Hu Moment Invariant: A New Method for Hearing Loss Detection

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Abstract. This paper proposed a novel hearing loss detection method. Our method first used seven Hu moment invariants to extract features. Afterwards, we used support vector machine to act as the classifier. The 10x5-fold cross validation shows our method yielded an overall accuracy of $77.47 \pm 1.17\%$. The sensitivities of healthy control, left-sided hearing loss, and right-sided hearing loss are $77.60 \pm 5.72\%$, $77.60 \pm 4.30\%$, and $77.20 \pm 5.98\%$, respectively. In all, our method is effective in hearing loss identification.

Introduction

Hearing loss (HL) [1] is a type of hearing impairment. It may be caused by ageing, noise, infection, genetics, etc. Hence, testing for poor hearing is recommended for all new-born babies. Nevertheless, more than half of hearing loss is preventable [2]. Therefore, it is important to early detect hearing loss, and then give patients proper treatments.

Currently, scholars proposed several feasible approaches. Li [3] proposed a fractional Fourier transform method. Jia [4] used deep autoencoder method. Wang [5] suggested to use dual-tree complex wavelet transform. Li [6] offered a new method using fitness-scaling adaptive genetic algorithm. Nayak [7] used stationary wavelet transform and Shannon entropy. Chen [8] gave a new method of using generalized eigenvalue proximal support vector machine. Gorriz [9] employed directed acyclic graph support vector machine. Except above literature, image processing [10, 11] techniques and artificial intelligence [12, 13] methods were already applied to medical image processing.

Nevertheless, those methods are too complicated and time-consuming. In this study, we proposed a novel method that combined Hu moment invariant (HMI) and support vector machine. Our method also achieves good results for hearing loss identification.

Materials

We collected 75 magnetic resonance brain images from local hospitals. The dataset can be divided into three categories, including 25 healthy images, 25 left deafness images, and 25 right deafness images. Written consents were obtained from all subjects. Different types of hearing loss images are shown below in Figure.1

(a) healthy control

(b) left-sided hearing loss

(c) right-sided hearing loss

Figure 1. Sample of brain images

Hu Moment Invariant

We used the image moment [14] as the shape descriptor. For a 2D healthy or hearing loss brain image $F(x, y)$, we can define the raw moment R of order $(b + d)$ as

$$R_{bd} = \sum_x \sum_y x^b \times y^d \times F(x, y) \quad (1)$$

where $b, d = 0, 1, 2, \dots$. The central moments μ replaced the raw moment R in formula.(1)

$$\mu_{bd} = \sum_x \sum_y (x - \bar{x})^b \times (y - \bar{y})^d \times F(x, y) \quad (2)$$

$$\bar{x} = \frac{R_{10}}{R_{00}}, \bar{y} = \frac{R_{01}}{R_{00}} \quad (3)$$

Central moments are translational-invariant [15]. It can be extended to be both translation- and scale- invariant [16]. The new moment was called normalized central moment Q .

$$Q_{bd} = \frac{\mu_{bd}}{\mu_{00}^{\left(\frac{b+d}{2}+1\right)}} \quad (4)$$

To enable invariance to rotation, Hu [17] proposed seven moments P as

$$P_1 = Q_{20} + Q_{02} \quad (5)$$

$$P_2 = (Q_{20} - Q_{02})^2 + Q_{11}^2 \quad (6)$$

$$P_3 = (Q_{30} - 3Q_{12})^2 + (3Q_{21} - Q_{03})^2 \quad (7)$$

$$P_4 = (Q_{30} + Q_{12})^2 + (Q_{21} + Q_{03})^2 \quad (8)$$

$$P_5 = (Q_{30} - 3Q_{12})(Q_{30} + Q_{12})[(Q_{30} + Q_{12})^2 - 3(Q_{21} + Q_{03})^2] + \\ (3Q_{21} - Q_{03})(Q_{21} + Q_{03})[3(Q_{30} + Q_{12})^2 - (Q_{21} + Q_{03})^2] \quad (9)$$

$$P_6 = (Q_{20} - Q_{02})[(Q_{30} + Q_{12})^2 - (Q_{21} + Q_{03})^2] + 4Q_{11}(Q_{30} + Q_{12})(Q_{21} + Q_{03}) \quad (10)$$

$$P_7 = (3Q_{21} - Q_{03})(Q_{30} + Q_{12})[(Q_{30} + Q_{12})^2 - 3(Q_{21} + Q_{03})^2] - \\ (Q_{30} - 3Q_{12})(Q_{21} + Q_{03})[3(Q_{30} + Q_{12})^2 - (Q_{21} + Q_{03})^2] \quad (11)$$

Hu moment invariants $P = [P_1, P_2, \dots, P_7]$ are a set of absolute orthogonal (i.e. rotation) moment invariants. Afterwards, we used support vector machine (SVM) [18-21] as the classifier. The optimal parameters of SVM were obtained by grid-searching method [22-25]. The 10x5-fold cross validation was employed. We did not use deep learning techniques [26-28], since our dataset is small and deep learning does not perform well on small-size dataset.

