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Intelligent Hearing Assistance using Self-Organizing Feature Maps

[1]Michael Hodges and [2]Mohamed Zohdy
[1]*Computer Science and Engineering, Oakland University, Rochester, MI, USA;*
[2]*Electrical and Computer Engineering, Oakland University, Rochester, MI, USA;*
[1]mjhodges@oakland.edu; [2]zohdyma@oakland.edu

ABSTRACT

A novel hearing assistance system is proposed which classifies sounds and selectively tunes them according to the needs of the hearing impaired. This differs from the usual hearing aids available today in that it uses computational intelligence to filter and tune sounds based on real life categorical classifications. The system can significantly improve audibility for the hearing impaired, including bringing completely inaudible tones into audibility. For classification a self-organizing feature map is used with a vector of sound features from the joint time-frequency domain. The map is trained with input sounds until a map of neurons is clustered according to these. The resulting map is used to classify new sounds. Based on this classification, a sound can be tuned to improve audibility for the hearing impaired. Techniques proposed for audio output include gamma tone frequency filtering, Fourier compression, low pass filtering, spectral subtraction, and an original algorithm to choose how to best boost the amplitude of deaf frequencies.

Keywords: self-organizing feature maps; Artificial Intelligence; machine learning; neural networks; pattern classification.

1 Introduction

Most common hearing aids today do not include computational intelligence mechanisms such as those which can classify the type of sound. Typically at best, one can find distinction between voice and noise. A deaf person could therefore not be able to separate the hearing aid processing of different categories of sound. For example, one may wish to amplify the sound of a baby while blocking out the sound of background nature sounds.

This research aims to define the development of a system which has the promise of achieving exactly this sort of intelligent classification for hearing aids. By using a self-organizing feature map as unsupervised learning to train a neural network to classify sound categories, the output can be adjusted based on such a classification.

Given a sound classification, this research further studies methods to adjust the output sound to improve hearing ability for a deaf user. Gamma tone filters and amplification can together separate a sound into its frequency components and boost a desired range. Fourier domain compression can recreate a sound with its Fourier signature shape intact while compressing the range of frequencies so

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that a high-frequency deafness or low-frequency deafness can be compensated. Additional algorithms can determine how to boost particular frequencies most efficiently without losing other audible tones. Noise reduction can be accomplished by low pass filter blurring, or by spectral subtraction of a target noise source Fourier signal.

Combining the intelligent sound classification with these methods of output tuning produces a robust system which can significantly improve hearing ability. This paper analyzes the amount of hearing improvement possible, which can range from a likely significant amount to occasionally great gains under specific circumstances.

A flow-graph of the proposed system is shown in (Figure 1).

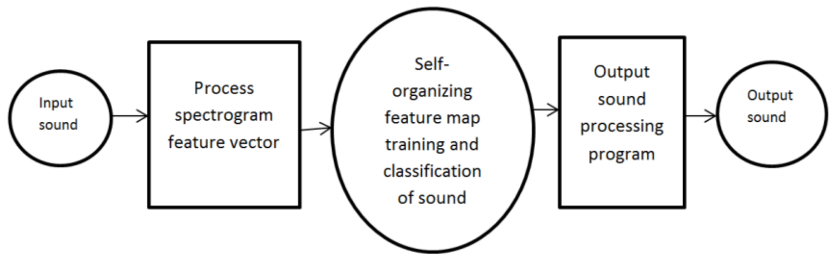


Figure 1: Flow-graph of the proposed system for intelligent sound classifying hearing assistance system.

The system starts with an input sounds, from which features are extracted to uniquely describe the sound. These features are fed into a self-organizing feature map which trains itself to classify sounds. Based on the map's classification, the sounds are fed to an output processing program, which tunes the output sound for the hearing impaired.

2 Modeling the System

Based on the diagram in (Figure 1), a model is created to demonstrate the flow of the system.

The input sound is a time series of amplitude values which can also be represented in frequency domain form. A number of these frequencies may likely have amplitudes below the threshold of hearing for a deaf person. Also the total range of frequencies present may extend beyond the capabilities of the hearing impaired. The output processing techniques described for this system perform amplification, frequency selective tuning, frequency compression, and computed algorithm-based sound adjustment.

