Structural attributes of the temporal lobe predict face recognition ability in youth

Jun Li, Minghao Dong, Aifeng Ren, Junchan Ren, Jinsong Zhang, Liyu Huang
School of Life Science and Technology, Xidian University, Xi’an, Shaanxi 710071, China

Abstract
The face recognition ability varies across individuals. However, it remains elusive how brain anatomical structure is related to the face recognition ability in healthy subjects. In this study, we adopted voxel-based morphometry analysis and machine learning approach to investigate the neural basis of individual face recognition ability using anatomical magnetic resonance imaging. We demonstrated that the gray matter volume (GMV) of the right ventral anterior temporal lobe (vATL), an area sensitive to face identity, is significantly positively correlated with the subject’s face recognition ability which was measured by the Cambridge face memory test (CFMT) score. Furthermore, the predictive model established by the balanced cross-validation combined with linear regression method revealed that the right vATL GMV can predict subjects’ face ability. However, the subjects’ Cambridge face memory test scores cannot be predicted by the GMV of the face processing network core brain regions including the right occipital face area (OFA) and the right face fusion area (FFA). Our results suggest that the right vATL may play an important role in face recognition and might provide insight into the neural mechanisms underlying face recognition deficits in patients with pathophysiological conditions such as prosopagnosia.

1. Introduction
The face recognition ability varies among individuals. Some people can easily recognize someone that they acquainted in the past, even after many years (Russell et al., 2009), while some, e.g. prosopagnosics, have difficulties even in recognizing faces of those they meet every day (McConachie, 1976). Normal face processing involves multiply hierarchical and parallel process, different impairments in face processing induces distinct different face recognition deficits (de Gelder and Van den Stock, 2015). Although the neural basis of face processing have been well studied by pervasive brain-imaging studies (Gauthier et al., 2003; Haxby et al., 2000; Ishai, 2008; Kanwisher, 2000), the neural mechanisms underlying inter-individual difference in face recognition ability are poorly understood (Tavor et al., 2014; Zhu et al., 2011). Regional gray matter volume (GMV) has been demonstrated to be related to inter-individual variability in basic and higher cognitive functions including perception, motor control, memory, aspects of consciousness and the ability to introspect (Kanai and Rees, 2011). For example, the positive correlation between the GMV and the human intelligence has been found by previous magnetic resonance imaging (MRI) studies (Flashman et al., 1997; Haier et al., 2004; Karp et al., 2011; McDaniel, 2005). These studies suggest that inter-individual brain structural differences provide a source of information linking human brain anatomy to behavior and cognition (Kanai and Rees, 2011). Regional GMV abnormalities have been frequently found in psychiatric or neurogenetic conditions, such as Alzheimer’s disease (Irish et al., 2013), autism (Nickl-Jockschat et al., 2012), schizophrenia (Hooker et al., 2011), and bipolar disorder (Bora et al., 2010). Interestingly, decreased GMV in face processing areas has been related to face recognition deficits in patients with chronic schizophrenia (Onitsuka et al., 2005, 2003), developmental prosopagnosia (Garrido et al., 2012), and bipolar disorder (Neves Mde et al., 2015). However, it remains unknown whether local GMV can predict the face recognition ability in healthy subjects.

The fusiform face area (FFA) and the occipital face area (OFA) which are in the “core system” (Gobbini and Haxby, 2007; Haxby et al., 2000) for face processing play an important role in initial face representation and facial identity recognition (Ishai et al., 2005; Kanwisher et al., 1997; Yovel and Kanwisher, 2004). Face processing deficits have been suggested to be related to functional and structural abnormalities in these “core regions” (Hadjikhani and...
de Gelder, 2002; Nestor et al., 2007; Onitsuka et al., 2005, 2003; Snowden et al., 2004; Van den Stock et al., 2012a, 2008). However, recent studies have found normal gray matter density and/or normal functional activation during face processing in the FFA and/or the OFA of patients with developmental or congenital prosopagnosia (Collins and Olson, 2014; Dinkelacker et al., 2011; Garrido et al., 2009; Van den Stock et al., 2012b). These findings suggest some other brain regions, in addition to the FFA and the OFA, such as the right ventral anterior temporal lobe (vATL) might be involved in face recognition (Anzellotti and Caramazza, 2014; Blank et al., 2014; Collins and Olson, 2014; Gegen et al., 2013; Nestor et al., 2011; Snowden et al., 2012). We hypothesized that the GMV in the vATL might be predictive of individual face recognition ability in healthy subjects using MRI. The face recognition ability of each subject was first measured using Cambridge Face Memory Test. Then, we determined regions of interests (ROIs) using a classical fMRI face processing localized paradigm and global GMV regression analysis. Finally, the ROI-average GMV-based prediction model was established and test–retested with the machine learning method of balanced cross-validation combined with linear regression (Cohen et al., 2010; Suppekar and Menon, 2012).