Experiments and Results

The statistical results are obtained and listed below in Table. Each fold contains five healthy controls, five left-sided hearing loss brains, and five right-sided hearing loss brains. The element in Table of $(a+b+c) = d$ means a healthy controls, b left-sided, and c right-sided were correctly identified. In total d brains were identified.

Table 1 Correctly identified results

	F1	F2	F3	F4	F5	Total
R1	5+3+3=11	2+4+4=10	5+4+3=12	4+3+5=12	5+5+3=13	21+19+18=58
R2	3+3+4=10	4+4+4=12	5+4+4=13	4+4+4=12	4+3+5=12	20+18+21=59
R3	4+4+4=12	4+3+4=11	4+5+4=13	4+5+3=12	4+4+3=11	20+21+18=59
R4	2+4+5=11	4+4+3=11	5+4+4=13	3+4+5=12	3+4+3=10	17+20+20=57
R5	3+4+3=10	3+3+5=11	3+4+4=11	4+4+4=12	4+4+5=13	17+19+21=57
R6	3+3+3=9	4+4+4=12	5+4+4=13	3+4+5=12	4+4+4=12	19+19+20=58
R7	4+5+4=13	5+2+4=11	3+5+3=11	4+4+4=12	4+3+4=11	20+19+19=58
R8	4+5+4=13	4+4+5=13	4+4+4=12	3+4+2=9	4+4+2=10	19+21+17=57
R9	3+4+5=12	4+2+5=11	5+4+4=13	3+4+2=9	5+4+5=14	20+18+21=59
R10	4+4+4=12	3+5+3=11	5+3+3=11	5+4+4=13	4+4+4=12	21+20+18=59

The total confusion matrix of 10 runs was listed in Table 2. Here C1 represents healthy control, C2 represents left-sided hearing loss, and C3 represents right-sided hearing loss. The sensitivities of each class are listed in Table 3. The average sensitivities of three classes are $77.60 \pm 5.72\%$, $77.60 \pm 4.30\%$, and $77.20 \pm 5.98\%$. The overall accuracies of the three classes over 10 runs are listed in Table 4. In average, the overall accuracy is $77.47 \pm 1.17\%$.

Table 2 Confusion matrix

	C1	C2	C3
C1	194	27	29
C2	31	194	25
C3	26	31	193

Table 3 Sensitivity of three classes of 10 runs

Healthy control							Left-sided hearing loss							Right-sided hearing loss						
	F1	F2	F3	F4	F5	T	F1	F2	F3	F4	F5	T	F1	F2	F3	F4	F5	T		
R1	100	40	100	80	100	84	60	80	80	60	100	76	60	80	60	100	60	72		
R2	60	80	100	80	80	80	60	80	80	80	60	72	80	80	80	80	100	84		
R3	80	80	80	80	80	80	80	60	100	100	80	84	80	80	80	60	60	72		
R4	40	80	100	60	60	68	80	80	80	80	80	80	100	60	80	100	60	80		
R5	60	60	60	80	80	68	80	60	80	80	80	76	60	100	80	80	100	84		
R6	60	80	100	60	80	76	60	80	80	80	80	76	60	80	80	100	80	80		
R7	80	100	60	80	80	80	100	40	100	80	60	76	80	80	60	80	80	76		
R8	80	80	80	60	80	76	100	80	80	80	80	84	80	100	80	40	40	68		
R9	60	80	100	60	100	80	80	40	80	80	80	72	100	100	80	40	100	84		
R10	80	60	100	100	80	84	80	100	60	80	80	80	80	60	60	80	80	72		

(F = Fold, R = Run, T = Total)

Table 4 Accuracy of three classes of 10 runs

	F1	F2	F3	F4	F5	Total
R1	73.33	66.67	80.00	80.00	86.67	77.33
R2	66.67	80.00	86.67	80.00	80.00	78.67
R3	80.00	73.33	86.67	80.00	73.33	78.67
R4	73.33	73.33	86.67	80.00	66.67	76.00
R5	66.67	73.33	73.33	80.00	86.67	76.00
R6	60.00	80.00	86.67	80.00	80.00	77.33
R7	86.67	73.33	73.33	80.00	73.33	77.33
R8	86.67	86.67	80.00	60.00	66.67	76.00
R9	80.00	73.33	86.67	60.00	93.33	78.67
R10	80.00	73.33	73.33	86.67	80.00	78.67

Conclusion

This study introduced to use Hu moment invariant, and proved its effectiveness in hearing loss detection. The future work is to test other manual features, and try to enroll more students to enlarge our dataset. In addition, transfer learning [29] technique and fractal [30] will be tested. Besides, our method can be applied to detect abnormal breast [31-33] and other diseases.

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