Non-local Fuzzy C-Means Clustering with Application to Automatic Brain Hematoma Edema Segmentation using CT

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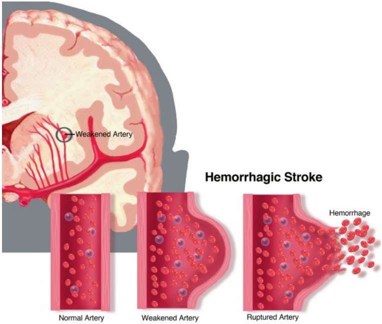
1. Motivation

2. Hematoma Segmentation

3. Edema Segmentation

Intracerebral hemorrhage (ICH)

- **Intracerebral hemorrhage** (ICH) is one kind of Hemorrhagic Strokes (about 12% of all strokes).
- It occurs when a diseased blood vessel within the brain bursts, allowing blood to leak inside the brain.
- The most common cause of ICH is high blood pressure.
- High mortality rate (about 30-40% within a month) since patients with ICH are more severe usually.



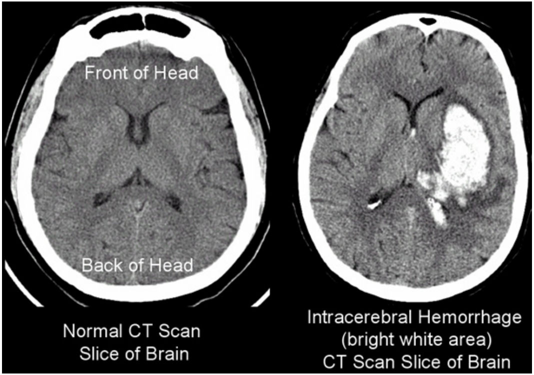
http://www.compelvisuals.com/

Hematoma and Edema

- **Hematoma** is a localized collection of blood outside of the blood vessels, usually in liquid form within the tissue.
- **Perihematomal edema** (PHE) is a marker of secondary injury in ICH, and it's an increase in the water content of brain tissue. Develops within 3 hours in most patients and reaches its maximum between 10 to 20 days. Such edema can cause an increase in brain volume and intracranial pressure.

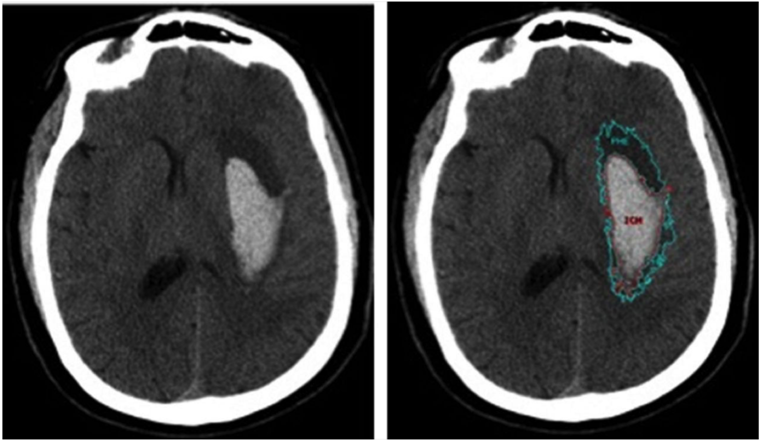
CT Scan

Computed tomography (CT) scans are usually used to determine whether patients have bleeding in or around your brain (ICH) since MRI scans are more problematic due to the movement in unstable patients with stroke, even though MRI are more sensitive to detect it.



http://www.uwmedicine.org/health-library/Pages/intracerebral-hemorrhage.aspx

Hematoma and Edema



Urday, Sebastian, et al. "Measurement of perihematomal edema in intracerebral hemorrhage." Stroke 46.4 (2015): 1116-1119.

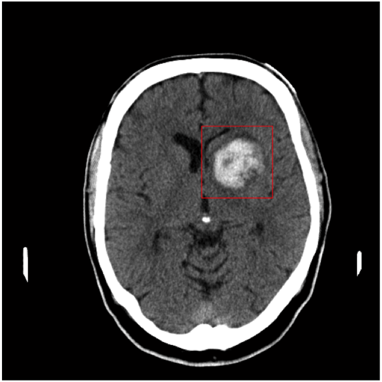
Why Segmentation?