2. Materials and methods

2.1. Subjects

Two datasets namely dataset 1 and dataset 2 were included in this study. Dataset 1 includes 33 healthy subjects that were recruited from multiple school districts in Chengdu, China. All 17 subjects in dataset 2 were recruited from multiple school districts in the Xi’an, China. The subject was included if he/she meets the following criteria 1) local residents, 2) Han Chinese, 3) right-handed by self-report, 4) had no history of psychiatric illnesses, neurological disorders, or reading disabilities, and 5) has not significant problems in everyday face recognition. All subjects signed informed consent before participant. The study protocol in dataset 1 was approved by the West China Hospital Review Board and that in dataset 2 by Xijing Hospital Review Board. Table 1 summarizes the demographic data.

2.2. Neuropsychological assessments

2.2.1. Cambridge face memory test

The face recognition ability was measured using the alternate version of Cambridge face memory test (CFMT) (Germine et al., 2011). The CFMT has been demonstrated to be capable of robustly isolating face-specific mechanisms, such as face recognition ability (Russell et al., 2009), and identifying face processing deficits (Duchaine and Nakayama, 2006; Lee et al., 2010). The alternate version of CFMT has similar psychometric properties and is an effective means used to assess face recognition ability (Bate et al., 2014; Germine et al., 2011; McKone et al., 2011; Wilmer et al., 2010). To minimize the influence of race of the stimuli pictures, the original Caucasian faces were replaced with East Asian faces (Fig. 1). The procedural paradigm was exactly identical to the usual CFMT (Duchaine and Nakayama, 2006). Each test consists of a learning phase and a test phase. During the learning phase, six target faces were introduced to subjects in three views and then tested with three forced-choice items, one of which is a target. The test phase consists two stages with increasing difficulties. Subjects were tested on 30 forced-choice items with novel views at the first stage and on 24 forced-choice items with novel views and added visual noise at the second stage (for full detail see Germine et al. (2011) and Duchaine and Nakayama (2006)). Subjects were seated comfortably in a quiet room with minimal distraction from the surroundings. The tests only began after the experimental procedures and requirements of the tasks were explained and understood by the subject.

2.3. Localizer stimulus paradigm

To locate the face sensitive regions in individual participants, the classic block experimental design was used in the fMRI experiment (Grill-Spector et al., 2004; Kanwisher et al., 1997; Spiridon et al., 2006). Each subject completed two sessions each of which consists six alternating blocks of faces, randomly selected objects, and scrambled pictures. Each block which was followed by a sixteen seconds fixation baseline condition consists 20 trials. For each trial, the stimulus was presented for 750 ms and the inter-trial interval was 250 ms. Subjects were also asked to perform a one-back detection task in which they were required to press the right button of a response device for any immediate repetitions (two per block).

2.4. Imaging protocol

Dataset 1. All images were collected using an 8-channel phased-array head coil on a 3.0 T Siemens scanner (MAGNETOM Trio Tim, Siemens, Erlangen, Germany) at West China Hospital, Chengdu, China.

MPRAGE T1-magnetization 3-dimensional anatomical image (1 × 1 × 1 mm resolution) were collected for each subject using the following parameters: TR/TE = 2000/30 ms, FA = 9°, FOV = 240 mm × 240 mm, data matrix = 256 × 256, and data matrix = 256 × 256. This yielded 176 contiguous 1 mm thick slices in the sagittal orientation. Two professional radiologists examined the T1 images and did not find any clinically silent lesions for any subjects.

