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Author
Yao, Yao

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Closure duration and VOT of word-initial voiceless plosives in English in spontaneous connected speech

Yao Yao

Abstract

This is a corpus study on closure duration and VOT in English voiceless stops in word-initial position. 19 speakers' (10 female, 9 male) data from the Buckeye Speech corpus are used in the study. The first half of the paper introduces a novel approach of automatically finding the point of stop release in large speech database, using Mel spectral templates and similarity scores. The performance and robustness of the algorithm is discussed in detail. To our knowledge, this is also the first automatic measure of closure duration and VOT that is reported in detail in the literature. The second half of the paper studies the closure duration and VOT as calculated by the procedure described in the first half, and investigate the correlation between these durations and a number of linguistic and extra-linguistic factors.

1 Introduction

Voice onset time (VOT) is a well-studied topic in phonetics. It has been shown that VOT in voiceless stops varies with a number of factors, among which the most established one is place of articulation. Zue (1976), Crystal and House (1987), and Byrd (1993) all find longer VOT for velars compared to labials and alveolars in connected read speech. Additionally, Crystal and House (1987) and Byrd (1993) both find that alveolars have on average longer releases than bilabials. In other words, the release duration increases as the point of contact moves from the lips to the velum. Cho and Ladefoged's (1999) cross-linguistic study of 18 languages suggests that this rule might be universally true.

In recent years, more and more studies have focused on the relation between VOT and other possible correlates. Roughly speaking, the proposed correlates can be divided into two categories, speaker-related and non-speaker-related. The most widely-studied speaker-related factors are gender, age, speaking rate, lung volume, and individual talking style. In addition to place of production, other non-speaker-related factors include phonetic context, word frequency, and laboratory environmental setting.

1.2 VOT and gender

Whiteside and Irving (1998) studied 36 isolated words spoken by 5 men and 5 women, all in their twenties or thirties, and showed that the female speakers had on average longer VOT for voiceless plosives than the male speakers, and the results were corroborated by several other studies (Koenig 2000, Ryalls et al. 1997, Whiteside and Marshall 2001, Robert et al. 2005, among others). Whiteside et al (2003) reported a developmental study on 5 groups of 46 boys and girls aged 5;8 (5 years, 8 months) to 13;2, all of whom were British English speakers, and the study suggested that sex differences in VOT, in the same form as found for adults, started to appear well before adolescence. The factors that contribute to the sex differences in VOT have not been fully studied, but it has been suggested that physiological and anatomical differences, as well as sociophonetic factors could at least partially account for the observed differences. However, it should be noted that there are also studies which report no significant sex differences found in VOT, e.g. Ryalls et. al (2002) (see the discussion in 1.3) and Syrdal (1996).

1.3 VOT and age

Petrosino et al's 1993 study on velar stop production in aged speakers found no significant differences in mean VOT of [k] and [g] across the three vowel contexts between two age groups, though differences in VOT variability (standard deviation) approached significance. Similarly, a study conducted by Neiman et al in 1983 on VOT in young and 70-year-old women found that VOT was generally the same in the two age groups, and it was only in certain phonetic contexts that older subjects demonstrated significantly shorter VOT.

However, Ryalls et al (2002) found significant age differences in VOT for English voiceless plosives. They replicated an earlier study (Ryalls et al. 1997) on younger speakers among older speakers. The earlier study found significant effects of gender and race on VOT in younger speakers, but the 2002 study found no significant effects of gender or ethnicity in older speakers. Interestingly, significant differences were found between the average VOT of the two age groups as older subjects' VOT's are consistently shorter than those of younger subjects (with the difference ranging from 12 ms to 20 ms for [p], [t], [k]). It was also found that the average syllable duration of older subjects, on the other hand, exceeded that of younger speakers by about 100 ms, which was counter-intuitive since a lower speaking rate ought to yield a longer VOT (the relation between VOT and speaking rate will be discussed in 1.4). A tentative explanation was the smaller lung volumes on the part of older speakers. But it is worth noticing from this study that aging might also affect VOT in an indirect way, by masking the effect of other factors, such as gender and race.

1.4 VOT, speaking rate and individual talker differences

VOT is found to be negatively correlated with speaking rate and the correlation is highly significant, especially for voiceless stop consonants (Kessinger and Blumstein 1998, Volaitis and Miller 1992). This is not surprising at all, since, intuitively, as a speaker slows down the speaking rate, all the phonetic segments would be stretched and therefore they should all show an increase in duration. Allen et al (2003) reported a study in which four female speakers and four male speakers were recorded saying a list of 18 monosyllabic English words beginning with voiceless stops. The results showed that 82% of the total variability was attributable to differences among talkers in overall speaking rate, while 43% of the remaining variability (or 8% of the total variability) was explained by individual talker identity, leaving 57% unexplained (i.e. true error). Meanwhile, intrinsic word duration (mostly due to the different vowels) was found to have no significant effect on VOT.

1.5 VOT and lung volume

Hoit et al (1993) found in a study of five adult male speakers that VOT was longer when produced at high lung volumes and shorter when produced at low lung volumes in most cases, which pointed out the need to take lung volume into account when studying the correlation between VOT and other factors. As mentioned above, Ryalls et al. (2002) considered relatively low lung volumes in older speakers as the main reason for their shorter VOT's compared to younger speakers.

1.6 VOT and other speaker-related factors

Other factors such as ethnic background (Ryalls et al. 1997), dialectal background (Schmidt and Flege 1996, Syrdal 1996), presence of speech disorders (Baum and Ryan 1993, Ryalls et al 1999), and hormone levels in female speakers (Whiteside et al. 2004b) have also been studied, but no convincing correlations have been established.

1.7 VOT and non-speaker-related factors

The most important non-speaker related factor is place of articulation. As mentioned in the beginning, it is widely acknowledged that VOT in English voiceless stops increases as the contact point moves from the lips to the velum. The other non-speaker factor that is often mentioned in the literature is the phonetic context, or more specifically, the following vowel. However, previous literature presents a split in opinion with regard to this point. Since most of the previous studies involving VOT are based on VOT values in syllables across different vowel types (most typically including the three extreme vowels, [a], [i], and [u]), many of them have reported that certain trends are only observed in certain vowel setting (Whiteside et al. 2004a, Neiman et al. 1983, etc). Nonetheless, as mentioned above in 1.4, Allen et al (2003) reported no significant effects of phonetic contexts on VOT.

Robb et al (2005) reported that the subjects produced longer VOT in a laboratory-setting than in a non-laboratory-setting, which suggested that environmental setting might have an effect on speech style, which in turn would affect the length of VOT.

1.8 Closure duration

Compared to the large literature on VOT in English, not many studies have investigated the closure duration. Zue (1976) found longer closure portions for [p] than [t] and [k]. However, Crystal and House (1987) reported that the duration of closure in alveolar stops are slightly but consistently shorter than that of bilabials and velars, while bilabials and velars are very similar in closure durations. Byrd's (1993) report on stops in TIMIT, on the other hand, supports Zue's finding of longer closure portions for [p].

1.9 Current study

In the broad literature on English VOT and its correlation with other factors, a wide range of speakers were studied, however, most of the studies relied on data from specifically designed lab experiments, usually in the form of reading word lists or producing target syllables in a carrier phrase. Therefore, these studies typically have a small pool of target syllables, a relatively low variability in phonetic context, as well as a small set of subjects. The only two exceptions are Byrd (1993) and Crystal and House (1987), both of which studied VOT in (read) connected speech corpus. The TIMIT corpus that Byrd studied in Byrd (1993) contains 2,342 different sentences read by 630 speakers (ten sentences per speaker). Crystal and House (1987) studied the readings of two scripts (totaling approximately 600 words) by 14 speakers.

The current study uses data from the Buckeye speech corpus (Pitt et al., 2005). The corpus was developed at Ohio State University (http://www.buckeyecorpus.osu.edu/), and consists of recordings of spontaneous speech of 40 speakers, all long-time local Ohio residents. The Buckeye Corpus is orthographically transcribed and phonetically labeled. However, it is not labeled for the point of release in stops. Thus the first half of this paper (mostly the methodology section) will introduce and discuss the technical details of a novel approach for automatically finding the point of release in voiceless stops. The second half of the paper is devoted to the discussion on the distribution of closure duration and VOT both inter- and intra- speakers and how they correlate with the following five factors: place of articulation, age, gender, speaking rate, and word frequency.

2. Methodology

2.1 Buckeye Corpus

The Buckeye Corpus contains recordings from 40 speakers (20 male, 20 female, 20 young – under 30, 20 old – over forty) in Columbus OH conversing freely with an interviewer. All speakers are Caucasian, long time local residents of Columbus. Each speaker was being interviewed for about an hour, not knowing the research purpose of the interview until the recording was done. The speech style was unmonitored casual speech. The acoustic signal was digitally recorded in a quiet room with a close-talking head-mounted microphone. Currently the recordings of 20 talkers (10 male, 10 female, 10 young, 10 old) have been transcribed and phonetically labeled. The data from all but one of these speakers are used in this study. A young male speaker's data were not included due to an inconsistency in the label files.

Two types of phonetic labeling are used in the corpus: word labeling and phone labeling. At the word level, an utterance of a word is stored with both the spelling form and the actual pronunciation, as well as a timestamp indicating the end of the word; at the phone level, each phone – an actual sound uttered by the speaker, not necessarily a sound in the citation form of the uttered word – is stored with the phone name and a timestamp indicating the end point of the phone. In addition, since labeling is done in an exhaustive way, i.e. every point in the recording has a corresponding label in the label files, there are also labels that represent non-linguistic sounds, including silence, noise, laughter, and interviewer sounds (interviewer's speech is not recorded or transcribed). Silence in a running speech flow of the speaker is not transcribed as silence, but attributed to the neighboring sounds.

The current study uses the data of 19 (out of 20) speakers whose transcription and label files are available. Table I shows the basic information of these speakers, as well as their coded names in this study.

Coded name in the Buckeye corpus	Coded name in the current study	Gender	Age (Y-young, O-old)
S02	F01	F	O
S03	M01	M	O
S04	F02	F	Y
S10	M02	M	O
S11	M03	M	Y
S12	F03	F	Y
S13	M04	M	Y
S14	F04	F	O
S15	M05	M	Y
S16	F05	F	O
S17	F06	F	O
S20	F07	F	O
S21	F08	F	Y
S22	M06	M	O
S24	M07	M	O
S25	F09	F	O
S26	F10	F	Y
S32	M08	M	Y
S33	M09	M	Y

Table I Speaker information

2.2 Material for this study

The target words for this study are words that are uttered with voiceless plosives in the initial position. It should be noted that we are looking at words that have [p], [t], [k] in the initial position in the phonetic transcription, which might not agree with the pronunciation of the citation form. Besides, since it is impossible to tell where the closure portion starts in an utterance-initial [p], [t], or [k], all utterance-initial target words will not be included in the study of closure duration. Table II shows the number of target words in each speaker. N_t is the total number of target words; $N_{non\text{-}utterance\text{-}initial}$ is the number of target words that are not utterance-initial.

	F01	F02	F03	F04	F05	F06	F07	F08	F09	F10
N_t	674	572	777	900	1243	490	231	449	699	412
$N_{non\text{-}utterance\text{-}initial}$	642	497	743	860	1136	453	217	391	639	363

	M01	M02	M03	M04	M05	M06	M07	M08	M09
N_t	564	1027	784	865	724	512	636	618	718
$N_{non\text{-}utterance\text{-}initial}$	514	931	624	793	657	406	541	557	628

Table II Count of target words in each speaker

2.2 Finding point of release

To our knowledge, there has not been much report on automatic measure of VOT in the literature. (Niyogi and Ramesh (1998) used an energy differential operator to automatically locate the point of burst, but didn't provide an error analysis.) In this section, we will discuss the use of similarity scores for automatic air burst detection in detail.

The Buckeye Corpus is hand-labeled only to the level of phones, so there is no information on the stop release in the label files. Therefore the first task is to find the point of release for the initial stop in each target case. A novel similarity scoring approach is utilized in the task. This approach was first introduced by Johnson (2006), as an attempt to automatically analyze large speech corpora in a speaker-independent way. The approach involves two steps. The first is to develop a set of phonetically meaningful templates for each speaker. To do this, a set of steady-state phones are first chosen as representing phonetically-important features (e.g. [s] represents energy in high frequencies while [sh] represents energy in lower frequencies), and a Mel spectral template is derived for each phone in the set by averaging over the Mel spectra at mid-point of all "long" examples (greater than median duration) within the same speaker. The second step is to measure the degree of similarity between a given chunk of acoustic data and each phone template. The higher the similarity score to a certain phone template is, the more similar that chunk of acoustic data is to the related phone (or the more likely it is for the acoustic data to have the phonetic feature that is represented by the phone). If one applies this step to a complete audio file, the end product would consist of a series of time-dependent similarity scores for each template. In other words, at each time point, there is a corresponding similarity score vector indicating how similar the acoustic data around this time point are to each phone template.

2.2.1 Feature templates

The criteria that we used to select phones for making templates are (i) they need to have a steady-state spectrogram, and (ii) they should be as independent from each other as possible, so that the entropy in the similarity score vector can be maximized. In fact, the second criterion is also part of what we mean by "phonetically meaningful". In the current study, the following 12 sounds are chosen to have templates: [f], [s], [sh], [h], [r], [n], [iy], [ae], [aa], [uw], [eh], and silence. The template for silence is acquired by averaging over the Mel spectra of which the containing time intervals are labeled as silence in the label files. The details of developing templates are presented below.

