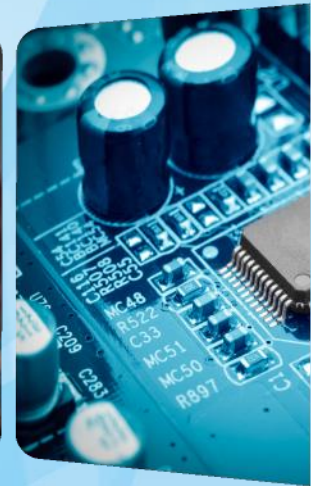
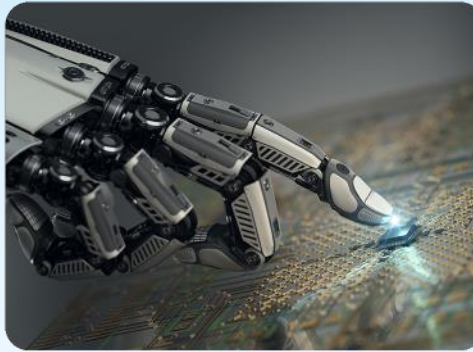


IEEE Region 3 SoutheastCon 2021



Modelling the Effects of Hearing Aid Algorithms on Speech and Speaker Intelligibility as Perceived by Listeners with Simulated Sensorineural Hearing Impairment

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Structure of the Presentation

The following topics will be covered in the presentation.

- The Research Problem
- Hearing Aid Fitting and Performance Issues
- Computational representation of the speech signal after processing by the human auditory peripheral system
- Representing Hearing Impairment Computationally
- The Novel Computational Model
- Experiments and Results
- Discussion and Conclusion
- References
- Acknowledgements

Research Problem

Prevalence and Impact of Disabling Hearing Impairment

- The WHO estimated that the number of people worldwide with disabling hearing impairment increased from 42 million in 1985 to about 360 million in 2011 and will reach 630 million by 2030 .
- Disabling hearing impairment may prevent a person from having verbal communication, especially in noisy environments.
- Disabling hearing impairment causes: Sadness and depression, dementia, worry and anxiety, and it affects the employability of the individual
- Disabling hearing impairment is a health and economic problem
 - It impacts the individual, families, communities and countries.

The Research Problem

Classifying Hearing Impairment and the Hearing Aid

- Hearing Impairment is generally classified as conductive, sensorineural or a mixture of both.
- Conductive HI can be remedied by treatment or surgery; however, sensorineural hearing impairment (SHI) is permanent.
- The Hearing Aid is the main aural rehabilitation device and restores hearing to almost normal levels for conductive hearing impairment.
- Partial restoration is achieved for listeners with sensorineural hearing impairment (SHI).
 - Its effectiveness depends on the severity of the hearing loss.

The Research Problem

Hearing Aids Limitations

- Current hearing aids do not perform well in noisy environments (Kochkin, 2010; Dillon, 2012; Harvey B. Abrams, 2015; Gygi and Ann Hall, 2016; Lopez-Poveda et al., 2017)
- Fitting of hearing aids can take days or even weeks (Fontan et al., 2017; Solheim et al., 2018).
- Dissatisfaction with hearing aids causes individuals to
 - Stop wearing the hearing aids
 - Avoid noisy environments
- Therefore the rehabilitation that the device aims to achieve is not fully met.

The Research Problem

Hearing Aid Algorithm Development Challenges

- Development of new hearing aid algorithms generally require clinical testing on multiple hearing impaired individuals. The challenges faced are:
- Time and expense to recruit hearing impaired individuals
 - Hearing impairment varies between individuals making it difficult to design robust experiments using multiple listeners.
 - It can take weeks for individuals to adjust to “new” speech signals from the hearing aid.

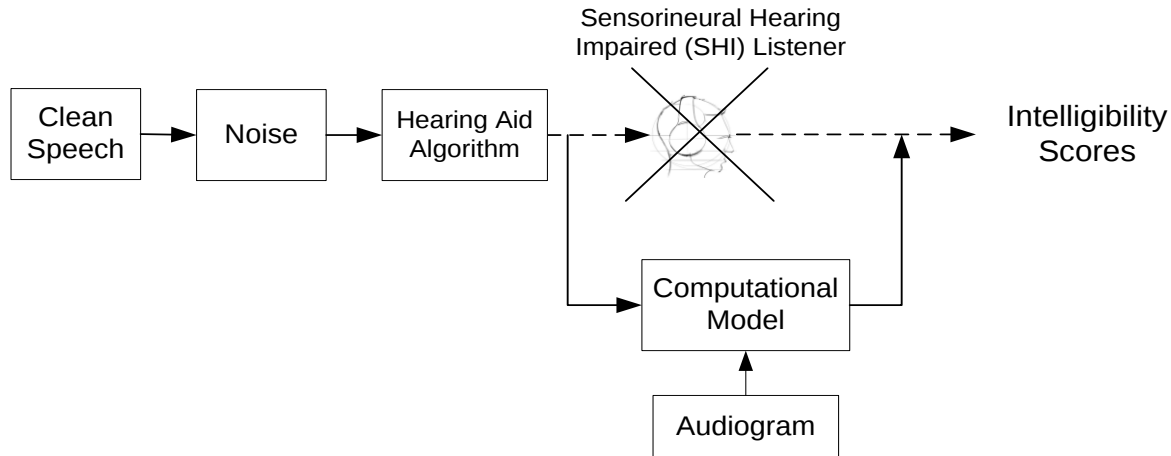
The Research Problem

Hearing Aid Algorithm Fitting Challenges

- Fitting hearing aids typically require the audiologist to conduct speech intelligibility tests on the listeners using different hearing aid settings.
- This testing can be laborious and time consuming (take days or weeks)
- Fitting may not be optimal because the listener become fatigue

Possible Solution

- Develop a computational model that can replace hearing impaired listeners during listening tests.



Research Objective

- This research aims to develop a computational model (CM) that will give insights into methods that can be used to create an application capable of replacing SHI listeners in listening tests used to evaluate hearing aid algorithms' performance and the fitting of hearing aids.
- The CM may aid in the rapid development and testing of hearing aid algorithms and reduce the time it takes to fit hearing aids.

