EXTENDING LOCAL BINARY PATTERNS TO 3D FOR THE DIAGNOSIS OF ALZHEIMER'S DISEASE

Pedro M. Morgado, Margarida Silveira and Jorge S. Marques
Instituto Superior Técnico, Institute for Systems and Robotics, Lisbon, Portugal

Introduction

Alzheimer's disease (AD) is the most common form of dementia. Its early detection (still at the Mild Cognitive Impairment (MCI) stage) is essential to improve patients' life quality and extend life expectancy.

This work explored the textural information of FDG-PET images to built an automated diagnostic system for AD and MCI.

Textural information was retrieved using a novel generalization of Local Binary Patterns to 3D. The proposed approach, unlike previous ones [1,2,3], is able to reproduce closely the uniformity and rotation invariance concepts in a 3D space.

Materials and methods

Automated diagnostic system

Image Preprocessing → Texture Extraction → Feature Selection → Classification

❖ **Image Preprocessing**

Reduce meaningless differences between images.

- Orientation alignment;
- Resolution and intensity normalization;
- Registration to the same anatomical space;

❖ **Texture Extraction**

Extract textural information from FDG-PET images.

- Local binary patterns;

❖ **Feature Selection**

Reduce the number of features by selecting the most relevant.

- Mutual information between each feature and the class;

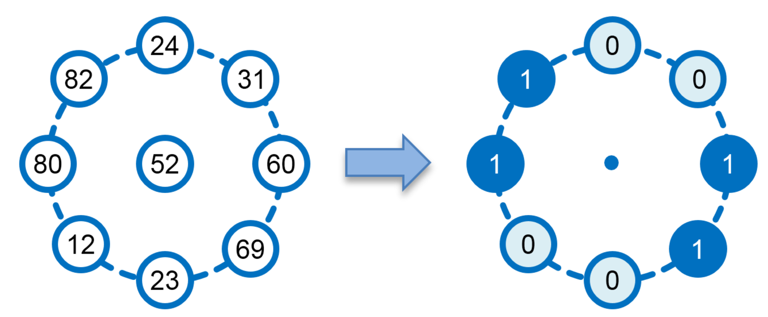
❖ **Classification**

- Linear SVM (support vector machine);

Local binary patterns (LBPs)

According to [4], textural information can be coded in the frequency of occurrence of differently labeled structures called LBPs.

Parameters: P – Number of neighbors; R – Radius;



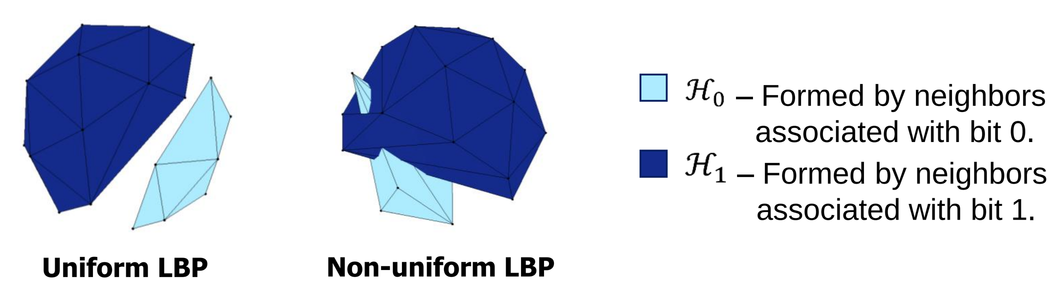
Example of construction of an LBP. The intensities of a set of neighbors are thresholded by the intensity of the central pixel.

Three-dimensional extension

LBPs in 3D were constructed using a neighbor set lying on a sphere.