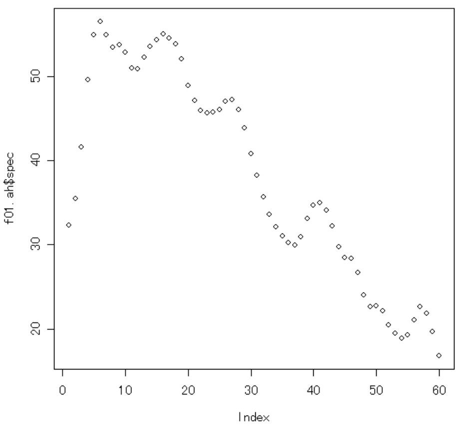
For each phone chosen, first, find all instances of the phone in the speaker, and get the medial phone duration. Second, disregard all instances with a shorter duration than the medial duration value (which would exclude half of the instances). Third, for each remaining instance, calculate a Mel frequency spectral vector using a 20 ms analysis window centered at the center of the phone and store the vector in a 60-bin array. This is done by the following XWAVES command:

(1) fft –z –wHamming –l$w –r$s:+$w-1 –o10 - - | melspec –n60 - -| pplain –fre_spec_val -

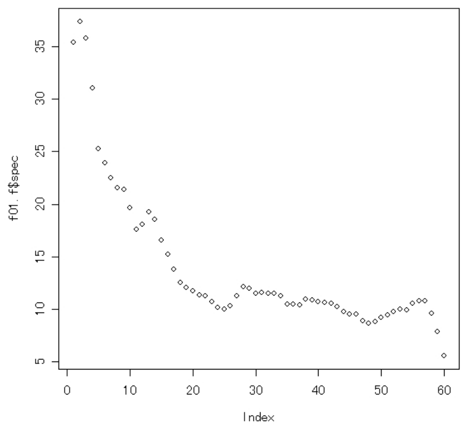
where $w is the variable that stores window size, and $s stores the starting point of the analysis window

Last, average over the Mel spectral vectors calculated in the previous step. The final template consists of an average spectral vector of 60 dimensions, as well as the standard deviation of each dimension.

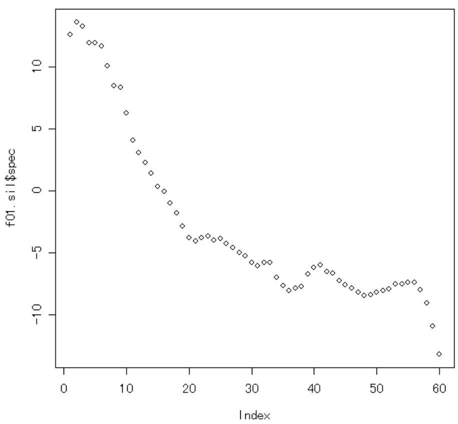
The spectral templates of some selected phones ([a], [f], and silence) of speaker F01 are shown below in Figure 1.



1a



1b



1c

Fig. 1a is the spectral template for [a]; Fig. 1b is the spectral template for [f]; Fig. 1c is the spectral template for silence. The X-axis represents 60 equidistant bins on the Mel scale from 0 to 8000. All figures are made by speaker F01's data.

2.2.2 Similarity Scores

A similarity score measures how similar the current frame (window size=20ms) is to a spectral template by comparing the Mel spectral vector of the current frame to the average Mel spectral vector of the template. The Mel spectral vector of the current frame is computed using the XWAVES commands in (1). If the current acoustic data is longer than 20ms, a similarity score will be calculated every 5ms (step size = 5ms). On the time scale, the calculated similarity score will be associated with the midpoint of the frame.

A similarity measure is calculated in two steps. First a distance measure between the two vectors is calculated using the following formula:

(2a) $$d_i = \frac{\sum_{j=1}^{i} | x_j - u_{j,i} | \frac{1}{sd_{j,i}}}{n}$$

(where d_i is the distance measure to between the current frame and template i; x_j is the jth coordinate in the current vector, and $u_{j,i}$ is the jth coordinate in the average spectral vector of template i; $sd_{j,i}$ is the standard deviation of the jth coordinate in the average Mel spectral vector of template i.)

Second, the distance measure is normalized using the exponential function with k=-0.005.

(2b) $S_i = e^{-0.005di}$

(where S_i is the similarity score of the current frame to template i.)

Figure 2 illustrates the similarity scores for two templates, [s] (in blue/grey) and silence (in black/dark), for the utterance of the word "*personality*" by speaker M08.

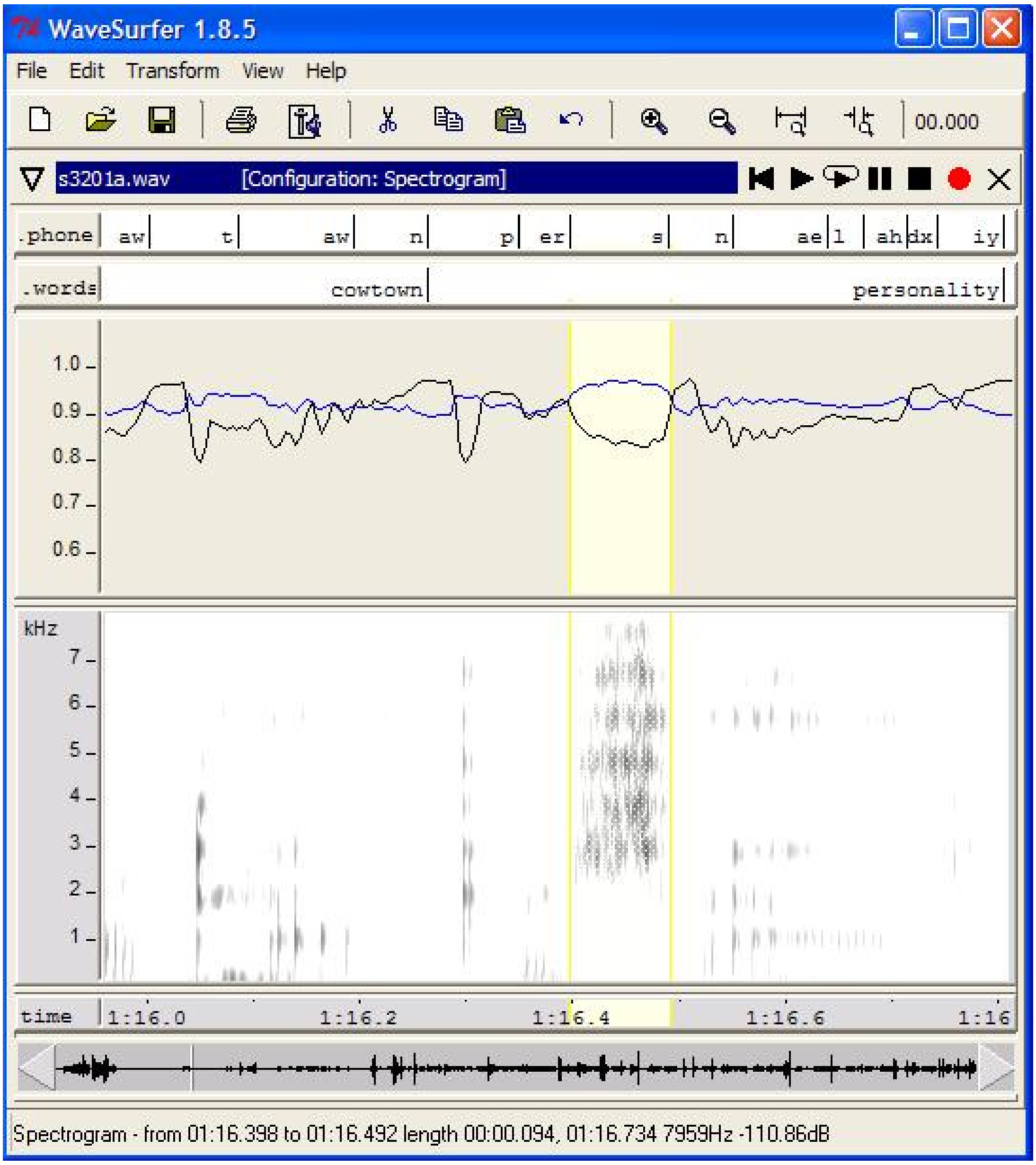


Figure 2 Illustration of similarity scores to [s] (in blue/grey) and silence (in black/dark) in an utterance by M08

The .words pane shows word transcription; the .phone pane shows phone transcription; the data pane shows the two similarity scores; both the spectrogram and the similarity score curves are highlighted during the duration of the phone [s] in "*personality*".

As shown in the highlighted section in Figure 2, during [s], the silence score is low while the s score is high, which is what one would expect given the definition of similarity scores.

2.2.3 Algorithm for finding the point of release

This section discusses how to use similarity scores to find the point of release in a voiceless stop. Intuitively, the similarity score measures how similar the acoustic data are to a phone template, and therefore in the closure portion of a stop, the silence score should be high, while in the release portion it should be much lower since the spectrogram is almost noise-like. In other words, at the point of release, there should be a significant drop in the silence score. Simultaneous with this change, there should be an increase in similarity scores to [h], [sh], and [s], since these phones are characteristic of energy across a wide range of frequency (cf. Figure 2). In fact, we do see this pattern in similarity scores around the point of burst. Figure 3 illustrates three target words said by speaker F01, which start with [p], [t], [k] respectively. In all three cases, the data pane shows similarity scores for silence, [sh], [s], and [h]. The order of the score curve is indicated in the box on the right. In all three figures, only the similarity scores in the target word are shown; elsewhere, they are merely straight lines connecting between target words. In Figure 3b and 3c, the point of burst is marked by the cursor (in red/grey), while in Figure 3a it is marked by a bi-directional arrow because the first release is very weak and the streak in spectrogram would easily be covered by the cursor line.

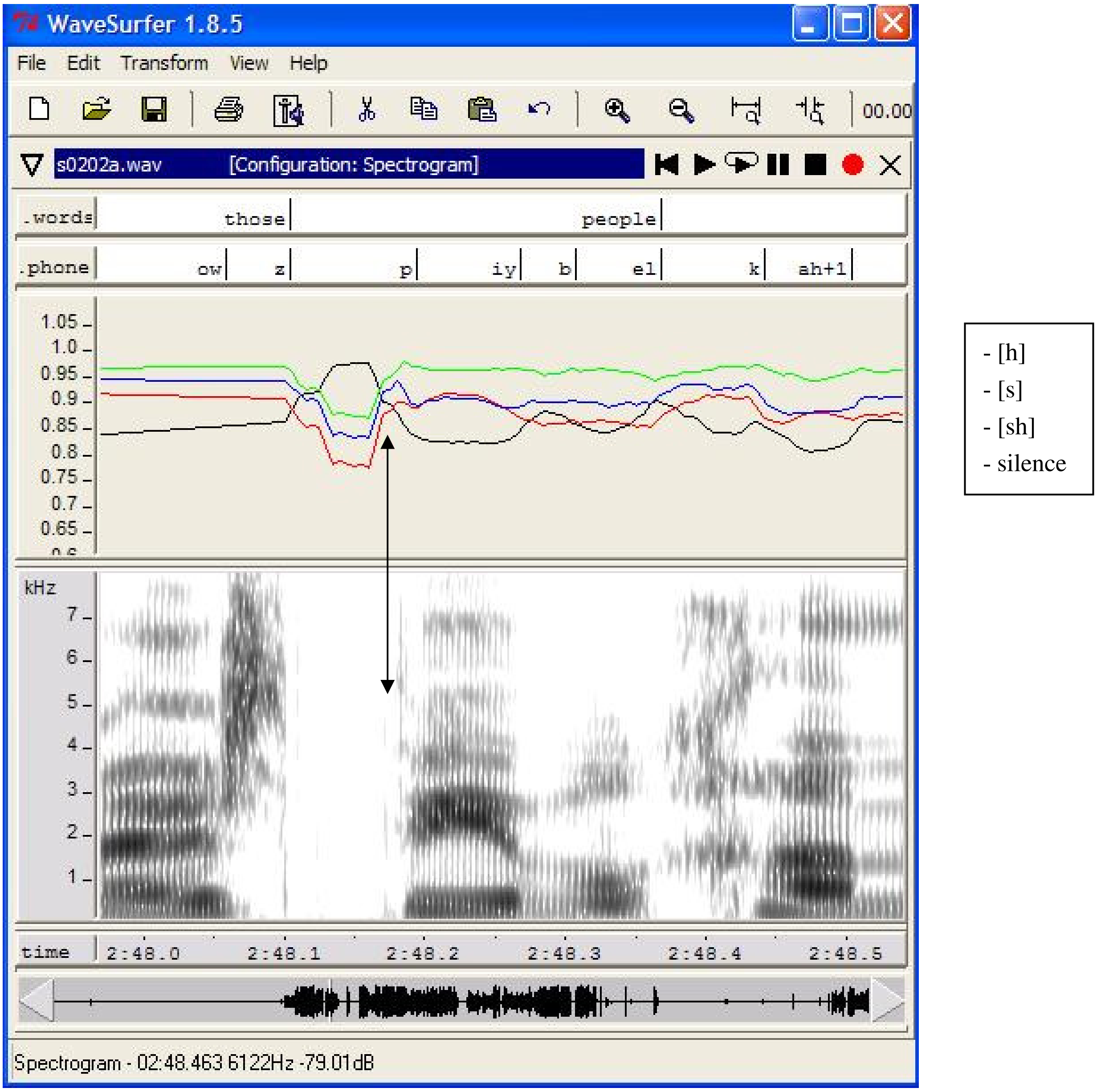


Figure 3a The word "*people*" by F01 with an initial [p] and the similarity scores for silence, [s], [sh], and [h]

