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Cerebral Microbleed Detection by Wavelet Entropy and Naive Bayes Classifier

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Abstract. (Aim) Current cerebral microbleed detection methods are too complicated, and difficult to train. (Method) We enrolled 10 subjects diagnosed as cerebral microbleed.Our method combined wavelet entropy and naive Bayes classifier. (Results) The simulation results over 10 times of 10-fold cross validation showed that the average sensitivity, average specificity, and average accuracy of our method are 76.90±1.81%, 76.91±1.58%, and 76.90±1.67%, respectively. Our method can identify the CMB areas using only 1.41 seconds. (Conclusion) Our method is effective and rapid.

Background

The cerebral microbleed (CMB)[1] is a prodromal symptom of stroke. Nevertheless, detection of CMB by traditional structural magnetic resonance imaging (sMRI)[2-9] is difficult. The susceptibility weighted imaging (SWI)[10] is now attracting attention from both clinicians and technicians, since it can provide better accuracy than sMRI in detecting CMB.

In the last year, scholars have proposed many methods to detect CMB in SWI scanning. For example, Chen (2016) [11] suggested a novel leaky rectified linear unit (LReLU) classifier. Hou and Chen (2016) [12] proposed a four-layer deep neural network (DNN) method. Chen (2017) [13] extended the four-layer to a seven-layer neural network based on sparse autoencoders.

Nevertheless, above methods are too complicated. The training of either LReLU or the deep neural network are extremely time-consuming. Besides, the training results heavily rely on the initialization.

Hence, we suggested in this study to use a simple but efficient method, which is based on wavelet entropy and naive Bayesian classifier.Next Section 2 gives the materials and methods. Section 3 provides the experiments and results. Section 4 concludes the paper.

Materials and Methods

We enrolled 10 subjects diagnosed with cerebral microbleed (CMB). Their SWI images were reconstructed by Syngo MR B17 software. The size of the 3D volumetric image of each subject is 364x448x48. An experienced physician is requested to label all the CMB areas, as shown in Figure 1.

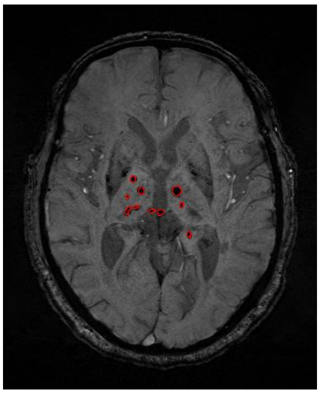

Figure 1 Samples of CMB areas

The sliding neighborhood processing technique is used to generate input and target samples from these 10 subjects. The sliding window size is chosen as 81x81. Finally, we generated (364-80)*(448-80)*48 = 5,016,576 samples per subject. In all, we have 50,165,760 samples for the total 10 subjects. Among them, 21965 samples are of CMB voxels, and the rest 50,143,795 samples are of healthy voxels.

To balance the dataset, we used random undersampling approach[14] to select 21981 healthy samples. Finally, our dataset contains 21965 CMB samples and 21981 healthy samples. Now this dataset is balanced.

The wavelet entropy[15-21] is successfully applied in many academic fields. In this study, it was employed to select important features from the sliding windows. We chose three-level decomposition. The wavelet family was selected as Haar wavelet.

The naive Bayes classifier [22] was used. It is a competitive method with state-of-the-art approaches, including support vector machines [23-26] and artificial neural networks[27-35].

Results and Discussions

The statistical results of our method are shown below in Table 1,
Table 2, and Table 3. Each row represents the result of one run, each column represents the result over each fold. The last column gives the total result over 10 folds.

Finally, the average sensitivity, average specificity, and average accuracy of our method are 76.90±1.81%, 76.91± 1.58%, and 76.90± 1.67%, respectively. This suggests the effectiveness of our method. For one slice image, our method can identify the CMB areas using only 1.41 seconds.

