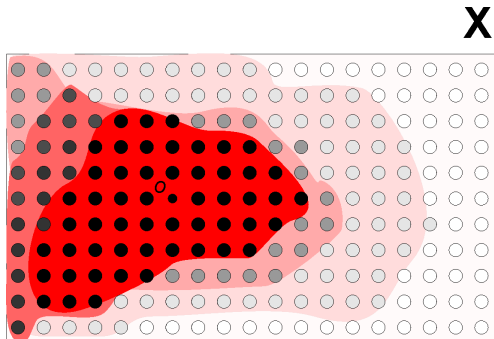
$$C_o = (C, f), \quad C \subset \mathbb{X}^n, f : C \rightarrow [0, 1]$$

Fuzzy connected object

Fuzzy $\kappa\theta_x$ object $\mathcal{O}_{\theta_x(\mathbf{o})}$ consists then of all the elements, including \mathbf{o} , connected with each other with the value greater x , where $x \in [0, 1]$, towards the defined fuzzy affinity relation κ

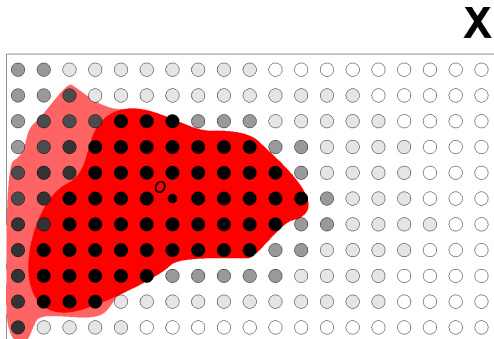
$$\mathcal{O}_{\theta_x(\mathbf{o})}(\mathbf{c}) = \begin{cases} 1 & \Leftrightarrow c \in C_o \geq x \\ 0 & \text{otherwise} \end{cases}$$

Fuzzy connected object



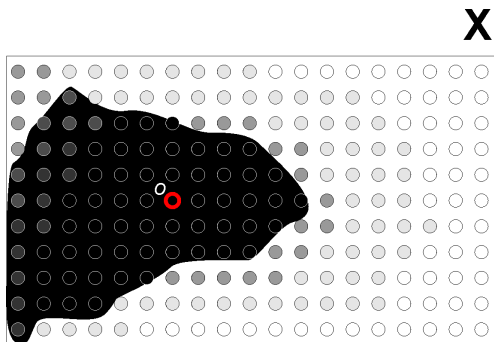
Fuzzy κ_{θ_x} object $\mathcal{O}_{\theta_x(o)}$ consists then of all the elements, including o , connected with each other with the value greater x , where $x \in [0, 1]$, towards the defined fuzzy affinity relation κ .

Fuzzy connected object



Fuzzy $\kappa\theta_x$ object $\mathcal{O}_{\theta_x(o)}$ consists then of all the elements, including o , connected with each other with the value greater x , where $x \in [0, 1]$, towards the defined fuzzy affinity relation κ .

Fuzzy connected object \rightarrow binary object



Defuzzification of fuzzy connected object $\mathcal{O}_{\theta_x}(\mathbf{o})$ results in binary object $\mathcal{O}_{\theta_x}(\mathbf{o})$, as a set of points in $\mathcal{O}_{\theta_x}(\mathbf{o})$.

Seed points

According to the already given definition, to obtain the fuzzy connected object is necessary to calculate fuzzy connectedness of all the pair of elements in \mathbb{X} .

Seed points selection procedure is then needed.

In different applications a multiseeded approach is used, where set O of $M(M > 1)$ points \mathbf{o}_i is required.

Fuzzy connectivity scene

In the segmentation procedure the **fuzzy connectivity scene** C_o is created by assigning a strength of connectedness to each possible path between some predefined seed point \mathbf{o} and any other image element:

$$C_o(\mathbf{c}) = \mu_K(\mathbf{o}, \mathbf{c}).$$

If there exists the set O of M ($M > 1$) points \mathbf{o}_i , then $C_o(\mathbf{c})$ is equal to the strongest of connectedness with points in O :

$$C_o(\mathbf{c}) = \max_i \{\mu_K(\mathbf{o}_i, \mathbf{c})\}.$$

The scene C_o for a set O is a fuzzy union:

$$C_o(\mathbf{c}) = \bigcup_{\mathbf{o}_i \in O} C_{\mathbf{o}_i} = \max_i \{\mu_K(\mathbf{o}_i, \mathbf{c})\}.$$

Fuzzy connectivity scene

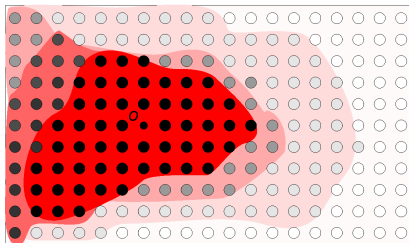
According to the reflexivity properties, for the point \mathbf{o} :

$$C_o(\mathbf{o}) = \mu_K(\mathbf{o}, \mathbf{o}) = 1.$$

The far from the starting point ^a, the smaller the fuzzy connectedness value is.

