

# Fuzzy Sets and Fuzzy Techniques

## Lecture 13 – Fuzzy connectedness

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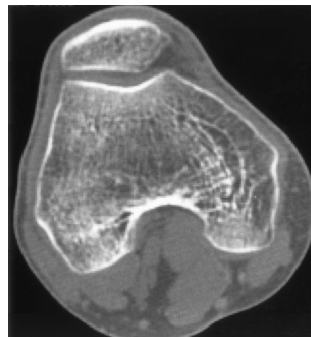
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## Outline

- 1 Motivation
- 2 Fuzzy sets (recap)
- 3 Fuzzy connectedness theory
  - Fuzzy digital space
  - Affinity and paths
  - Fuzzy connected object
  - Algorithm
- 4 FC variants and details
  - Defining fuzzy spel affinity
  - Efficient computation
  - Vectorial and relative fuzzy connectedness
- 5 Applications

## Object characteristics in images



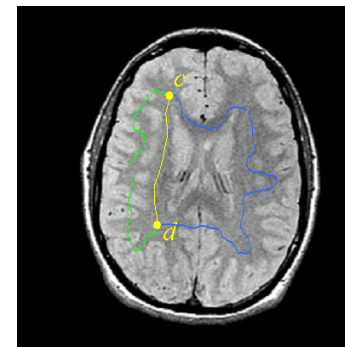
### Graded composition

heterogeneity of intensity in the object region due to heterogeneity of object material and blurring caused by the imaging device

### Hanging-togetherness

natural grouping of voxels constituting an object a human viewer readily sees in a display of the scene as a Gestalt in spite of intensity heterogeneity

## Basic idea of fuzzy connectedness



- local hanging-togetherness (affinity) based on similarity in spatial location as well as in intensity(-derived features)
- global hanging-togetherness (connectedness)

## Fuzzy set and relation

A **fuzzy subset**  $\mathcal{A}$  of  $X$  is

$$\mathcal{A} = \{(x, \mu_{\mathcal{A}}(x)) \mid x \in X\}$$

where  $\mu_{\mathcal{A}}$  is the **membership function** of  $\mathcal{A}$  in  $X$

$$\mu_{\mathcal{A}} : X \rightarrow [0, 1]$$

A **fuzzy relation**  $\rho$  in  $X$  is

$$\rho = \{((x, y), \mu_{\rho}(x, y)) \mid x, y \in X\}$$

with a membership function

$$\mu_{\rho} : X \times X \rightarrow [0, 1]$$

## Properties of fuzzy relations

$\rho$  is **reflexive** if

$$\forall x \in X \quad \mu_{\rho}(x, x) = 1$$

$\rho$  is **symmetric** if

$$\forall x, y \in X \quad \mu_{\rho}(x, y) = \mu_{\rho}(y, x)$$

$\rho$  is **transitive** if

$$\forall x, z \in X \quad \mu_{\rho}(x, z) = \bigcup_{y \in X} \mu_{\rho}(x, y) \cap \mu_{\rho}(y, z)$$

$\rho$  is **similitude** if it is reflexive, symmetric, and transitive

Note: this corresponds to the equivalence relation in hard sets.

## Operations on fuzzy sets

## Intersection

$$\mathcal{A} \cap \mathcal{B} = \{(x, \mu_{\mathcal{A} \cap \mathcal{B}}(x)) \mid x \in X\} \quad \mu_{\mathcal{A} \cap \mathcal{B}} = \min(\mu_{\mathcal{A}}, \mu_{\mathcal{B}})$$

## Union

$$\mathcal{A} \cup \mathcal{B} = \{(x, \mu_{\mathcal{A} \cup \mathcal{B}}(x)) \mid x \in X\} \quad \mu_{\mathcal{A} \cup \mathcal{B}} = \max(\mu_{\mathcal{A}}, \mu_{\mathcal{B}})$$

## Complement

$$\bar{\mathcal{A}} = \{(x, \mu_{\bar{\mathcal{A}}}(x)) \mid x \in X\} \quad \mu_{\bar{\mathcal{A}}} = 1 - \mu_{\mathcal{A}}$$

$\cap$  and  $\cup$  are also called T-norm and T-conorm (S-norm).  
Several (corresponding pairs) of T- and S-norms exist.  
In the FC framework min and max are used.

## Fuzzy digital space

**Fuzzy spel adjacency** is a reflexive and symmetric fuzzy relation  $\alpha$  in  $Z^n$  and assigns a value to a pair of spels  $(c, d)$  based on how close they are spatially.

## Example

$$\mu_{\alpha}(c, d) = \begin{cases} \frac{1}{\|c - d\|} & \text{if } \|c - d\| < \text{a small distance} \\ 0 & \text{otherwise} \end{cases}$$

## Fuzzy digital space

$$(Z^n, \alpha)$$

**Scene** (over a fuzzy digital space)

$$\mathcal{C} = (C, f) \quad \text{where } C \subset Z^n \text{ and } f : C \rightarrow [L, H]$$

## Fuzzy spel affinity

**Fuzzy spel affinity** is a reflexive and symmetric fuzzy relation  $\kappa$  in  $Z^n$  and 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).

$$\mu_{\kappa}(c, d) = h(\mu_{\alpha}(c, d), f(c), f(d), c, d)$$

## Example

$$\mu_{\kappa}(c, d) = \mu_{\alpha}(c, d) (w_1 G_1(f(c) + f(d)) + w_2 G_2(f(c) - f(d)))$$

$$\text{where } G_j(x) = \exp\left(-\frac{1}{2} \frac{(x - m_j)^2}{\sigma_j^2}\right)$$

## Paths between spels

A **path**  $p_{cd}$  in  $\mathcal{C}$  from spel  $c \in C$  to spel  $d \in C$  is any sequence  $\langle c_1, c_2, \dots, c_m \rangle$  of  $m \geq 2$  spels in  $C$ , where  $c_1 = c$  and  $c_m = d$ .