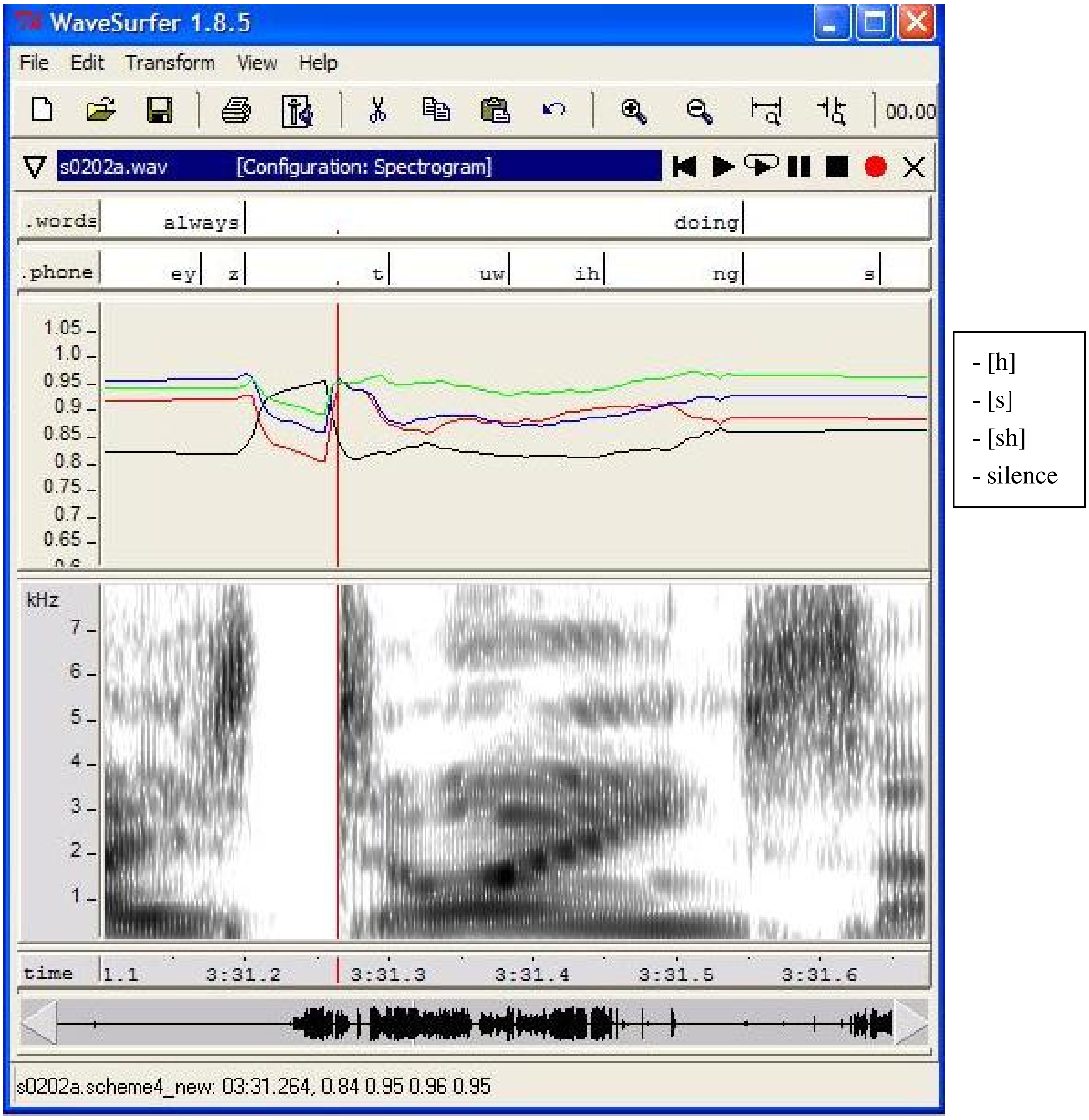


Figure 3b The word "*doing*" by F01 with an initial [t] and the similarity scores to silence, [s], [sh], and [h]

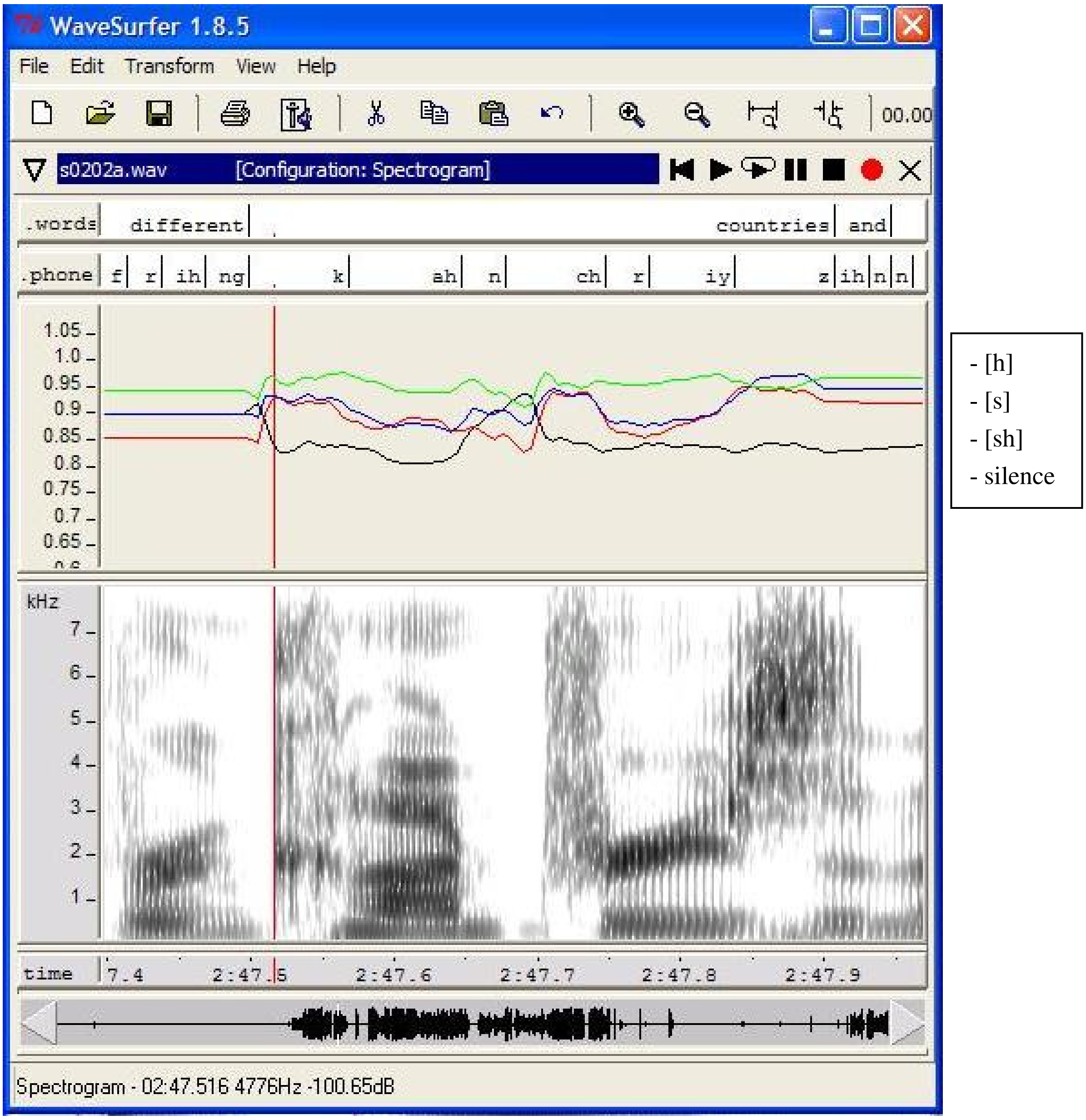


Figure 3c The word "*countries*" by F01 with an initial [k] and the similarity scores to silence, [s], [sh], and [h]

As seen from above, the similarity scores for [sh], [s], and [h] (for the sake of simplicity, they will be referred to as <sh> score, <s> score, and <h> score respectively) rise significantly around the point of burst, where the <silence> score drops significantly. In view of this, we first implemented an algorithm that found the time points corresponding to the highest peaks in <sh> score, <s> score, and <h> score, and the time point corresponding to the lowest valley in <silence> score. Therefore, the algorithm produced four candidates for the point of burst for each target case. In order to test the results, we hand tagged the point of release in all target cases of speaker F07. This speaker was chosen both because she has the smallest target set among all speakers and because her average speaking rate (measured in the number of syllables per sec) is the lowest (which probably make automatic processing easier). When deciding the point of burst manually, we mainly relied on the cues in the spectrogram, and in cases where it's hard to decide from the spectrogram, we also used waveforms as second evidence. If the phone has more than one release, the earliest one will be taken to be the real point of burst. The comparison of the true values and the four candidates given by the program showed that the best prediction was made by the <silence> score, with an average error (RMS (error)) of around 10ms. However, 10ms of error is still higher than tolerable for studying the distribution of VOT and closure durations. We also tried fitting the data with linear regressions of different combinations of the four estimates, but it didn't reduce the error significantly.

More careful observation of the scoring pattern revealed that slope was a better predictor than absolute score value for the point of burst because the lowest valley or highest peak in <silence> score could occur either before, around or after the point of burst, but the most drastic dropping or rising in scores (i.e. the point with the greatest slope) occurs consistently near (usually a few milliseconds before) the burst. Figure 4 illustrates the problem with a [k]-initial target word said by speaker M01. Only two scores, <silence> (in black/dark) and <sh> (in red/grey), are shown for simplicity. It can be seen that the true burst point (where the lower arrow points to on the spectrogram) is very close to the end point of the most drastic dropping in <silence> score and the most drastic rising in <sh> score, as pointed by the bi-directional arrow. After the release, <silence> score keeps dropping and <sh> score keeps rising, both at slower rate though, and as a result, both the valley in <silence> score and the peak in <sh> score (pointed approximately by the two unidirectional arrows) occur tens of milliseconds after the release.

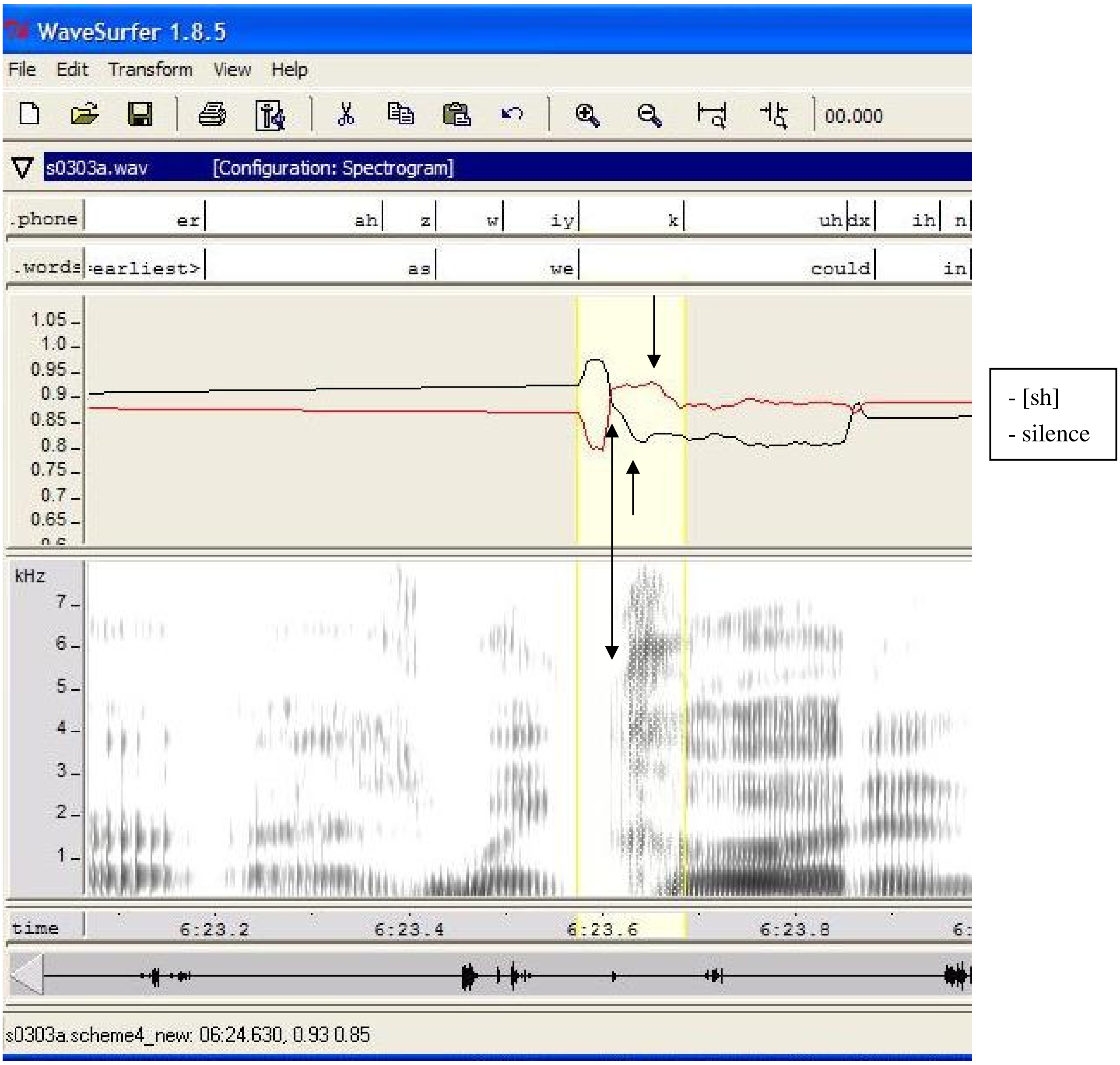


Figure 4 The word "*could*" said by speaker M01

Highlighted area corresponds to the duration of the initial [k]; two similarity scores are shown: <silence> score (in black/dark) and <sh> score (in red/grey)

In view of this, we implemented a new algorithm which found not the time point corresponding to the peak or valley of the score, but the end point of the most drastic change in similarity score (the most drastic rising in the <sh> score and the most drastic falling in the <silence> score). We also reduced the number of scores in consideration from four to two by dropping the h score and the s score since they were shown to have a similar pattern as the <sh> score. So now the program only finds two candidates for the point of release in each target case, one from <silence> score and the other from <sh> score, and returns the mid point of the two. If no decreasing period is found in <silence> score or no increasing period is found in <sh> score, the target case would be disregarded from the target set.