^ain the meaning of connectedness

X



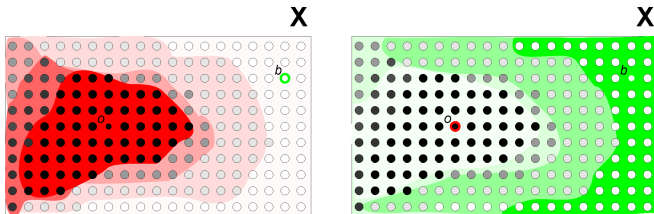
Relative fuzzy connectedness

The relative fuzzy connectedness (RFC) variant uses the second object, treated as a background region with its own seed point \mathbf{b} , to determine $O_{\kappa_x}(\mathbf{b})$ in a rivalry mode.

Spel $\mathbf{c} \in C$ belongs to an object according to affinity κ and connectedness K if $\mu_K(\mathbf{o}, \mathbf{c}) > \mu_K(\mathbf{b}, \mathbf{c})$. It leads to fuzzy connectivity scenes C_o and C_b and their comparison in a form of a "division of spoils".

Relative fuzzy connectedness

After creating scenes C_o and C_b each point \mathbf{c} is assigned to the region (eg. object and background), with which starting point is connected stronger.

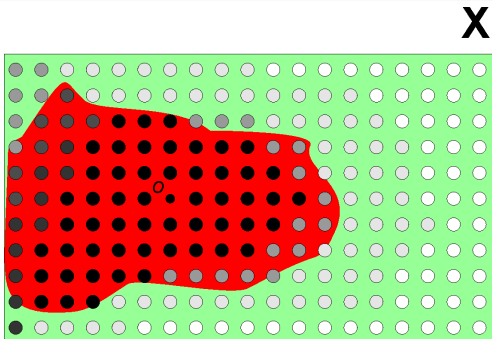


$$\mathbf{c} \in P_{ob_K} \Leftrightarrow C_o(\mathbf{c}) > C_b(\mathbf{c}).$$

Fuzzy connectedness

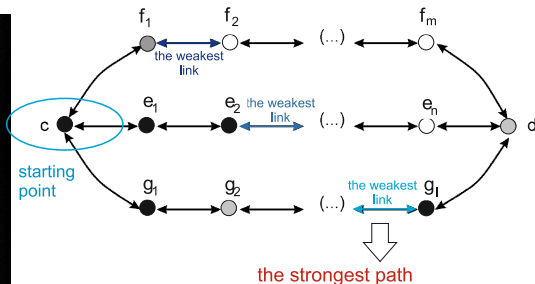
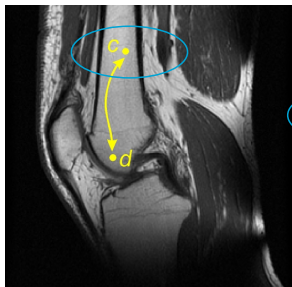
Relative fuzzy connectedness

After creating scenes C_o and C_b each point \mathbf{c} is assigned to the region (eg. object and background), with which starting point is connected stronger.



$$\mathbf{c} \in P_{ob_{\kappa}} \Leftrightarrow C_o(\mathbf{c}) > C_b(\mathbf{c}).$$

3-D relative fuzzy connectedness analysis:



- 1 Find the set of objects and background starting points respectively
- 2 Chose the fuzzy spel affinity κ and fuzzy adjacency ρ
- 3 Extract the fuzzy relative connected objects

Fuzzy connectivity scene creation - implementation

Fuzzy connectivity scene C_o creation - graph searching:

- dynamic programming approach (Udupa and Samarasekera, 1996)
- Dijkstra algorithm (Carvalho et al., 1999)
- matrix transformation-based approach (Kawa, 2007)

Implementation - dynamic programming

- The DP algorithm uses queue Q , into/from which successive image points are inserted or removed.
- In a single iteration t one point (\mathbf{d}) from the front of queue is taken. All its neighboring pixels (voxels) are tested.
- It is checked, if there exists a path p_{cd} , connecting points \mathbf{c} and \mathbf{d} with stronger path, then previously estimated $C_o(\mathbf{d})$.
- If yes, $C_o(\mathbf{d})$ is updated, and all the neighbors of \mathbf{d} are put into queue Q .

