MULTI-VIEW FEATURES FUSION FOR ALZHEIMER'S DISEASE PROGNOSIS

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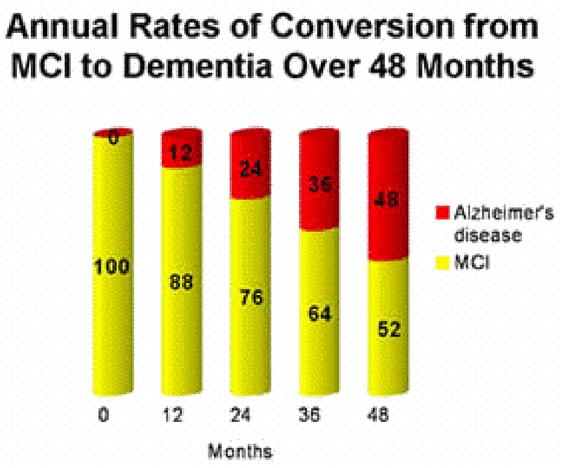
Alzheimer's Disease & Mild Cognitive Impairment (MCI)

Alzheimer's Disease (AD)

- is the most common form of dementia.
- Usually happens to people over 65 years old.
- Leads the brain to shrink.
- Causes memory loss, paranoia and trouble expressing thoughts.
- By 2050, Alzheimer's disease is predicted to affect 1 in 85 people all around the world.

Mild Cognitive Impairment (MCI)

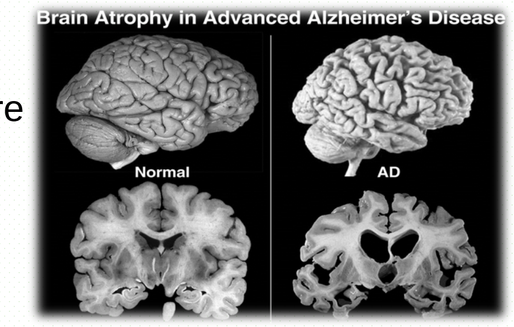
- Is usually considered as the prodromal stage of Alzheimer's disease.
- MCI is not significant enough to interfere with people daily life.
- MCI could be further classified as MCI converter (cMCI) and MCI non-converter (ncMCI) depending on whether patients would convert to AD in three years.
- The conversion rate from MCI to AD is 10% to 15% per year.

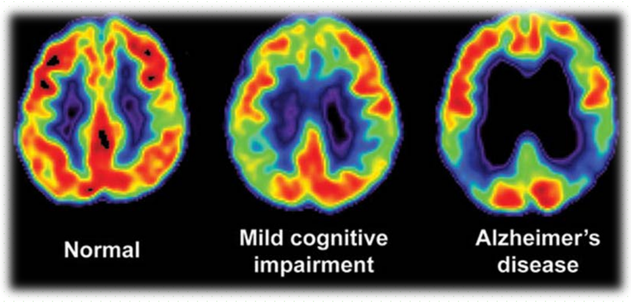


Neuroimaging Biomarkers for AD and MCI

Magnetic Resonance Imaging (MRI)

- Is the most widely used neuroimaging biomarker for AD.
- Can be used to visualize internal structure of the body.
- Allows accurate measurement of the brain structures.
- Captures brain atrophy patterns and geometric variations.





Positron Emission Tomography (PET)

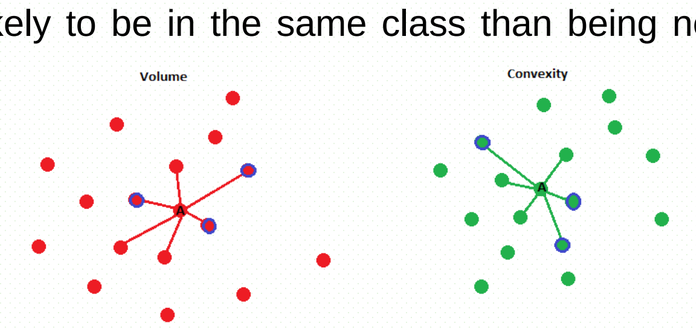
- Is a widely used functional biomarker for AD, especially in early anomaly detection.
- Can be used to investigate changes in cerebral glucose metabolism, various neurotransmitter systems, neuroinflammation, and the protein aggregates that are characteristic of the disease.
- Captures the hypo-metabolism patterns and the neurodegenerative lesions.

Proposed Solution

co-neighbor

We proposed the '**co-neighbor**' method for feature fusion.

- 'Co-neighbor' is an enhanced neighbor selection strategy.
- Given the th view, consider an arbitrary instance and its *k* nearest neighbors; suppose is one of nearest neighbors of in the th view, if the number of views where is a neighbor of , we discard this neighborhood in all views.
- We came up with the 'co-neighbor' strategy based on the assumption that if two instances are neighbors among multiple views, then they are more likely to be in the same class than being neighbors in the single view.