The system model can be viewed as a sound input that goes through processing stages until a final output emerges according to the needs of a hearing impaired person. The input is the original sound to be processed. This can be obtained from a microphone and stored in a memory buffer while processing occurs. In a hardware oriented system processing can be much faster as it can be done in hardware.

Parallel to the input is the training of a self-organizing feature map neural network. Given a set of sounds from different categories, a neural map is trained which clusters the sound inputs and enables classification. The inputs to this system are mathematical feature vectors describing several training sounds.

After the input enters the system, it will need to use the trained map to classify the sound into one of a selected number of defined categories. When the category is determined, the input is given such a tag, and it proceeds to the output processing stage.

In the output processing stage, frequencies are tuned and compressed, algorithms search for optimal hearing improvement techniques, and amplification occurs. Based on the category from the previous step, these settings can be controlled to filter certain types of noises while tuning others to be heard. For example, music may be processed for output while nature sounds may be muted. This would give an output of music sounds while tuning out sounds classified as nature sounds.

The output then emerges from a speaker so the hearing impaired person can receive the entire processed sound from all the stages of the model. In (Figure 2) is a class diagram of the system.

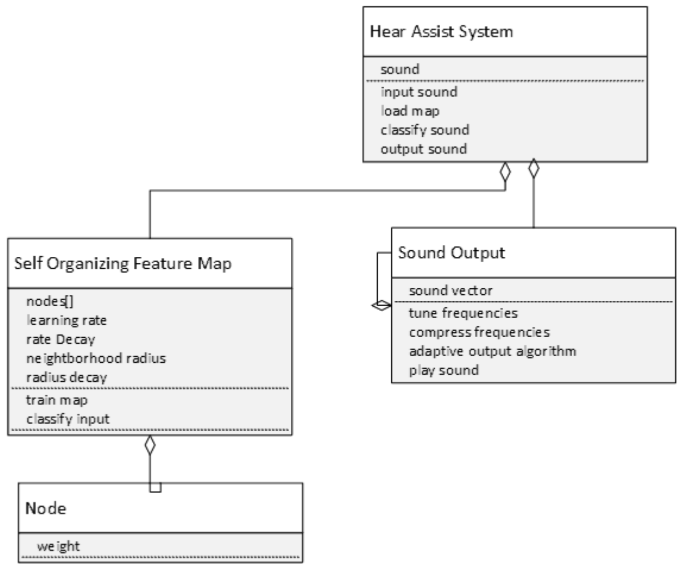


Figure 2: Class diagram model of the proposed system.

It shows that the main system contains subsystems of the self-organizing feature map and the output system. The self-organizing map contains an array of nodes. The map object trains and classifies sounds. The output object tunes these sounds for the hearing impaired. The main system object connects these two parts.

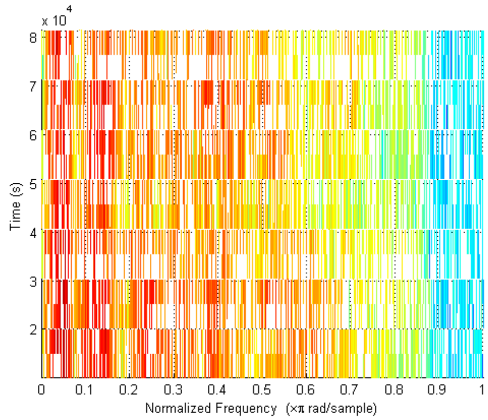
3 Spectrograms

Like the Fourier series a spectrogram divides a signal into its frequency components. However, a difference is that the components of a spectrogram have differing lengths in time duration along with a frequency. Therefore spectrograms can be used to visualize a signal's duration as well as frequency content.