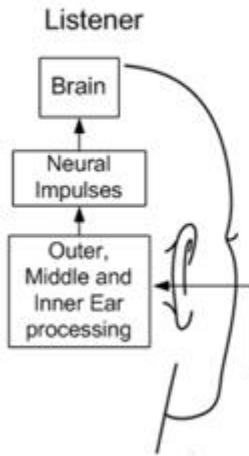
METHODOLOGY

Developing a Physiologically Inspired Computational Model

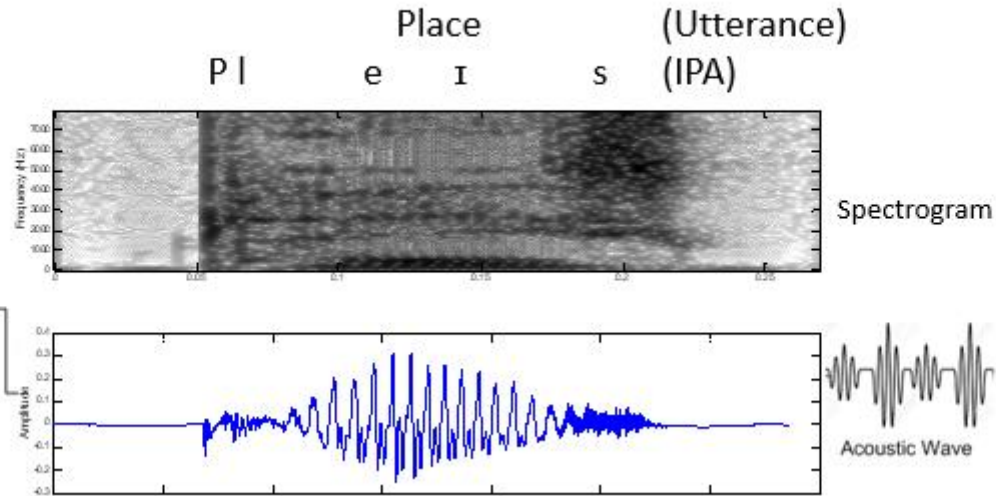
- Using ratemaps (spectral features) to represent the processing of sound in the human auditory periphery (Brown and Cook 2004).
- Using an hearing impairment simulator configured with an audiogram to represent hearing loss.
- Using a GMM-HMM machine learning model to represent knowledge of impaired speech.

Speech and Hearing

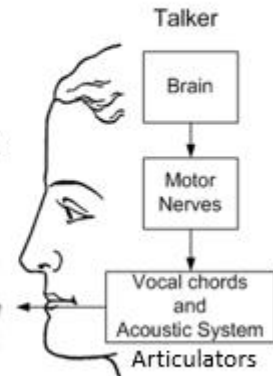
Hearing



Representation of the Speech Signal

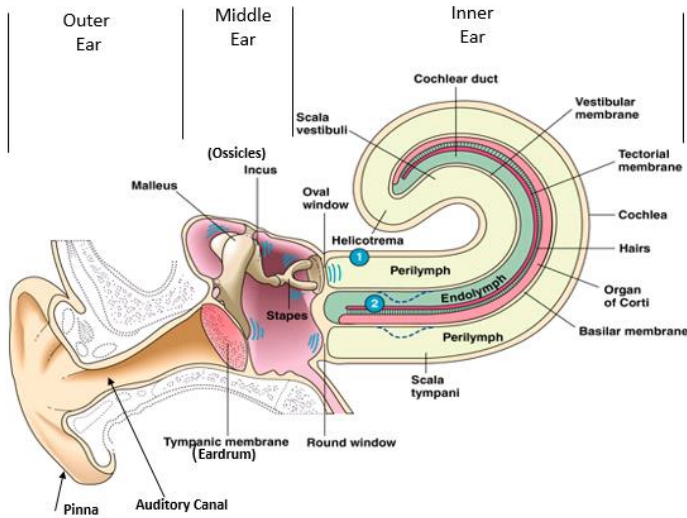


Speech

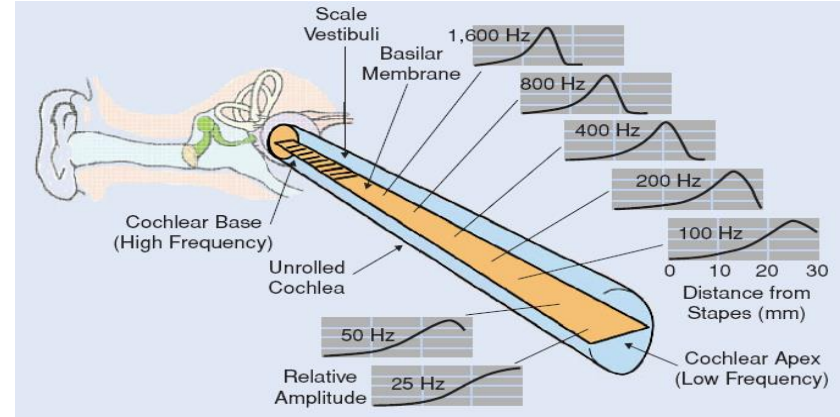


Hearing

The Human Auditory Peripheral System



The Human Auditory Peripheral System
©2001 Brooks/Cole – Thompson Learning

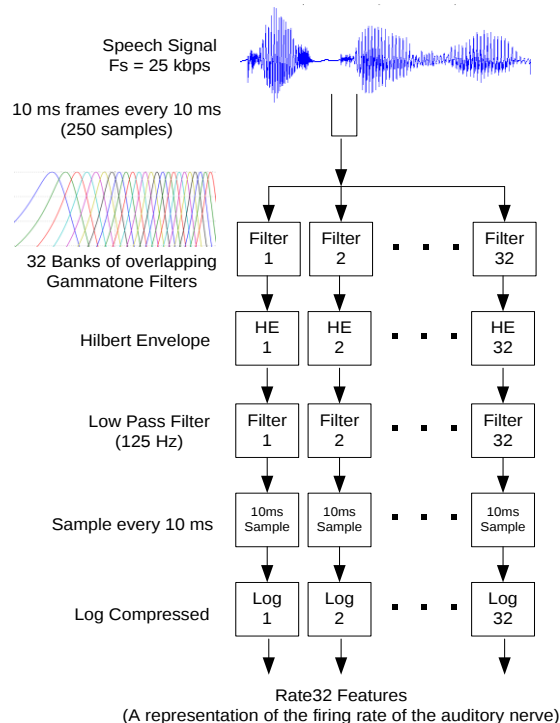


The uncoiled cochlea

Munkong, Rungsun, and Biing-Hwang Juang. "Auditory perception and cognition."
IEEE signal processing magazine 25, no. 3 (2008).

