FMRI assessment

1.1. Stimuli

Sixteen visual words were used during each fMRI assessment. They were French concrete, middle frequent (mean of frequency of occurrence = 35.66) nouns composed of 5-8 letters. Half of words were of the grammatical feminine gender and the other one grammatical masculine gender. Words were written in white “Courier New” font, size 40.

1.2. Tasks

Encoding and recognition tasks were performed during two sessions, one before and another one after the rehabilitation program. Encoding task consists of a grammatical genre categorization task (implicit encoding session). The patient was not explicitly instructed to subsequently remember the items, in order to encourage the ecological encoding and avoiding the use of memorization strategies. The type of response (feminine or masculine) was not used in any subsequent parts of the fMRI analysis. Recognition task was performed 30 minutes after encoding. During this task, the 60 words presented during encoding session were randomly mixed with 60 novel words (taken from the same database). BL was instructed to indicate whether the presented words were already seen or not (New items).

1.2. Functional MRI Paradigm

Stimuli were generated by means of E-prime (Psychology Software Tools Inc., Pittsburgh, USA) running on a PC computer. They were presented in the middle of a screen during 3.5 seconds with a 0.5 seconds fixation cross between stimuli and transmitted into the magnet by means of a video projector (Epson EMP 8200), a projection screen situated behind the magnet, and a mirror centered above the participant’s eyes.

For both encoding and recognition tasks a mixed block-event related fMRI paradigm (including one functional run for encoding and two for recognition), was designed based on the optimization of the onset for each type of stimuli. A total of 60 stimuli were presented in block of 10 words followed by a rest condition (28s.) during each run. Further, to stabilize the magnetic field in the MRI scanner, five “dummy” scan were added at the beginning of the run and were removed from subsequently analyses. Overall, 293 functional volumes were acquired during each run. The fMRI session was preceded by a training session with stimuli that were different of those presented during the experiment.

1.3. Data Acquisition

Functional MRI data were acquired using a whole-body 3T scanner (BrukerMedSpec S300). Functional images were obtained using a T2*-weighted, gradient-echo, echoplanar imaging (EPI) sequence with whole-brain coverage (TR = 3 s, spin echo time = 40 ms, flip angle = 77). Thirty-nine axial slices parallel to the antero-posterior commissural plane were acquired in interleaved order (3 * 3 mm in plane resolution with a slice thickness of 3.5 mm). A B0 fieldmap was also acquired from two gradient echo data sets with a standard 3D FLASH sequence (ΔTE = 9.1 ms). In addition, a high-resolution T1-weighted whole-brain structural image was acquired for each participant (MP-RAGE, volume of 256 × 224 × 176 mm 3 with a resolution of 1.33 × 1.75 ×1.37 mm3).

1.4. fMRI data processing

Data were analyzed using the SPM8 software package (Welcome Department of Imaging Neuroscience, Institute of Neurology, London, UK) running on Matlab 7.9 (Math-works, Natick, MA, USA). The brain regions involved in the different contrasts we examined were labeled using a macroscopic parcellation of the MNI single subject.

1.4.1. Spatial pre-processing

The functional images were time- corrected (slice timing). All volumes were then realigned to correct for head motion. To correct images for geometric distortions induced by local B0 inhomogeneity, unwarping was performed by using the individually acquired B0 fieldmap. The T1-weighted anatomical volume was coregistered to mean image created by the realignment procedure and was normalized to the MNI space using a trilinear interpolation. The anatomical normalization parameters were then used for the normalization of functional volumes. All functional images were then smoothed using an 8-mm full-width at half maximum Gaussian kernel to improve the signal-to-noise ratio and to compensate for the anatomical variability among individual brains.

1.4.2. Statistical analyses

Encoding session: six different regressors were modeled by using the General linear model. First of all we constructed two experimental condition for each of session (before and after rehabilitation) according to the behavioral performances during de subsequently recognition task. We constructed two Successful encoding (SE) condition one for the before (SEB) and another one for the after (SEA) session. Thus, SE corresponds to the encoding task events that were successful recognized during the subsequently recognition task. We also constructed two Unsuccessful Encoding (UE) one for the before (UEB) and other one for the after (UEA) session. UE corresponds to the encoding task events that were not recognized during recognition task. Furthermore, resting event (R) were also included in the statistical model as regressor of interest one for the before (RB) and another one for the after (RA) sessions. These event classifications allowed us to perform the six regressors: SEB, SEA, UEB, UEA, RB and RA. The realignment parameters were also included in the design matrix as covariates of no interest.

Recognition session: six regressors were modeled by using the General linear model. To construct the four first regressors we take in account the behavioral responses (correctly recognized words, CR), and we constructed one regressors for each session (before and after reeducation program). Regressors were: correct recognized words before (CRB) and after (CRA) rehabilitation program, incorrect recognized words before (IRB) and incorrect recognized after (IRA) rehabilitation program. Furthermore, as performed in the encoding task, we also included the resting event for the before (RB) and after (RA) rehabilitation. The realignment parameters were also included in the design matrix as covariates of no interest.

For both task, the blood-oxygen-level dependence response for each event was modeled using a canonical hemodynamic response function (HRF). Before estimation, a high pass filtering with a cutoff period of 128s was applied. Beta weights associated with the modeled HRF responses were then computed to fit the observed blood-oxygen-level dependence signal time course in each voxel for each condition mentioned previously.

Two different statistical analysis were performed for each task (encoding and recognition).The first analysis is performed to identify the cerebral network involved during before and after rehabilitation program separately for both encoding (SEB vs RB and SEA vs RA) and recognition (CRB vs RB and CRA vs RA) tasks. The second analysis evaluate specifically the main effect of rehabilitation program by means of direct comparison between before and after rehabilitation program, for both encoding (SEB vs SEA and SEA vs SEB) and recognition (CRB vs CRA and CRA vs CRB) task. The results are reported at a $p < 0.005$ uncorrected (cluster extent of 10 voxels).