In the functional localizer paradigm, whole brain images were acquired with a gradient-echo single-shot echo planar imaging sequence using the following parameters: TR/TE = 2000/30 ms, FA = 90°, FOV = 240 mm × 240 mm, data matrix = 64 × 64, 32 interleaved axial slices were oriented parallel to each subject’s anterior commissure-posterior commissure (AC-PC) line, in-plane resolution 3.75 mm × 3.75 mm, slice thickness 5 mm thick with no gaps.

Table 1

Demographic data of dataset 1 and dataset 2. SD, standard deviation; CFMT, Cambridge Face Memory Test.

<table>
<thead>
<tr>
<th></th>
<th>Dataset 1</th>
<th>Dataset 2</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (mean ± SD, range)</strong></td>
<td>23.3 ± 3.1, 19–28</td>
<td>23.8 ± 2.6, 19–27</td>
</tr>
<tr>
<td><strong>Education (mean ± SD, range)</strong></td>
<td>14.3 ± 1.9, 14–18</td>
<td>15.8 ± 1.6, 14–18</td>
</tr>
<tr>
<td><strong>Gender (male/female)</strong></td>
<td>17/16</td>
<td>9/8</td>
</tr>
<tr>
<td><strong>CFMT accuracy (mean ± SD, range)</strong></td>
<td>75.0 ± 12.1, 43.1–95.8</td>
<td>73.2 ± 13.3, 47.2–93.1</td>
</tr>
</tbody>
</table>
Dataset 2. Structural and functional images of dataset 2 were collected on a 3.0 T MRI scanner (Discovery MR 750, General Electric Medical Systems, US) with an 8-channel RF head coil array in Xijing Hospital, China.

3-dimensional T1-weighted structural images were acquired sagittal with an isotropic MPRAGE sequence: TR/TE/TI = 8.13/3.18/450 ms, FA = 12°, FOV = 256 mm × 256 mm, matrix = 256 × 256, 1 mm × 1 mm in plane resolution, slice thickness = 1 mm, 188 sagittal slices with no gaps. All images were visually inspected by two neuroradiologists. Subjects with structural lesions were excluded from this study.

The stimulus protocol was the same to that used in dataset 1. A gradient-echo single-shot EPI sequence was performed using the following parameters: TR/TE = 2000/45 ms, FOV = 220 mm × 220 mm, matrix = 64 × 64, providing an in-plane spatial resolution of 3.44 × 3.44 mm, FA = 90°, slice thickness 4 mm, 32 interleaved transverse slices with a gap 0.5 mm.

2.5. Data processing

2.5.1. fMRI data processing and ROIs of “core face processing regions”

Imaging data were analyzed using statistical parametric mapping software (SPM8, Wellcome Department of Cognitive Neurology, London, UK, http://www.fil.ion.ucl.ac.uk/spm). EPI volumes were performed in turn removal of the first three volumes, slice-timing correction, spatial realignment, normalization to the MNI152 standard space (Montreal Neurological Institute), resliced voxel resolution to 1.5 mm × 1.5 mm × 1.5 mm, and smoothed using an isotropic 6-mm Gaussian kernel. A high-pass filter with a cutoff period of 128 s was applied to remove low frequency noise possibly containing scanner drift.

A general linear model (GLM) with three conditions of interests (face, object, and scrambled image) was used for first-level statistical analysis. Head movements correction parameters were included as additional regressors. Then, one sample t test on the group BOLD responses contrast (face vs. non-face including objects and scrambled images). The “core face processing regions” which include the right OFA and the right FFA were identified for later prediction analysis. Here, we used a stringent statistical threshold, i.e., p < 0.05, FWE corrected, spatial extent threshold of 10 voxels.