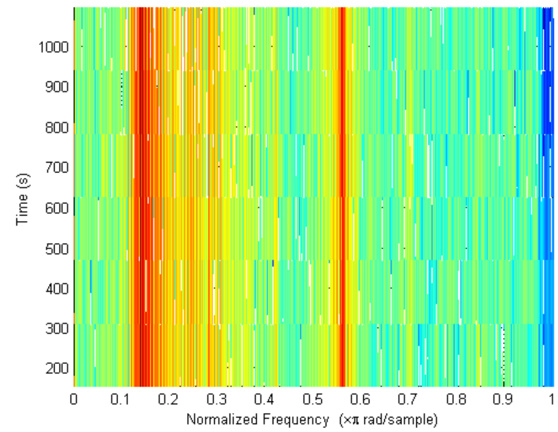
The theory of using spectrograms for this application comes from the human hearing and brain system role as a spectral analyzer [1] [2]. The ear and brain search for dominant components in a spectrum. From this fact it is likely that sounds with similar spectrums should be similar and separable from other sounds.

Because of the logarithmic separation of frequency sensors in the inner ear, low frequencies have high frequency resolution while high frequencies exhibit high time resolution. This makes the dual time and frequency representation of spectrograms useful for such an application. The descriptive features of sounds in our classification system are therefore based on spectrograms, explained here.

A spectrogram is similar to the Fourier transform but differs in important ways. A spectrogram is a plot of a function in the domain of time and frequency. It can be plotted as time vs. frequency with an amplitude and drawn using color intensity. Examples are shown in (Figure 3).



(a) Spectrogram of baby sounds



(b) Spectrogram of farm animal sounds.

Figure 3

A form of a spectrogram can be created with the short time Fourier transform, defined as [3]:

$$X(\tau,\omega)=\int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-j\omega t}dt \qquad (1)$$

Its discrete form is [9]:

$$X(m,\omega)=\sum_{n=-\infty}^{\infty} x(n)w(n-m)e^{-j\omega n} \qquad (2)$$

In these two equations w is the window function, a particularly shaped sampling of the data outside the bounds of which the value is 0. The variables τ and m are used for sample shifts.

The spectrogram value used for feature description in our system is the magnitude of this transform squared.

4 Intelligent Unsupervised Learning using Self-Organizing Feature Maps

To classify a sound, we propose an unsupervised application of self-organized feature maps. To classify the sounds, a self-organizing feature map was trained, as explained in this section. The trained map can then classify new sounds into a particular category to control output adjustment accordingly. For example, a deaf person may choose to tune music sounds and block out animal sounds. This system proposes a method to reach this goal.

The method starts with a feature vector describing a sound sample. By dividing the sound's spectrogram values into four quadrants, then dividing the most densely valued quadrant into four more quadrants, a total of seven quadrants is obtained. The mean and range values of each of these quadrants were used to produce a feature vector of size 14. This choice of features captures the bio inspired qualities of a spectrogram, focusing on the most significant regions of this graph as the brain recognizes dominant patterns in the audio spectrum. Patterns which are similar to each other are recognized which can be used to separate different categories of sounds.

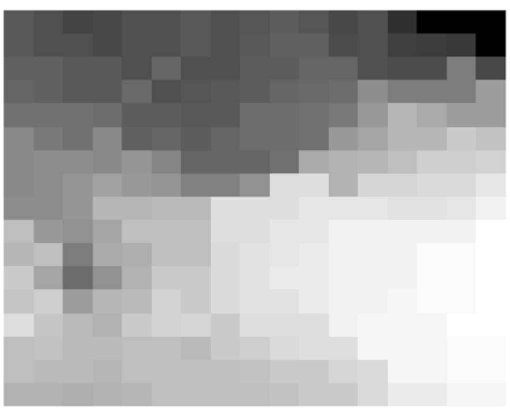
Once the feature vectors for a training set are calculated, they are fed into a self-organizing feature map network. This is a two-dimensional matrix of neurons, each with a weight of dimension equal to that of the feature vector. The matrix starts with randomized weight values which are to be adjusted so as to cluster the map into training categories. As a feature vector is fed to the system, the closest weight node and its immediate neighbors are adjusted in weight to be slightly more similar to the feature vector. Through repeated iterations, similar feature qualities will congregate together and separate themselves from differing ones, producing a clustering of the map based on patterns in the feature data.

