Automatic Classification of FDG-PET imaging data in Disorders of Consciousness

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Introduction

The difficulty of correctly diagnosing different states of consciousness is reflected by the high error rate of misdiagnosis [1]. Currently, there is no equipment that can give an objective measure of consciousness and therefore multiple clinical examinations are required for the evaluation of a patient's consciousness state. In this study we aim to develop an evaluation method by teaching a machine to detect the state of consciousness using fluorodeoxyglucose PET (18F-FDG-PET) scans.

Data:

PET images with computed tomography attenuation correction:

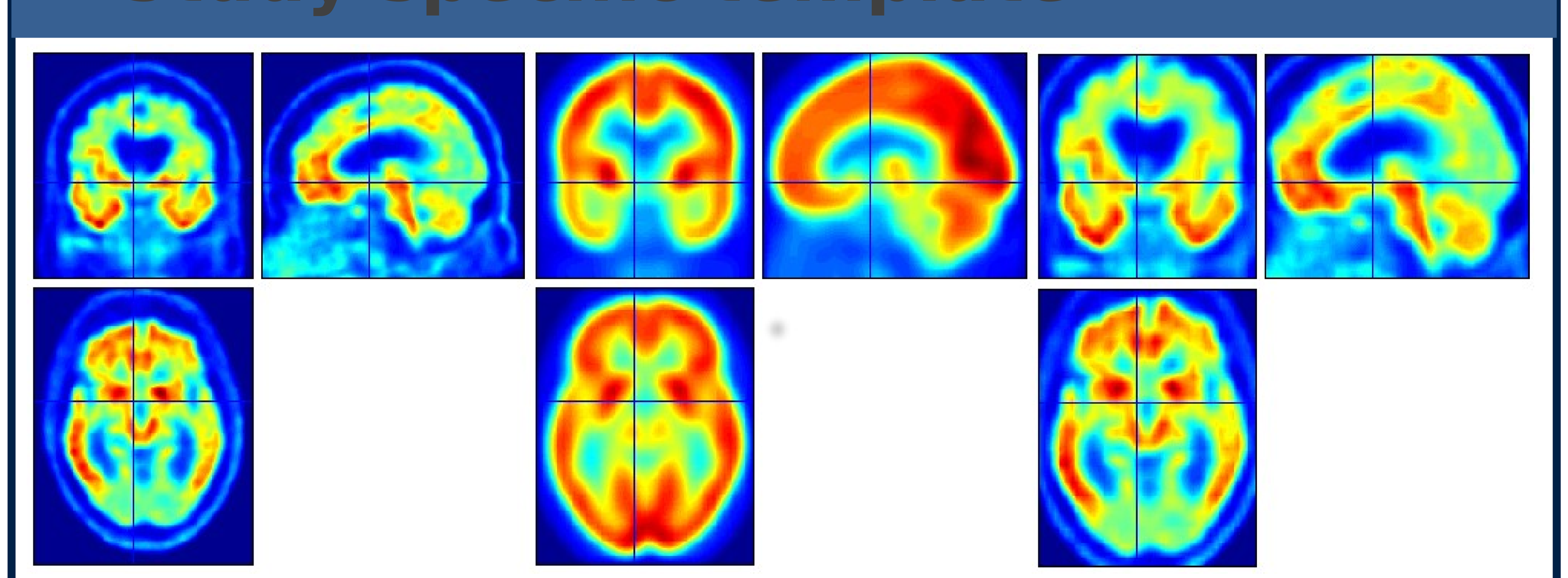
- 140 patients with different states of consciousness (mean age 34.82 years old, ± 14.7 SD)
- 35 healthy subjects

Preprocessing

Each patient's state of consciousness was evaluated with repeated assessments of Coma Recovery Scale.
Data were preprocessed and analyzed by means of statistical parametric mapping (SPM12).