Implementation - dynamic programming

Features:

- A single iteration t takes short time.
- A lot of iterations is required.
- One point can be analyzed several times.

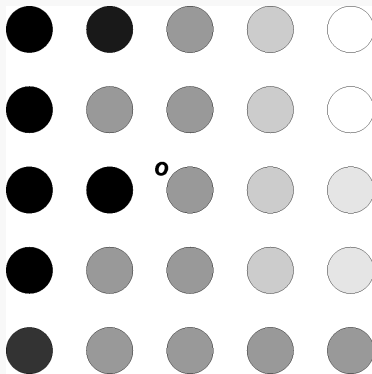
Implementation - dynamic programming

=== Algorithm 1. Dynamic Programming ===

```
1: Initialize scene  $C_o$  with zeros;
2: Set  $C_o(\mathbf{o}_i) = 1$  for all the starting points  $\mathbf{o}_i$ ;
3: Put into the queue  $Q$  all  $\mathbf{c} : \mu_\kappa(\mathbf{o}_i, \mathbf{c}) > 0$ ;
4: Until  $Q$  is not empty
5:   Take and remove  $\mathbf{c}$  from the front of queue  $Q$ ;
6:    $f_{max} = \max_{\mathbf{d}} [\min \{ C_o(\mathbf{d}), \mu_\kappa(\mathbf{c}, \mathbf{d}) \}]$ ;
7:   If  $f_{max} > C_o(\mathbf{c})$ 
8:      $C_o(\mathbf{c}) = f_{max}$ ;
9:   Then put to  $Q$  all  $\mathbf{e} : \mu_\kappa(\mathbf{c}, \mathbf{e}) > 0$ ;
10:  end
11: end
```

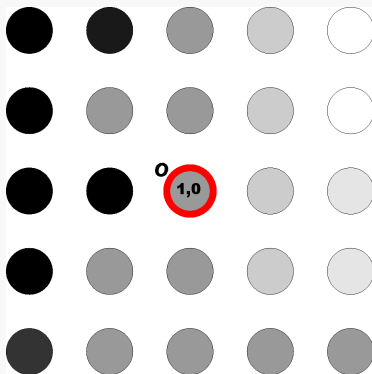
=====

Dynamic programming



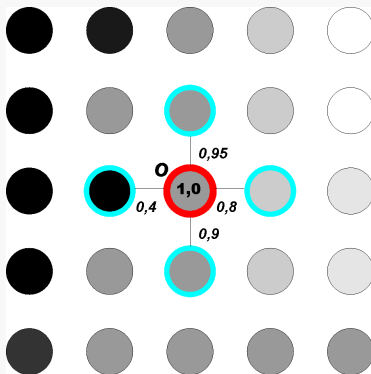
1: Initialize scene C_0 with zeros;

Dynamic programming



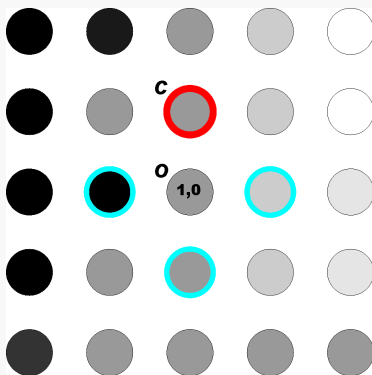
2: Set $C_o(\mathbf{o}_i) = 1$ for all starting points \mathbf{o}_i ;

Dynamic programming



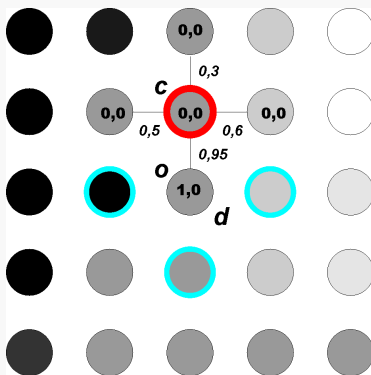
3: Put to the queue Q all $\mathbf{c} : \mu_{\kappa}(\mathbf{o}_i, \mathbf{c}) > 0$;