Using the new algorithm, the root mean square of error is 7.22ms, which shows a significant improvement over the 10ms error of the previous algorithm. Moreover, it is found that the error values (i.e. real point of burst - estimate) are mostly distributed around 5ms (as shown in Figure 5 below), with a mean of 5.35ms.

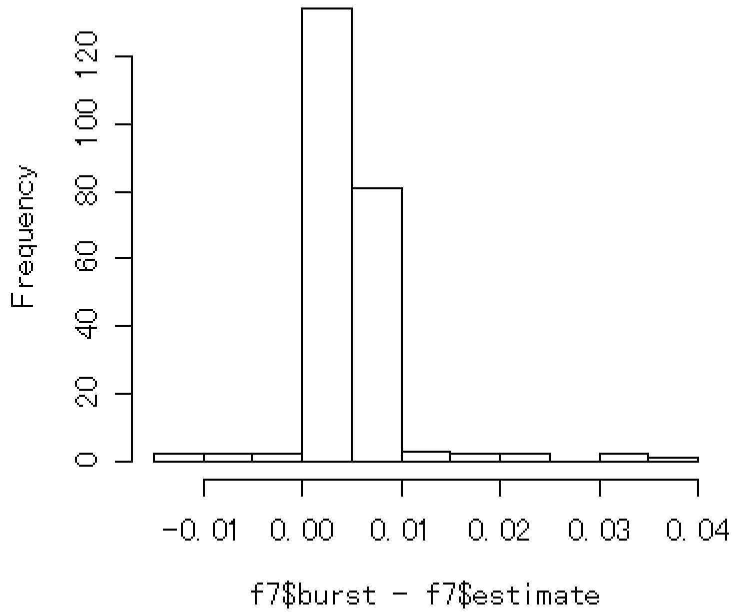


Figure 5 Distribution of error values (in s) in F07, using the new algorithm
X-axis shows the error intervals in s, and Y-axis is the number of cases in the error interval

If 5ms is added to all estimated values, the RMS of error is further reduced to 4.85ms, across 231 target cases.

In order to test the robustness of the algorithm, we used part of the data from another speaker, M08, to do a similar test. Speaker M08 was chosen because he seemed to be the opposite of speaker F07 in every aspect. As shown in Table III below, F07 is a female, older speaker with on average a low speaking rate (in fact the lowest among all 19 speakers), while M08 is a male, younger speaker with the fastest speaking rate among all talkers. Average speaking rate is measured in the average number of syllables produced per second.

	Gender	Age	Average Speed	Speed rank
F07	F	old	4.02	#19
M08	M	young	6.43	#1

Table III Comparing speaker F07 and M08

The same procedures were applied to M08's data. First, the first 261 target cases of M08 were chosen to comprise a target sample with a comparable size to F07's data. Next, all of the 261 cases were hand-tagged for the point of burst in the initial plosive. This process proved to be much harder than dealing with F07's data.

M08 being both a fast and extremely soft talker (which might actually be due to the low gain setting during the recording), his data contain many cases in which even an experienced phonetician would have problems deciding where the point of burst is. In particular, in some cases, it is clear that the burst doesn't exist. That is to say, even if the phone is transcribed as a word-initial voiceless plosive, there is no closure-release transition during the duration of the phone – either all silence or all noise throughout the duration. In other cases, the burst is not significant enough. Some problematic cases are shown below in Figure 6a-c.

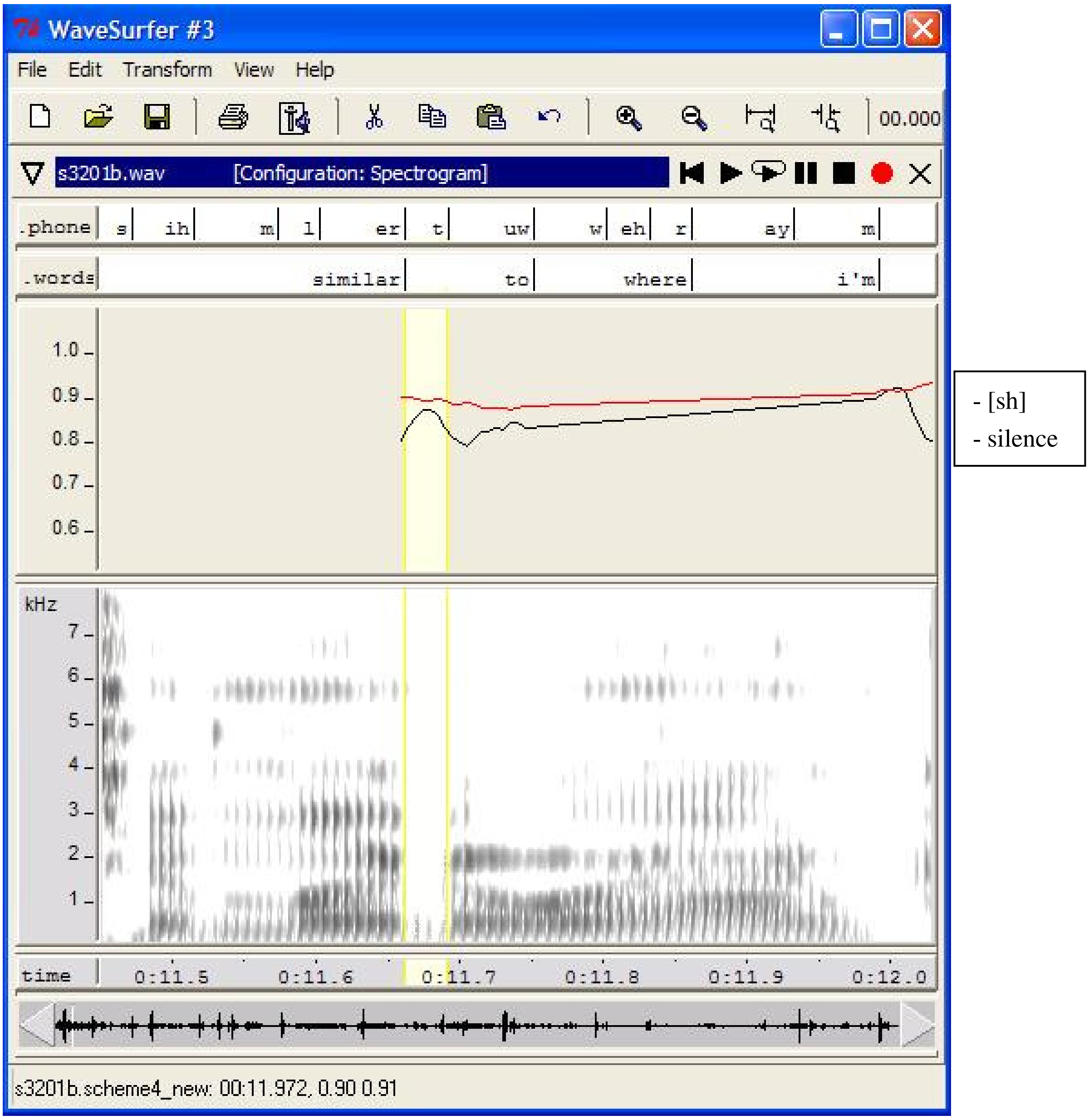


Figure 6a "*to*" said by speaker M08

Highlighted area corresponds to the duration of the initial [t]; two similarity scores are shown: <silence> score (in black/dark) and <sh> score (in red/grey)

In Figure 6a, the transcribed duration of [t] is basically all blank in spectrogram, and the production of the following vowel starts right after the silence – in other words, the stop is incomplete since it doesn't have a release.

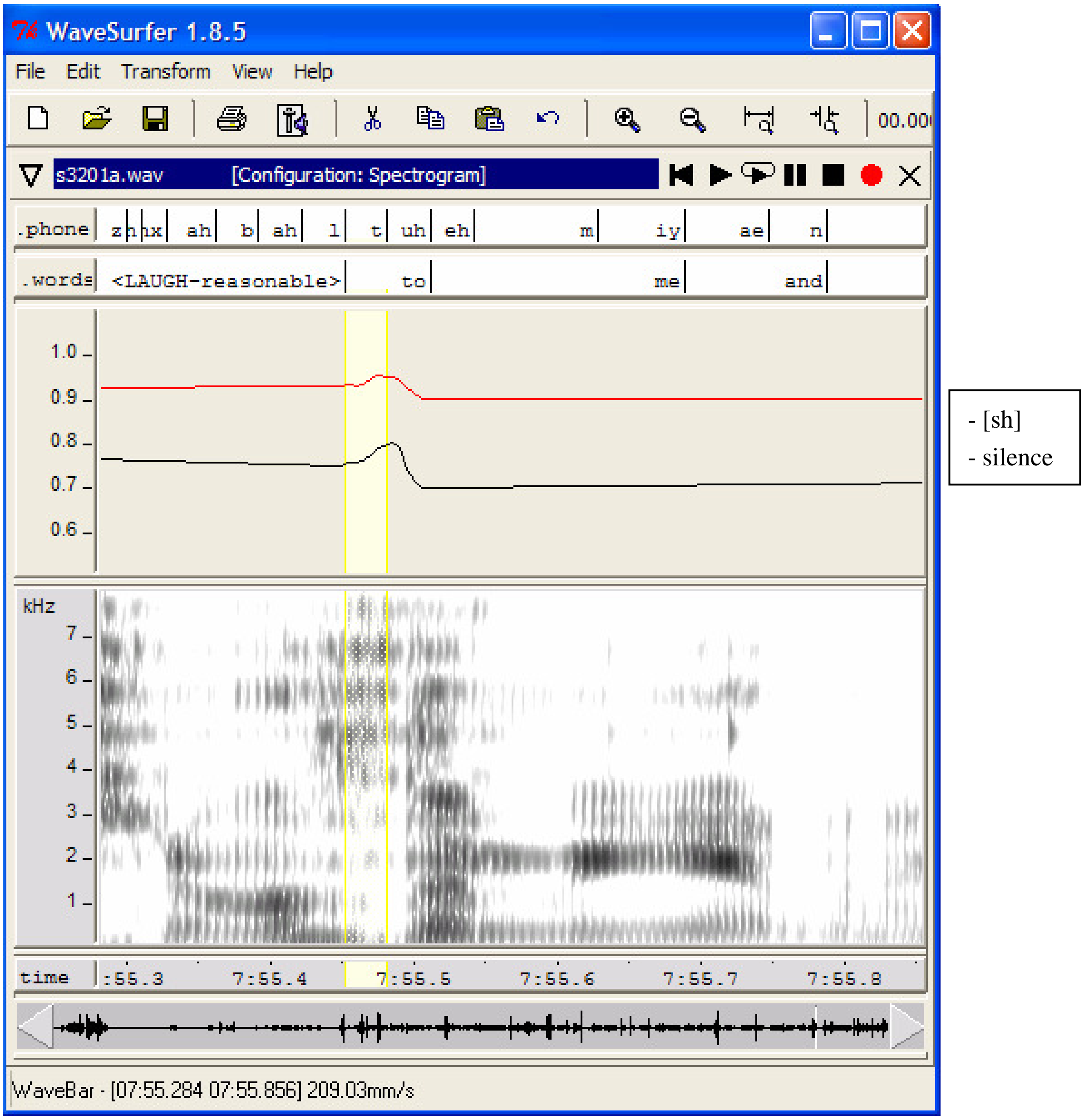


Figure 6b “*to*” said by speaker M08

Highlighted area corresponds to the duration of the initial [t]; two similarity scores are shown: <silence> score (in black/dark) and <sh> score (in red/grey)

Figure 6b shows a case where the transcribed duration of the stop is all noise in spectrogram, with no closure portion.

