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Contributions

- Development of new texture-based grading framework.
- Innovative adaptive fusion strategy based on local confidence criterion.
- New weak-classifier aggregation based on histogram.
- Improvement of the patch-based methods to AD classification task.

Materials

- MRI data are from ADNI1.

| Characteristic / Group | CN | sMCI | pMCI | AD |
|------------------------|------------|------------|------------|------------|
| Number of subjects | 226 | 223 | 165 | 186 |
| Ages (Years) | 76.0 ± 5.0 | 75.1 ± 7.5 | 74.5 ± 7.2 | 75.3 ± 7.4 |
| MMSE | 29.0 ± 0.9 | 27.1 ± 2.5 | 26.3 ± 2.0 | 22.8 ± 2.9 |

Methods

1 Texture extraction:

The input images are filtered with Gabor filters within different directions.

2 Patch-based grading:

Each texture maps are processed with a patch-based grading method (1) focused to the hippocampus structure.

3 Adaptive fusion:

All grading maps of the same subject are fused by our adaptive fusion method (2).

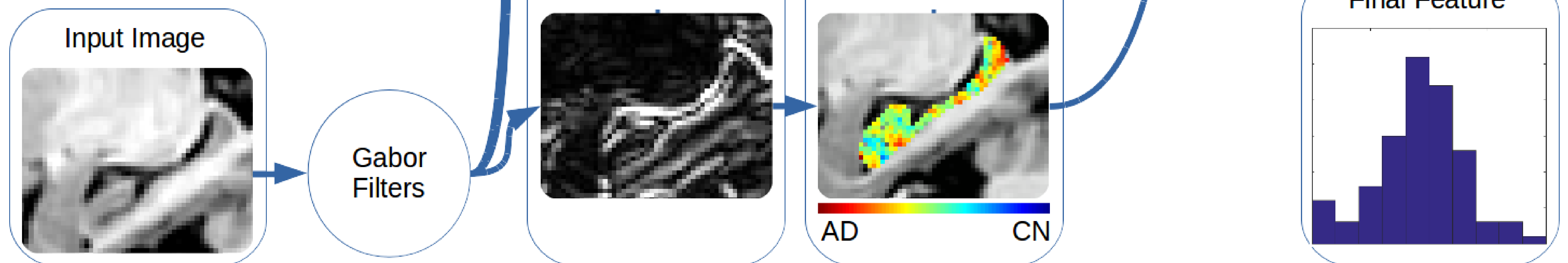
$$g_m(x_i) = \frac{\sum_{x_{j,t} \in K} \omega(x_i, x_{j,t}) p_t}{\sum_{x_{j,t} \in K} \omega(x_i, x_{j,t})} \quad (1), \quad g_M(x_i) = \frac{\sum_{m \in M} \alpha_m g_m(x_i)}{\sum_{m \in M} \alpha_m} \quad (2),$$

4 Weak classifiers aggregation:

The distributions of the weak classifier values are estimated by a histogram.

5 Classification step:

A SVM method performs the classification results into a LOOCV procedure.



Results

- Comparison Intensity vs Texture.

| Features | CN vs AD (AUC in %) | CN vs pMCI (AUC in %) | AD vs sMCI (AUC in %) | sMCI vs pMCI (AUC in %) |
|-----------------|---------------------|-----------------------|-----------------------|-------------------------|
| T1-w Grading | 93.5 | 90.0 | 81.1 | 73.6 |
| Proposed Method | 94.2 | 90.9 | 81.3 | 75.4 |

- Comparison to the state-of-the-art methods based on a hippocampus and whole brain analysis.

| Methods | Registration | Features | CN vs AD (ACC in %) | sMCI vs pMCI (ACC in %) |
|--------------------------|--------------|-----------|---------------------|-------------------------|
| Hippocampus | | | | |
| Original Grading [1] | Affine | Intensity | 88.0 | 71.0 |
| Sparse-based Grading [4] | Affine | Intensity | - | 66.0 |
| Sparse-based Grading [4] | Non Linear | Intensity | - | 69.0 |
| Proposed Method | Affine | Texture | 91.3 | 71.1 |

Whole brain

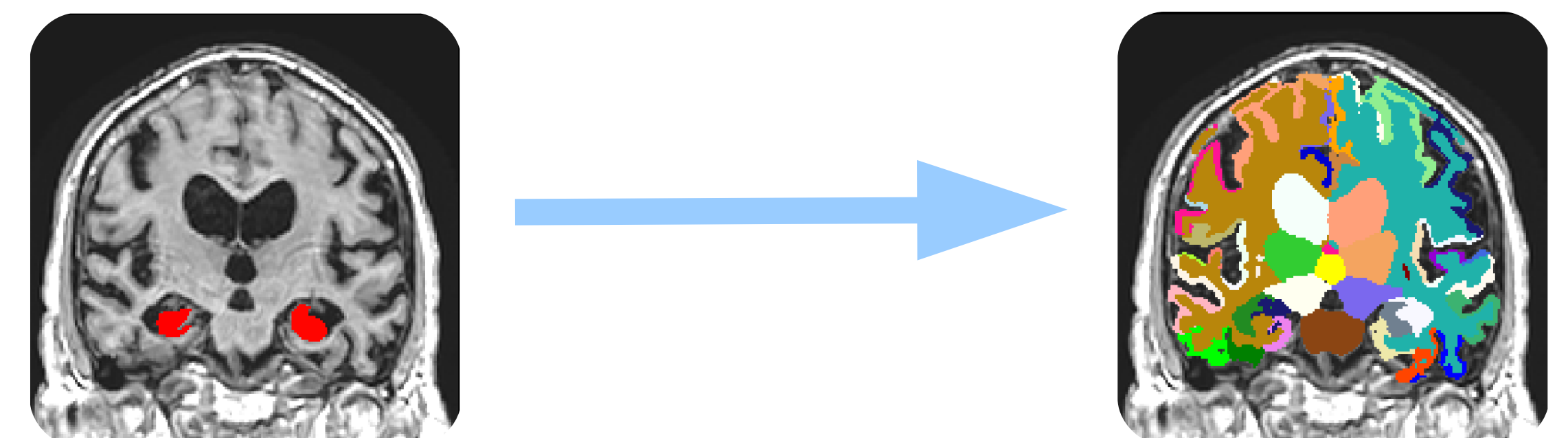
| | | | | |
|-----------------------------|------------|-----------|------|-------------|
| Ensemble Grading [3] | Non Linear | GM | - | 75.6 |
| Sparse-based Grading [4] | Non Linear | Intensity | - | 75.0 |
| Sparse Ensemble Grading [2] | Non Linear | GM | 90.8 | - |
| Deep Ensemble Learning [5] | Non Linear | GM | 91.0 | 74.8 |

Conclusions

- We propose a new patch-based grading framework based on texture extraction.
- Textural informations improve classification performances.
- Our method is competitive especially for CN vs. AD comparison.
- Whole brain analysis provides better classification results for early stages of AD.

Perspectives:

- Extension of our framework to a whole brain analysis to outperform the hippocampus analysis in the early stages comparison.



Bibliography

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- [4] Tong et al. 2017, IEEE TBE
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Fundings

- Program IdEx Bordeaux (ANR-10-IDEX-03-02).
- Cluster of excellence CPU and TRAIL (HL-MRI ANR-10-LABX-57).