Let  $P_{cd}$  denote the set of all possible paths  $p_{cd}$  from  $c$  to  $d$ . Then the set of all possible paths in  $\mathcal{C}$  is

$$P_{\mathcal{C}} = \bigcup_{c, d \in C} P_{cd}$$

## Strength of connectedness

The **fuzzy  $\kappa$ -net**  $\mathcal{N}_{\kappa}$  of  $\mathcal{C}$  is a fuzzy subset of  $P_{\mathcal{C}}$ , where the membership (**strength of connectedness**) assigned to any path  $p_{cd} \in P_{cd}$  is the smallest spel affinity along  $p_{cd}$

$$\mu_{\mathcal{N}_{\kappa}}(p_{cd}) = \min_{j=1, \dots, m-1} \mu_{\kappa}(c_j, c_{j+1})$$

The **fuzzy  $\kappa$ -connectedness** in  $\mathcal{C}$  ( $K$ ) is a fuzzy relation in  $\mathcal{C}$  and assigns a value to a pair of spels  $(c, d)$  that is the maximum of the strengths of connectedness assigned to all possible paths from  $c$  to  $d$  (global hanging-togetherness).

$$\mu_K(c, d) = \max_{p_{cd} \in P_{cd}} \mu_{\mathcal{N}_{\kappa}}(p_{cd})$$

Fuzzy  $\kappa_{\theta}$  component

Let  $\theta \in [0, 1]$  be a given threshold

Let  $K_{\theta}$  be the following binary (equivalence) relation in  $\mathcal{C}$

$$\mu_{K_{\theta}}(c, d) = \begin{cases} 1 & \text{if } \mu_{\kappa}(c, d) \geq \theta \\ 0 & \text{otherwise} \end{cases}$$

Let  $O_{\theta}(o)$  be the equivalence class of  $K_{\theta}$  that contains  $o \in C$

Let  $\Omega_{\theta}(o)$  be defined over the fuzzy  $\kappa$ -connectedness  $K$  as

$$\Omega_{\theta}(o) = \{c \in C \mid \mu_K(o, c) \geq \theta\}$$

Practical computation of FC relies on the following equivalence

$$O_{\theta}(o) = \Omega_{\theta}(o)$$

## Fuzzy connected object

The **fuzzy  $\kappa_\theta$  object**  $\mathcal{O}_\theta(o)$  of  $\mathcal{C}$  containing  $o$  is

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

that is

$$\mu_{\mathcal{O}_\theta(o)}(c) = \begin{cases} \eta(c) & \text{if } c \in \Omega_\theta(o) \\ 0 & \text{otherwise} \end{cases}$$

where  $\eta$  assigns an objectness value to each spel perhaps based on  $f(c)$  and  $\mu_K(o, c)$ .

Fuzzy connected objects are robust to the selection of seeds.

## Fuzzy connectedness as a graph search problem

- Spels  $\rightarrow$  graph nodes
- Spel faces  $\rightarrow$  graph edges
- Fuzzy spel-affinity relation  $\rightarrow$  edge costs
- Fuzzy connectedness  $\rightarrow$  all-pairs shortest-path problem
- Fuzzy connected objects  $\rightarrow$  connected components

## Computing fuzzy connectedness

Dynamic programming

### Algorithm

**Input:**  $\mathcal{C}$ ,  $o \in \mathcal{C}$ ,  $\kappa$

**Output:** A K-connectivity scene  $\mathcal{C}_o = (\mathcal{C}_o, f_o)$  of  $\mathcal{C}$

**Auxiliary data:** a queue  $Q$  of spels

**begin**

set all elements of  $\mathcal{C}_o$  to 0 except  $o$  which is set to 1

push all spels  $c \in \mathcal{C}_o$  such that  $\mu_\kappa(o, c) > 0$  to  $Q$

**while**  $Q \neq \emptyset$  **do**

remove a spel  $c$  from  $Q$

$f_{\text{val}} \leftarrow \max_{d \in \mathcal{C}_o} [\min(f_o(d), \mu_\kappa(c, d))]$

**if**  $f_{\text{val}} > f_o(c)$  **then**

$f_o(c) \leftarrow f_{\text{val}}$

push all spels  $e$  such that  $\mu_\kappa(c, e) > 0$   $f_{\text{val}} > f_o(e)$   $f_{\text{val}} > f_o(e)$  and  $\mu_\kappa(c, e) > f_o(e)$

**endif**

**endwhile**

**end**

## Fuzzy connectedness variants

- Multiple seeds per object
- Scale-based fuzzy affinity
- Vectorial fuzzy affinity
- Absolute fuzzy connectedness
- Relative fuzzy connectedness
- Iterative relative fuzzy connectedness