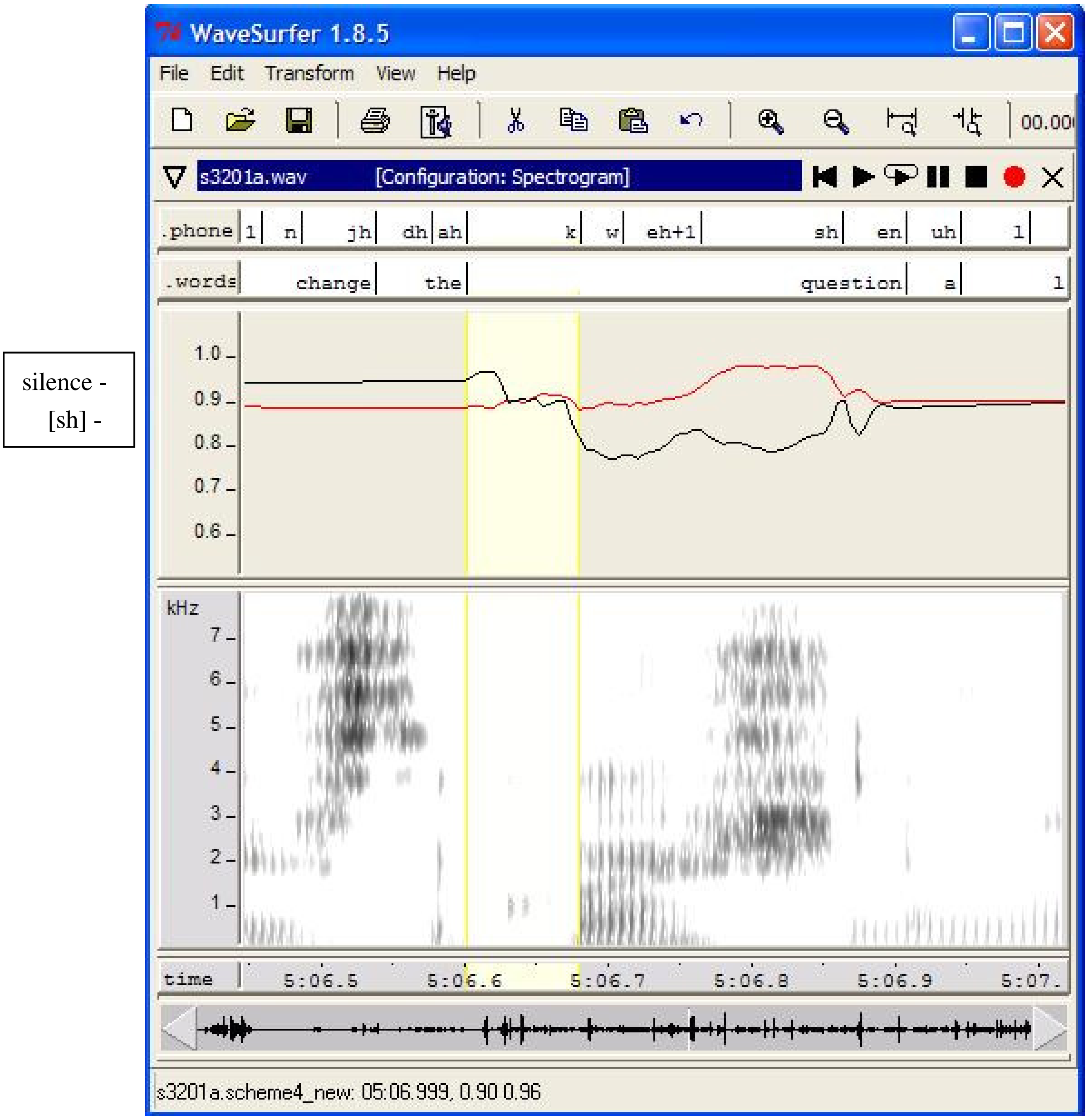


Figure 6c "*question*" said by speaker M08

Highlighted area corresponds to the duration of the initial [k]; two similarity scores are shown: <silence> score (in black/dark) and <sh> score (in red/grey)

Figure 6c shows a word-initial [k] in speaker M08. This velar stop is weakly (and doubly) released, which corresponds to only two faint streaks on the spectrogram around the mid point of the duration of the phone, with no noise-like distribution of energy following the release. The waveform shows no periodicity after the hypothesized release either, until the following vowel starts. Besides, when listening to the audio, we can't hear a velar release throughout the duration of the phone. All the evidence points to the conclusion that the streak in the spectrogram might just be a spurious burst, and therefore it shouldn't be counted as a velar release.

Altogether 23 problematic cases are found among the 261 cases of M08 that are hand-tagged, and the three cases shown in Figure 6a-c are typical of most of them.

The real points of burst are designated to be the starting point of the phone, in order to make it possible to calculate the average error value. If anything, this distortion increases the error value. The RMS error is 13.11ms. The histogram in Figure 7 shows that the majority of errors are in the interval [0, 20ms], however, there exist a number of outliers with large error values.

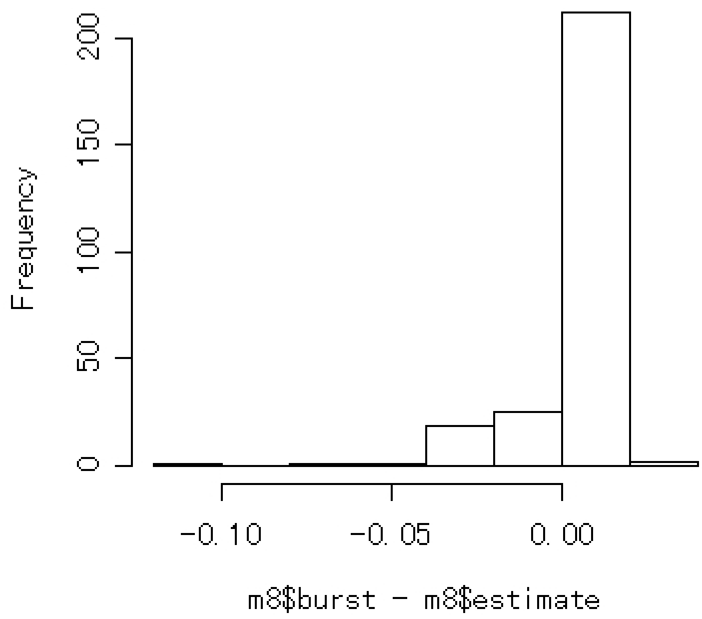


Figure 7 Error distribution in M08 after the first rejection rule is applied
X-axis shows the error intervals in s; Y-axis is the number of cases in the error interval; dataset size = 261 cases

Not surprisingly, the outliers are mostly those problematic cases. If the stop doesn't contain a release in the first place, whatever release point found by the program would be an error. To solve this problem, the algorithm needs to be able to detect cases with no significant releases and reject them. A rejection rule is implemented for this purpose.

(3) First rejection rule
A target word will be rejected if the most drastic changes found in scores are not drastic enough. The delta criterion is defined as a rising rate of 0.02 per step (i.e. per 5 ms) for <sh> score and a dropping rate of 0.04 per step for the <silence> score. If the <silence> score and <sh> score don't meet the delta criterion, the case will be rejected.

The two cutoff numbers, 0.02 and 0.04, are decided based on M08's test dataset. It is observed that when used together, these two cutoff numbers are able to block a highly exhaustive and exclusive set of the problematic cases of M08, as shown in the table below.

	N	N_P	N_R	$N_{P\wedge R}$
M08	261	23	28	19

Table IV Number of cases rejected in M7's examined data, using the cutoff points 0.02 and 0.04

N is the number of all cases that are examined in speaker M08; N_P is the number of problematic cases found in M08; N_R is the number of cases that are rejected using the two cutoff points; $N_{P\wedge R}$ is the number of problematic cases that are rejected.

After rejecting 28 cases, the RMS of the error goes down to 9.27ms. Figure 8 shows the histogram of the error distribution.

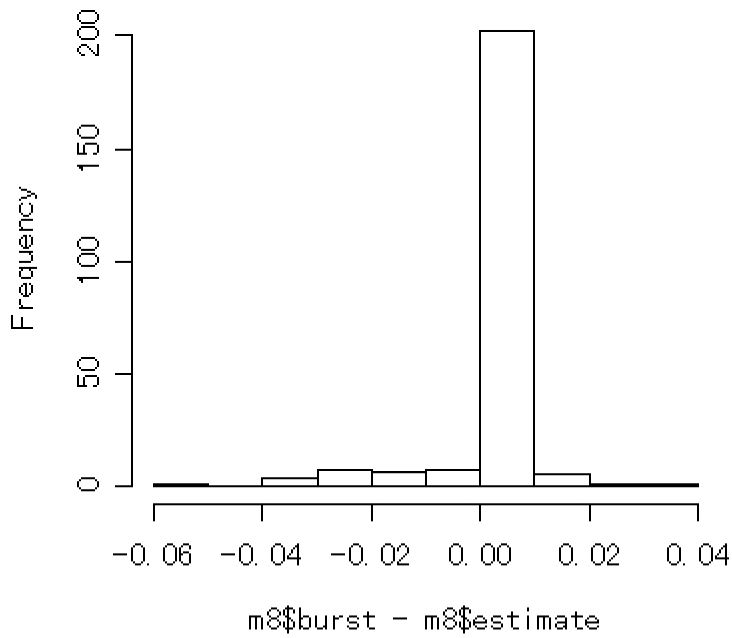


Figure 8 Error distribution in M08 after the first rejection rule is applied

X-axis shows the error intervals in s; Y-axis is the number of cases in the error interval; data set size = 233 cases

As shown above, most of the error values are distributed in the interval [0,10ms], which is consistent with the finding from speaker F07's data that the found point of release is on average 5 ms earlier than the real point. However, the overall performance is dragged down because of the existence of a number of outliers whose estimated points of burst are more than 20ms away from the true values. And even shifting the estimate values by 5ms to the right doesn't help improve the error value, only yielding an error value of 9.26ms.

Now that the cases with insignificant bursts are mostly excluded after the first rejection rule, the found release points in the remaining cases should all indicate real bursts. Therefore, if the found points don't coincide with the real values, the most natural explanation is that the automatic program is finding wrong points of burst. If the found point is significantly earlier than the real point of burst, it is most likely that the program finds a spurious burst (e.g. a transient), which is part of the residual after the first rejection rule. If the found point is significantly later than the real point of release, it most likely is a case of multiple release. Multiple release is known to occur most often in velar stops. In fact, the case with the greatest error value (error = -60ms) is a multiply-released initial [k], shown in the figure below.

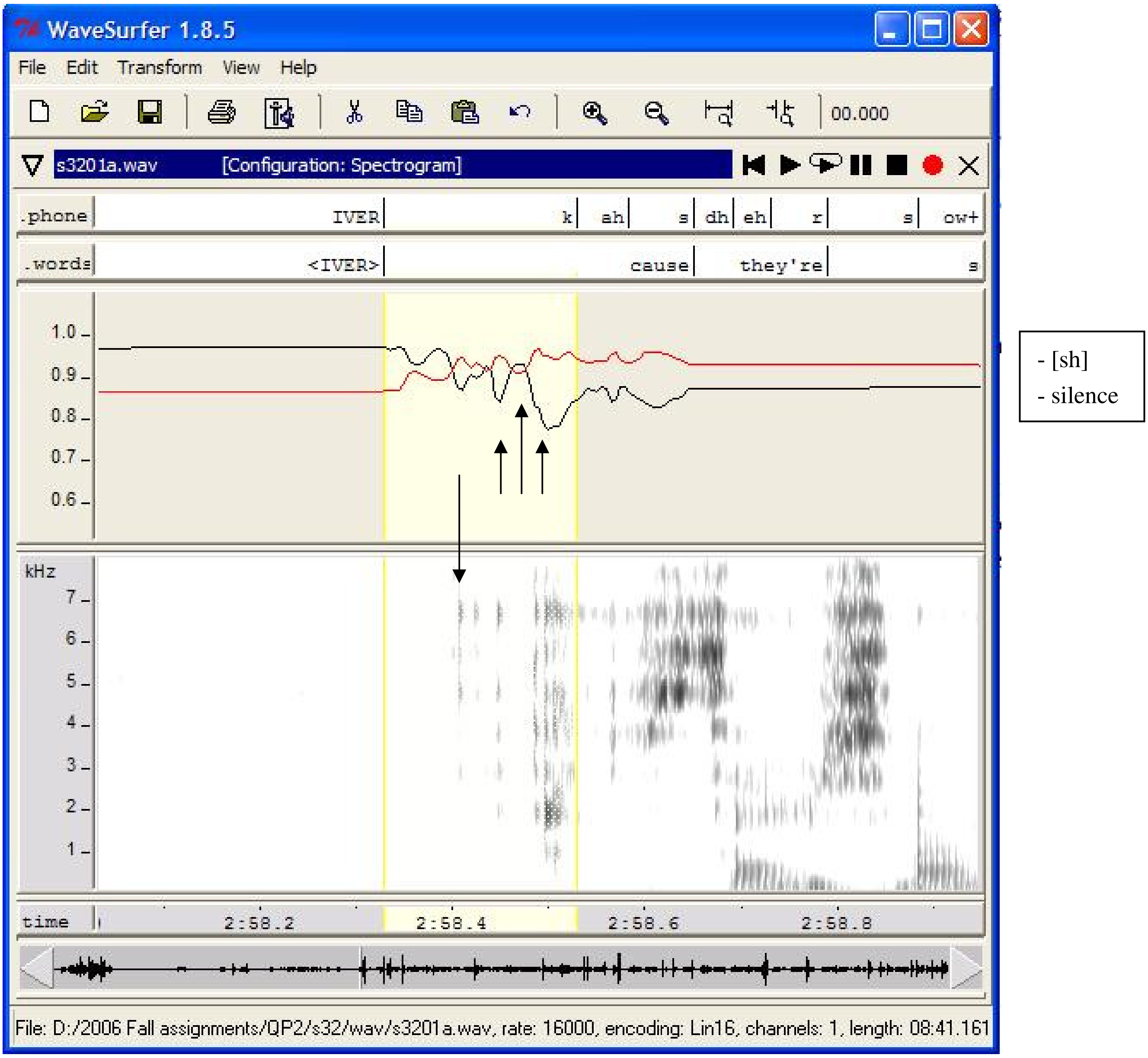


Figure 9 The word "*cause*" with an initial [k] said by speaker M08
Highlighted area corresponds to the duration of the initial [k]; two similarity scores are shown: <silence> score (in black/dark) and <sh> score (in red/grey)

The initial [k] in "*cause*" as shown in the figure above is unusual, not only in the multiple releases but also in the fact that first three (or four) releases are widely apart. As shown above, instead of finding the first release (roughly pointed by the downward arrow), the <silence> score tracker finds the second major release (pointed by the leftmost upward arrow) while the <sh> score tracker finds the third major release (pointed by the rightmost upward arrow), and the program in turn returns the mid point of the two (as pointed by the middle upward arrow).