Dynamic programming



5: Take and remove c from the front of queue Q ;

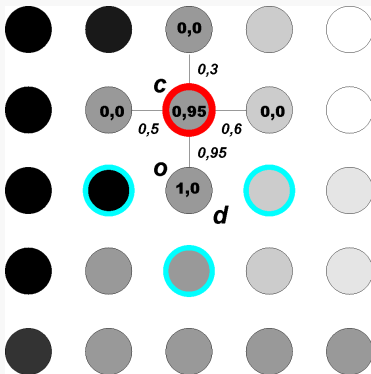
Dynamic programming



6:
$$f_{max} = \max_d [\min \{ C_o(d), \mu_{\kappa}(c, d) \}];$$

Fuzzy connectedness

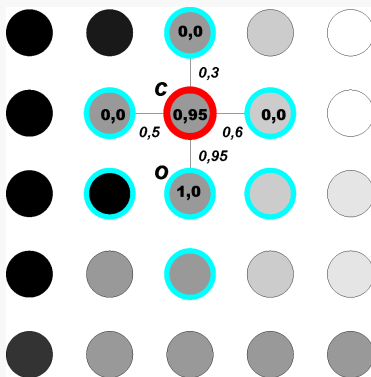
Dynamic programming



7: If $f_{max} > C_o(\mathbf{c})$

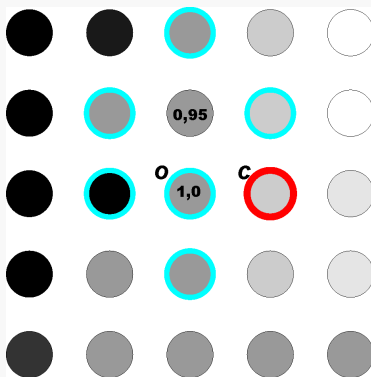
$$8: \quad C_o(\mathbf{c}) = f_{max};$$

Dynamic programming



9: Put to Q all $e : \mu_{\kappa}(c, e) > 0$;

Dynamic programming

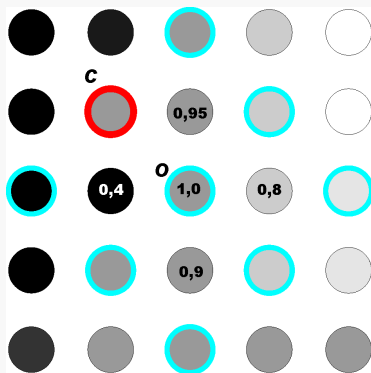


5: Take and remove **c** from the front of queue *Q*;

Dynamic programming

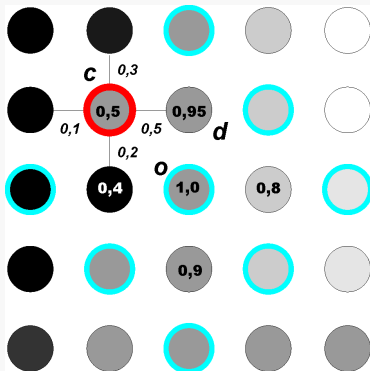
After a while...

Dynamic programming



5: Take and remove **c** from the front of queue Q ;

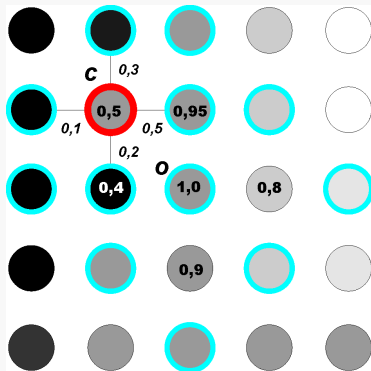
Dynamic programming


$$6: \quad f_{max} = \max_{\mathbf{d}} [\min \{ C_o(\mathbf{d}), \mu_{\kappa}(\mathbf{c}, \mathbf{d}) \}];$$

7: If $f_{max} > C_o(\mathbf{c})$

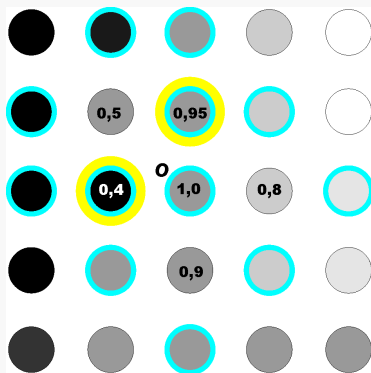
8: $C_o(\mathbf{c}) = f_{max};$

Dynamic programming



9: Put to Q all $e: \mu_{\kappa}(c, e) > 0$;

Dynamic programming



The selected points are put into the queue once again!