The equation for the training of a self-organizing feature map is [4]:

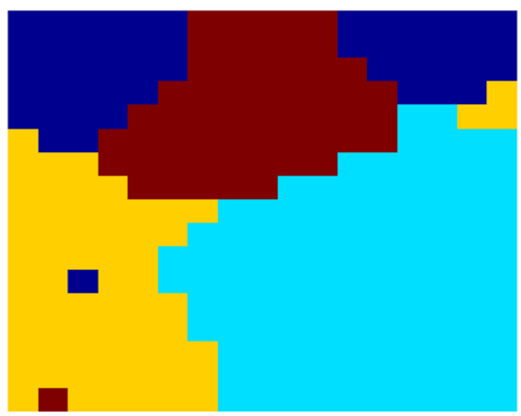
$$W_v(t+1)= W_v(t)+ \alpha(t)*\beta(t)*\left[dist(t)-W_v(t)\right] \tag{3}$$

For this weight adjustment, increase t, which is a positive constant and repeat from 2 while $t< \lambda$. The parameters are t, the current iteration; λ, the limit on time iteration; W_v, the current weight vector of node v; dist(t), the target input data vector; $\alpha(t)$, the learning restraint due to time; and $\beta(t)$, the restraint due to distance from the best matching node, usually called the neighborhood function.

Once a map is trained, it can be used to classify new data. As the self-organizing feature map's signature difference from a typical neural network is its visual interpretation, one can examine the trained maps to see how well the sounds are clustered. The map can be plotted based on vector magnitude, as in (Figure 4a), or color coded based on classifications such as those based on Euclidean distance from a training average, as in (Figure 4b).



(a) Clustered SOFM map shaded based on vector magnitude intensity.



(b) Color coded classifications of the same SOFM map. Sound classifications are: dark blue–voice; light blue–household sounds; yellow – nature sounds; brown– music.

Figure 4

5 Output Processing

To produce the goal of amplifying deaf frequencies for hearing improvement, a number of techniques can be used. Our implementation includes a gamma tone filter deconstruction of a sound to be processed. A gamma tone filter can be defined in the time domain as:

$$g(t)= t^{n-1}e^{-2\pi bt}\cos(2\pi f_0t+ \phi) \tag{4}$$

In this equation, the order of the filter is n which relates to the sharpness of the transition from stop band to pass band and to the gain of each filter. An order 4 filter was used in the system described, which is considered ideal for auditory processing and modeling the human hearing system [5]. The variable b, in Hertz, controls the duration of the impulse response. The variable f_0 is the center frequency. Phi is a phase shift, which represents relative position of the cosine term.

After this filter is applied, a sound will be broken up into a number of samples centered at different frequencies. For quality reconstruction, we used 40 channels, or center frequencies. These were divided logarithmically, in accordance with the logarithmic frequency sensing of the human hearing system.

Once the filter has divided the sounds by their center frequencies, particular deaf frequencies can be boosted as needed, while others are correspondingly lowered. We designed an algorithm to find how to best boost a deaf frequency without sacrificing audible sounds. Given a deaf frequency threshold from 0 to 1 and a hearing frequency threshold from 0 to 1, these define what level of amplitude is required to hear this tone. Next is to define what frequency is deaf.

The algorithm attempts to boost this frequency from below the threshold to above the threshold as required, and measures the loss of the other frequency weights to determine whether they have been lowered beyond audible range. A range of thresholds above and below the input thresholds are tried so the algorithm is adaptive to future changes in hearing ability. The best hearing improvement is used for the output.

Another technique for hearing improvement we used was Fourier compression. After transforming a sound signal into the Fourier domain, we simply compress it by interpolation. This keeps the nature of the frequency signal intact while reducing the range in which it is output. This is useful when a deaf person cannot hear very high or very low frequencies.

Fourier compression in our system is applied using interpolation. In this method, a Fourier spectrum plot is recreated using different frequency axis separations ordered as natural numbers to produce a new plot that is compressed in the x axis direction. For example, a plot 1000 values wide can be compressed to 800 values wide by sampling the plot at intervals of 1000/800, and numbering them from 100 to 900 for a compressed plot.

Noise reduction was applied in two ways. First, a low pass blurring filter was used in anticipation of high frequency noise. However, the noise may not always originate from such a source. The source may be a fan, vacuum cleaner, traffic, or other such disturbances. For this we take a sample of such a sound and transform it into the Fourier domain. To the output signal we subtract the Fourier mean in the frequency domain. This assumes that the sound was the desired sound with an additional frequency signal from the disturbance. After subtracting this disturbance, the sound can be more faithfully produced for output.