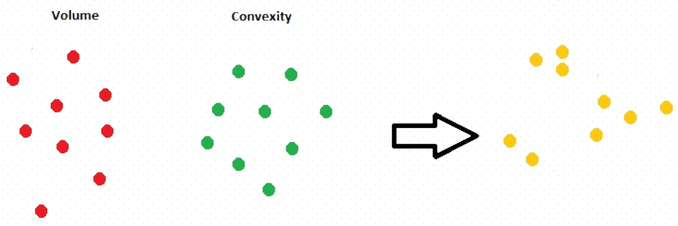
To increase the effectiveness of the 'co-neighbors', we add the weights to distances from the target to the neighbors:

$$d^*\left(x_j^{(i)}, x_l^{(i)}\right) = \left\|x_j^{(i)}, x_l^{(i)}\right\|^2 / number\ of\ views\ they\ are\ neighbors^{\beta}$$

The more views is neighbor of , more likely they are with the same classification label, based on this, distances from to would be updated with relative weights.

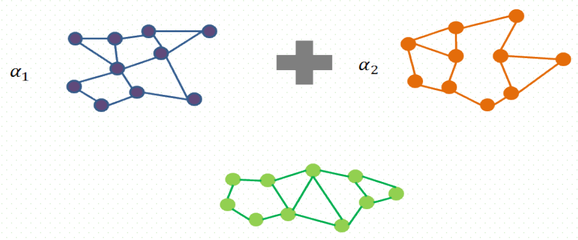
Feature Fusion

- Nowadays, multi-view feature situation is very popular, because they could provide complementary information to each other.
- Fused feature space could represent the patient more accurately.
- The challenge is how to keep the important information and discard the noise.



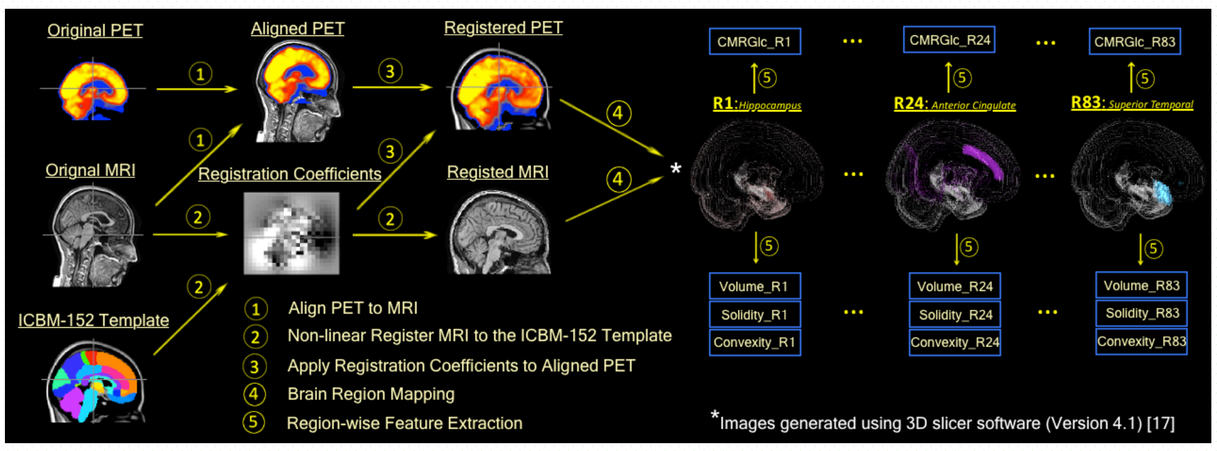
Motivation

- Existing feature fusion methods, such as 'MSE', combines multiple views by adding relative weights to each view.
- More important view is supposed to have larger weight.
- We would enhance feature fusion by integrating neighborhood affinity into traditional MSE.



Dataset and Pre-processing

- We use neuroimaging dataset from Alzheimer's Disease Neuroimaging Initiative (ADNI) which is the biggest dataset of neuroimaging world around.
- Pre-processing workflow is shown as below:



Multiview Feature Extraction

There are totally **7** features extracted and used to validate our algorithm**.**

MRI:

- Brain region volume
- Solidity

PET:

- CMRGLC
- Mean index ratio
- Lesion area
- Lesion contrast
- Lesion mean value

Performance Evaluation

We evaluated the proposed algorithm using content-based retrieval and Mean Average Precision (MAP) to measure the performance.

Experimental Results

The experimental results show that the proposed method generally performs better than some widely used algorithms and MSE.

Algorithm	NC	ncMCI	cMCI	AD	Average
Best single view(volume)	67.00	68.59	59.01	64.84	65.32
Elastic Net	66.65	71.15	62.73	68.91	67.83
ISOMSP(d= 100,k=40)	59.20	70.77	64.04	64.09	65.00
MSE(d=50,γ=7,k=25)	64.15	71.22	65.09	63.59	66.37
Proposed Method(d=50,γ=7,k=40,β = 3)	69.68	71.59	63.70	68.14	68.66

The proposed method achieves the best performance of NC, ncMCI and average. Generally, the proposed method is better than best single view, Elastic Net, ISOMAP and MSE.

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