## Components of fuzzy affinity

**Fuzzy spel adjacency**  $\mu_\alpha(c, d)$  indicates the degree of spatial adjacency of spels

The **homogeneity-based component**  $\mu_\psi(c, d)$  indicates the degree of local hanging-togetherness of spels due to their similarities of intensities

The **object-feature-based component**  $\mu_\phi(c, d)$  indicates the degree of local hanging-togetherness of spels with respect to some given object feature

## Defining fuzzy spel affinity

### Fuzzy spel affinity

$$\mu_\kappa(c, d) = \mu_\alpha(c, d)g(\mu_\psi(c, d), \mu_\phi(c, d))$$

Expected properties of  $g$

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

### Examples

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

$$\mu_\kappa = \mu_\alpha\sqrt{\mu_\psi\mu_\phi}$$

## Homogeneity-based component

Non-scale-based

### Homogeneity-based component

$$\mu_\psi(c, d) = W_\psi(|f(c) - f(d)|)$$

Expected properties of  $W_\psi$

- range within  $[0, 1]$  and  $W_\psi(0) = 1$
- monotonically non-increasing
- should also be related to overall homogeneity

### Examples

the right-hand-side of an appropriately scaled box, trapezoid, or Gaussian function

## Object-feature-based component

Non-scale-based

### Object-feature-based component

$$\mu_\phi(c, d) = \begin{cases} 1 & \text{if } c = d \\ \frac{\mathcal{W}_o(c, d)}{\mathcal{W}_b(c, d) + \mathcal{W}_o(c, d)} & \text{otherwise} \end{cases}$$

$$\mathcal{W}_o(c, d) = \min[W_o(f(c)), W_o(f(d))]$$

$$\mathcal{W}_b(c, d) = \max[W_b(f(c)), W_b(f(d))]$$

Expected properties of  $W_o$  and  $W_b$

- range within  $[0, 1]$
- monotonically non-increasing

### Examples

an appropriately scaled and shifted box, trapezoid, or Gaussian function

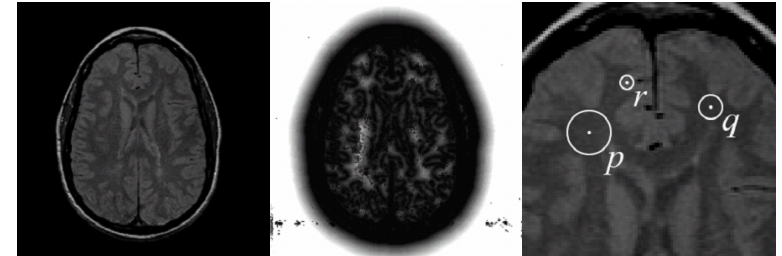
## Scale-based affinity

Considers the following aspects

- spatial adjacency
- homogeneity (local and global)
- object feature (expected intensity properties)
- object scale

## Object scale

**Object scale** in  $\mathcal{C}$  at any spel  $c \in \mathcal{C}$  is the radius  $r(c)$  of the largest hyperball centered at  $c$  which lies entirely within the same object region



The scale value can be simply and effectively estimated without explicit object segmentation

## Computing object scale

## Algorithm

**Input:**  $\mathcal{C}$ ,  $c \in \mathcal{C}$ ,  $W_\psi$ ,  $\tau \in [0, 1]$

**Output:**  $r(c)$

**begin**

$k \leftarrow 1$

**while**  $FO_k(c) \geq \tau$  **do**

$k \leftarrow k + 1$

**endwhile**

$r(c) \leftarrow k$

**end**

Fraction of the ball boundary homogeneous with the center spel

$$FO_k(c) = \frac{\sum_{d \in B_k(c)} W_{\psi_s}(|f(c) - f(d)|)}{|B_k(c) - B_{k-1}(c)|}$$

Neighborhood selection for  
scale-based computations

For properties based on a single spel  $c$  use

$$B_r(c) = \{e \in \mathcal{C} \mid \|e - c\| \leq r(c)\}$$

For properties based on a pair of spels  $c$  and  $d$  use

$$B_{cd}(c) = \{e \in \mathcal{C} \mid \|e - c\| \leq \min[r(c), r(d)]\}$$

$$B_{cd}(d) = \{e \in \mathcal{C} \mid \|e - d\| \leq \min[r(c), r(d)]\}$$

## Intensity variations in neighborhoods

Intensity variations (inhomogeneity) surrounding  $c$  and  $d$   
( $\mu_\alpha(c, d) > 0$ )

- intra-object variation  
(expected to be random and to have a zero mean)
- inter-object variation  
(expected to have a direction and to be larger than the intra-object variation)

## Homogeneity-based component

Scale-based

Directional inhomogeneity over the regions around  $c$  and  $d$

$$D(c, d) = \sum_{\substack{e \in B_{cd}(c) \\ e' \in B_{cd}(d) \\ e - c = e' - d}} (1 - W_h(f(e) - f(e'))) \omega_{cd}(\|e - c\|) \frac{f(e) - f(e')}{|f(e) - f(e')|}$$

## Homogeneity-based component

$$\mu_{\psi_s}(c, d) = 1 - \frac{|D(c, d)|}{\sum_{e \in B_{cd}(c)} \omega_{cd}(\|e - c\|)}$$