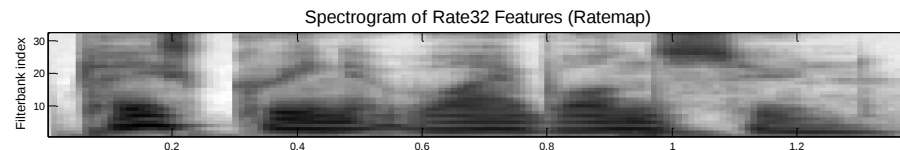
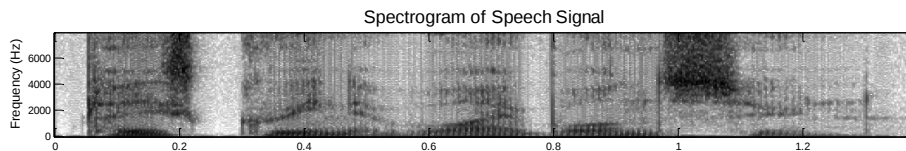
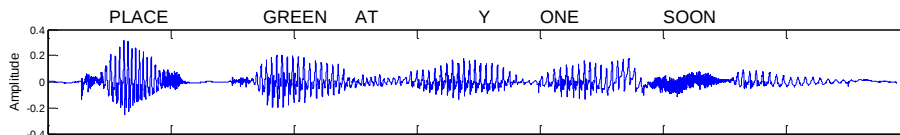
Mimicking Frequency Analysis in the Cochlea

Ratemap (Rate32) Feature Extraction

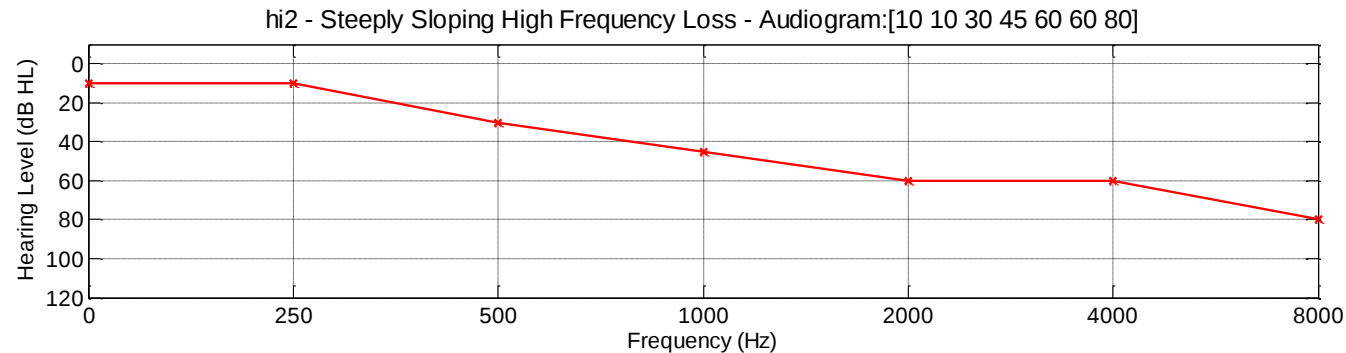
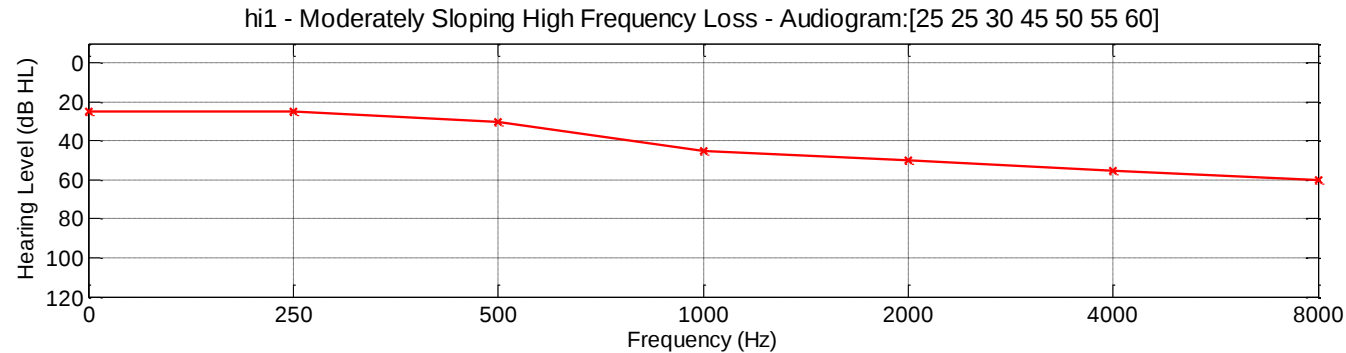


Brown and
Cooke, 2004

Place green at Y one soon (Utterance)
pleɪs gri:n æt waɪ wʌn su:n (IPA)



Audiograms used in the Experiments

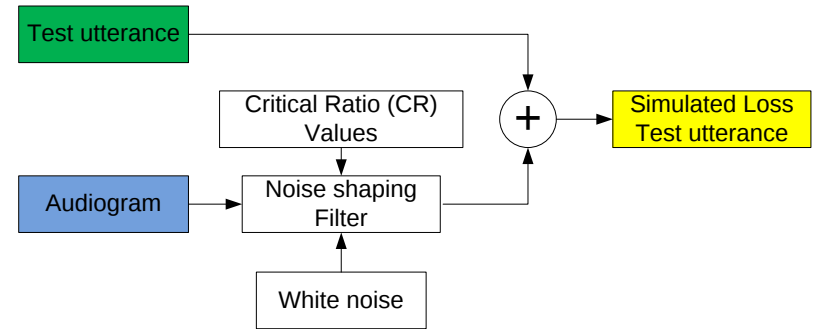


Hearing Impairment Simulation

Using methods from Desloge et al (2010), sensorineural hearing impairment was modelled using:

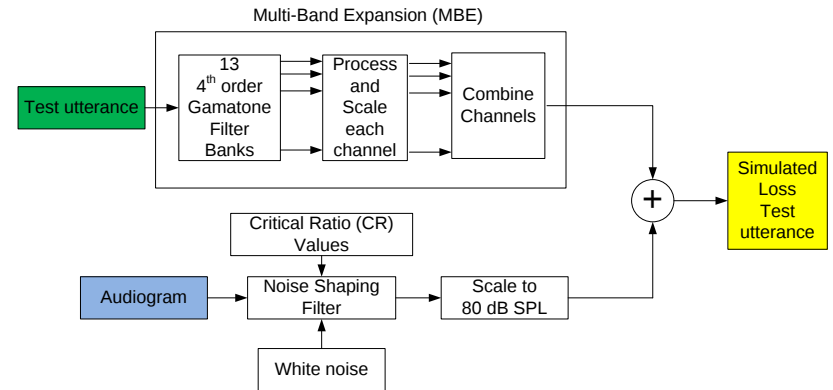
1. Additive Threshold Noise (TN)

- For threshold loss ≤ 60 dB HL
- Spectrally shaped white noise added to signal to simulate hearing loss.