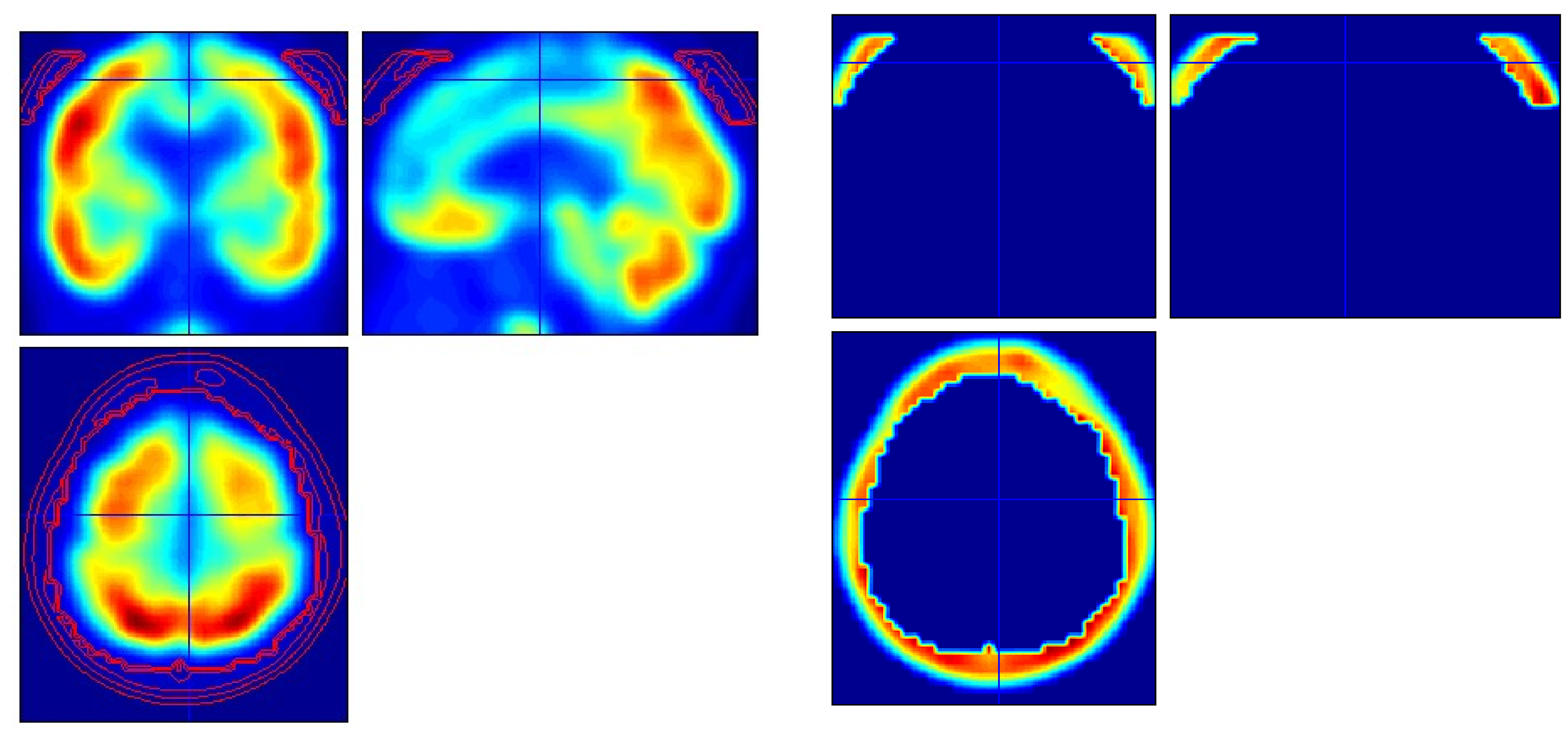
- PET images were normalized in MNI space using typical preprocessing [2].
- A study specific template was created by averaging the normalized PET-scans.
- PET scans were scaled down with a unique value for each image, extracted from skin voxels (skin was selected as a point that is not related to consciousness).

Study specific template



First scan represents a raw PET-scan . Middle image depicts the study specific template used for the for the final normalization created by the average of MNI normalized scans. The third image is the first one normalized in the study specific template.

Skin Extraction



Skin voxels are selected for intensity normalization, as a reference point of glucose consumption that is not related to consciousness state.