## Object-feature-based component

Scale-based

Filtered version of  $f(c)$  taking into account the neighborhood

$$f_a(c) = \frac{\sum_{e \in B_r(c)} f(e) \omega_c(\|e - c\|)}{\sum_{e \in B_r(c)} \omega_c(\|e - c\|)}$$

## Object-feature-based component

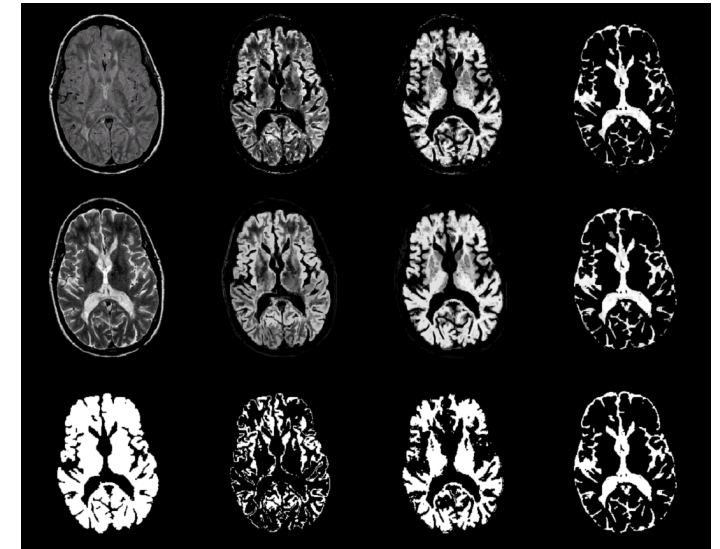
$$\mu_{\phi_s}(c, d) = \begin{cases} 1 & \text{if } c = d \\ \frac{\mathcal{W}_{os}(c, d)}{\mathcal{W}_{bs}(c, d) + \mathcal{W}_{os}(c, d)} & \text{otherwise} \end{cases}$$

$$\mathcal{W}_{os}(c, d) = \min[\mathcal{W}_{os}(f_a(c)), \mathcal{W}_{os}(f_a(d))]$$

$$\mathcal{W}_{bs}(c, d) = \max[\mathcal{W}_{bs}(f_a(c)), \mathcal{W}_{bs}(f_a(d))]$$

## Brain tissue segmentation

FSE



## Efficiency problems with FC (1)

### Problem

it takes too long to compute

### Solution

use more powerful computer

- scales with CPU speed but also depends on the algorithm

## Efficiency problems with FC (2)

### Problem

most time is spent with affinity computation

### Solution

compute affinity only for spels that are used

- can reduce 35–55 % depending on the object

## Efficiency problems with FC (3)

### Problem

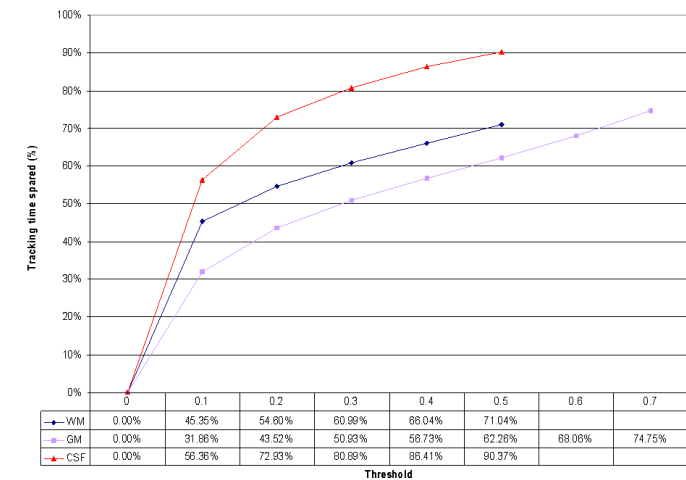
many spels are unnecessarily visited

### Solution

use pre-determined connectedness thresholds

- can reduce 70–90 % depending on the object

## Effect of affinity thresholds





## Efficiency problems with FC (4)

### Problem

many spels are “revisited”

### Solution

reduce the number of “revisits” by ordering

- label-correcting vs. label-setting algorithms
- binary, d-ary, and Fibonacci heaps
- LIFO and FIFO lists
- hash tables of various sizes with various hash functions
- additional pointer arrays

## Computing fuzzy connectedness

Dynamic programming

### Algorithm

**Input:**  $\mathcal{C}$ ,  $o \in \mathcal{C}$ ,  $\kappa$

**Output:** A K-connectivity scene  $\mathcal{C}_o = (C_o, f_o)$  of  $\mathcal{C}$

**Auxiliary data:** a queue  $Q$  of spels

**begin**

  set all elements of  $\mathcal{C}_o$  to 0 except  $o$  which is set to 1

  push all spels  $c \in C_o$  such that  $\mu_\kappa(o, c) > 0$  to  $Q$

**while**  $Q \neq \emptyset$  **do**

    remove a spel  $c$  from  $Q$

$f_{\text{val}} \leftarrow \max_{d \in C_o} [\min(f_o(d), \mu_\kappa(c, d))]$

**if**  $f_{\text{val}} > f_o(c)$  **then**

$f_o(c) \leftarrow f_{\text{val}}$

      push all spels  $e$  such that  $\mu_\kappa(c, e) > 0$   $f_{\text{val}} > f_o(e)$   $f_{\text{val}} > f_o(e)$  and  $\mu_\kappa(c, e) > f_o(e)$