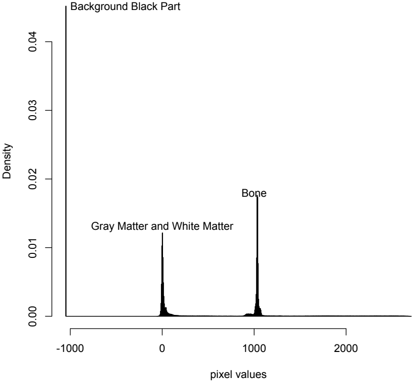
- Studies (J.M. Gebel, 2002) have reported that relative edema volume (edema volume divided by hematoma volume) is strongly predictive of functional outcome in patients with hyperacute supratentorial.
- To study the behaviour of hematoma and edema volume changing over time across different subjects.

The goal of the study is to provide an automatic, consistent and accurate segmentation of hematoma and edema.

Hematoma Segmentation

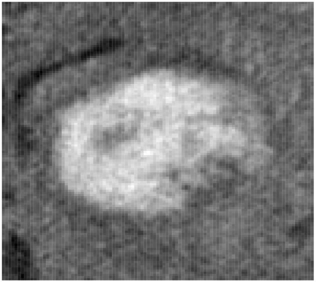
Each CT slice has size 512*512 (each pixel about $0.468 \times 0.468 mm^2$) with thickness 5 mm, and each patient has 30 slices. CT scans were performed within 24 hours.

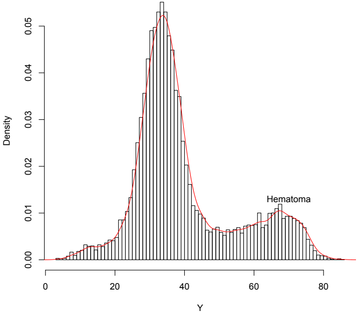




Hematoma Segmentation

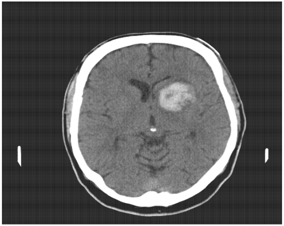
Within the region of interest (ROI), hematoma (white part) has higher pixel values than the rest part, which is the key part in the hematoma segmentation.



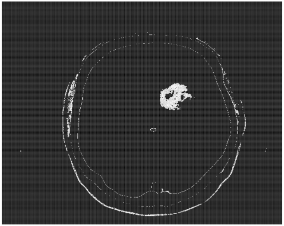


Hematoma Segmentation

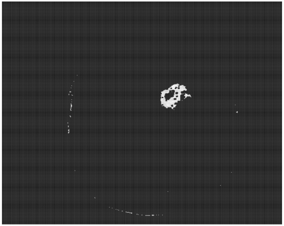
Original CT Scan



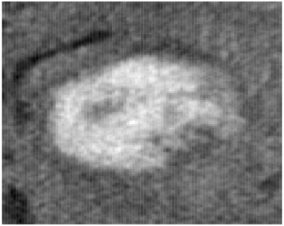
Filtered using interval [60,80]



Erosioned image

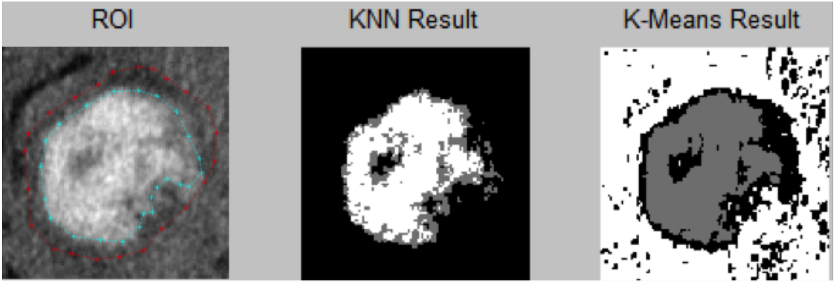


Selected ROI



Edema Segmentation

k-nearest neighbours algorithm was applied using 5 slices as training data, and test in the other slice, and all 6 slices from same patient, and $k = 8$. K means Clustering algorithm was also tried with 3 clusters.