6 Results and Discussion

6.1 Intelligent classification

Based on visual observation and statistical training data, map parameters may need to be adjusted to produce well clustered results. To try to produce an optimal situation for map training, we tested different parameter values for classification success while holding the others constant. We used a training sample of voice sounds, household sounds, nature sounds, and music sounds.

Learning rate was varied from 0.775 to 1.00 in increments of 0.025. Learning rate decay was varied from 0.775 to 1.00 in increments of 0.025. Neighborhood radius was varied from 0.8 to 8.0 in increments of 0.8. Radius decay was varied from 0.775 to 1.00 in increments of 0.025. Therefore there were ten different values of each of four parameters, for 10 000 combinations for each sample sound set.

The results are shown in (Table 1). These results show the best classifications for each sound set and the parameters in which this classification was made. It is therefore desirable to use these parameters to test the SOFM maps for classification accuracy, described next.

Table 1: Calculated parameters to optimize self-organizing feature map training classification of sounds from voice, household, nature, and music categories.

Test #	Learn Rate	Learn Rate Decay	Radius	Radius Decay	Average Classification Rate
1	0.93	0.98	5.60	0.90	0.85
2	0.80	0.98	8.00	0.88	0.89
3	0.80	0.90	6.40	0.83	0.78
4	0.78	0.90	4.00	0.90	0.63
5	0.90	0.90	8.00	0.78	0.64

Based on the optimal parameters for each set of sounds, 100 tests each were done of the same sound samples in which a SOFM map was generated and input sounds were classified as described. Significant results of classification rates are shown in (Table 2).

Table 2: Significant classification results of 24 total voice, household, nature, and music sounds.

Result #	Voice	Household	Nature	Music
1	1.00		0.82	0.78
2	1.00	0.74	0.93	0.87
3	0.998		0.80	
4	0.98			0.82
5	1.00			0.93

Further tests were made to classify different categories of sounds, as shown in (Table 3).

Table 3: Significant classification results of three sets of 24 total sounds each set of different categories.

Sound Selection	Classification category 1	Classification category 2	Classification category 3	Classification category 4	Average Classification
Babies, Emergency, Fireworks, Livestock	0.67		0.67	0.67	0.60
Bells, Crowds, Emergency, Vehicles	0.83	0.83	0.67		0.64
Babies, Trains, Crowds, Livestock	0.67		0.67		

Our results show that intelligent classification is definitely possible. A practical implementation can successfully distinguish certain sounds from each other and process the output accordingly. The weaknesses are that sweeping generalizations cannot easily be made, and perfect results cannot be expected for what are clearly human defined categories. In the worst cases careful engineering is required to choose training sounds. In any case, some sound samples cluster better than others, and the human intelligence aspect of the system is a subject for further study.

6.2 Output Processing

Our adaptive output algorithm is demonstrated in (Figure 5).

