

A Multimodal Corpus of Expert Gaze and Behavior during Phonetic Segmentation Tasks

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Abstract

Phonetic segmentation is the process of splitting speech into distinct phonetic units. Human experts routinely perform this task manually by analyzing auditory and visual cues using analysis software, which is an extremely time-consuming process. Methods exist for automatic segmentation, but these are not always accurate enough. In order to improve automatic segmentation, we need to model it as close to the manual segmentation as possible. This corpus is an effort to capture the human segmentation behavior by recording experts performing a segmentation task. We believe that this data will enable us to highlight the important aspects of manual segmentation, which can be used in automatic segmentation to improve its accuracy.

Keywords: eye tracking, gaze analysis, manual segmentation behavior

1. Introduction

Speech segmentation is the process of splitting the acoustic speech signal into distinct units by placing timestamped boundaries. This forms a crucial data processing step for phonetic analysis, as well as speech technology applications such as text-to-speech synthesis and automatic speech recognition. The results and output quality depend on accurately segmented speech data.

Speech segmentation can be done manually, using specialized software, e.g., *Praat* (Boersma, 2001), *Wavesurfer* (Beskow and Sjölander, 2000), *ELAN* (Sloetjes and Wittenburg, 2008), and *EMU webapp* (Winkelmann and Raess, 2014). In this workflow, a speech recording is displayed as a waveform and/or spectrogram, and boundaries are inserted using the mouse or keyboard (cf. Figure 2). Short audio segments can be played back to validate the boundary placement. This process is repeated till the whole audio file is segmented. Manual segmentation by experts is the best phonetic segmentation one can achieve for any given data (Svendsen and Soong, 1987; Wesenick and Kipp, 1996). One reason for this is because they combine experience with multiple sources of information. However, there are some critical drawbacks of manual segmentation which makes it impractical for large speech data. The first one is that it is very laborious and time consuming; on average, manual segmentation can take up to 30 s per phone (Stolcke et al., 2014; Leung and Zue, 1984) to segment. As a result, newly recorded speech data cannot be used quickly if manual segmentation is desired. Secondly, the exact placement of boundaries is subjective, and there may be disagreement between multiple experts.

The second method of segmentation is doing it automatically, by training a model on the audio data, and then using it to segment speech. In this method, the accuracy of the segmented speech directly depends on the quality of the trained model which itself depends on the quality

of training data. People have used different approaches for automatic segmentation. For a long time, researchers have used hidden Markov models (HMMs) for automatic segmentation (Toledano et al., 2003; Juang and Rabiner, 1991; Rabiner, 1989; Brognaux and Drugman, 2016). Others have used neural networks for automatic segmentation (Karjalainen et al., 1998; Schwarz et al., 2006). One commonality of these approaches is the use of only audio for input features; for training the model, the audio is processed to extract acoustic features from it, which are then used for training the model. The most commonly used features are mel-frequency cepstral coefficients (MFCCs) (Logan, 2000) and Perceptual Linear Prediction (PLP) (Hermansky, 1990). While the use of only audio for model features produces acceptable results for most segmentation requirements, humans use more than audio for segmenting speech. To improve automatic segmentation, we therefore want to add more modalities to model it as closely as possible to the manual segmentation. We hope that in this way the modeling of automatic segmentation will produce better results.

To this end, we first need to analyze the human segmentation behavior and highlight the key information sources that humans experts use to segment speech. To the best of our knowledge, this is the first corpus that records the human segmentation in such a setup. Our data includes gaze information, which shows where the humans look on the screen, the audio to which the experts listen during segmentation, video of the expert from a webcam attached to the monitor, and a screen recording of what they are viewing.

The rest of the paper is organized as follows. In Section 2, the details of how the data was recorded is provided along with the format and structure. In Section 3, we show the results of some experiments conducted on the data. Finally, the conclusion and future use of the data is mentioned in Section 4.

2. The Corpus

In order to study the behavior of human experts during speech segmentation tasks, we designed and recorded the multimodal corpus described in this section.

2.1. Preparation

We recorded a native speaker of Scottish English, reading the standard passage, “The North Wind and the Sun” (International Phonetic Association, 1999). The recording was made in a sound-attenuated booth, with a close-talking microphone, sampling at 48 kHz with 24 bit quantization. The resulting file has a duration of 46 s.

2.2. Data Collection

We recorded seven subjects, with the instruction that they were to segment (but not label) the recording into phones. All of the subjects who participated in the data collection are trained phoneticians with varying amounts of experience; details are given in Table 1.