**endif**

**endwhile**

**end**

## Computing fuzzy connectedness

Dijkstra's-like

### Algorithm

**Input:**  $\mathcal{C}$ ,  $o \in \mathcal{C}$ ,  $\kappa$

**Output:** A K-connectivity scene  $\mathcal{C}_o = (C_o, f_o)$  of  $\mathcal{C}$

**Auxiliary data:** a priority queue  $Q$  of spels

**begin**

  set all elements of  $\mathcal{C}_o$  to 0 except  $o$  which is set to 1

  push  $o$  to  $Q$

**while**  $Q \neq \emptyset$  **do**

    remove a spel  $c$  from  $Q$  for which  $f_o(c)$  is maximal

**for each** spel  $e$  such that  $\mu_\kappa(c, e) > 0$  **do**

$f_{\text{val}} \leftarrow \min(f_o(c), \mu_\kappa(c, e))$

**if**  $f_{\text{val}} > f_o(e)$  **then**

$f_o(e) \leftarrow f_{\text{val}}$

        update  $e$  in  $Q$  (or push if not yet in)

**endif**

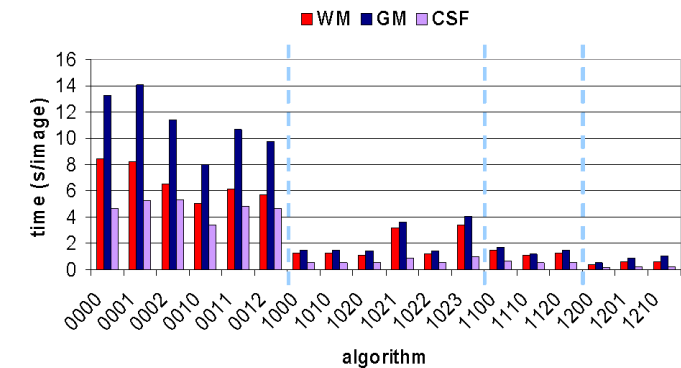
**endfor**

**endwhile**

**end**

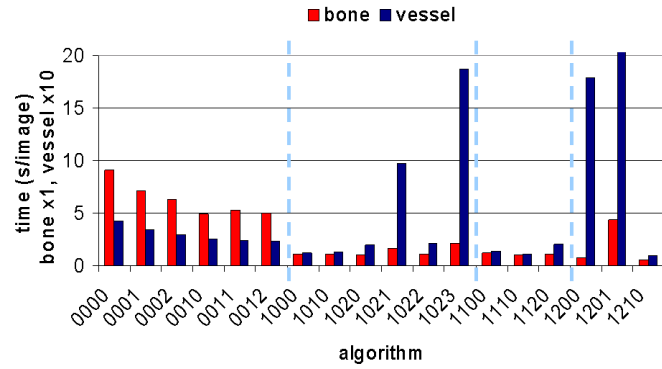
## FC with threshold

MRI



## FC with threshold

CT and MRA



## Vector-valued scenes

## Scene

$$\mathcal{C} = (C, \mathbf{f}) \quad \text{where } C \subset Z^n \text{ and } \mathbf{f} = (f_1, f_2, \dots, f_l)^T$$

$$\mathbf{f} : C \rightarrow [L_1, H_1] \times [L_2, H_2] \times \dots \times [L_l, H_l]$$

## Object scale

$$FO_k(c) = \frac{\sum_{d \in B_k(c)} W_h(\mathbf{f}(c) - \mathbf{f}(d))}{|B_k(c) - B_{k-1}(c)|}$$

$$W_h(\mathbf{x}) = \exp\left(-\frac{1}{2}\mathbf{x}^T \boldsymbol{\Sigma}_h^{-1} \mathbf{x}\right)$$

## Homogeneity-based component

Vectorial scale-based

Total unidirectional inhomogeneity over the scale regions  
around  $c$  and  $d$

$$\mathbf{D}(c, d) = \sum_{\substack{e \in B_{cd}(c) \\ e' \in B_{cd}(d) \\ e - c = e' - d}} (1 - W_h(\mathbf{f}(e) - \mathbf{f}(e'))) \omega_{cd}(\|e - c\|) \frac{\mathbf{f}(e) - \mathbf{f}(e')}{|\mathbf{f}(e) - \mathbf{f}(e')|}$$

$$\mu_{\psi_{vs}}(c, d) = 1 - \frac{|\mathbf{D}(c, d)|}{\sum_{e \in B_{cd}(c)} \omega_{cd}(\|e - c\|)}$$

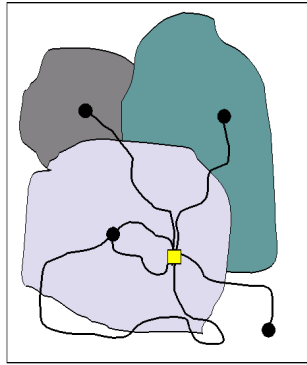
## Object-feature-based component

Vectorial scale-based

$$W_o(\mathbf{f}_a(c)) = \exp\left(-\frac{1}{2}(\mathbf{f}_a(c) - \mathbf{M}_o)^T \boldsymbol{\Sigma}_o^{-1} (\mathbf{f}_a(c) - \mathbf{M}_o)\right)$$

$$\mu_{\phi_{vs}}(c, d) = \begin{cases} 1 & \text{if } c = d \\ \min[W_o(\mathbf{f}_a(c)), W_o(\mathbf{f}_a(d))] & \text{otherwise} \end{cases}$$