2.5.2. VBM analysis and ROIs defined by global GMV regression analysis

T1 images were processed using optimized VBM technology (Good et al., 2001) which has been implemented in VBM8 toolbox (http://dbm.neuro.uni-jena.de/vbm/). In brief, T1 images were first aligned to conventional anterior commissure (AC)-posterior commissure (PC) space using manual landmarks identifying tool in SPM8. The resulting images were checked visually and by the automated quality assurance protocol in VBM8. Then, the aligned images were spatially normalized to the Montreal Neurological Institute (MNI) stereotactic space using segmentation and no-linear normalization with the DARTEL algorithm. To correct for individual brain size differences, voxel volumes were modulated by the nonlinear effects derived from the spatial normalization, resulting in relative GMV. The modulated images were further smoothed using a Gaussian kernel with a FWHM of 10 mm as suggested by Superka et al. (2013). Finally, voxel-wise whole-brain multiple regression analysis was performed using GMV as dependent variable and CFMT accuracy as independent variable. Brain structural changes have been known to be associated with normal age (Craik and Salthouse, 2007; Raz et al., 2005; Raz and Rodrigue, 2006), gender (Cahill, 2006; Gur et al., 1999; Ruggiero et al., 2014) and learning (Holzel et al., 2011; Linkersdorfer et al., 2014; Mechelli et al., 2004). To account for these nuisance effect on our results, we include age, gender and education years as covariates in our data analysis. Those regions associated with CMFT scores were also defined as other ROIs used in GMV-based prediction analysis; The results demonstrated the association was only found in voxels within the region of right vATL, and then the region was defined as an ROI in GMV-based prediction analysis.

2.5.3. ROI-average GMV

We extracted the average GMV values from two localizer paradigm ROIs (the right OFA and the right FFA) and one regression analysis ROI (the right ventral anterior temporal lobe, vATL). We adjusted the T threshold in xjView toolbox (http://www.alivelearn.net/xjView) such that all ROIs have the same volume size. All ROIs were cut into eight ROIs of the same selected volume sizes of 101 mm3 (30 voxels), 270 mm3 (80 voxels) or 439 mm3 (130 voxels). The ROI-average GMV values were extracted using DPABI toolbox (http://rfmri.org/DPABI).

2.5.4. GMV-based prediction analysis

To examine the predictive ability of ROI-average GMV values in CMFT scores, the balanced cross-validation combined with multiple linear regression machine learning method (Cohen et al., 2010) which has been implemented in the Python regression cv toolbox (https://github.com/poldrack/RegressionCV) was used. Prediction of individual CMFT score from ROI-average GMV values was performed using Gaussian process regression (age, education years and gender were included as covariates).

Firstly, a linear regression model was estimated using a balanced 4-fold cross validation procedure within dataset 1. On each run, each subject was randomly assigned to one of the four folds, with the constraint that the mean GMV did not differ across folds (one-way ANOVA p > 0.98), such that the distributions of dependent and independent variables were balanced across folds. A linear regression model was built using 3 folds leaving one fold out. Predicted values were obtained for the observations in the left-out fold. This procedure was repeated 4 times, and then the correlation between predicted values from the regression model and actual values, r(pred, actual) was computed using Pearson correlation analysis. Finally, the statistical significance of the model was assessed using nonparametric test. A empirical null distribution of the correlation was obtained by calculating the r(pred, actual) from 1000 surrogate datasets which was generated by assigning randomly permuted actual CMFT scores. The p value was calculated as the ration between the number of the permuted r(pred,actual) which is larger than the actual r(pred,actual) and the number of permutations (1000 in our case).

To examine whether the trained model can be population-dependent, we test the resulting model trained in dataset 1 on dataset 2 and calculated the r(pred, actual).

3. Results

3.1. Behavioral data

The average accuracy was 75.0% (SD = 12.1%) out of 72 faces in dataset 1 of all 33 subjects. The individual accuracy of the 33 subjects were in an approximate uniform distribution (range from 43.1% to 95.8%). Within dataset 2, the average percentage of the correct scores was 73.2% (SD 13.3%) and ranging from 47.2% to 93.1%. Dataset 1 and dataset 2 did not differ in accuracy (p = 0.65, two-tailed samples t test), age (p = 0.78), education years (p = 0.82) and sex (p = 0.924, χ² test).

3.1.1. Localizer fMRI

Fig. 2 indicates the group level analysis results of the localizer task in dataset 1. Statistically significant activations (p < 0.05, FWE corrected, extent cluster > 10 voxels) were found in the right middle fusiform gyrus (peak MNI coordinates, 42, −56, −16; peak T value, 6.86; 129 voxels), the right occipital cortex (peak MNI coordinates, 24, −82, −10; peak T value, 6.25; 54 voxels) and the left occipital cortex (peak MNI coordinates, −24, −84, −12; peak T value, 6.37; 50 voxels). The peak coordinates of these regions were consistent with the loci of the FFA and the OFA reported in previous studies (Grill-Spector et al., 2004; Kanwisher et al., 1997; Li et al., 2009, 2010). The results of localizer task in dataset 2 were similar to that in dataset 1 (right FFA peak MNI coordinates, 44, −58, −18; peak T value, 6.52; 120 voxels; right OFA peak MNI coordinates, 20, −80, −9; peak T value, 6.41; 68 voxels).