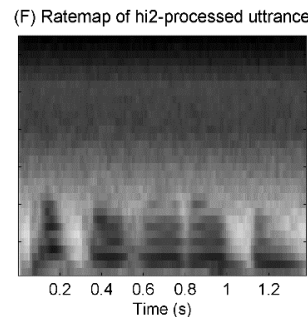
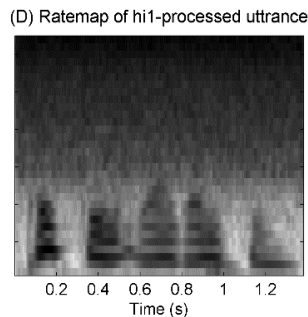
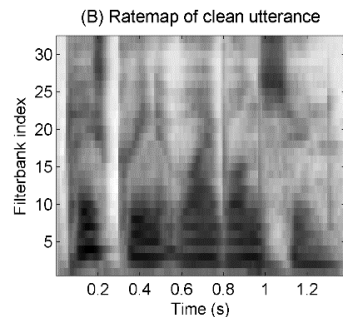
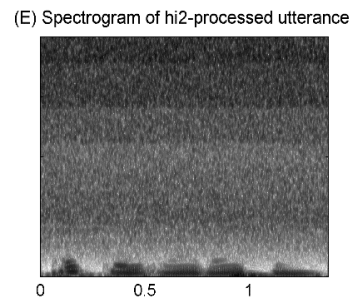
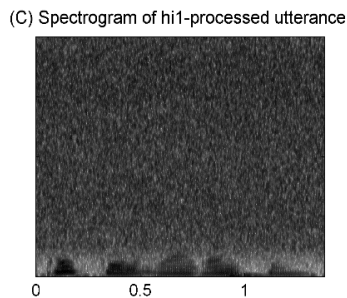
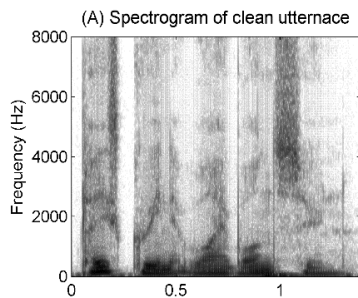


2. Multiband Expansion (MBE)

- For threshold loss $> 60 - 70$ dB HL
- Additive threshold noise alone would be uncomfortably high.
- Signal is attenuated and loudness recruitment is also simulated.



Spectrograms and Ratemaps of Clean and Hearing Impaired Simulated Grid utterances "Place green at y 1 soon"



Clean Utterance



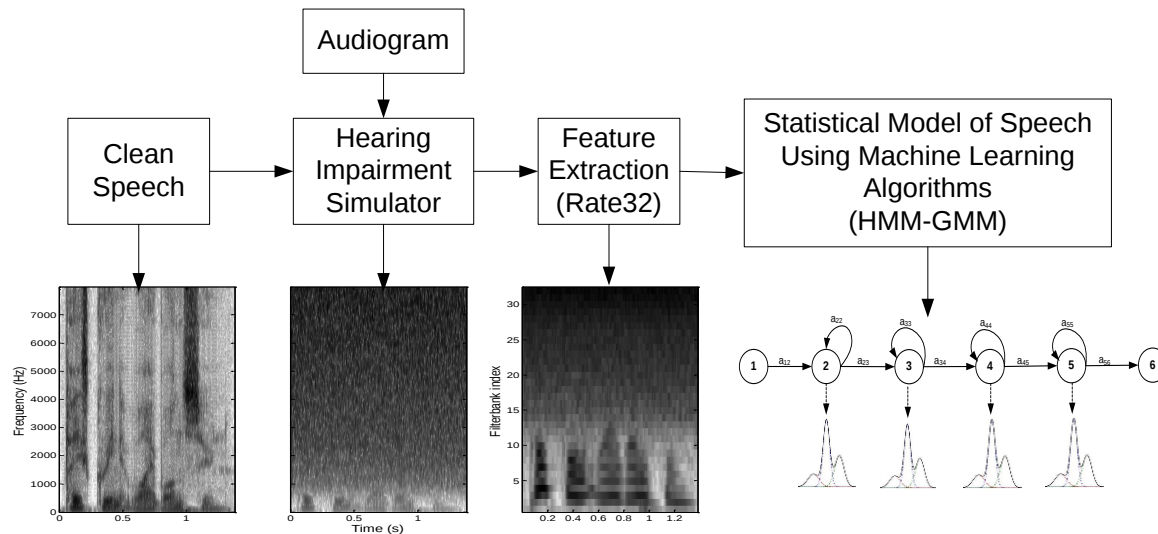
Hi1 simulated
utterance



Hi2 simulated
utterance

Representing Hearing Impairment Computationally

- The approach mimics (in a crude way) how an hearing impaired listener learns and recognises speech.