Fuzzy C Means

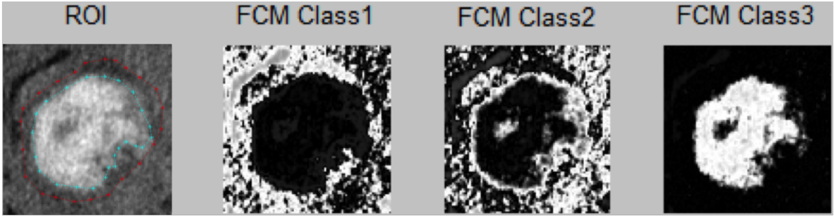
Different than hard clustering like K means, fuzzy (soft) clustering like Fuzzy C-Means (Bezdek 1981) allow each data point belongs to more than one cluster with a membership level. FCM is derived to minimize the following objective function w.r.t. membership function u_{jk} and the centroids v_k

$$J_{FCM} = \sum_{j \in \Omega} \sum_{k=1}^{C} u_{jk}^{q} ||y_j - v_k||^2,$$

where $\sum_{k=1}^{C} u_{jk} = 1$, and $1 \leq q$ controls the degree of "fuzziness". As q increases, the membership functions become fuzzier. Like K means, the algorithm converges to a local minimum or a saddle point.

Fuzzy C Means Result

FCM with $q = 2$ is applied, and the membership matrix to each cluster is plotted below. Class 1, 2 and 3 represents other tissue, edema and hematoma respectively. As we can see, the results of FCM suffers from image inhomogeneity and noises, and the edema regions are hard to identify.



Spatial Fuzzy C Means

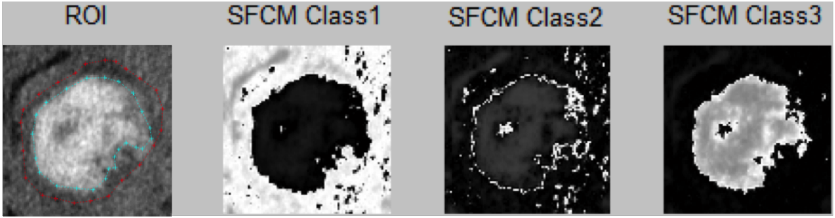
One disadvantage of FCM is that it does not incorporate information about spatial context, making it sensitive to noise and other imaging artifacts. By adding a penalty function to J_{FCM} (D.L. Pham, 2001), the objective function becomes

$$J_{SFCM} = \sum_{j \in \Omega} \sum_{k=1}^{C} u_{jk}^{q} ||y_j - v_k||^2 + \frac{\beta}{2} \sum_{j \in \Omega} \sum_{k=1}^{C} u_{jk}^{q} \sum_{l \in N_j} \sum_{m \in M_k} u_{lm}^{q},$$

where N_j is the set of neighbours of pixel j, and $M_k = \{1, ..., C\} \setminus \{k\}$, the parameter β controls the trade-off between minimizing the standard FCM objective function and obtaining smooth membership function. The minimization problem can be solved by Lagrange Multiplier.

SFCM results

SFCM with $q = 2$ and the patch N_j is a 11*11 square, and $\beta = 100$, a criterion based on cross-validation can be developed to choose an appropriate value of β.



Compare to results of FCM, SFCM smoothed out some background noise, however, it's easy to be disturbed by speckle and poor in terms of the region uniformity. Local spatial information is not enough to regularize the FCM to suppress these noises.

Non Local Mean Filter

For every pixel i in an image $v = \{v(i) \mid i \in \Sigma\}$, the estimated value $NL[v](i)$ using non local mean algorithm is a weighted average of "all" pixels in the image,

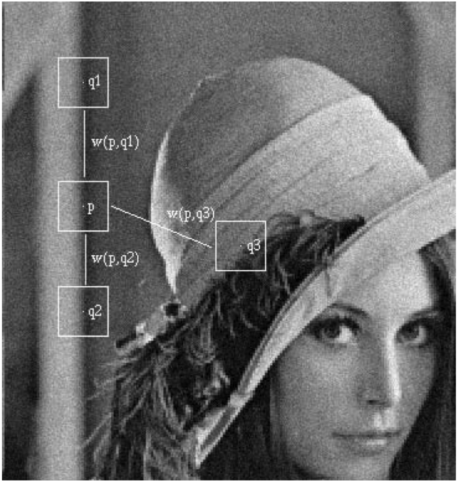
$$NL[v](i) = \sum_{j \in \Sigma} w(i,j) v(j),$$

where the weights $\{w(i,j)\}_j$ depends on the similarity between the pixels i and j satisfying $0 \leq w(i,j) \leq 1$ and $\sum_j w(i,j) = 1$. They are defined as,

$$w(i,j) = \frac{1}{Z(i)} e^{-\frac{||v(N_i) - v(N_j)||_{2,a}^2}{h^2}}.$$

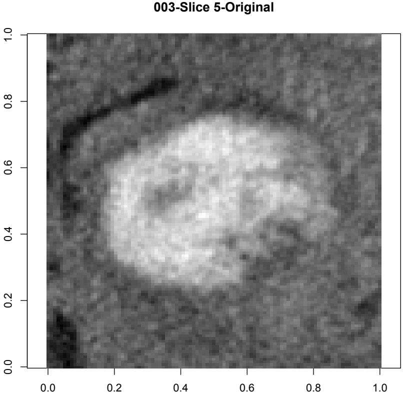
N_i denotes a square (or other shape) neighbourhood of fixed size and center at pixel i, and h is a smoothing parameter.