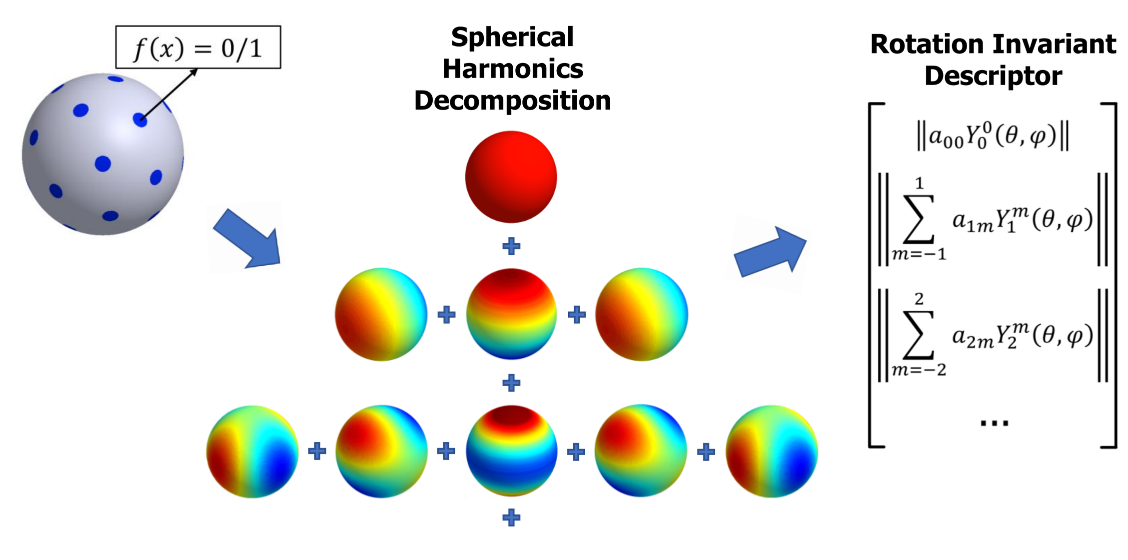
- **Uniformity**

LBPs were considered to be uniform if and only if two convex hulls, $\mathcal{H}_0$ and $\mathcal{H}_1$, do not intersect. All non-uniform patterns were grouped into the same label. In practice, the linear separability of the two groups of points was checked (as in [5]).



- **Rotation invariance**

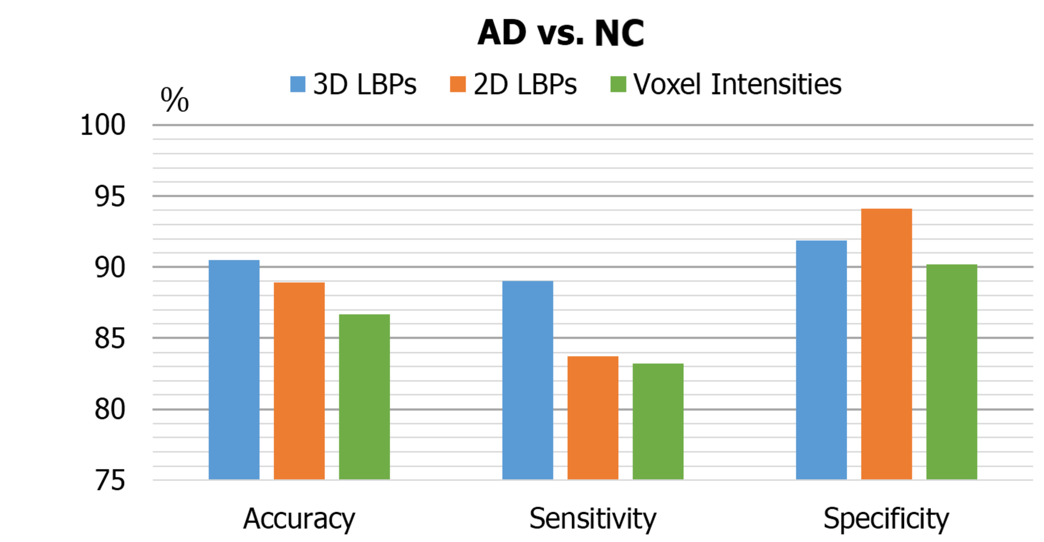
Uniform LBPs which are invariant under rotation were also merged into the same label. Rotation invariance was achieved using the energy of a spherical function, representative of each LBP, at different frequencies (as in [6]).

