Anatomical Location and Multi-features based Computer Aided Detection of Cerebral Microbleeds on MR Images

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Purpose

Cerebral microbleeds (CMBs) are known to be highly prevalent in patients admitted with ischemic stroke and intracerebral bleeding [1, 2]. Recent researches have presented that MR imaging has its potential for visualization of these asymptomatic small lesions (diameter <5-10 mm) in brain images. Although the inter- and intra-expert consistency has been improved by using Microbleed Anatomical Rating Scale (MARS) [3], experience depended manual detection is still time-consuming and has limited reproducibility [4]. Further improvement of identification and quantification is expected. In the present study, we propose a computer aided system (CAD) that could be used in detection of CMBs automatically.

Materials and Methods

Data source: Eighty-one patients (mean age 65.8 ± 12.1 years, range 16-100 years) were recruited in this study, containing a total of 337 microbleeds in four typical slices. All MR images were carried out at 1.5-T field strength using three different MRI systems with different parameters. Thirty-five patients were imaged on a Siemens Avanto system (Berlin and Munich, Germany). Twenty-four patients were imaged on a GE Medical Genesis Signa system (GE HealthCare, Waukesha, WI) with an eight-channel phase array head coil. Twenty-two patients were imaged on a Philips whole-body system (Philips Healthcare,Cleveland, OH). The imaging sequence parameters were as follows: Axial T2*-weighted images: gradient recalled echo (GRE) sequence, TR = 600/500/545(ms), TE = 26/15/23(ms), slice thickness =6/6/5(mm), matrix = 256×202/256×256/256×256, field of view (FOV) = 18.6×23/24×24/23×23(cm^2). Axial T1-weighted images: Fast Spin Echo (FSE) sequence, TR = 500/440/431.5(ms), TE = 10/13/13(ms), slice thickness =6/6/5(mm), matrix = 256×208/320×224/512×512, FOV = 18.6×23/24×24/23×23(cm^2). Axial T2-weighted images: FSE sequence, TR = 3500/4000/4365.7(ms), TE = 99/104.7/120(ms), slice thickness =6/6/5(mm), matrix = 256×202/320×256/512×512, FOV = 18.6×23/24×24/23×23(cm^2). Manual reviews of the data were performed independently by two over-5-years experienced neuro-radiologists using the MARS standard.

Pre-processing: The T1-weighted images, T2-weighted images and GRE T2*-weighted images were first scaled to 512×512 pixels and rigidly registered. After that, skull-stripping, ventricle, cerebrospinal fluid and meninges removing in the GRE T2*-weighted images were performed according to the T1 and T2-weighted images. Subsequently, isolated islands of points were removed while the holes were restored to avoid over segmentation. After thresholding the images conservatively, the remaining marked voxels were sorted into connected clusters as candidates. To remove the unrealistically large or small candidates, we finally filtered the connected components with a bounding-box.

Identification model: The anatomical location information of the CMBs was used to calculate the probability density templates. For further identification of each candidate, we used a Random Forest (RF) model to distinguish CMBs from all the other marked clusters (so-called mimics [5]). Seven features were extracted from the shape (area and roundness), the intensity (average, average of the boundary and contrast), the shape-intensity value and the location-score (according to the probability density templates for different slices, as shown in Fig.1) of each candidate. The Leave-one-out cross-validation method was used to separate the dataset into a training set and a test set. With this method, one candidate was used to test the classifier each time, while the others were used to train the classifier. This procedure was repeated until each of the candidates had been tested. Receiver operating characteristic (ROC) analysis was performed for all the candidates, and the area under the ROC curve (AUC) was used to evaluate the performance of this CAD system.

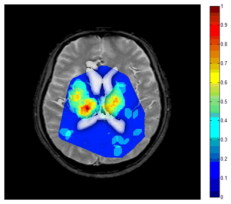
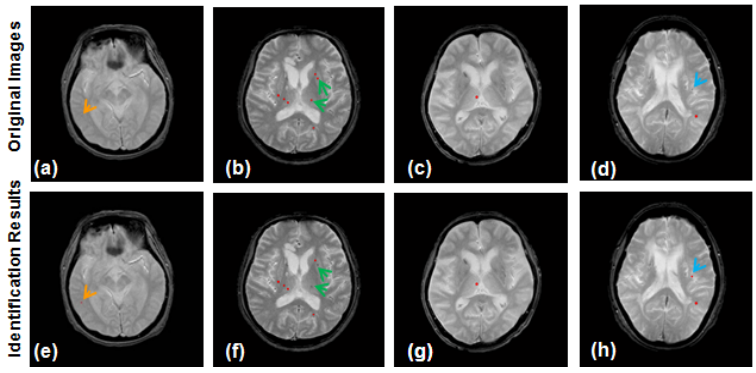


Fig.1 A probability density template of a typical slice.

Result

Fig.2 shows the typical recognized results of the system. The detection model clearly identified the CMBs located in the different brain regions. The initial candidates selection has a high sensitivity of 0.902(304/337), missing 33 CMBs out of 337. However, it has a very large number of false positives (5889 mimics), as it was designed to mark all the hypo-intense structures in the image. The RF model eliminates most of the false-positives while maintaining a reliable sensitivity of 0.987(300/304) and specificity of 0.979(5765/5889). The Positive Predictive Value (PPV) is 0.717(300/424) and the Negative Predictive Value (NPV) is 0.999(5765/5769). As shown in Fig.3, the AUC is 0.998 for the detection model. By selecting appropriate cut-off of 0.058, the accuracy of classification reached 0.979(6065/6193), which were higher than any of the other methods presented before [6, 7].The automated processing has an overall sensitivity of 0.890(300/337), producing on average 1.530 false-positives per subject compared with the gold standard of manual review. The whole process was completed in less than 10 seconds.



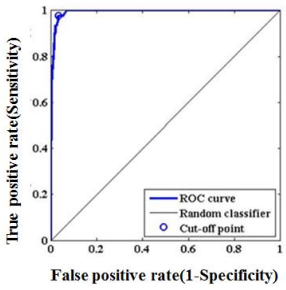


Fig.3 ROC curve for the identification model (n=6193).

Fig.2 Four typical slices of axial GRE T2*-weighted images which have been successfully detected of CMBs based on our method: (a)-(d) Manually marked results. (e)-(h) Automatically marked suspected CMBs. The red spots in (e)-(h) without any arrows indicate bleeds that were identified in both methods. The green arrows point to those CMBs that were missed by the automated method, the blue arrows point to the false-positives from the automated methods, and the yellow arrows point to the CMBs missed by the manual method but identified by the automated method.

Conclusion

The detection system can lead to more consistency between the observers and reduce the processing time at the same time. The anatomical location information of the true positive candidates is considered. Higher accuracy, sensitivity, specificity, PPV and NPV are achieved when compared with the other methods presented before. The results indicate that the proposed strategy is technically feasible and effective, and has the potential to be used as a convenient tool for clinical detection of CMBs.

References

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