The participants took different amounts of time (44 to 96 min) to complete the task. The normalized session duration for all the subjects is shown in Figure 1. We did not control the speed in which the participants completed the task, so each took time according to his or her preference, which resulted in different session durations.

For each subject we first calibrated a Tobii TX300 eye-tracker,¹ and then used it to capture where the subject looked on the computer screen during the entire session, at a sampling rate of 120 Hz. Using the *TobiiStudio* software, we also recorded the screen content itself (at a resolution of 1920 × 1200 pixels), as well as any audio the subjects played back from the recording during the segmentation task. In addition to the gaze information and screen recording, *TobiiStudio* also allowed us to log any keystrokes and mouse clicks during the recording session, as well as the video from a webcam facing the subject, at a resolution of 640 × 480 pixels. The screen capture and webcam were intended to validate the subjects’ head movements and input device logging.

In addition to these modalities, we polled the application state of the Praat GUI, once per second, in order to log the zoom level of the audio recording shown and other application-specific data. Finally, the segmentation itself, produced by each subject over the course of the session, was also saved as a TextGrid.

2.3. Data Processing

After each recording session, the logs from *TobiiStudio* and Praat were exported to ASCII text files and compressed. The screen recordings and webcam videos, as well as the audio playback recordings, were exported from *TobiiStudio* in ASF containers, in TechSmith Screen Capture Codec (TSCC), Microsoft Video 1, and MP3 format, respectively, the latter at 22 kHz and 16 bit quantization, at a bitrate of 128 kbit/s.

In order to manipulate the multimedia streams from each recording session more efficiently, we first converted the

video to H.264 format (which allowed more robust seeking and reduced the file sizes – from 52 GB to 3 GB without noticeable loss in quality), transcoded the audio to FLAC format,² and multiplexed all three streams into single Matroska video containers,³ using FFmpeg.⁴

Next, we parsed the Praat logs to identify time segments in each recording session during which the subject was viewing the same zoom level and interval of the audio recording; doing this allowed us to treat them as quasi-static *scenes* viewed by the subject. The session times as well as the audio recording times of each scene were collected into a YAML file.

By calculating the offset between the Praat and *TobiiStudio* logs, we could then select the gaze data related to each scene and store it in a structured format, validating it via the screen recording. The resulting YAML files and multimedia streams were finally packaged and provided as a data dependency for analysis.

3. Experiments

We started our experiments by analyzing the eye tracking data. The main aim of the data corpus was to analyze the manual segmentation behavior and to identify modalities and features useful for modeling segmentation. The user interface on the screen is divided horizontally into three sections, each representing a different portion of the Praat interface. We refer to these sections as *Waveform*, *Spectrogram* and *Annotation*, as shown in Figure 2. The *Waveform* represents the signal part of the audio recording in Praat. The *Spectrogram* section represents the time-frequency representation of the signal; the x axis represents time and y axis, the frequency of the signal. The *Annotation* section is used by the subjects to place the boundaries. This is the only section which can be edited by creating and manipulating time-aligned annotations.

3.1. Fixations

One of the most important question is: *where the subjects are looking on the screen during the manual segmentation task*. To answer this question, we calculated the proportion of gazes in the three sections of the screen. Figure 3 shows the percentage of fixations in each of the three screen sections for all participants. The fixations in the *Annotation* area can be disregarded, because in order to place the boundary, the subjects have to carefully “click” in the right location and during this process, a lot of gaze activity may occur in this section. The fixations in the *Waveform* and *Spectrogram* sections are important and have a mixed pattern. All subjects have a higher number of fixations in the *spectrogram* section than in the *Waveform* section.⁵

4. Conclusion and Outlook

In this paper, we have presented a multimodal corpus of phoneticians performing a manual speech segmentation

¹<https://www.tobiiipro.com/product-listing/tobii-pro-tx300>

²<https://xiph.org/flac/>

³<https://matroska.org/>

⁴<https://ffmpeg.org/>

⁵The exception is subject 06; this may be because she had the least amount of segmentation experience (see Table 1) and relied more on the waveform section to segment.