Implementation - Dijkstra algorithm

- In a single iteration t the point **is not** from the front of queue Q , but the point with \mathbf{c} with the maximal value $C_o(\mathbf{c})$.
- It is treated as the second last point of the path leading to each of its neighbors \mathbf{d} .
- If it causes the improvement of $C_o(\mathbf{d})$, then the value $C_o(\mathbf{d})$ is updated and \mathbf{d} is put into the queue.

Implementation - Dijkstra algorithm

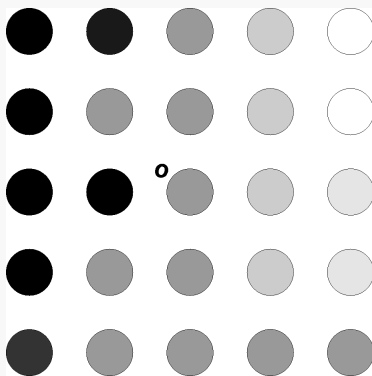
Features:

- A point c taken from the queue **is not** put there again - the number of iterations T does not exceed the number of image points.
- It is necessary to perform time consuming maximum operation.

Implementation - Dijkstra algorithm

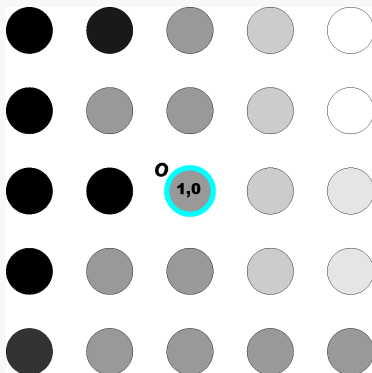
```
=== Algorithm 2. Dijkstra algorithm =====  
1:   Initialize scene  $C_o$  with zeros;  
2:   Set  $C_o(\mathbf{o}_i) = 1$  for all the starting points  $\mathbf{o}_i$ ;  
3:   Put into the queue  $Q$  all  $\mathbf{o}_i$ ;  
4:   Until  $Q$  is not empty  
5:     Take and remove from the queue  $Q$  the point  $\mathbf{c}$   
        with maximum  $C_o(\mathbf{c})$ ;  
6:     For all  $\mathbf{d}$ :  $\mu_\kappa(\mathbf{c}, \mathbf{d}) > 0$   
7:        $\nu = \min \{C_o(\mathbf{c}), \mu_\kappa(\mathbf{c}, \mathbf{d})\}$ ;  
8:       If  $\nu > C_o(\mathbf{d})$   
9:          $C_o(\mathbf{d}) = \nu$ ;  
10:      Put  $\mathbf{d}$  into  $Q$ ;  
11:    end  
12:  end  
13: end  
  
=====
```

Implementation - Dijkstra algorithm



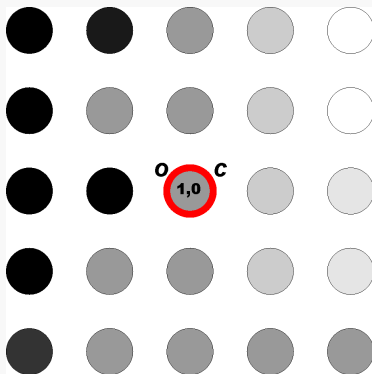
1: Initialize scene C_o with zeros;

Implementation - Dijkstra algorithm



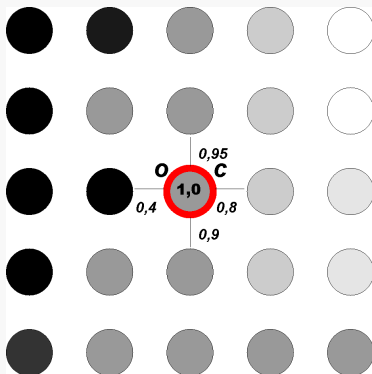
- 2: Set $C_o(\mathbf{o}_i) = 1$ for all starting points \mathbf{o}_i ;
- 3: Put into the queue Q all \mathbf{o}_i ;