Ideally we would want the program to be able to find the first significant release in cases like the above, but in reality, we just tell the program to ignore them. Apart from the obvious benefit of keeping the program simple (relatively!), there are actually also a couple of rational reasons for doing so. The most important one is that simply favoring the earliest found point would interfere with the rejection of spurious releases. Currently the rejection of spurious releases is not only done by the first rejection rule, but also built-in in the algorithm, since the program looks for the most likely point of release, not the first point of release, with the underlying assumption that the point of burst (i.e. the first release if multiple releases exist) should also be the point of the most abrupt changes in <silence> score and <sh> score. That being said, though favoring temporal precedence might help solve the problem of these unusual multiple releases, it would probably affect the estimation for other cases, which are the majority of the data set. In view of all these, we implemented the second rejection rule, which states as follows:

(4) Second rejection rule
If the two found points, one from the <sh> score and one from the <silence> score, differ from each other by more than 4 steps (i.e. 20 ms), the case will be rejected and dropped from the data set.

According to the second rejection rule, the case in Figure 9 will be rejected because the two found values differ by 40ms. It should be noted that by applying this rejection rule, we are not excluding all cases with multiple releases. The reason is that in most cases, the repeating releases are quite close, within 20ms from each other. Therefore, if the two found points do belong to two separate releases that are within 20ms from each other, the error value by returning the midpoint of the two instead of the first point would be less than 10ms, which is considered tolerable (if it only happens occasionally, of course!). What if the two found points belong to the same release but that release is not the first one in the series? The program with the two rejection rules will have no way to detect this problem. However, hopefully it won't happen very often, since it is only possible if (i) the multiple releases are more than 20ms apart, and (ii) one of the (non-initial) releases is found by both <silence> score and <sh> score.

Let's take M08's data for illustration. After applying the second rejection rule, 20 cases are dropped and the new distribution of error is shown in the figure below. This time the mean absolute value of error is 4.50ms, still around 5ms. The RMS error is 5.64ms, and after adding 5ms to the estimate values, the root mean square is reduced to 3.44ms. Notice that this error value is near-optimal since the step size is 5ms, and theoretically the best error value that can be achieved is 5/2=2.5ms. Notice also that the number of outliers (i.e. residual after the rejection rules) is reduced to only 2, one on the positive side and one on the negative side.

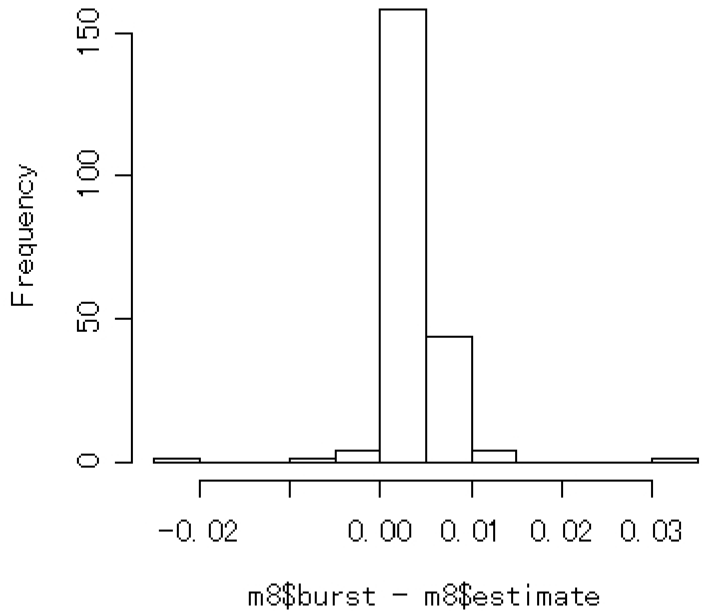


Figure 10 Error distribution in M08 after the first rejection rule is applied

X-axis shows the error intervals in s; Y-axis is the number of cases in the error interval; dataset size = 213 cases

We have seen that the two rejection rules significantly improve the performance of the program. Now the question is: are they speaker independent? To test this, we apply the rules to the estimated values in speaker F07's target set. Table V shows the results after the rejection rules in F07's data, and for comparison, we also include M08's results here.

	F07				M08			
	size	error	$error_{+5}$	sd	size	error	$error_{+5}$	sd
before rejection	231	7.22	4.85	4.85	261	13.11	14.00	13.17
after 1st rejection	227	6.81	4.19	4.19	233	9.27	9.26	8.94
after 2nd rejection	224	6.02	3.22	3.23	213	5.64	3.44	3.41

Table V Results with speaker F07's and speaker M08's test data

Size is the number of cases in the dataset; error is the RMS error value; $error_{+5}$ is the RMS error after the estimates are shifted by 5ms to the right; sd is the standard deviation of error.

Overall, 7 of 231 cases are dropped in F07's data (rejection rate = 3.03%), and the RMS error is improved by 33.6%; in M08's data, 48 of 261 cases are dropped (rejection rate = 15.05%), and the RMS error is improved by 75.4%. In both speakers, the shifted error value is significantly better than the unshifted one, which means the point found by the program consistently occurs about 5ms earlier than the real point of burst; both RMS and the standard deviation of the error is significantly reduced after the rejection rules, in both speakers. Besides, both speakers achieved a RMS error lower than 3.5ms after the rejection rules. The large difference in rejection rate, 3.03% vs. 15.05%, suggests that the rejection rates are speaker-dependent. Remember that speaker F07 and M08 are chosen because they are vastly different from each other in their basic information, and also considering the fact that speaker M08's data contain a significant portion of problematic cases that need to be dropped while no particularly difficult cases were noticed in F07's data during the hand-tagging process, the low rejection rate in F07 and the relatively high rejection rate in M08 suggests that the algorithm, together with the rejection rules, is robust enough to be applied to a wide range of speakers without any changes. The complete process for finding the point of release is illustrated in the flow chart below.

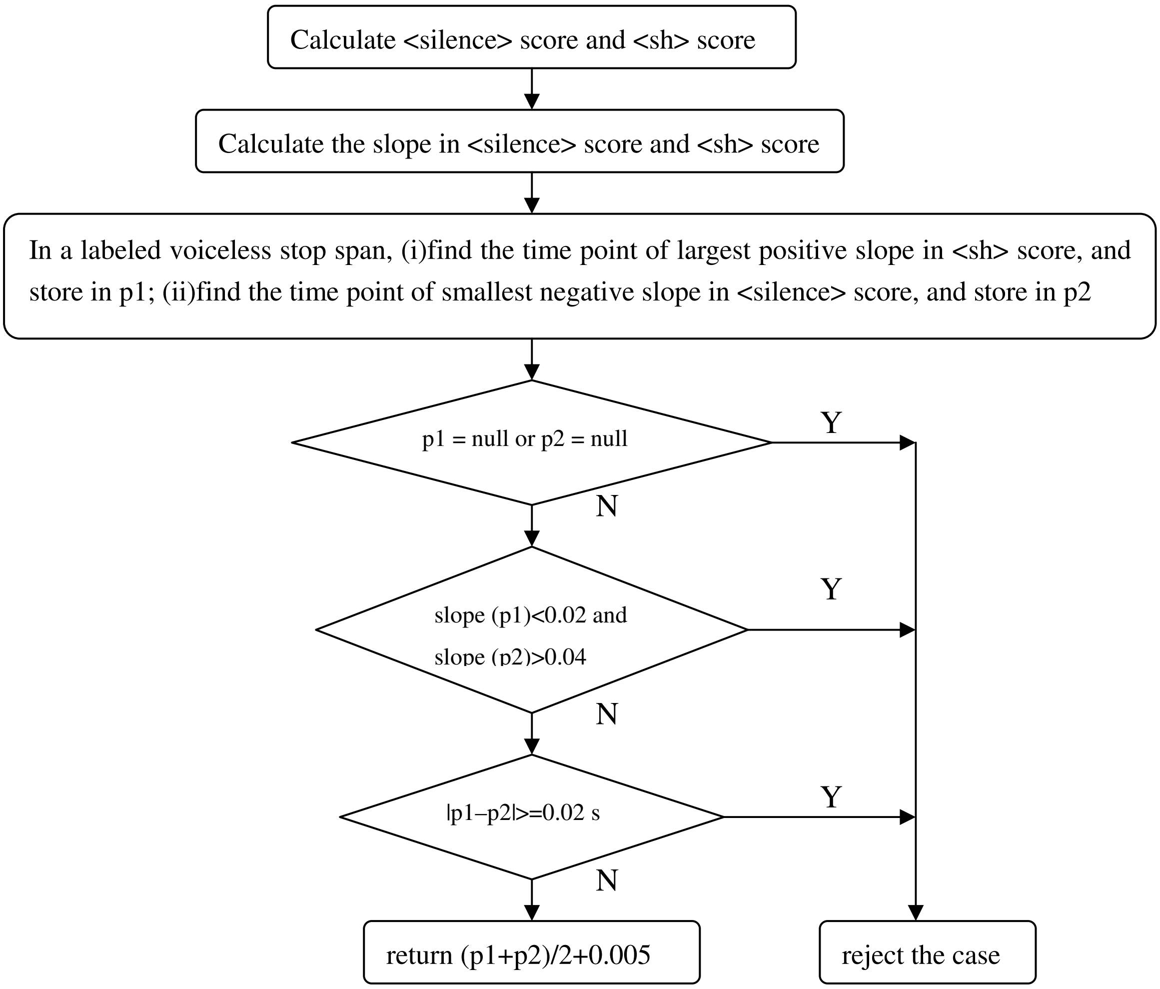


Figure 11 Flow chart for finding the point of release

We applied the above procedure to all speakers' data, and the rejection rate ranges from 3.03% to 30.5%, with the average value of 13.13% and a standard deviation of 8.6%. The details of rejection in all speakers are attached in appendix I. Being cautious, we compiled a random list of 50 target cases from all speakers, in which about half of the cases were from speakers with a high rejection rate (>20%), and manually checked the estimated values. In the 43 cases that are not rejected, error is always within 5ms; in the 7 cases that are rejected, 3 of the 4 cases rejected by the first rule and 2 of the 3 cases rejected by the second rule are legitimate. The two wrongly rejected cases are shown in Figure 12a-b below.

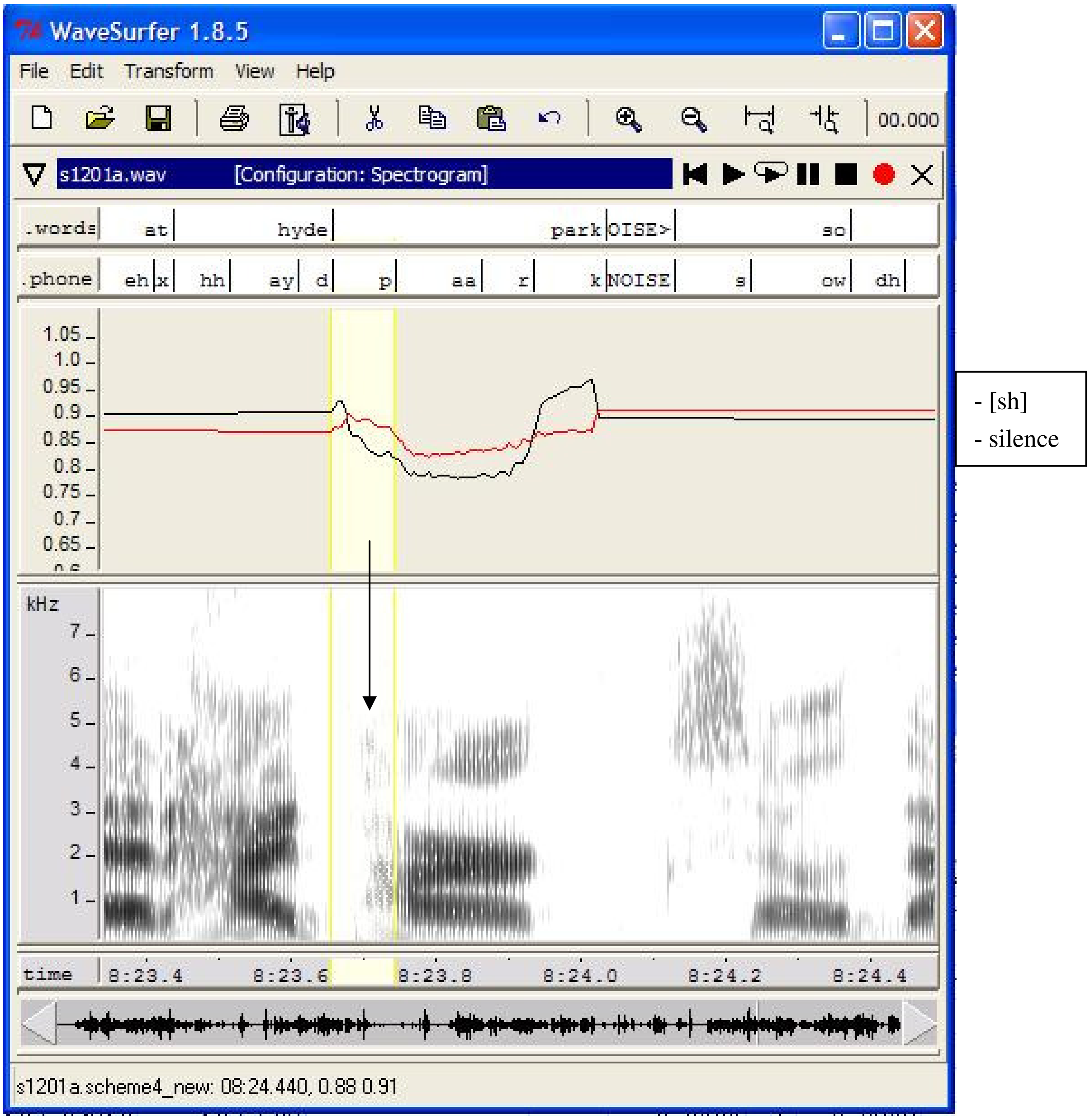


Figure 12a "park" said by speaker F02 (rejection rate = 30.5%), which is rejected for having insignificant changes in <silence> and <sh> score. A phonetician might want to consider the point around the arrow as the release point.