## Relative fuzzy connectedness



- always at least two objects
- automatic/adaptive thresholds on the object boundaries
- objects (object seeds) “compete” for spels and the one with stronger connectedness wins

## Relative fuzzy connectedness

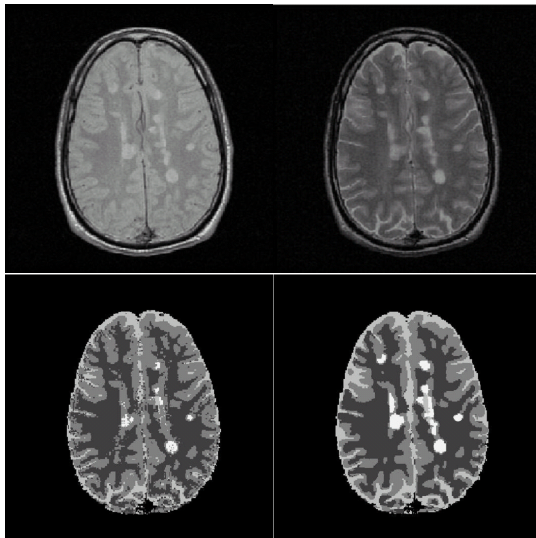
Let  $O_1, O_2, \dots, O_m$ , a given set of objects ( $m \geq 2$ ),  
 $S = \{o_1, o_2, \dots, o_m\}$  a set of corresponding seeds, and let  
 $b(o_j) = S \setminus \{o_j\}$  denote the ‘background’ seeds w.r.t. seed  $o_j$ .

- 1 define affinity for each object  $\Rightarrow \kappa_1, \kappa_2, \dots, \kappa_m$
- 2 combine them into a single affinity  $\Rightarrow \kappa = \bigcup_j \kappa_j$
- 3 compute fuzzy connectedness using  $\kappa \Rightarrow K$
- 4 determine the fuzzy connected objects  $\Rightarrow$

$$O_{ob}(o) = \{c \in C \mid \forall o' \in b(o) \quad \mu_K(o, c) > \mu_K(o', c)\}$$

$$\mu_{O_{ob}}(c) = \begin{cases} \eta(c) & \text{if } c \in O_{ob}(o) \\ 0 & \text{otherwise} \end{cases}$$

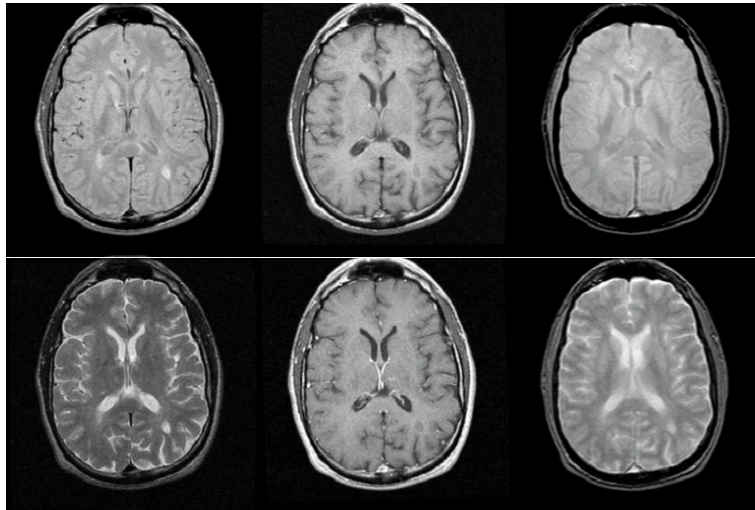
## kNN vs. VSRFC



## Image segmentation using FC

- MR
  - brain tissue, tumor, MS lesion segmentation
- MRA
  - vessel segmentation and artery-vein separation
- CT bone segmentation
  - kinematics studies
  - measuring bone density
  - stress-and-strain modeling
- CT soft tissue segmentation
  - cancer, cyst, polyp detection and quantification
  - stenosis and aneurism detection and quantification
- Digitized mammography
  - detecting microcalcifications
- Craniofacial 3D imaging
  - visualization and surgical planning

## Protocols for brain MRI



## FC segmentation of brain tissues

- 1 Correct for RF field inhomogeneity
- 2 Standardize MR image intensities
- 3 Compute fuzzy affinity for GM, WM, CSF
- 4 Specify seeds and VOI (interaction)
- 5 Compute relative FC for GM, WM, CSF
- 6 Create brain intracranial mask
- 7 Correct brain mask (interaction)
- 8 Create masks for FC objects
- 9 Detect potential lesion sites
- 10 Compute relative FC for GM, WM, CSF, LS
- 11 Verify the segmented lesions (interaction)

## Segmentation in two phases

### Phase 1: Training

performed once for each task (protocol, body region, organ)

- a few datasets are selected and used to extract the values for the parameters
- mostly requires continuous user control

