EXPLORATORY ANALYSIS OF SPEECH FEATURES RELATED TO DEPRESSION IN ADULTS WITH APHASIA

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Background

Aphasia is an acquired communication disorder resulting from brain damage and impairs an individual’s ability to use, produce, and comprehend language. Loss of communication skills can be stressful and may result in depression, yet most depression diagnostic tools are designed for adults without aphasia. This project is a research effort to examine acoustic profiles of adults with aphasia who have been assessed as having possible depression based on tools completed by their caretakers.

Data Collection

Recording Material:
- 2 Picture Descriptions
- Speech components of the Western Aphasia Battery Protocol¹

Data Analyzed:
- 14 Participants selected:
  - 6 female, 8 male
  - 50% depressed from each gender
  - Balance participants based on gender and depression label
  - Used only phrase responses
  - 33 utterances per person

Participant Characteristics

Age
Gender
Aphasia Type (WAB)¹
Aphasia Quotient (WAB)¹
Depression (SADQ)²
Dysarthria (FDA-2)³
Apraxia (ABA-2)⁴
Stress
Mood

Characteristics of Speech

Feature Extraction and Classification

Pre-Processing
- Segment recordings into individual responses
- Voiced Speech Detection

Feature Extraction
- Pitch + Jitter
- Root Mean Square (RMS) Energy
- Harmonic-to-Noise Ratio (HNR)
- Cepstral Peak Prominence (CPP)
- Mel-Frequency Cepstral Coefficients (MFCC)
- Line Spectral Frequencies (LSF)

Experiment Setup in Weka
- Feature Selection
- Leave-one-participant-out train/test sets

Results and Discussion

Table 1: Classification results by feature subtype in assigning the correct depression label to each utterance. All categories except ‘All’ are based on the reduced feature subset after feature selection.

<table>
<thead>
<tr>
<th>Features (no. of features)</th>
<th>Avg. Recall</th>
<th>Avg. Precision</th>
<th>Avg. Accuracy (standard dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All (874)</td>
<td>0.359</td>
<td>0.411</td>
<td>0.422 (0.264)</td>
</tr>
<tr>
<td>Reduced (41)</td>
<td>0.459</td>
<td>0.447</td>
<td>0.446 (0.325)</td>
</tr>
<tr>
<td>Pitch + Jitter (7)</td>
<td>0.394</td>
<td>0.399</td>
<td>0.400 (0.303)</td>
</tr>
<tr>
<td>RMS-Energy (8)</td>
<td>0.814</td>
<td>0.487</td>
<td>0.478 (0.478)</td>
</tr>
<tr>
<td>HNR (10)</td>
<td>0.545</td>
<td>0.472</td>
<td>0.468 (0.311)</td>
</tr>
<tr>
<td>CPP (6)</td>
<td>0.563</td>
<td>0.634</td>
<td>0.619 (0.190)</td>
</tr>
<tr>
<td>MFCC+delta (19)</td>
<td>0.432</td>
<td>0.588</td>
<td>0.502 (0.349)</td>
</tr>
<tr>
<td>LSF+delta (20)</td>
<td>0.308</td>
<td>0.286</td>
<td>0.374 (0.246)</td>
</tr>
</tbody>
</table>

References


Acknowledgements

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