3.2. Global GMV regression analysis

Fig. 3 illustrates the positive correlation between the GMV in the right vATL and the CMFT score (p < 0.05, FWE corrected). The right OFA or the right FFA GMV did not correlate with the CMFT score (p > 0.05, FWE corrected).
parametric test). Table 2 summarizes these results. The results were not found to be predictive of CFMT scores (p < 0.01, non-parametric test). The GMV values in the right OFA and the right FFA were not found to be predictive of CFMT scores (p > 0.23, non-parametric test). Table 2 summarizes these results. The results are not affected by the volumes of the OFA, FFA and vATL used in the analysis (Table 3).

3.3. Prediction analysis results

In this study, the prediction of CFMT scores by ROI-average GMV values were examined using machine learning method of balanced cross-validation combined with linear regression. The model was built on dataset 1 and tested in both dataset 1 and dataset 2 (see Section 2). The high r(pred, actual) indicates that the right vATL GMV can predict the CFMT score (p < 0.01, non-parametric test). The GMV values in the right OFA and the right FFA were not found to be predictive of CFMT scores (p > 0.23, non-parametric test). Table 2 summarizes these results. The results are not affected by the volumes of the OFA, FFA and vATL used in the analysis (Table 3).

4. Discussion

In this study, we studied the neural predictors of the face recognition ability which was measured by CFMT scores in youth. The main finding was that the GMV in the right vATL is positively correlated with the CFMT scores. The following machine learning analysis revealed that the right vATL GMV values can predict subjects’ CFMT scores. However, the GMV values in the classical face processing network “core regions”, i.e. the right OFA and the right FFA, were not predictive of individual face recognition ability. These findings support the notion that the right vATL plays an important role in face recognition.

In our localizer paradigm experiment, we did not find any statistically significant activation of the right vATL. The activation of the right vATL (Anzellotti and Caramazza, 2014; Blank et al., 2014; Collins and Olson, 2014) in face perception has been less reported compared the right FFA and the right OFA (Ishai et al., 2005; Kanwisher and Yovel, 2006). The lack of the vATL activation might because that it is near sinuses, which may degrade the signal detection in fMRI (Axelrod and Yovel, 2013; Bonner and Price, 2013; Jonas et al., 2015). Moreover, the location of the right vATL revealed in the present study is more posteriorly and medially than the usual location (Axelrod and Yovel, 2013; Collins and Olson, 2014; Nasr and Tootell, 2012; Pinsk et al., 2009; Pyles et al., 2013; Rajimehr et al., 2009; Rossion et al., 2012; Tsao et al., 2008). The discrepancy might be induced by the different localizer methods. Previous studies have adopted fMRI tasks to localize the vATL, while we use global GMV regression analysis. However, the location of right vATL in this study is very near to that defined by high-resolution fMRI (Kriegeskorte et al., 2007), suggesting our results is inherently consistent with the findings of previous fMRI studies.

The main function of the vATL in face recognition has been suggested to be linking perceptual representations of individual identity with person-specific knowledge (Collins and Olson, 2014; Snowden et al., 2012) which is different from the function of the right OFA and the right FFA of converting a perceptual face into an inner abstract face representation (Collins and Olson, 2014; Haxby et al., 2000). For example, both classical visual processing theory (Simmons and Barsalou, 2003) and brain imaging studies (Peelen and Caramazza, 2012) have suggested that the ventral temporal lobe plays an important role in encoding subjects’ abstract conceptual property information. Morphometric abnormalities and intracerebral stimulation of the vATL can lead to deficits in face recognition (Behrmann et al., 2007; Busigny et al., 2009, 2014; Jonas et al., 2015; Joubert et al., 2003; Olson et al., 2015; Williams et al., 2006). Moreover, patients suffering from face recognition deficits have been found to have reduced functional connectivity between the ATL and other important face processing regions, such as the hippocampus (Pantazatos et al., 2014). The right vATL has been suggested to be a hub of face identification, which integrates information of face features represented by different brain regions such as amygdala, hippocampus and orbitofrontal cortex via the uncinate fasciculus (Morecraft et al., 1992; Thomas et al., 2015). More importantly, the inferior longitudinal fasciculi (ILF) connects the temporal lobe and occipital lobe and passes through the most important regions of OFA and FFA in face processing (Gschwind et al., 2012; Pyles et al., 2013; Suzanne Scherf et al., 2013). A larger micro-structural property value of ILF is related to better face recognition ability (Gomez et al., 2015; Tavor et al., 2014) and the reduction of its structural connectivity has been suggested to be related to congenital prosopagnosia.