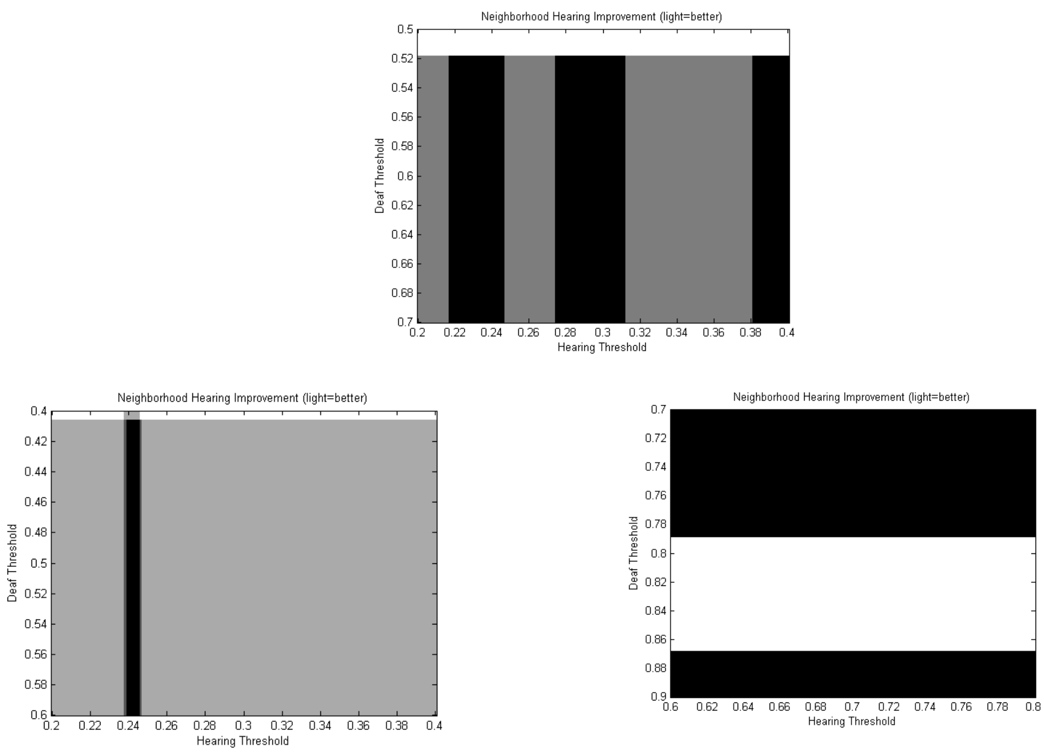
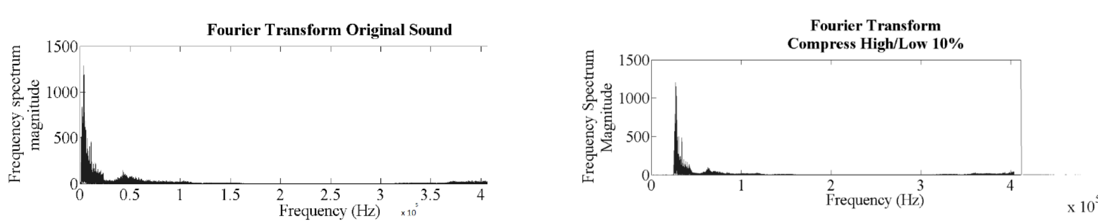


Figure 5: (a) – (c) Example cases of our adaptive output algorithm optimization maps for deaf thresholds and hearing thresholds at optimized improvement ratios.. For a person who needs the two particular threshold levels to hear, and who cannot hear a target frequency, the algorithm calculates hearing improvement for surrounding thresholds based on trying to boost the deaf frequency and considering the loss of audible frequencies in the processing.

In this figure, the thresholds are defined along the axes, and the hearing improvement possible is shaded in the grid. The best improvement is the lightest shades, and the corresponding thresholds are what were used in the calculation.

Results from Fourier compression techniques are shown in (Figure 6).

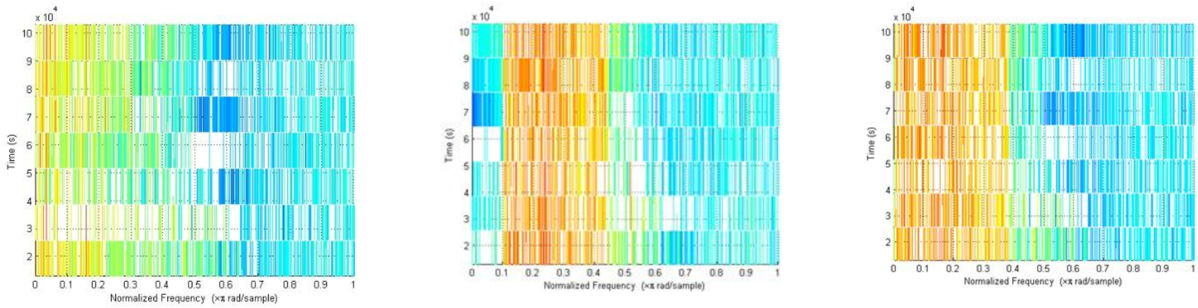


(a)
Original sound Fourier transform

(b)
Results from compression of the same sound's high and low frequencies a total of 10%. The Fourier transform is shown

Figure 6

Spectrogram output results are shown in (Figure 7). The figure shows the original spectrogram and the spectrogram from a 10% high and low compression, then a 10% reduction in amplitude of the highest 30% of frequencies.