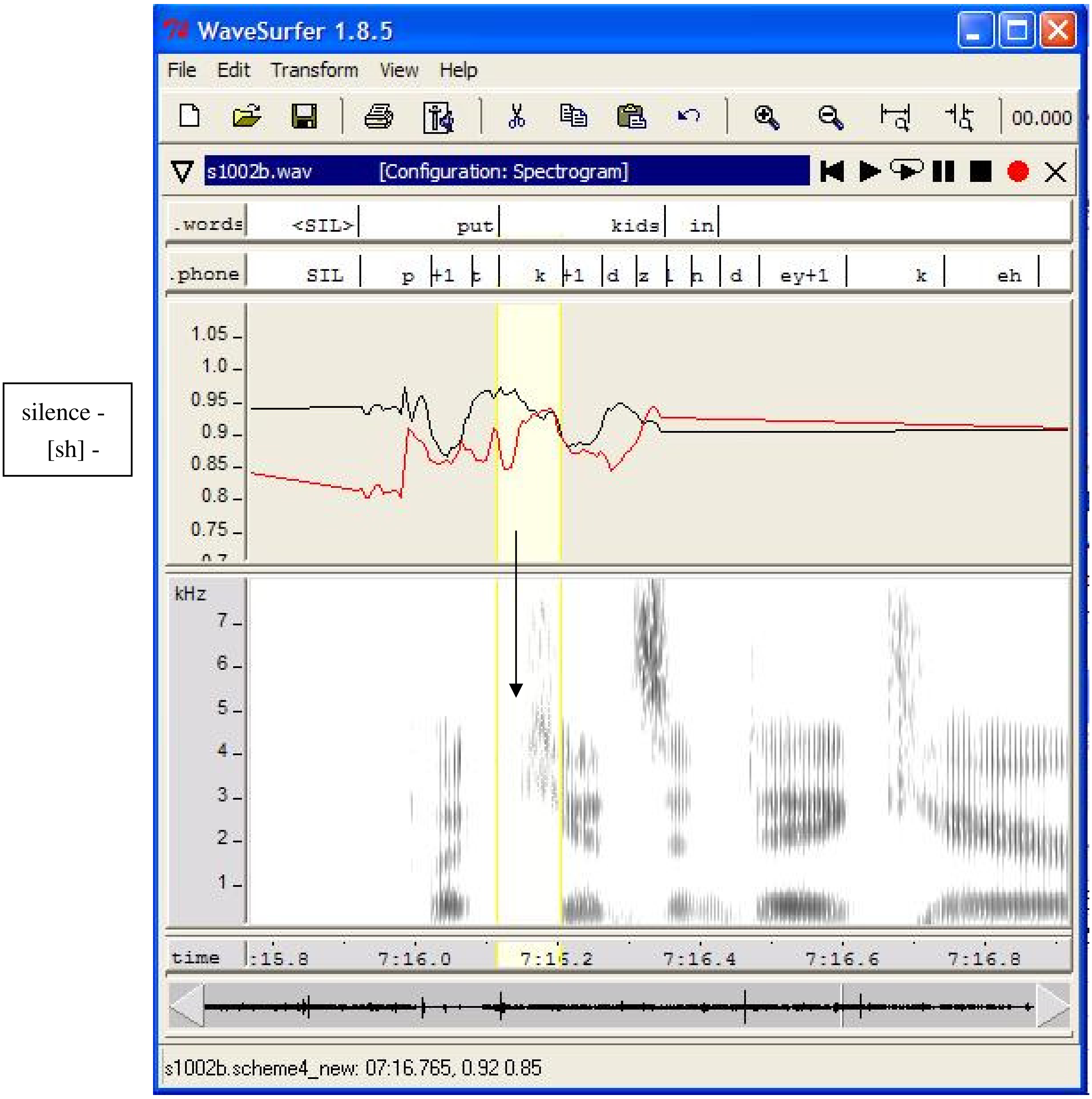


Figure 12b “kids” said by speaker M02 (rejection rate = 21.7%), which is rejected for having two peaks that are two far apart. A phonetician might want to consider the point around the arrow as the release point.

3. Results

This section shows average closure and release duration across speakers, and discusses the correlation between closure duration and VOT on one hand and a number of linguistic and extra-linguistic factors on the other hand. All durational values shown in this section are predicted by the burst-detecting program. For the purpose of comparing closure and release, only non-utterance-initial cases are included in the statistical analysis in this section. As shown in Table II in the previous section, non-utterance-initial words make up of around 80%-95% of the target set in each speaker.

3.1 Distribution of average duration of closure and release across speakers and place of articulation

Table VI lists the mean and standard deviation of closure duration, VOT, and total duration by place of articulation.

	labial ([p])	alveolar ([t])	velar ([k])
N	2461	4142	3566
Mean(D_c)	69.5	48.9	54.9
Sd (D_c)	36.4	23.9	22.9
Mean(D_r)	48.0	51.2	57.9
Sd (D_r)	25.1	27.5	26.0
Mean(D_t)	117.6	100.2	112.9
Sd (D_t)	46.5	41.2	37.7

Table VI Duration (in milliseconds) of non-utterance-initial (but word-initial) voiceless stops

N = total number of tokens; D_c = closure duration; D_r = release duration; D_t = total duration

Compared with the average durations found in Byrd (1993) for read speech in TIMIT (cf. Table VII below), the Buckeye values are very similar, though the release duration is a little bit longer.

	p	t	k
Mean(D_c)	69	53	60
Sd (D_c)	24	29	26
Mean(D_r)	44	49	52
Sd (D_r)	22	24	24

Table VII Duration (in milliseconds) values from Byrd (1993)

Our data show the same general pattern in duration by place of articulation as in Byrd (1993). [p] on average has a greater closure duration than [t] and [k] in our data , which is in line with the finding of both Byrd (1993) and Zue (1976) but not Crystal and House (1988a). The average VOT follows the pattern claimed in many previous studies that VOT increases as the place of contact moves from lips to the velum.

Figure 13 shows the average closure and release durations in each speaker.

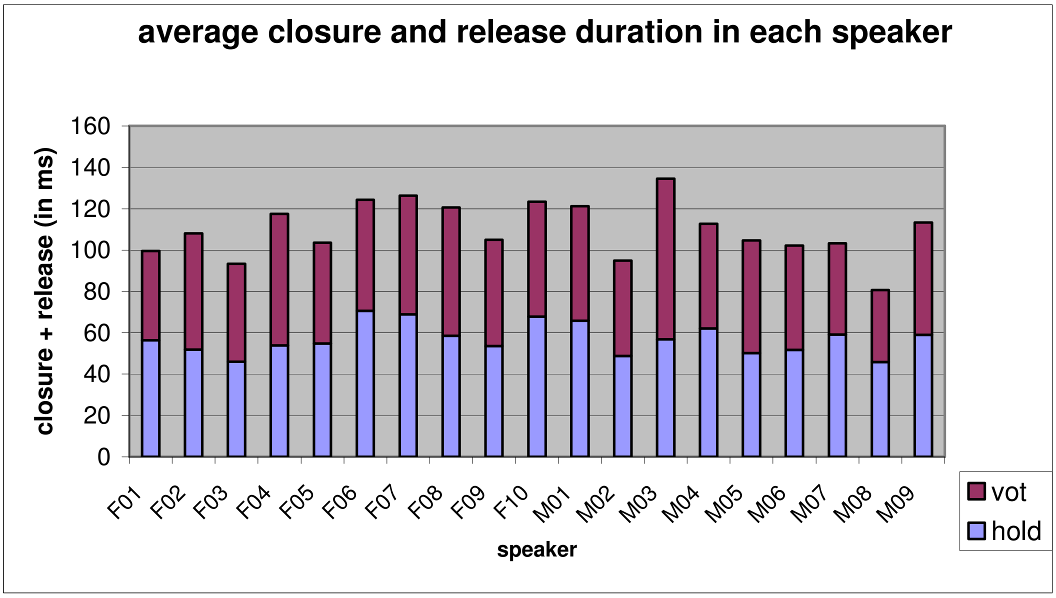


Figure 13

In Figure 13, we see some individual differences in terms of average length of closure and release. Speaker M03 has on average the longest VOT (=77.7 ms), as well as the longest total duration (=134.5 ms), though his average closure duration (=56.8s) is not among the longest ones. Speaker M08, on the other hand, has the shortest total duration (80.6s), the shortest VOT (=34.8s), as well as the shortest closure duration (=45.8s). As the figure shows, speaker M03's average VOT is almost twice as long as that of speaker M08's. Checking the speaker information table (Table I) in section 2, we find that speaker M03 and M08 are both younger male speakers, but they do show a difference in average talking speed. As mentioned in section 2, speaker M08's data (together with speaker F07's) were chosen to train the burst detector partly because this speaker is ranked # 1 in average talking speed, with on average 6.43 syllables produced per second. Speaker M03, on the other hand, produces 4.87 syllables per second, and is ranked # 13 among the 19 speakers. (A complete table on average talking speed among speakers can be found in appendix II.) This preliminary comparison seems to suggest that age and sex might not contribute to the variability in these duration measures as much as speaking rate does. This issue will be further investigated in section 3.2.

Figure 14 shows the average proportion of closure and release in the total duration of the phone across speakers.

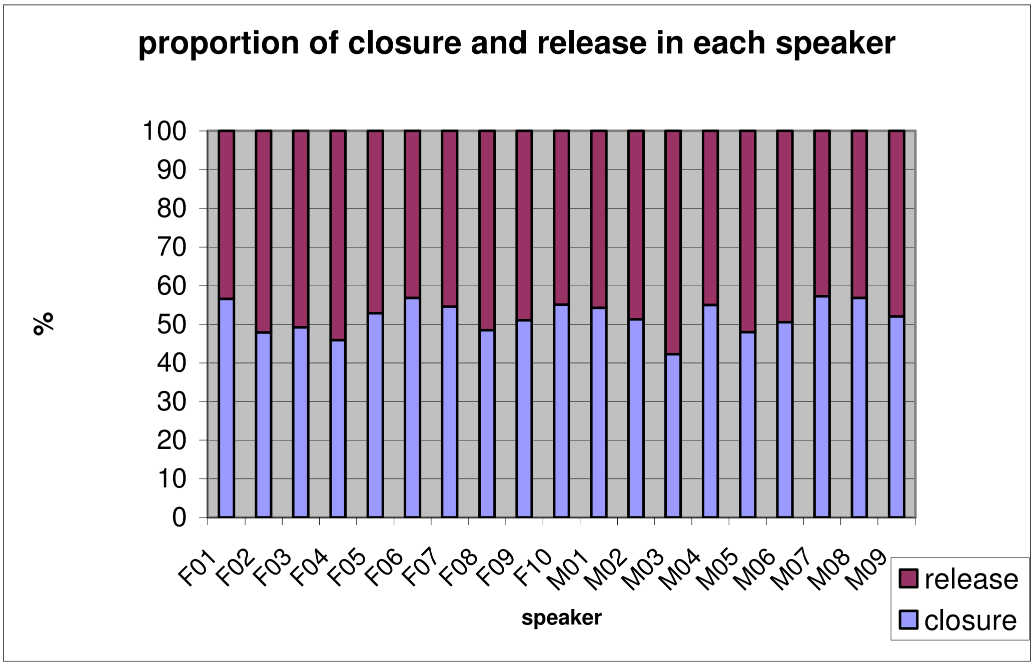


Figure 14

Similarly, Figure 14 shows individual differences in terms of ratio of closure and release, which suggests that the ratio is not constant across speakers.

Figure 15a-c show the average closure and release duration, as well as the proportion of closure in total duration, in each place of production, across speakers.