The right OFA and the right FFA are the core regions of face processing network (Calder and Young, 2005; Haxby et al., 2000). However, the GMV of the FFA and the OFA are not correlated with the face recognition ability in the present study. As noted above, the right vATL might also play an important role in face recognition. The model of face processing network (Haxby et al., 2000) and the function of the right vATL related to face recognition (Collins and Olson, 2014) suggest that the right FFA plays the role of assembling the face base components approved by the right OFA into an abstract face, which is further used by the right vATL for face identification. This notion is supported by a recent fMRI.

<table>
<thead>
<tr>
<th>Region</th>
<th>Volume (mm³)</th>
<th>Threshold T value</th>
<th>Dataset 1 r (pred, actual)</th>
<th>Dataset 2 r (pred, actual)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Right OFA</td>
<td>415</td>
<td>5.92</td>
<td>0.274</td>
<td>0.345</td>
</tr>
<tr>
<td></td>
<td>286</td>
<td>6.25</td>
<td>0.262</td>
<td>0.363</td>
</tr>
<tr>
<td></td>
<td>98</td>
<td>6.34</td>
<td>0.283</td>
<td>0.358</td>
</tr>
<tr>
<td>Right FFA</td>
<td>432</td>
<td>5.80</td>
<td>0.233</td>
<td>0.420</td>
</tr>
<tr>
<td></td>
<td>270</td>
<td>6.05</td>
<td>0.246</td>
<td>0.410</td>
</tr>
<tr>
<td></td>
<td>101</td>
<td>6.30</td>
<td>0.243</td>
<td>0.393</td>
</tr>
<tr>
<td>Right vATL</td>
<td>439</td>
<td>5.98</td>
<td>0.846</td>
<td>0.732</td>
</tr>
<tr>
<td></td>
<td>270</td>
<td>6.30</td>
<td>0.848</td>
<td>0.733</td>
</tr>
<tr>
<td></td>
<td>98</td>
<td>6.63</td>
<td>0.851</td>
<td>0.740</td>
</tr>
</tbody>
</table>

* Means P < 0.01. OFA, occipital face area; FFA: fusiform face area; vATL, ventral anterior temporal lobe.
study which suggested that the FFA and the vATL play a role in face detection and face identification separately (Kriegeskorte et al., 2007). The damage to any of these regions might induce prosopagnosia.

We acknowledge a few limitations of this study. In the present study, all subjects were tested only for face recognition ability but not of other objects ability such as character recognition. More studies are needed to answer whether the right vATL underlies a specific or more general mechanism for face recognition. Another limitation is that the right ATL ROI was determined using the VBM-based regression analysis, which is different from that of ROIs of the right FFA and the right OPA. Newly developed fMRI image protocol which might overcome the information losing faults in the region of the ATL (Axelrod and Yovel, 2013) might be adopted to study the ATL activation and its relationship with the right FFA and the right OPA in future studies.

5. Conclusion

In this study, we demonstrated that the GMV of the right vATL can predict the face recognition ability in youth. No such effects were found in the right OPA and the right FFA. Our results suggest that the right vATL may play an important role in face recognition and might provide insight into the neural mechanisms underlying face recognition deficits in patients with pathophysiologic conditions such as prosopagnosia.

Acknowledgements

This study is supported by the Project for the National Key Basic Research and Development Program (973) under Grant No. 2011CB707700, the National Natural Science Foundation of China under Grant nos. 8100640, 31271063, 81401478, 81471738 and 81071221, the Natural Science Basic Research Plan in Shaanxi Province of China under Grant No. 2015J08474, the International cooperation project of Shaanxi science and technology research and development plan under Grant No. 2014kw19-02, the Fundamental Research Funds for the Central Universities and General Financial Grant of the China Postdoctoral Science Foundation under Grant No. 2014M552416.

References