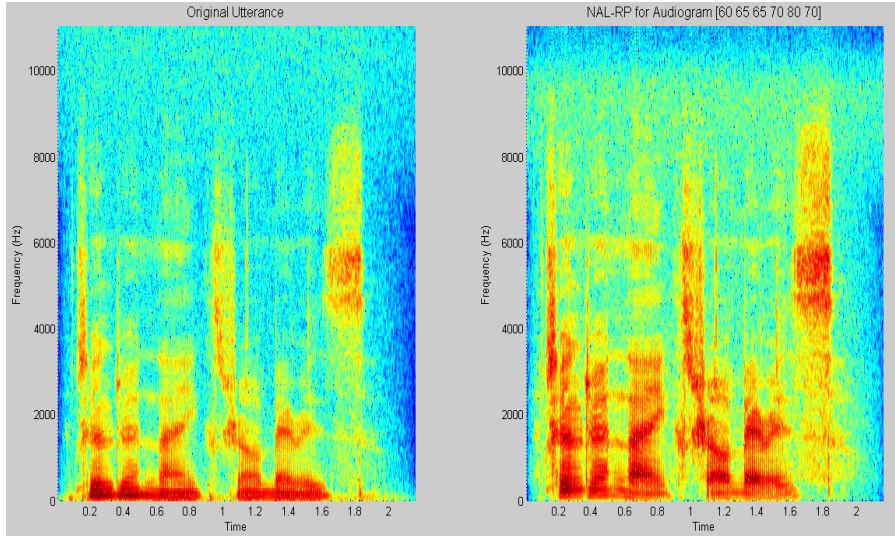
HMM-GMMs were trained using the HMM Toolkit (Young et al., 2002)

Hearing Aid Algorithms

➤ Two hearing aids algorithms were used in the study, namely:

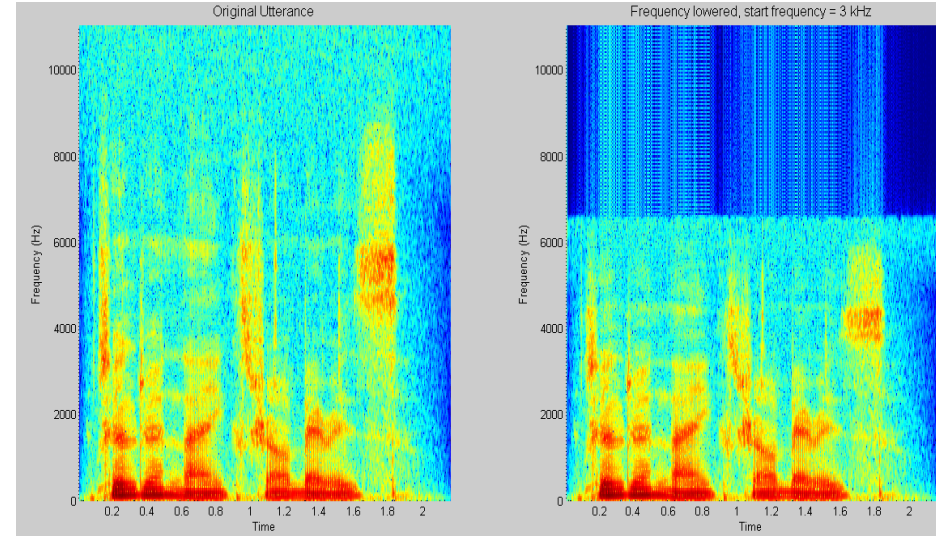
- NAL-RP (National Acoustic Laboratory - Revised Profound)
 - This is a linear algorithm that uses the audiogram to calculate the gain at specific frequency bands to maximised speech intelligibility at levels preferred by the hearing aid wearer (Byrne, 1991)
- SED (Spectral Envelope Decimation) Frequency Lowering Algorithm
 - The SED is a frequency lowering algorithm that moves high frequency sounds into lower frequency regions. This is achieved by decimating by two the amplitude spectrum of each frame from a start frequency and end frequency; the phase at each frequency remains the same (Alexander et al., 2014).

Spectrograms of NAL-RP and SED HA Algorithms Processing



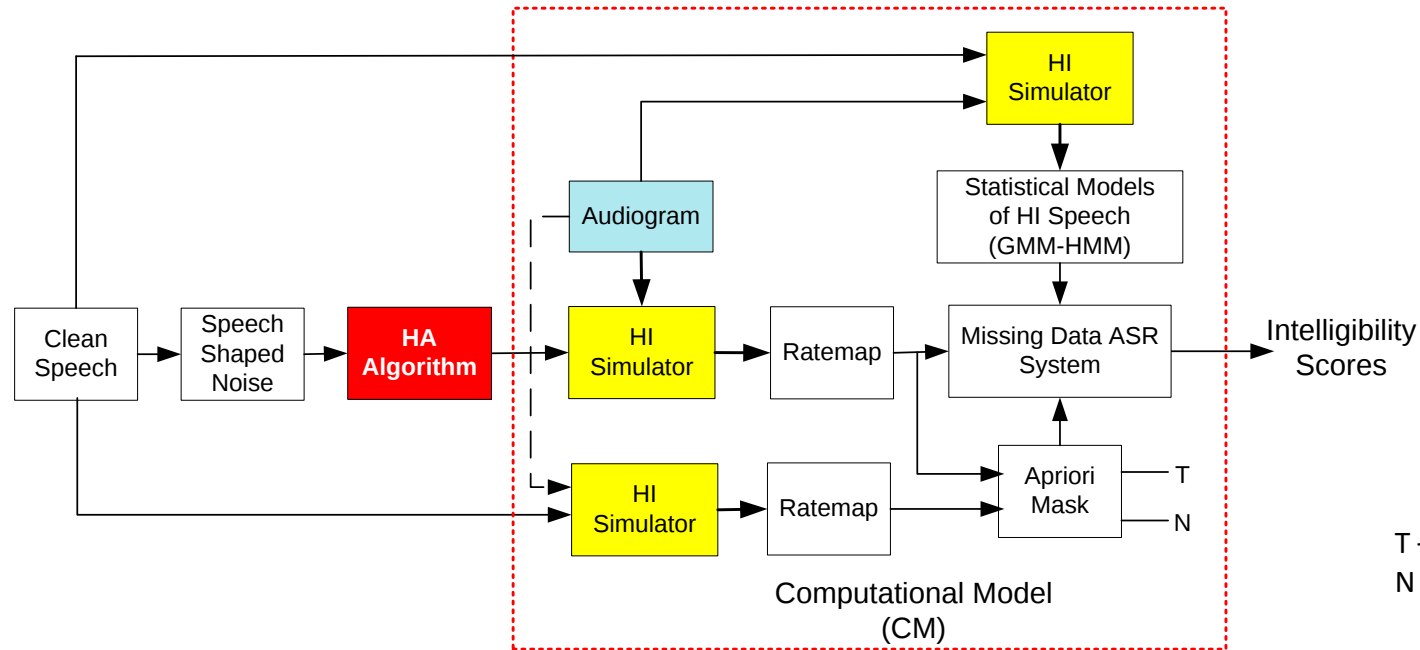
Spectrograms showing original utterance (left panel) and utterance processed by NAL-RP (right panel)