Classification

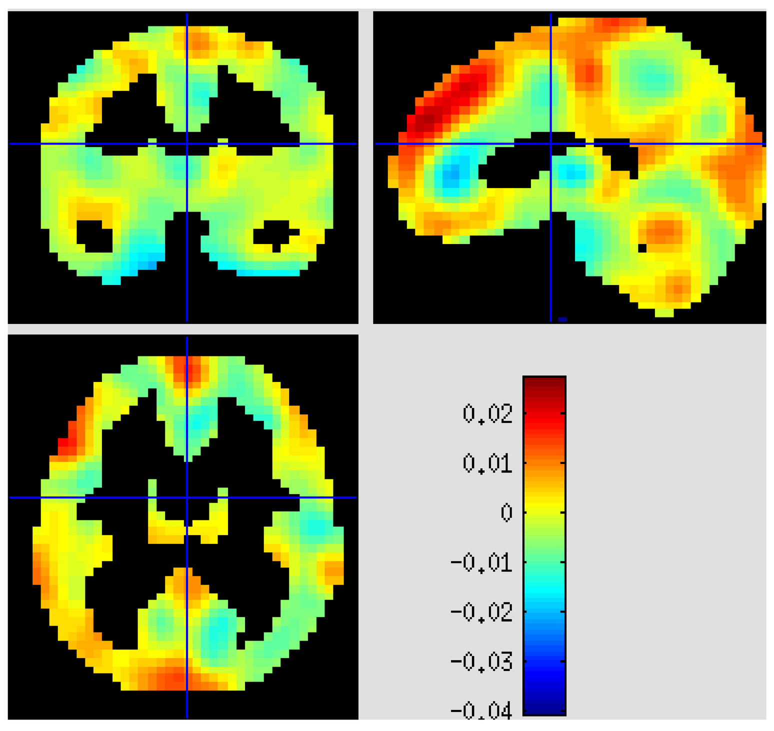
We tried to discriminate the Minimally Conscious State (MCS) patients from those being in Unresponsive Wakefulness State (UWS). We used 50 MCS and 46 UWS.

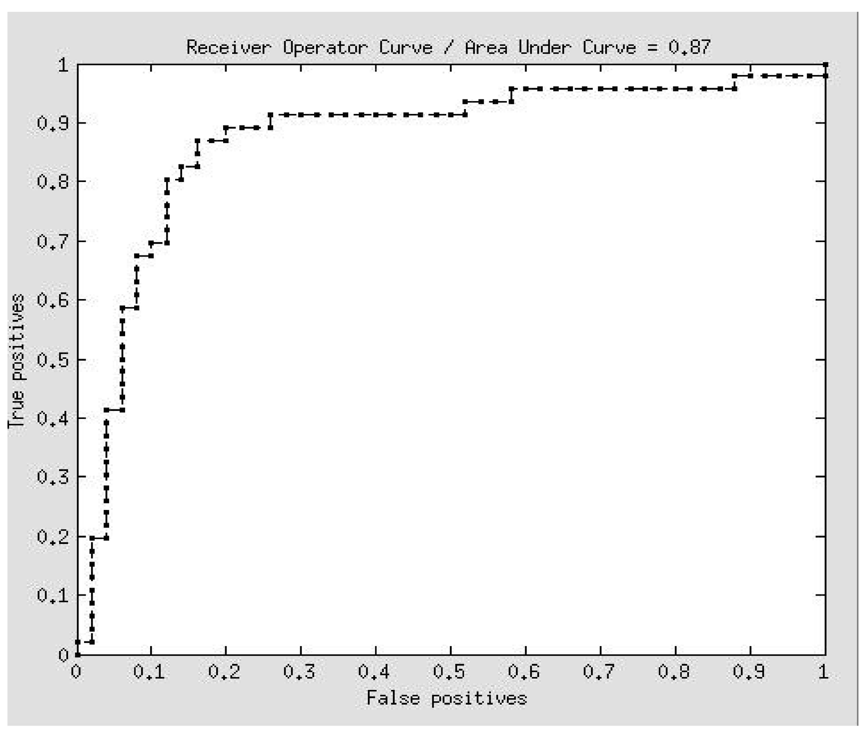
A Gaussian Process Classifier, embedded in the Pattern Recognition for Neuroimaging Toolbox [3], was chosen to classify the PET images. As features for the classification process we used the voxels that had porbability more than 60% to belong to gray matter.

Since Gaussian Process Classification assigns one value to each voxel, this can be displayed as weight map.
In order to estimate the accuracy of the Classifier, leave one out - scheme was used.

A total accuracy of 81.25% was achieved, MCS detection rate was 72% and UWS was 91.3%, ($p<0.002$ for both classes)

Weight Map & ROC curve





Conclusion & Discussion:

Medial and lateral frontoparietal cortices and brain stem appear to play a key role in consciousness state, as shown from the weights assigned by the classifier to the voxels. Besides the absolute cortical metabolic activity [5], glucose consumption in different brain regions can affect the state of consciousness. The MCS correct classification rate is a critical point and needs to be improved. Some reasons that could develop it are:

- Skin mask is often not able to select skin voxels due to severe deformations of patients' heads.
- A few patients included in the study changed state of conscious after some time.
- The significant size of the ventricles seem to "push" the voxels in the edge to higher weights.

References

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