(a)
Spectrogram of a music sound

(b)
Spectrogram after 10% high and low total Fourier compression applied

(c)
Spectrogram after highest 30% of frequencies are reduced 10%

Figure 7

6.3 Hearing metrics

A goal is to describe a metric to measure hearing improvement for the system's adjustable frequencies. Each volume bar in the program controls a range of frequencies f_{low} to f_{high}. In a specific case of the sliding bars, a particular frequency is raised from level x_i to x_f, while the other bars are lowered from y_i to y_f for each bar.

The total proportion weight of the initial state for a target frequency, is:

$$w_i = \frac{x_i}{\sum_y y_i + x_i} \quad (5)$$

The proportion weight of the final state for the target frequency is:

$$w_f = \frac{x_f}{\sum_y y_f + x_f} \quad (6)$$

For a deaf person who cannot hear the target frequency normally, the total improvement in proportion of the target frequency weight from initial to final can be obtained by dividing equation (6) by equation (5):

$$w_{imp} = \frac{w_f}{w_i} \quad (7)$$

The proportional amount of frequency range adjusted by changing a particular sliding bar is:

$$f_{adj} = \frac{\int_{f_{low}}^{f_{high}} f}{\int_0^{f_{max}} f} \quad (8)$$

Using the preceding definitions, the amount of hearing gain proportion obtained by adjusting a particular deaf person's target frequency range, is:

$$\text{Hearing improvement} = w_{imp} f_{adj} \quad (9)$$

This means that for f_{adj} percent of the overall frequency content improved by w_{imp}, the resulting overall hearing improvement can be calculated. This calculation must consider that the y frequencies are not lowered below an audible amplitude when adjusting f.

To describe a metric for the compression in the output program, consider the following. The amount of frequency of the initial sound can be called f. The adjusted frequency is c*f, where c is the compression proportion factor.

The total frequency range of the sound sample is:

$$f_{total} = \int_0^{f_{max}} f_{sample} \tag{10}$$

A target frequency range, based on the deaf person's needs, can be defined from its low to high frequency as:

$$f_{target} = \int_{f_{low}}^{f_{high}} f_{sample} \tag{11}$$

For compression, consider when the target frequency of the sound is brought into audible range. The amount brought into audible range is the hearing improvement proportion (multiply by 100 for percent):

$$\text{hearing improvement} = \frac{f_{target}}{f_{total}} \tag{12}$$

In this case, an example is bringing frequencies 3600 – 4000 in a maximum 4000 frequency sample into the audible range by high compression. The improvement would be 400/4000, or 10%, meaning that 10% of the sample has now been changed and brought into the audible range.

The adaptive output algorithm will generally improve hearing ability a minimum of 10%. This is in the case that a deaf frequency can be boosted into hearing range without sacrificing audible frequency ranges. For ten different frequency ranges, if 1 of 10 is deaf, boosting it will improve audibility 10%. In the case where less than 10 of the bands are represented in the output, the hearing improvement will be even greater.

Fourier compression of x percent can bring x percent of the sound into audible range. Therefore, a 10% compression can improve hearing ability 10%, while a 30% compression can improve 30%. However, care must be taken because large amounts of compression can tend to distort the quality of the signal, and even create a ringing effect.

While the hearing improvements may seem somewhat modest, it is very significant that the system allows entirely unheard frequencies to be brought audible. This is an immeasurable improvement because it performs like a miracle to allow a deaf person to hear a brand new part of a sound sample.

7 Conclusions

The project we designed contributes a unique implementation that is not currently readily available in hearing aids. It incorporates intelligent computing to expand the domain of hearing aid technology. Its results are successful to a significant extent, although not perfect. The concept is novel and practical at the same time.

The output processing system we described can produce significant and sometimes drastic improvements in hearing ability. These methods are shown to be practical and effective in the goal of hearing improvement.

The techniques we used were successfully chosen to produce positive results. The feature vector uncovered patterns in sounds to classify them into categories. The self-organizing feature map was a useful tool to cluster and classify sounds. The output techniques each contribute in their own way to an improvement in hearing ability for the hearing impaired.

Further study and tuning of these types of systems can provide more robust and finely engineered solutions capable of practical use in real world applications.

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