Audiogram [60 65 65 70 80 70]



Spectrograms showing Original utterance (left panel) and linear frequency utterance (right panel). Start frequency of 4 kHz and end frequency of 10 kHz;

The Novel Computational Model



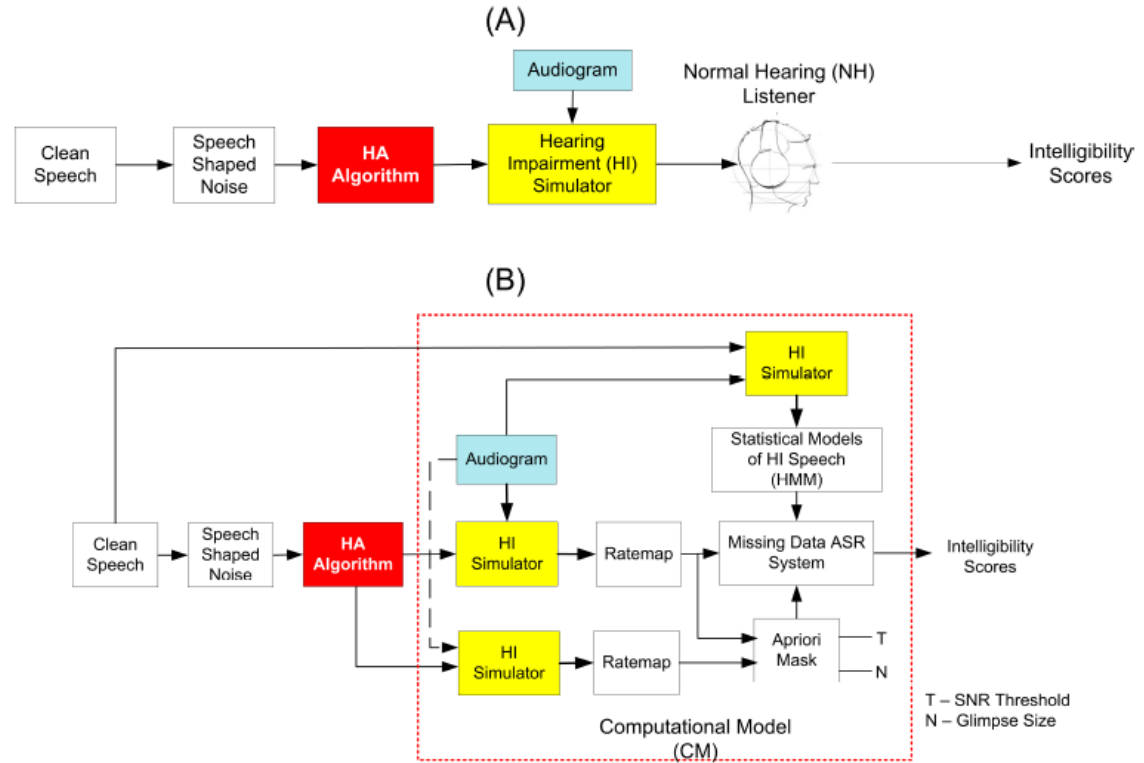
Experiment with Listeners and the Model

Twenty (20) Normal-Hearing Listeners with hi1 and hi2 simulated hearing impairment participated in experiments.

The tasks of the listeners and model were to identify the letters and digits heard in the utterances.

HA Algorithms used

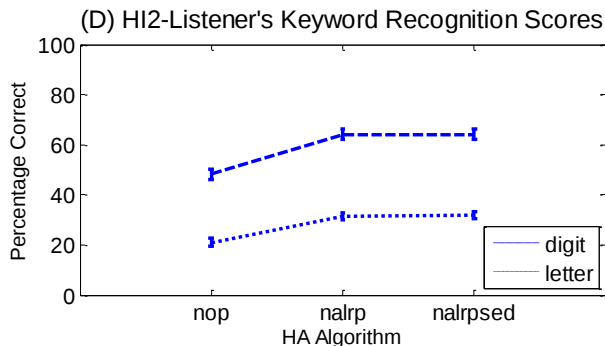
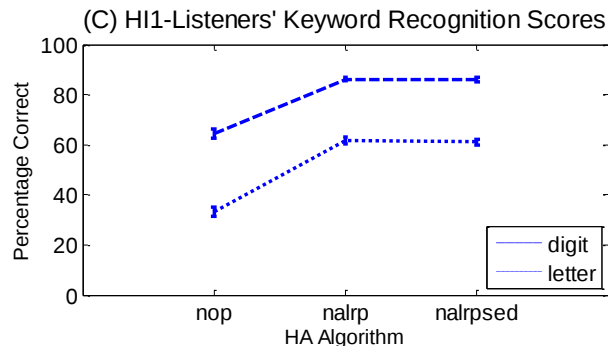
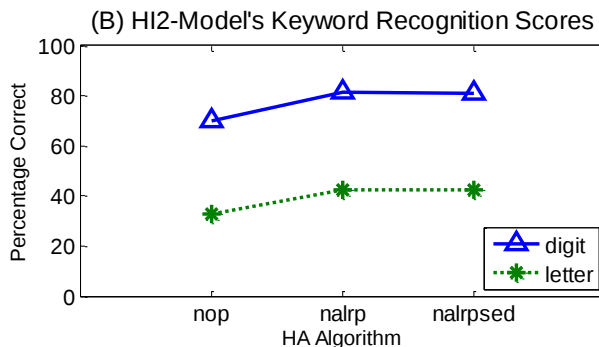
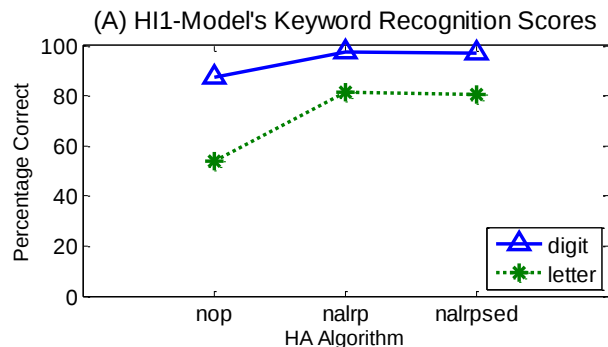
- No processing (NOP)
- NALRP
- NALRPSED (NALRP + SED)



