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Runpeng Gao, and John Liu

Hearing Loss Identification by Wavelet Entropy and Cat Swarm Optimization

Runpeng Gao[1, 2, a)], and John Liu[3)]

[1]State Key Laboratory of Digital Publishing Technology, Beijing, China.
[2]Nanjing Normal University, Nanjing 210023, China.
[3]College of Engineering, Michigan State University, East Lansing, MI 48823, USA.

[a)]Corresponding author email: 619191046@qq.com

Abstract. In this study, we try to give a new algorithm for detect hearing Loss patients using magnetic resonance images. It already has several solutions, but they are not suitable for practice. We use Wavelet Entropy (WE) and Cat Swarm Optimization (CSO) in proposed algorithm. In the final, we prove our algorithm in 5-fold Cross Validation. The overall accuracy of our method achieved 84.50± 0.81%.

Key words: Hearing Loss; Wavelet Entropy; Cat Swarm Optimization.

INTRODUCTION

Hearing loss (HL) [1] is a kind of impairment that may happened in ears. When children have HL, it may cause loss of spoken ability. In adults, it also destroys the connection of the society. Even in soldiers, post-war mental syndrome is a big problem for government. Magnetic resonance imaging (MRI) [2-6] is widely used in detect hearing loss by experts.

Some different methods have been provided for detect HL, for instance: Keefe, Goodman, Ellison, Fitzpatrick and Gorga [7] used click-evoked otoacoustic emissions. Kothiyal, Cox, Ebert, Husami, Kenna, Greinwald, Aronow and Rehm [8] gave a new method of Wavelet entropy and directed acyclic graph in MRI scanning. Gorriz and Ramírez [9] proposed a resequencing microarrays method. Those methods are based on complicated algorithm and it is hard for implement. Some of methods take lots of time with medical equipment which is impossible use in daily life. Pereira [10] used Hu moment invariant (HMI) approach. Nayeem [11] used genetic algorithm (GA).

So, we give a new algorithm combined with wavelet entropy and Cat Swarm Optimization (CSO). Compared with others, it will be more convenient, efficient and useful. Deep learning methods [12-20] are not used, since we do not have a large enough dataset. We hope our method make a contribution in detect HL.

METHODOLOGY

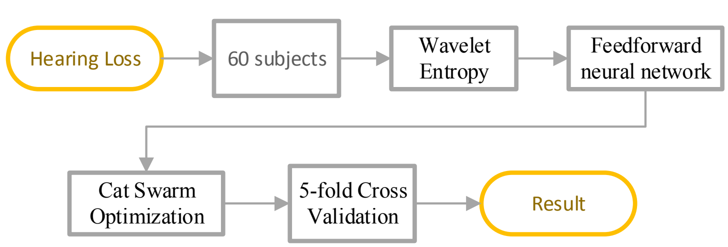

FIGURE 1. Flowchart of our methodology

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FIGURE 1 shows the flowchart of our methodology. We shall enroll 60 subjects, and use "wavelet entropy" as the feature extraction method. The feedforward neural network will be used as the classifier, which is trained by cat swarm optimization. Finally, 5-fold cross validation will be employed to estimate the performance of our proposed method.

Subjects

We enrolled in total 60 subjects, among which 20 are left-sided sensorineural hearing loss (LSHL) patients, 20 are right-sided sensorineural hearing loss (RSHL) patients, and the rest 20 are healthy control (HC) subjects. The demographic data of 60 subjects are listed below in TABLE 1.

TABLE 1. Demographic data of 60 subjects

	LSHL	RSHL	HC
Age (year)	51.3 ± 9.8	53.5 ± 8.2	53.6 ± 5.4
Gender (m/f)	10/10	9/11	8/12
Education level (year)	12.4 ± 1.8	12.2 ± 2.2	11.5 ± 3.2
Disease duration (year)	17.5 ± 17.2	14.4 ± 15.0	-
PTA of left ear (dB)	78.2 ± 17.6	21.9 ± 3.4	22.2 ± 2.1
PTA of right ear (dB)	20.6 ± 4.1	80.7 ± 17.7	21.3 ± 2.2

Wavelet Entropy

Entropy is a general concept which is the average amount of information. In information theory, it be used to show the informational degree [21] and the uniformity of signal probability distribution. Wavelet is a time frequency analysis tool compared with Fourier transform which can be used in image and signal process. Wavelet usually use to analyze the non-stationary signal in the frequency-domain and time-domain simultaneously [22].