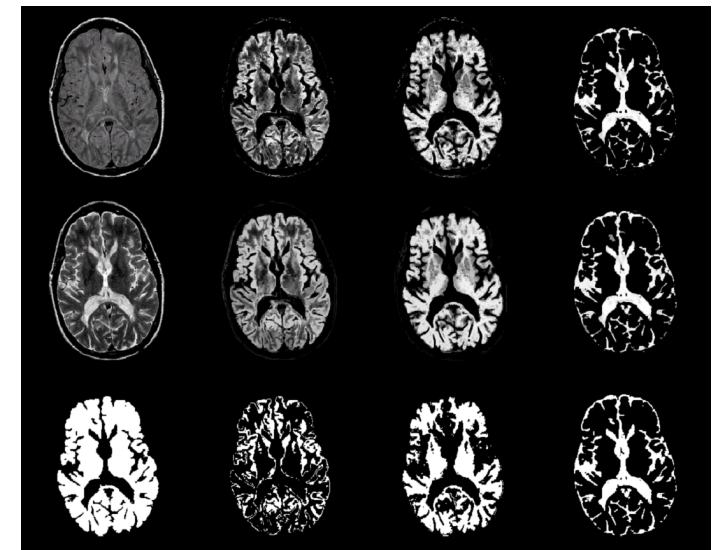
### Phase 2: Segmentation

performed for each individual dataset

- most steps are automatic (parameters are fixed in Phase 1)
- interactive steps require
  - mouse clicks from the user to specify points
  - “cut” and “add” when correcting the brain mask