RESULTS

Using Listener's Results to Validate the Model's Performance

Average Keyword Intelligibility Score using different HA algorithms



Correlation Results

Model Vs Listener - Digits

HI1: $r = 0.9994$ (p-value = 0.0226)

HI2: $r = 0.9987$ (p-value = 0.0324)

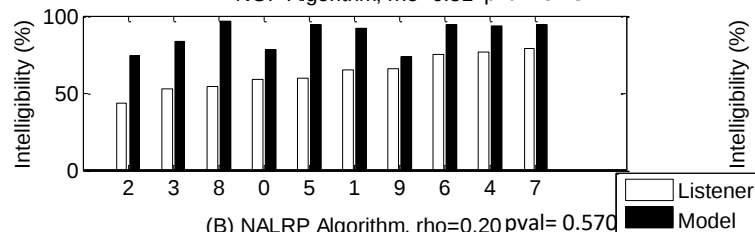
Model Vs Listener - Letters

HI1: $r = 0.9997$ (p-value 0.0148)

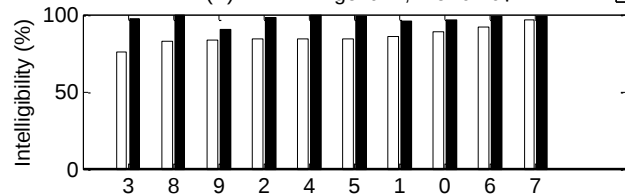
HI2: $r = 0.9986$ (p-value = 0.0332)

Predicting Digits Intelligibility

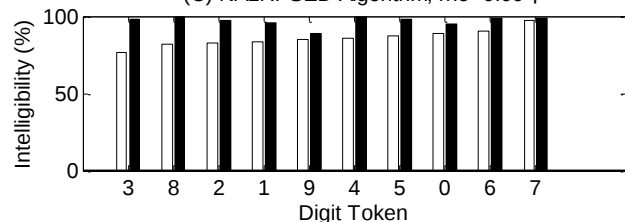
(A) Listeners Vs Model - Digit Intelligibility Scores using HI1 processing
NOP Algorithm, $\rho=0.51$ $pval=0.131$



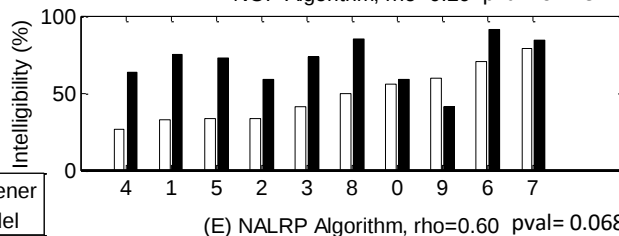
(B) NALRP Algorithm, $\rho=0.20$ $pval=0.570$



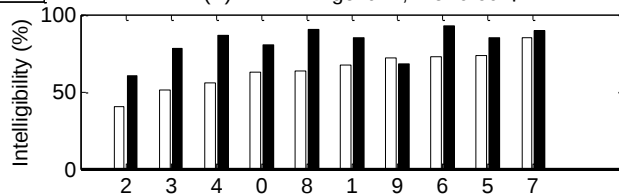
(C) NALRPSED Algorithm, $\rho=0.09$ $pval=0.8$



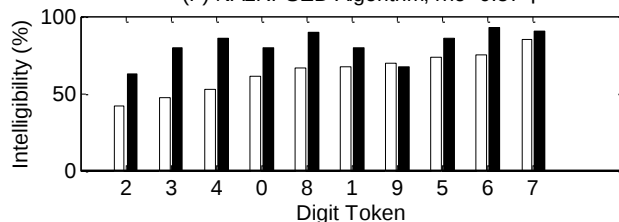
(D) Listeners Vs Model - Digit Intelligibility Scores using HI2 processing
NOP Algorithm, $\rho=0.29$ $pval=0.423$



(E) NALRP Algorithm, $\rho=0.60$ $pval=0.068$

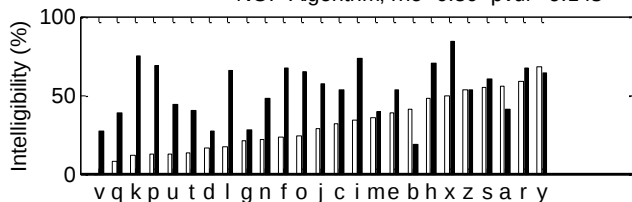


(F) NALRPSED Algorithm, $\rho=0.57$ $pval=0.086$

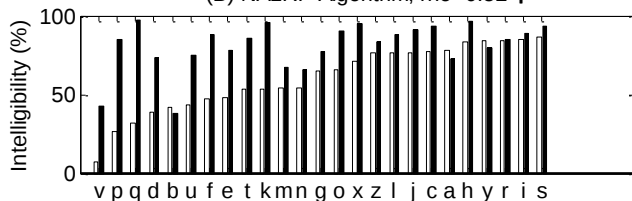


Predicting Letters Intelligibility

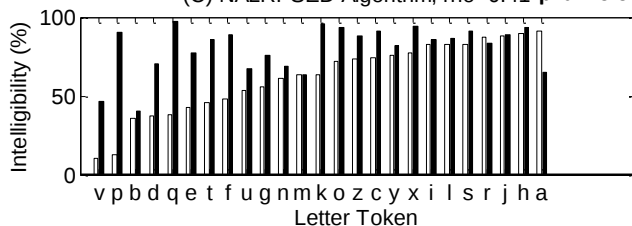
(A) Listeners Vs Model - Letter Intelligibility Scores using HI1 processing
NOP Algorithm, $\rho=0.30$ $pval=0.145$



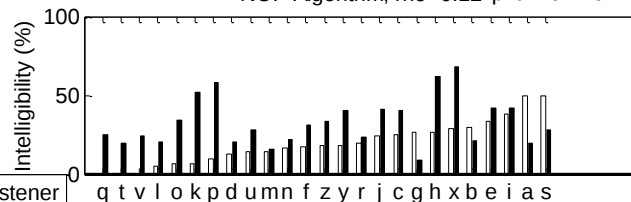
(B) NALRP Algorithm, $\rho=0.52$ $pval=0.008$