Participant	Gender	Age (years)	Native Language	Experience (years)	Segmentation Time (min)
P01	F	26	German	7	44
P02	M	47	German	20	55
P03	M	37	German	15	73
P04	F	35	Polish	10	96
P05	F	27	German	4	71
P06	F	22	German	1.5	80
P07	F	22	German	4	92

Table 1: Age, gender, native language, and segmentation experience of the subjects who participated in the data collection

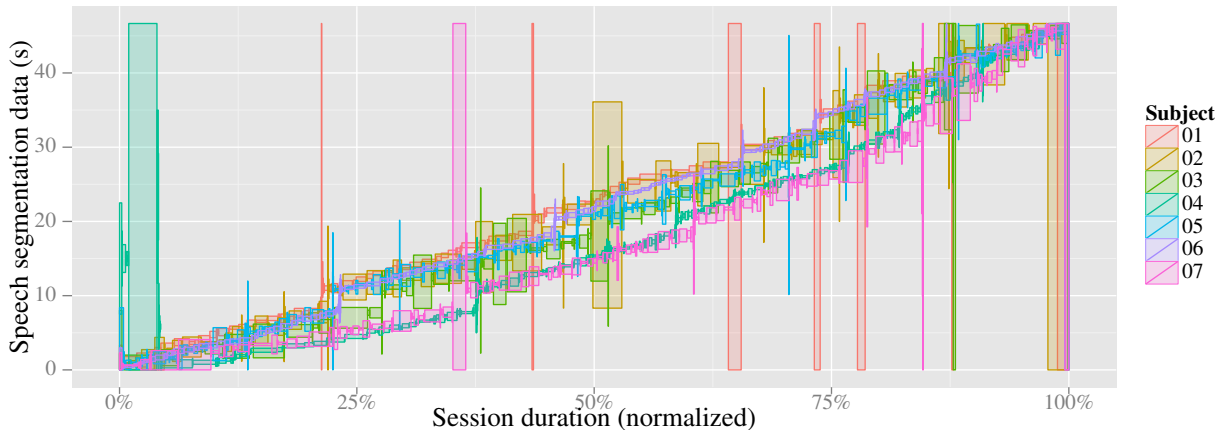


Figure 1: Speech segmentation data spans which were viewed as scenes over the (normalized) duration of the segmentation task. Each rectangle represents the portion of time (rectangle width) spent segmenting a span of recorded speech, while the rectangle height represents the duration of that span.

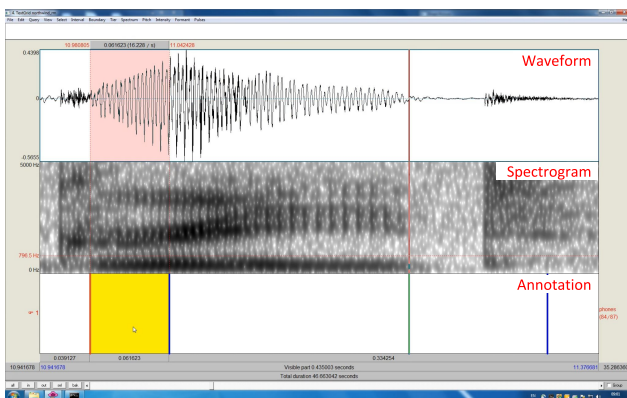


Figure 2: A screenshot of a sound recording and annotation in Praat. The screen can be split into three sections: Waveform, Spectrogram, and Annotation.

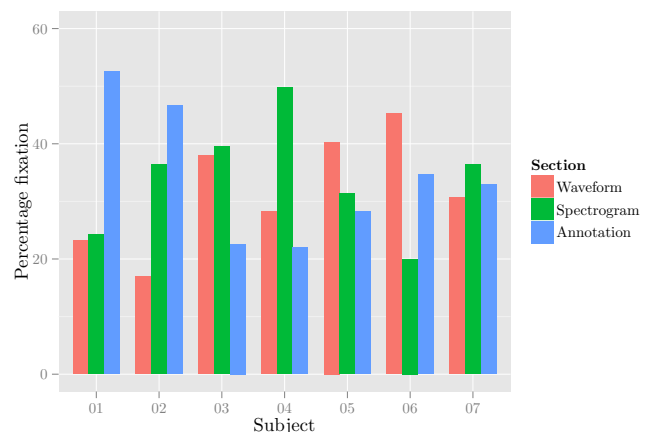


Figure 3: Average fixations for each participant in the three sections of the Praat interface.

task. All important information sources that are relevant to the segmentation task were recorded. This includes gaze data, audio, video, and screen recording. The output segmentation and the Praat log are also saved. We believe that this data will prove valuable for research in observing and understanding manual segmentation.

Moreover, this corpus will help identify critical information sources used by humans during manual segmentation, which can be modeled to improve the accuracy of automatic segmentation. In addition, this data can be useful in analyz-

ing the interaction of phoneticians with speech segmentation software (Praat) and can be used to improve the design of such software.

The processed data (cf. Section 2.3) will be released under a Creative Commons license and published on GitHub,⁶ along with the processing recipes. This public release *excludes* the webcam videos, in order to protect the privacy of our participants.

⁶<https://github.com/m2ci-msp/eyetracking-data>

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