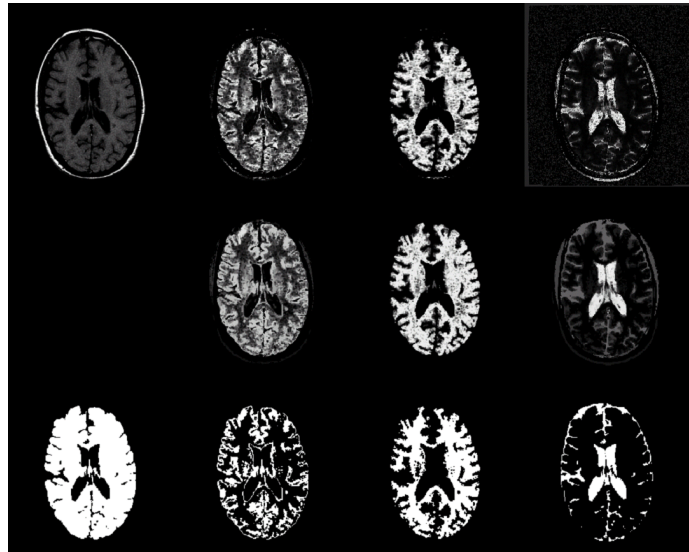
## Brain tissue segmentation

FSE



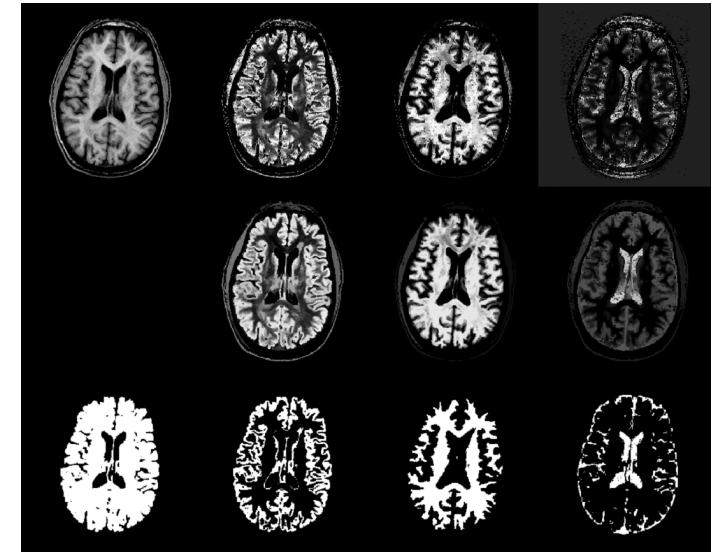
## Brain tissue segmentation

T1



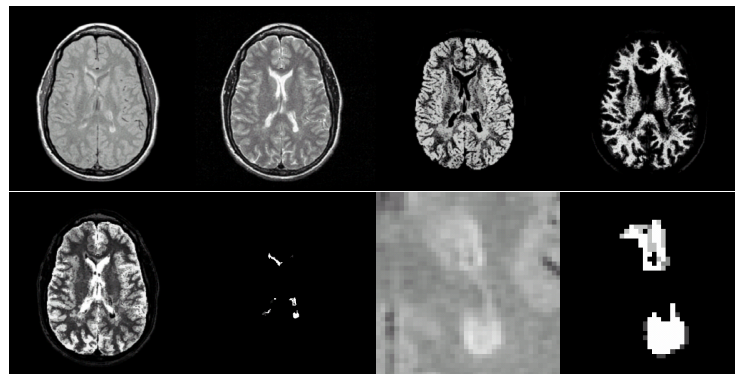
## Brain tissue segmentation

SPGR



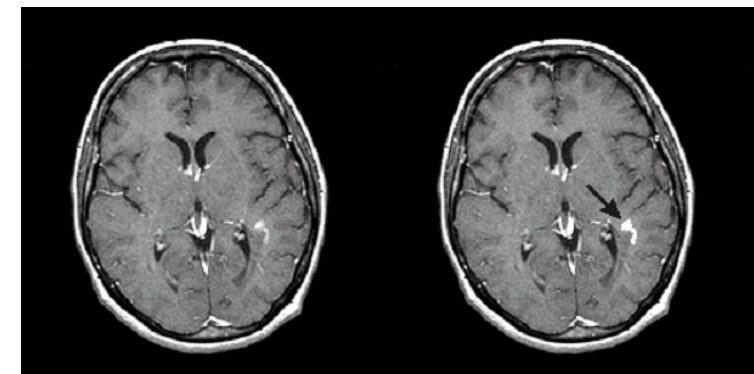
## MS lesion quantification

FSE



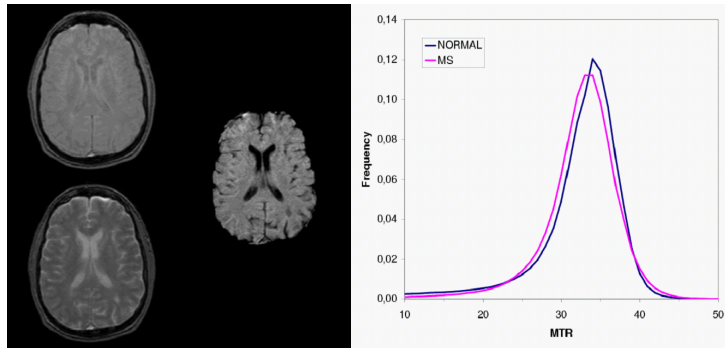
## MS lesion quantification

T1E

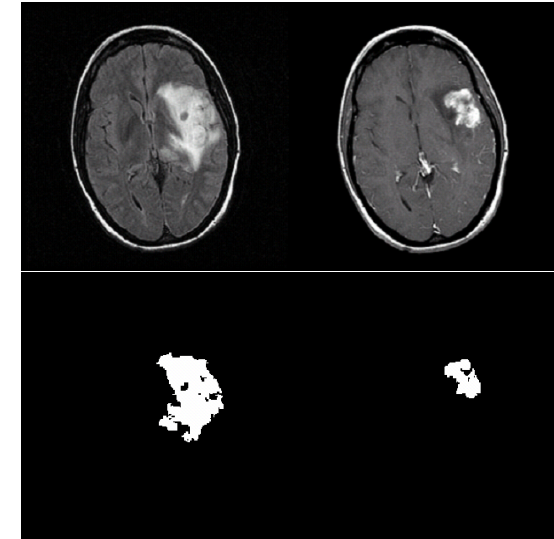




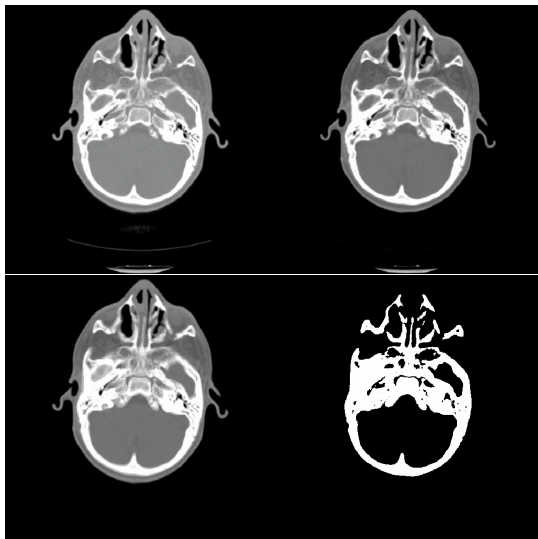
## MTR analysis



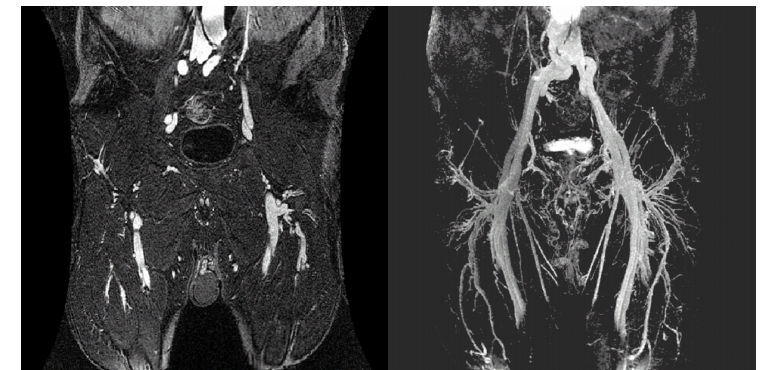
## Brain tumor quantification



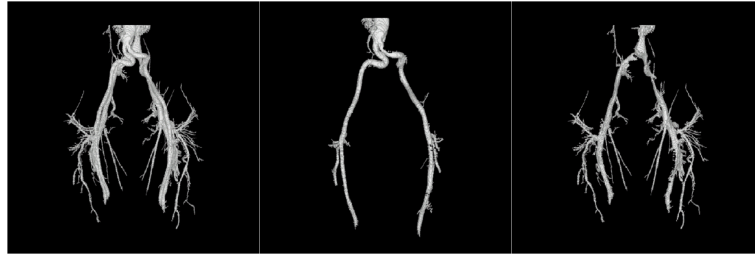
## Skull object from CT










## MRA slice and MIP rendering



## MRA vessel segmentation and artery/vein separation



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