The wavelet entropy combines the entropy and wavelet, which put the advantage of wavelet in processing of the irregular signal and entropy's statistical properties together [23-26]. It can reflect the short abnormal signal. At the same time window, the sum of each power Powerj is equal to the total power Powertotal of signal x (n). So,

$$p_j = \frac{power_j}{power_{total}} \tag{1}$$

Is defined to normalized power and it is clear that

$$\sum_{j=1}^{M+1} p_j = 1 \tag{2}$$

In the time window, the wavelet entropy is

$$\mathrm{WE} = -\sum_{j=1}^{M+1} p_j \times \ln p_j \tag{3}$$

Cat Swarm Optimization

Cat swarm optimization is an optimization which simulated the natural behaviors of cats [27]. This optimization simulates two modes of cats, which are 'Seeking mode' and 'Tracing mode'. We use those two modes for best solution.

In the seeking mode, the cats still alert the surroundings even they are in rest time. The cats have time to decide and consider the next movement in this mode [28, 29]. Four essential parameters used are: seeking memory pool (SMP), seeking range of the selected dimension (SRD), counts of dimension to change (CDC) and self-position consideration (SPC) [30]. For every point, the fitness values (FS) is calculated. If the function is finding the least solution,$FS_b = FS_{max}$ else, $FS_b = FS_{min}$. So,

$$P_j = \frac{|FS_j - FS_b|}{FS_{max} - FS_{min}}, 0 < j < k \tag{4}$$

The Tracing mode is used for the situation when cats are tracing some targets. Cats spend high energy for tracing targets. Here the cat keeps moving as per its own velocity for each dimension [31]. The position of cat is change by follow Eq.

$$X_v = X_v + R \times C \times (X_{best} - X) \tag{5}$$

X_v is the position of cat, R is a random number in the range of [0,1], X_{best} is the best position of cat and X is the current solution. In the future, we shall test the performance of other bio-inspired algorithms [32-34].

K-fold Cross Validation

Cross-validation is a validation method for evaluating the error of prediction of the model performance. More and more attention has been attracted in this validation. K-fold cross validation is one of this method. In K-fold cross validation, all the data will be divided into K groups. The model in classification is trained and tasted as many times [35-37]. The K-1 groups are used for training data, the remaining group will be used to test the accuracy of the metamodel. FIGURE 2 shows the pipeline of a 5-fold cross validation.

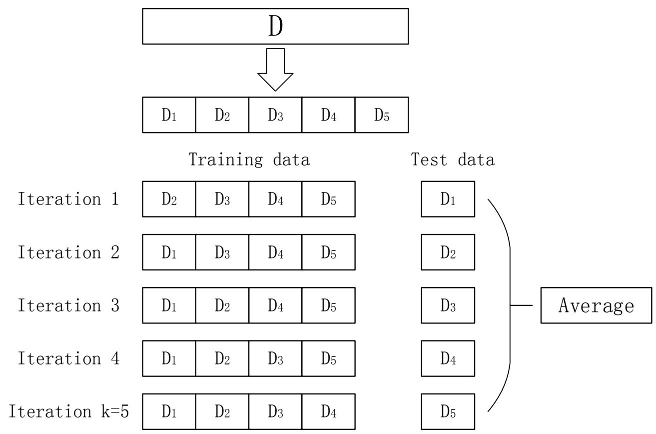

FIGURE 2. Pipeline of a 5-fold cross validation

EXPERIMENTS AND RESULTS

We run a 5-fold cross validation 10 times on this 60-image dataset, so each fold contains 4 LSHL, 4 RSHL, and 4 HC images. We reported the performance of our classifier in terms of the sensitivities of all three classes and the overall accuracy. The results are shown in TABLE 2.

TABLE 2. Performance of proposed method

	LSHL	RSHL	HC	Overall
R1	90	80	85	85.00
R2	80	85	90	85.00
R3	85	80	90	85.00
R4	85	85	85	85.00
R5	85	75	90	83.33
R6	85	85	80	83.33
R7	75	90	90	85.00
R8	90	90	75	85.00
R9	90	90	75	85.00
R10	80	75	95	83.33
Mean+SD	84.50± 4.97	83.50± 5.80	85.50± 6.85	84.50± 0.81

Finally, we compare our "WE-CSO" method with state-of-the-art approaches in terms of overall accuracy. The results are shown below in TABLE 3. Obviously we can find that our method procured better overall accuracy than two state-of-the-art approaches: HMI [10] and GA [11]. The former obtained an overall accuracy of 77.47%, and the latter obtained an overall accuracy of 81.11%.

TABLE 3. Algorithm comparison

APPROACH	OVERALL ACCURACY
HMI [10]	77.47± 1.17
GA [11]	81.11 ±1.34
WE-CSO (Ours)	84.50± 0.81

CONCLUSION

In this study, we use wavelet entropy and cat swarm optimization to detect hearing loss disease. This algorithm was proved by a strict K-fold cross validation experiment. After testing in 60 subjects, we find our "WE-CSO" can procure high accuracy. Our new algorithm has some break in HL and it is ease for use in routine check of hospitals. We hope it can be used widely.

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