Table 1. Sensitivity of our method

Run	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	79.19	77.24	81.42	74.56	77.42	76.78	79.38	74.73	76.64	76.88	77.42
R2	74.95	78.37	75.73	79.33	80.70	77.78	78.06	80.43	78.15	77.06	78.06
R3	77.37	75.36	69.44	74.10	72.63	74.74	74.65	73.37	73.42	71.31	73.64
R4	74.13	75.23	75.74	75.60	73.54	78.78	74.01	75.24	75.56	79.19	75.70
R5	74.42	76.50	75.69	77.33	80.20	73.59	73.68	78.42	76.10	77.46	76.34
R6	74.37	78.28	80.51	79.47	80.33	77.00	84.07	82.42	80.29	78.38	79.51
R7	76.14	75.06	76.65	74.87	78.37	72.36	75.33	76.05	78.23	79.43	76.25
R8	74.41	78.10	75.47	72.59	77.38	76.05	70.87	76.06	77.19	76.15	75.42
R9	77.56	77.73	77.79	74.82	78.14	79.10	73.36	78.06	76.74	79.70	77.30
R10	80.52	80.70	77.32	78.61	82.29	80.70	78.01	78.73	78.33	77.82	79.30

Table 2. Specificity of our method

Run	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	76.48	79.75	77.98	78.16	78.66	74.89	76.11	79.03	77.67	77.89	77.66
R2	77.12	79.25	78.90	78.21	76.25	77.53	79.85	77.48	76.62	78.43	77.96
R3	73.66	73.52	75.39	76.34	78.53	72.47	73.44	74.07	76.57	77.02	75.10
R4	75.34	76.89	75.11	75.22	76.34	72.20	73.34	75.07	76.07	76.16	75.17
R5	79.53	76.16	74.43	76.21	75.11	73.75	77.02	75.20	74.48	76.03	75.79
R6	78.62	78.34	77.84	81.03	76.07	79.31	79.03	83.44	80.48	79.03	79.32
R7	77.93	74.61	76.39	77.12	76.03	75.61	77.48	75.43	77.39	78.30	76.63
R8	77.17	76.43	76.93	74.34	76.11	76.11	74.43	72.66	73.38	75.48	75.31
R9	78.16	76.80	77.16	79.31	76.21	76.57	75.39	77.34	76.11	77.80	77.08
R10	75.89	82.26	80.80	77.13	78.43	80.35	78.80	78.53	77.80	80.98	79.10

Table 3 Accuracy of our method

Run	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	Total
R1	77.83	78.50	79.70	76.36	78.04	75.83	77.75	76.88	77.16	77.38	77.54
R2	76.04	78.81	77.32	78.77	78.48	77.65	78.95	78.95	77.38	77.75	78.01
R3	75.51	74.44	72.42	75.22	75.58	73.61	74.04	73.72	74.99	74.17	74.37
R4	74.74	76.06	75.43	75.41	74.94	75.49	73.67	75.15	75.81	77.67	75.44
R5	76.97	76.33	75.06	76.77	77.66	73.67	75.35	76.81	75.29	76.75	76.07
R6	76.50	78.31	79.18	80.25	78.20	78.16	81.55	82.93	80.39	78.70	79.42
R7	77.04	74.84	76.52	76.00	77.20	73.99	76.41	75.74	77.81	78.86	76.44
R8	75.79	77.26	76.20	73.46	76.75	76.08	72.65	74.36	75.28	75.81	75.37
R9	77.86	77.26	77.47	77.06	77.17	77.83	74.37	77.70	76.43	78.75	77.19
R10	78.20	81.48	79.06	77.87	80.36	80.52	78.40	78.63	78.07	79.40	79.20

Conclusion and Future Research

In this paper, we have proposed a novel CMB detection approach, based on wavelet entropy and naive Bayes classifier. The method achieved good results. In the future, we shall make tentative results on advanced feature extraction, such as wavelet Tsallis entropy [36-38]. Advanced classification methods shall be tested, including extreme learning machine [39] and linear regression classifier [40, 41].

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