Implementation - Dijkstra algorithm



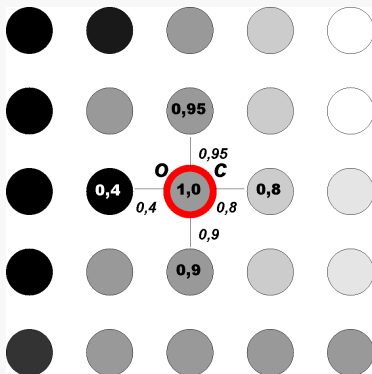
5: Take and remove from the queue Q the point c

Implementation - Dijkstra algorithm



- 6: For all \mathbf{d} : $\mu_{\kappa}(\mathbf{c}, \mathbf{d}) > 0$
7: $\nu = \min \{C_o(\mathbf{c}), \mu_{\kappa}(\mathbf{c}, \mathbf{d})\};$

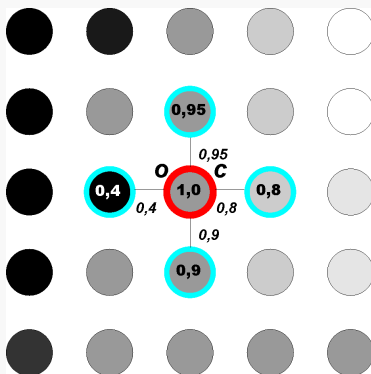
Implementation - Dijkstra algorithm



8: If $\nu > C_o(\mathbf{d})$

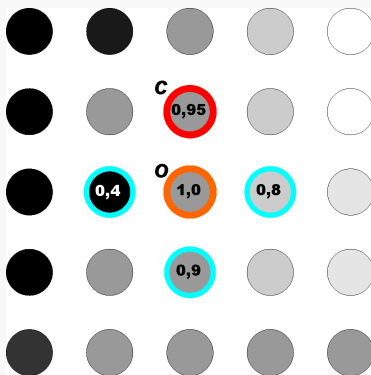
9: $C_o(\mathbf{d}) = \nu;$

Implementation - Dijkstra algorithm



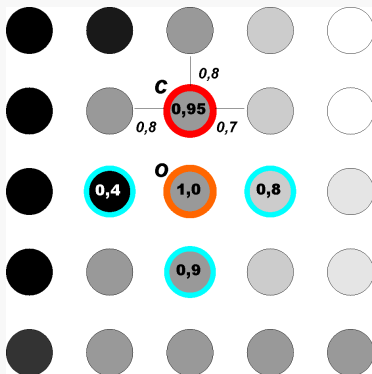
10: Put **d** into *Q*;

Implementation - Dijkstra algorithm



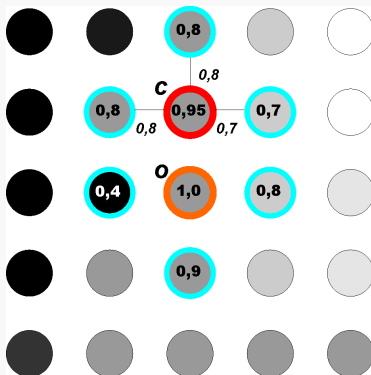
5: Take and remove from the queue Q the point c

Implementation - Dijkstra algorithm



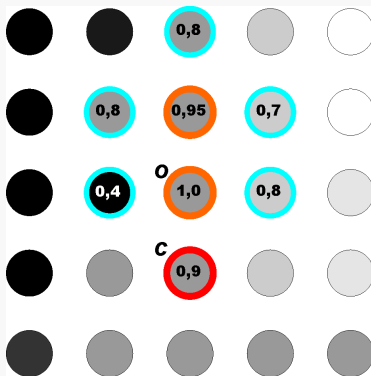
- 6: For all \mathbf{d} : $\mu_{\kappa}(\mathbf{c}, \mathbf{d}) > 0$
7: $\nu = \min \{C_o(\mathbf{c}), \mu_{\kappa}(\mathbf{c}, \mathbf{d})\};$

Implementation - Dijkstra algorithm



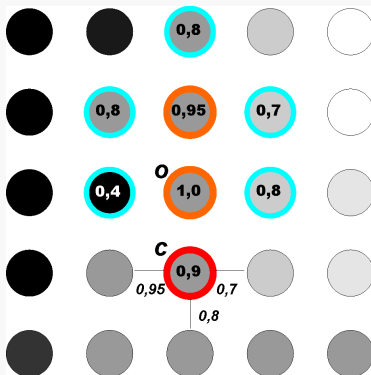
```
8:      If  $\nu > C_o(\mathbf{d})$ 
9:           $C_o(\mathbf{d}) = \nu$ ;
10:      Put  $\mathbf{d}$  into  $Q$ ;
```