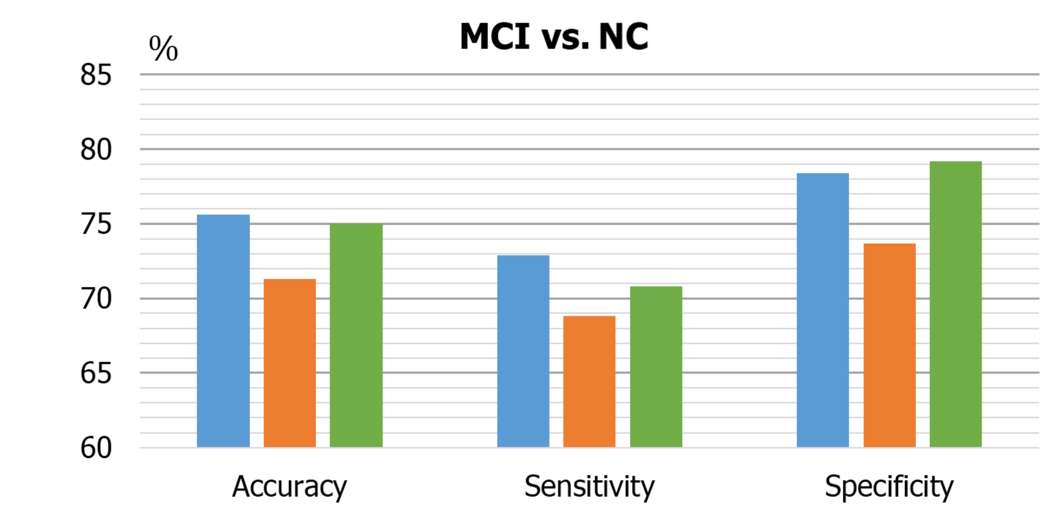


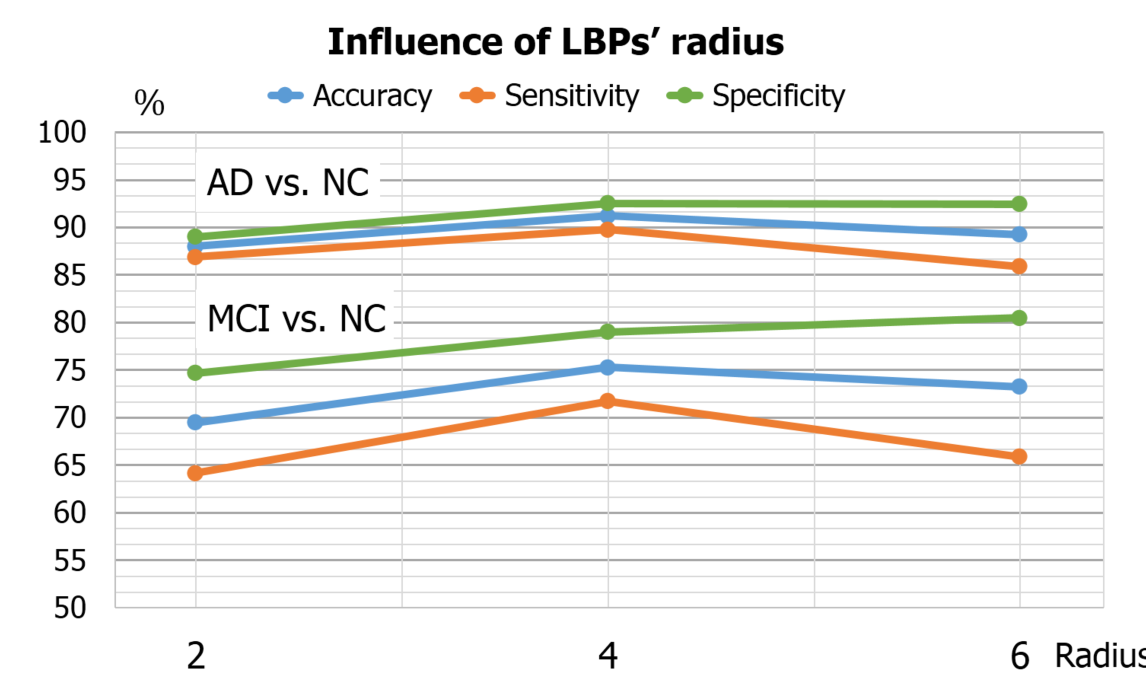
Results

We compared the novel LBP extension, in the diagnosis of AD and MCI (against normal controls (NC)), with two approaches:

- Using the original 2D LBPs as the texture extraction procedure;
- Using the voxel intensities directly as features.







Discussion

Most LBP structures are non-uniform. However, the few uniform LBPs are the most frequent. Therefore, we avoid the use of frequencies of occurrence of rare LBPs as features.

Uniformity and rotation invariance reduced greatly the number of features. In our experiments, they were reduced from 2^{24} to 96.

The proposed approach achieved the best accuracy in both diagnostic problems, indicating that extremely relevant features are extracted using 3D LBPs.

Limitations:

The novel 3D LBP scheme is limited computationally by the number of neighbors, because every structure have to be classified as uniform or non-uniform. (Number of LBPs = 2^P)

Although 3D LBPs had improved significantly the sensitivity in both diagnostic problems, the same was not observed for specificity.

Conclusions

- The proposed generalization of LBPs is able to closely replicate in three dimensions the key concepts proposed for 2D texture analysis.
- The texture of FDG-PET images contains discriminative information for the diagnosis of AD and MCI.
- Texture features extracted with the novel procedure based on 3D LBPs outperformed the original 2D LBPs applied to axial cuts of the image and the common approach based directly on the voxel intensities.

References

[1] G. Zhao and M. Pietikainen, "Dynamic texture recognition using local binary patterns with an application to facial expressions," Pattern Analysis and *Machine Intelligence, IEEE Transactions on*, vol. 29, no. 6, pp. 915–928, 2007.
[2] J. Fehr, "Rotational invariant uniform local binary patterns for full 3D volume texture analysis," *Finnish Signal Processing Symposium, Proc.*, 2007.
[3] J. Fehr and H. Burkhardt, "3D rotation invariant local binary patterns," *Pattern Recognition, 19th International Conference on*, pp. 1–4, 2008.
[4] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 24, no. 7, pp. 971–987, 2002.
[5] D. Elizondo, "The linear separability problem: some testing methods," *Neural Networks, IEEE Transactions on*, vol. 17, no. 2, pp. 330–344, 2006.
[6] M. Kazhdan, T. Funkhouser, and S. Rusinkiewicz, "Rotation invariant spherical harmonic representation of 3D shape descriptors," *Geometry Processing, Proceedings of the 2003 Eurographics/ACM SIGGRAPH symposium on*, pp. 156–164, 2003.

Acknowledgments

This work was supported by Fundação para a Ciência e Tecnologia (FCT/MCTES) through the ADIAR project (PTDC/SAU-ENB/114606/2009) and through the Strategic Project (PEst-OE/EEI/LA0009/2011).

Data used in the preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report.

FCT Fundação para a Ciência e a Tecnologia
MINISTÉRIO DA EDUCAÇÃO E CIÊNCIA