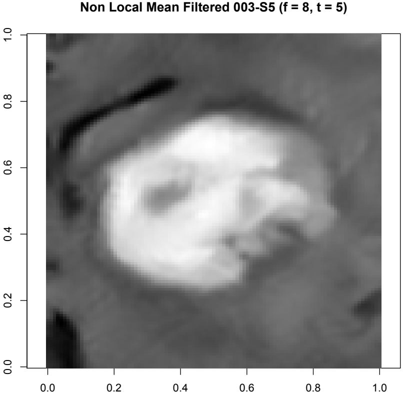
Non Local Mean Filter



Buades, Antoni, Bartomeu Coll, and Jean-Michel Morel. "A non-local algorithm for image denoising." Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on. Vol. 2. IEEE, 2005

Non Local Mean Filter Example





SFCM with NLM weights

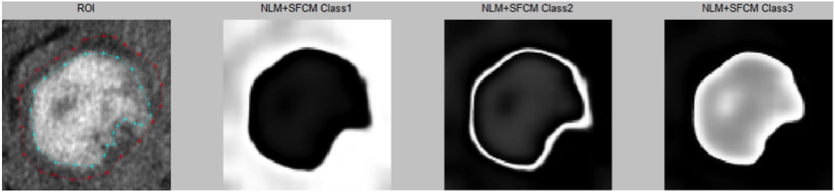
Combining the non-local weight with the SFCM, we obtain a fully non-local regularised objective function (B. Caldairou, et al. 2011), which enables us to simultaneously deal with noise and inhomogeneity artifacts.

$$J_{NLM-SFCM} = \sum_{j\in\Omega}\sum_{k=1}^{C}\sum_{n\in N_j} w_{jn} u_{jk}^{q} ||y_j - v_{kn}||^2 + \frac{\beta}{2}\sum_{j\in\Omega}\sum_{k=1}^{C} u_{jk}^{q} \sum_{n\in N_j^R} w_{jn} \sum_{m\in M_k}^{C} u_{lm}^{q},$$

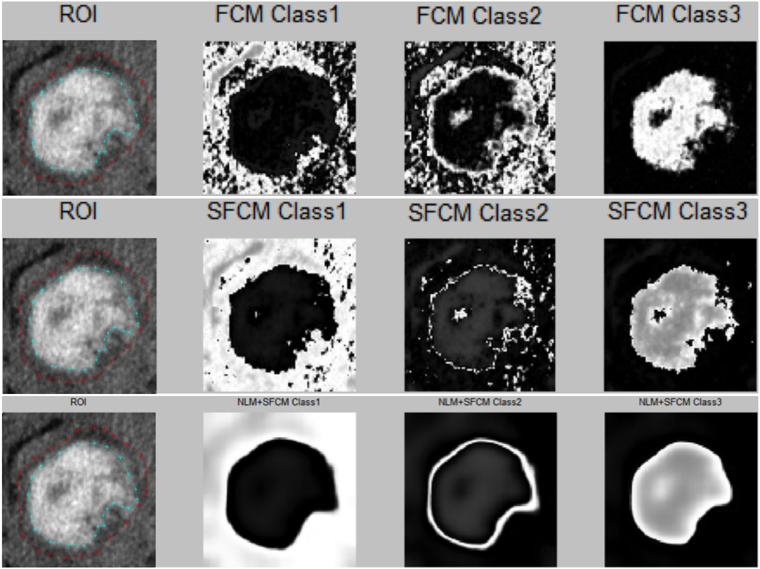
where w_{jn} is the non local mean weight between j and n as defined before. The minimization of $J_{NLM-SFCM}$ can be solved using Lagrange Multiplier.

NLM-SFCM Results

The results below are done slice by slice, however, the method can also apply to a 3D object by combining the slices together. We can see that local pixel's abnormal features have been greatly corrected by the NL mean filter compared to SFCM, and the results are very close to the manual segmentation result.



Final comparisons of methods



Future Work

- Increase the robustness of the proposed method against a "worse" condition, e.g. fuzzier boundary between edema/hematoma, multiple areas with ICH.
- Optimal parameter choose.
- Test the methods on more dataset.

References

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Thank you!