Implementation - Dijkstra algorithm



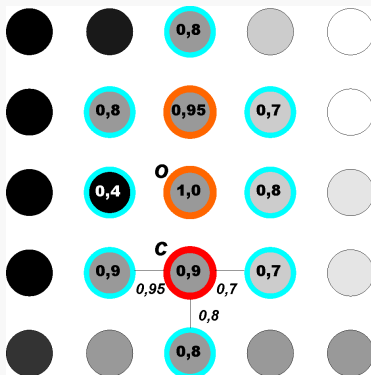
5: Take and remove from the queue Q the point c

Implementation - Dijkstra algorithm



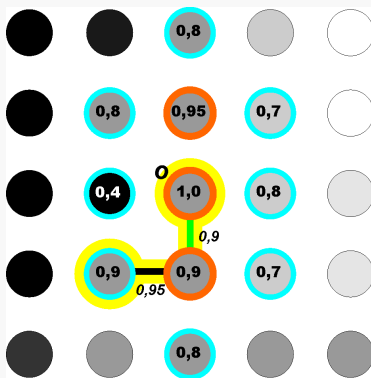
- 6: For all \mathbf{d} : $\mu_{\kappa}(\mathbf{c}, \mathbf{d}) > 0$
7: $\nu = \min \{C_o(\mathbf{c}), \mu_{\kappa}(\mathbf{c}, \mathbf{d})\}$;

Implementation - Dijkstra algorithm



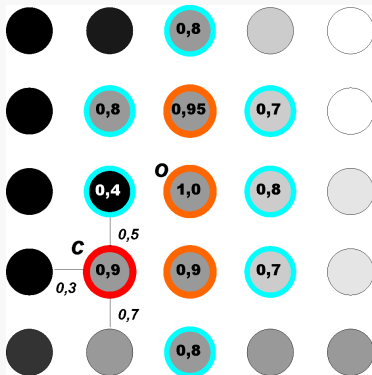
```
8:      If  $\nu > C_o(d)$ 
9:           $C_o(d) = \nu$ ;
10:      Put  $d$  into  $Q$ ;
```

Implementation - Dijkstra algorithm



The path to the selected point and its weakest link.

Implementation - Dijkstra algorithm

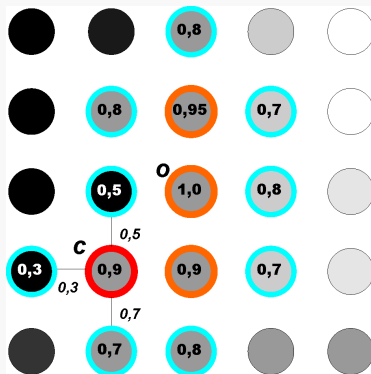


- ```

5: Take and remove from the queue Q the point \mathbf{c}
6: For all $\mathbf{d} : \mu_{\kappa}(\mathbf{c}, \mathbf{d}) > 0$
7: $\nu = \min \{C_o(\mathbf{c}), \mu_{\kappa}(\mathbf{c}, \mathbf{d})\}$;

```

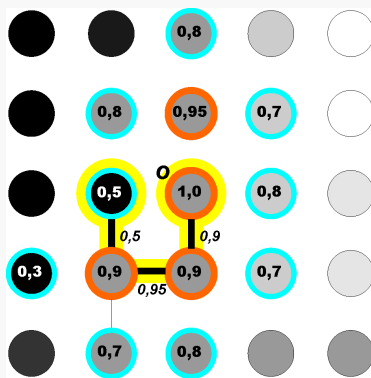
## Implementation - Dijkstra algorithm



```
8: If $\nu > C_o(\mathbf{d})$
9: $C_o(\mathbf{d}) = \nu$;
10: Put \mathbf{d} into Q ;
```



## Implementation - Dijkstra algorithm



A stronger path is found!

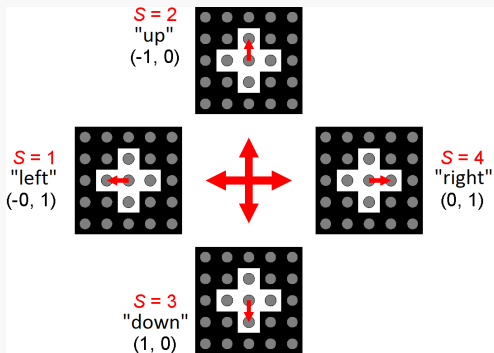
## Implementation - Matrix transformation-based algorithm

- The approach uses analogy to shifts resulting from the shape of structural element in mathematical morphology.
- The previously obtained matrix of shifts makes it possible to calculate the "min" and "max" values in more efficient way, to dynamically change the fuzzy connectivity scene.