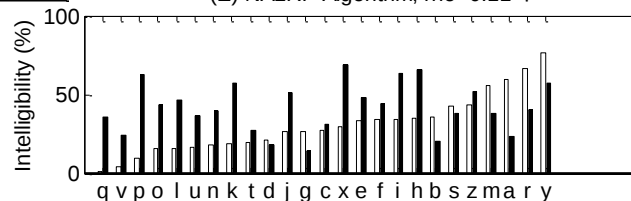
(C) NALRPSED Algorithm, $\rho=0.41$ $pval=0.045$



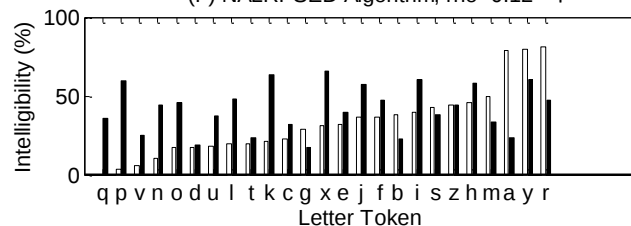
(D) Listeners Vs Model - Letter Intelligibility Scores using HI2 processing
NOP Algorithm, $\rho=0.12$ $pval=0.116$



(E) NALRP Algorithm, $\rho=0.11$ $pval=0.617$



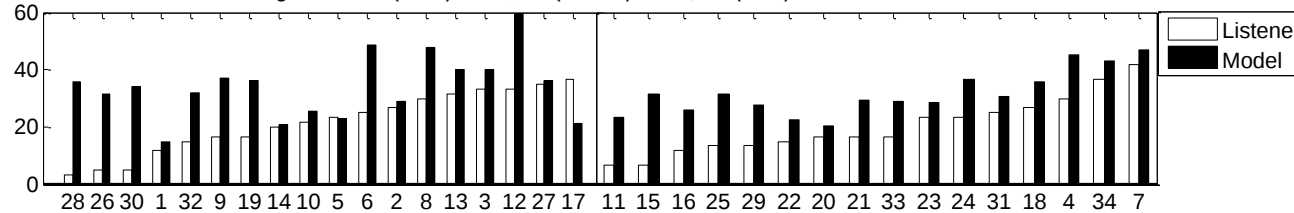
(F) NALRPSED Algorithm, $\rho=0.12$ $pval=0.552$



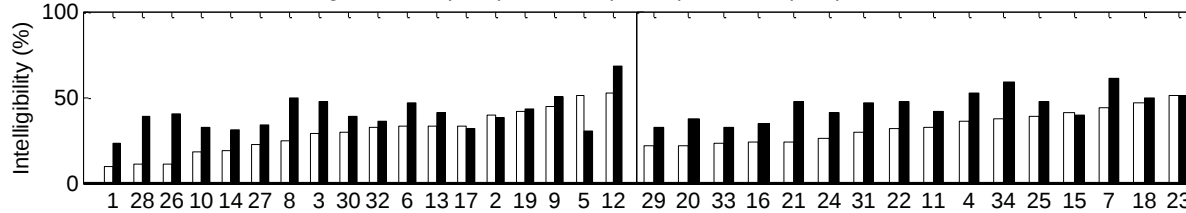
Predicting Individual Speaker Intelligibility

Listeners Vs Model - Female and Male Speakers Intelligibility Scores with H12 processing

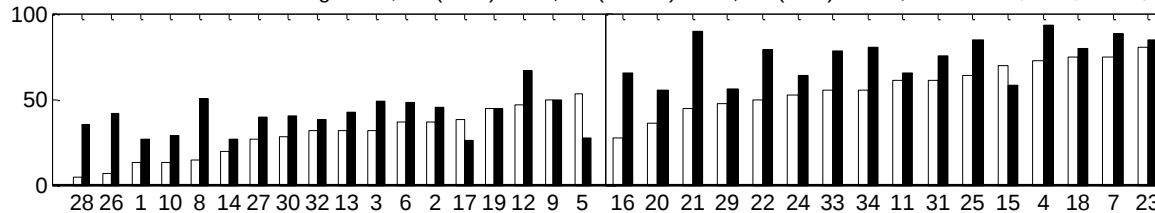
NOP Algorithm, $\rho(\text{male})=0.29$; $\rho(\text{female})=0.82$; $\rho(\text{both})=0.49$ pval= 0.2366 (male), **0.0001 (Female)**



NALRP Algorithm, $\rho(\text{male})=0.50$; $\rho(\text{female})=0.69$; $\rho(\text{both})=0.58$ pval= **0.036 (male)**, **0.0031 (Female)**



NALRPSED Algorithm, $\rho(\text{male})=0.32$; $\rho(\text{female})=0.49$; $\rho(\text{both})=0.40$ pval= 0.194 (male), **0.05 (Female)**



Discussion

- Using Pearson correlation of listeners' and model's results with NOP, NAL-RP and NAL-RP + SED HA algorithms, and hi1 and hi2 simulated hearing impairments. Statistical significant results were obtained for the following intelligibility measures:
 - Average Keyword Intelligibility – For all HA algorithms and hi1 and hi2 simulated HI.
 - Letter Intelligibility – Using NALRP and NALRP-SED for hi1 simulated HI.
 - Speaker Intelligibility – Using NALRP and NALRP-SED for male and female speakers using hi2 HI.
- The model successfully predicted the improvement in the intelligibility of keywords using NAL-RP HA algorithm.
- No noticeable improvement was detected using the SED HA algorithm, for both listeners and model.

Conclusion and Further Work

➤ The model's deviation from human performance may be related to:

- The listeners may need more time to adjust to the new speech signals.
- GMM-HMM has an inherent weakness in modelling speech signals because of its independence assumption between feature vectors and its inability to model the fine structure of the speech signal.
- Require longer listening test so that listeners hear more keywords from a particular speaker using a specific HA algorithm. This may improve the prediction of individual keywords and speakers intelligibility.

➤ Future work

- Use Deep Neural Network and HMM (DNN-HMM) or Recurrent Neural Networks (RNN) to implement the ASR system in the computational model.
- Use listeners with real sensorineural hearing impairment.

Acknowledgements

➤ Primary Supervisor

- Dr Andre Coy, University of the West Indies, Jamaica

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➤ Research Advisor

- Dr Paul Aiken, University of the West Indies, Jamaica



The University
of the West
Indies



The
University
Of
Sheffield.



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Thank you!

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