## Implementation - Matrix transformation-based algorithm

### Matrices adjacency:

- the exemplary crisp 4-adjacency relation  $\alpha_4 = 4$  shifts  $s_i$  from the position of central pixel:



## Implementation - Matrix transformation-based algorithm

= Algorithm 3. Matrix transformation-based algorithm =

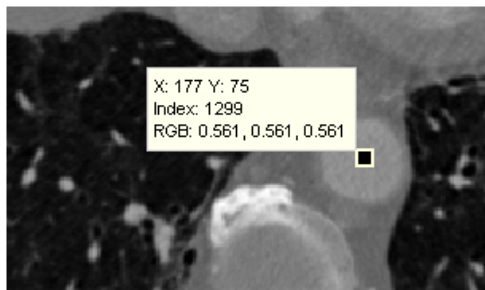
- 1: Chose the hard adjacency relation  $\alpha$ ;
- 2: Decompose  $\alpha$  to the series of shifts  $s$  denoting neighboring elements;
- 3: Preprocess the original image by padding rows, columns and layers as not to permit for wrapping the original values in the later steps;
- 4: Precompute the fuzzy affinity values for each neighborhood member (one table  $T_s$  containing the affinity values for each  $\alpha$ -connected member; e.g. 4 tables if 4-connectivity has been chosen; e.g.  $T_1$  for the one to the left);

## Implementation - Matrix transformation-based algorithm

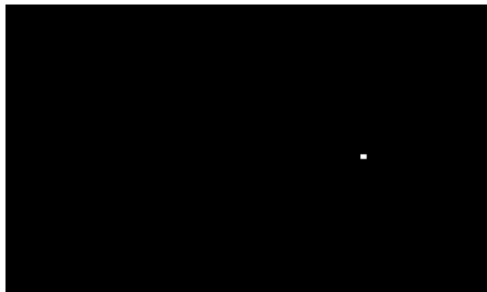
```
5: By using circular shift of the precomputed fuzzy
affinity tables ensure, that the element of a new
 $T_s(\mathbf{c})$ denotes the affinity of original spel \mathbf{c} with respect
to the s -th neighbor; e.g. for a pixel $\mathbf{c} = (c_x, c_y)$,
 $T_1(c_x, c_y)$ contains $\mu_k(\mathbf{c}, \mathbf{d})$ with respect to
the left pixel $\mathbf{d} = (c_{x-1}, c_y)$;
6: Initialize scene C_o with values zeros;
7: Set $C_o(\mathbf{o}_i) = 1$ for all the starting points \mathbf{o}_i ;
7: Repeat
8: For each shift s
9: $T = \min(C_o, T_s)$; % matrix operation
10: $C_o = \max(C_o, T)$; % matrix operation
11: end
12: until C_o does not change
```

=====

## Implementation - example



## Implementation - example



## Implementation - example





## Implementation - example



## Implementation - example



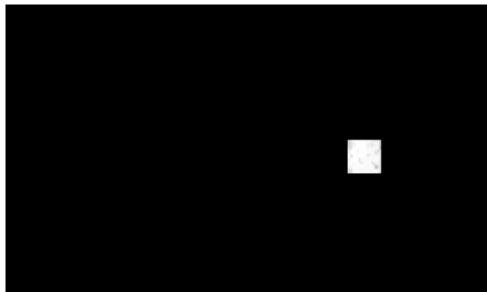
## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example





## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example



## Implementation - example

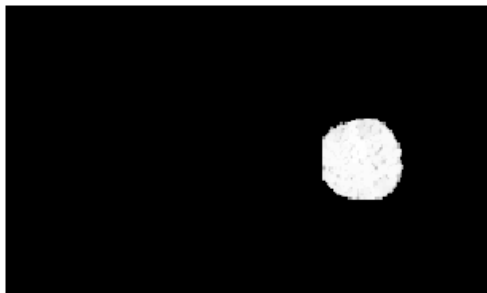


## Implementation - example





## Implementation - example



## Implementation - example



To sum up....

- Free to choose starting points
- Possibility to choose different features
- Free to select the threshold
- Simultaneous segmentation of different objects

## Active Contour Model