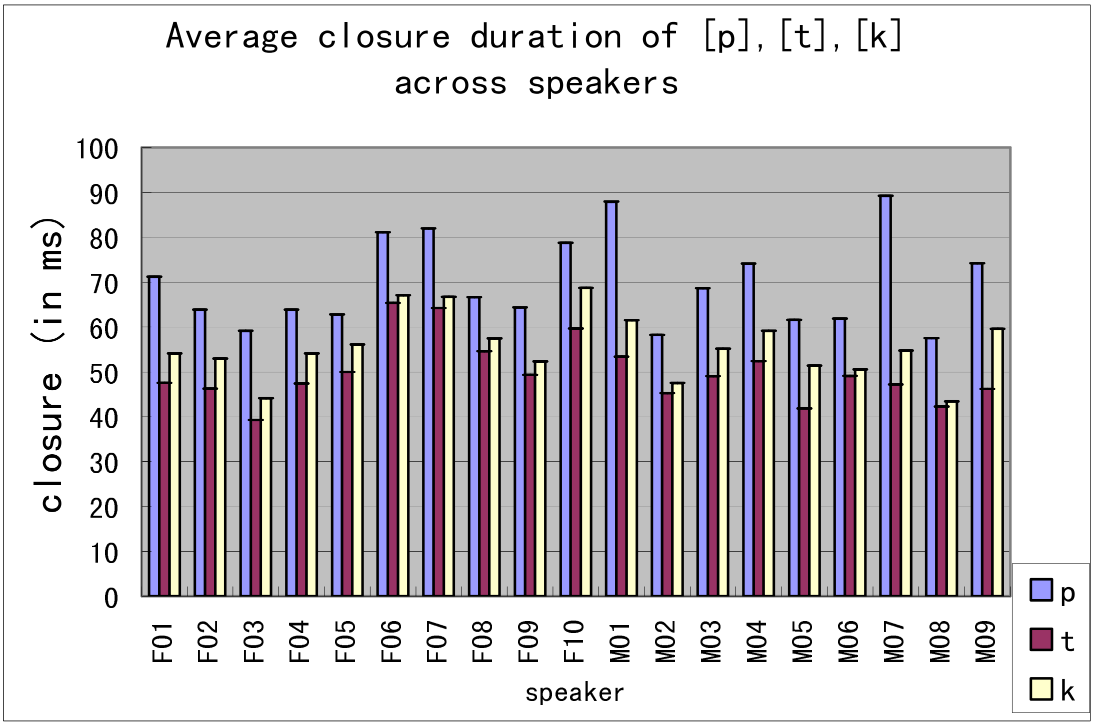


Figure 15a

It is clear from the above figure that the average closure duration of [p] is consistently and significantly greater than [t] and [k] in all speakers. A student's t-test on place confirms that the average closure duration of [p] across speakers is significantly different from that of [t] and [k] ([p] and [k]: t = -5.0663, df = 32.487, p <0.001; [p] and [t]: t = -7.0883, df = 32.275, p <0.001). This provides further support for the finding in Table VI with regards to closure durations by showing that the pattern is highly robust across speakers. From the figure we can tell that the average closure duration of [k] is greater than [t] in all speakers, though to a lesser degree compared to the difference between [p] and the other two stops. A t-test confirms that the difference in average closure duration in [k] and [t] is much less significant (p = 0.020).

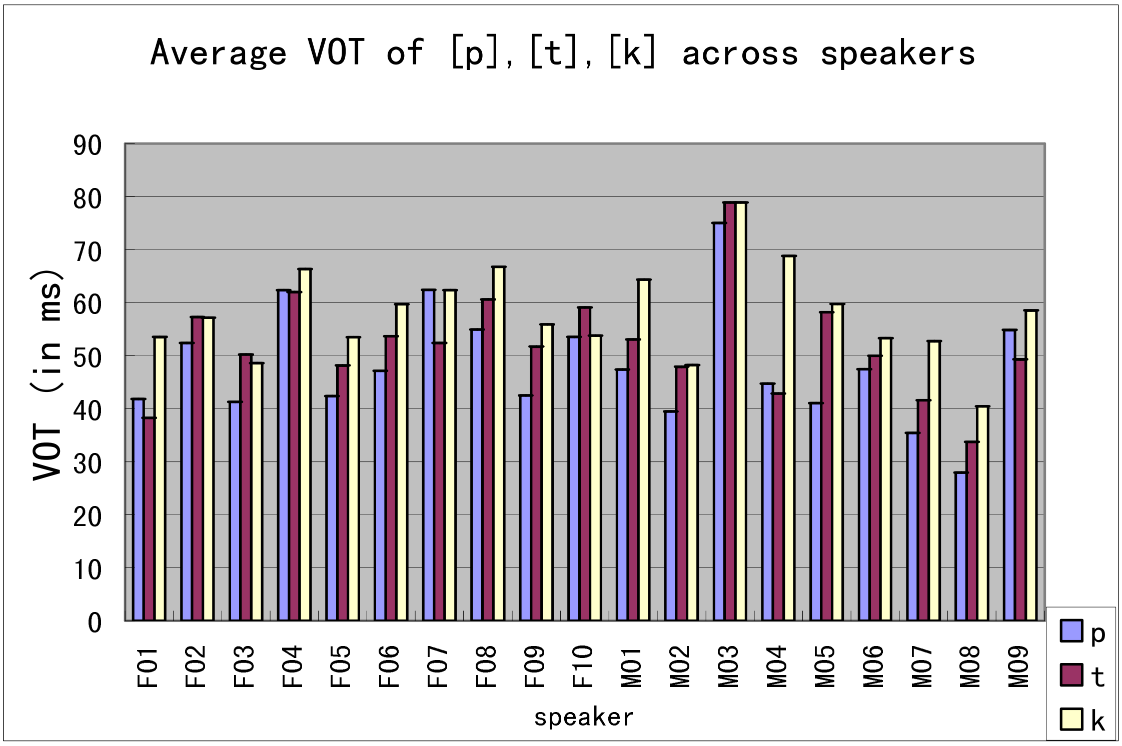


Figure 15b

Figure 15b illustrates average VOT by place across speakers. Unlike closure duration, the pattern of VOT by place shows much more variation across speakers. First of all, not every speaker follows the pattern [k]>[t]>[p] regarding VOT. In fact, just from the figure one can already tell that in at least two speakers' data (F03 and F10), VOT of [k] is clearly exceeded by that of [t], and that in at least four other speakers' data (F02, F07, M02 and M03), it is hard to tell if [k] has the longest VOT of the three. In other words, in almost one-third of the speakers, average VOT of [k] is not necessarily longer than that of [p] or [t]. A t-test shows that average VOT in [k] across speakers is not significantly different from VOT in [t] (t = -1.9723, df = 35.413, p = 0.056), though it is more different from [p] (t = -3.1011, df = 34.395, p = 0.004). Furthermore, [p] and [t] are even more similar to each other in terms of VOT across speakers (t = -1.1646, df = 35.712, p = 0.2519). That said, even if we do see in the figure that most speakers' data follow the rule of [k]>[t]>[p] in average VOT (which explains why the grand means in Table VI follow the pattern too), there is a great deal of individual difference that might be masked if we only look at the grand mean values.

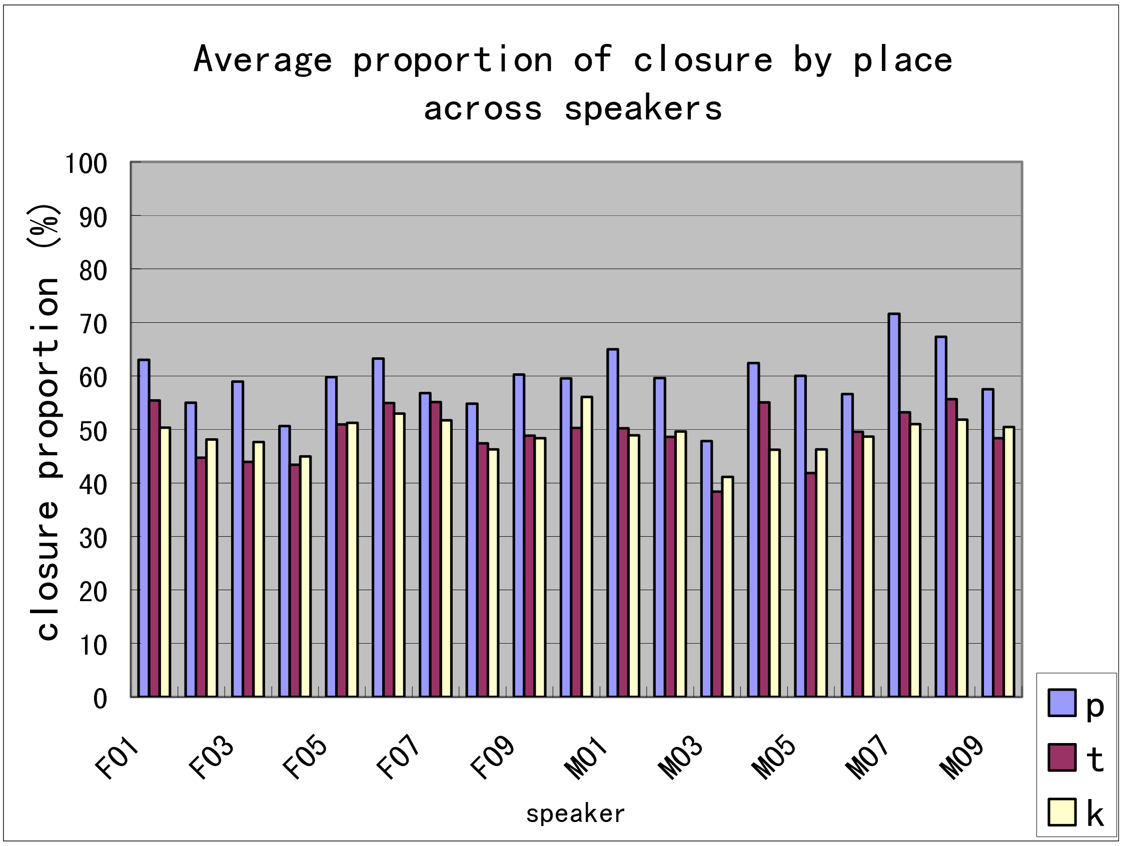


Figure 15c

Figure 15c shows the average closure-total ratio by place in all speakers. Similar to Figure 14, no constancy is observed here, either across place of articulation or across speakers. The most salient pattern, though, is that closure has a greater proportion in the production of a [p] sound than in [t] and [k], consistently across speakers.

In this subsection, we have briefly talked about the overall distribution of duration values by place, by speaker and by both. The grand mean values predicted for the (partial) Buckeye speech files (by the burst detecting program described in section 2) are in general close to the measurements of the TIMIT speech database. However, a great deal of variation across speakers and across phones has been observed. In the following subsection, we will investigate the correlation between the variation and a number of factors. We divide these factors into several largely independent groups, including place of production, speaker background, speaking rate, phonetic context, and word frequency.

3.2 Factors for variance in duration values

3.2.1 Place of production

As discussed in previous sections, place of production has been considered as a highly correlated factor with closure and release durations in voiceless stops in English and many other languages (Cho & Ladefoged 1999).

An ANOVA on phone type ([p],[t],[k]) and release duration shows that phone type has a significant effect on VOT ($F(2,10166) = 115.51$, $p<0.001$). But it only accounts for 2.2% of the variability in VOT. An ANOVA on phone type and closure duration shows that it also has a significant effect on closure duration ($F(2,10166) = 447.95$, $p<0.001$). It accounts for 8.1% of the variability in closure duration.

3.2.2 Factors of speaker background

Gender and age are the two most well-studied speaker-background factors in determining VOT. As mentioned in the introduction, a number of studies claimed that women have longer VOT than men and younger speakers have longer VOT than older speakers. The explanation for the difference usually has to do with physiological and anatomical differences as well as sociophonetic factors. However most of these studies are based on results from well-controlled experiments with a small number of stimuli.

Using the Buckeye data, a two-factor ANOVA testing the effect of age and gender and their interaction, on release duration shows that there is some effect of both age ($F(1,10165) = 20.068$, $p<0.001$) and gender ($F(1,10165)= 47.336$, $p<0.001$), as well as their interaction ($F(1,10165)=38.466$, $p<0.001$). But altogether they can only account for 1% of the variability in VOT.

Individual talker difference is another speaker factor that has been investigated (Allen et al. 2003, Pitt et al. 2005 among others). In our data, the speaker identity factor shows an effect on VOT ($F(1,10150) = 58.855$, $p<0.001$)[1] and it alone accounts for 9.29% of the variability in VOT.

Similarly, speaker identity factor also shows an effect on closure duration ($F(1,10150) =22.916$, $p<0.001$) and accounts for 3.7% of the variability. Age and gender, together with their interaction, only accounts for less than 1% of the variability in closure duration.

3.2.3 Factors of speaking rate

In section 2, we briefly mentioned the use of (global) average speaking rate, measured in number of syllables produced per second, as part of the speaker information used in selecting pilot study subjects. In this subsection, we will test two local speaking rate measures. The first one is similar to the global speaking rate measure, but in a more local environment. The locality of this measure is defined as the speech stretch (naturally delimited by silence, laughter, noise and other non-linguistic sounds) that contains the target phone. This rate measure, referred to as the local stretch speed and measured in number of syllables per second, represents the characteristic speaking rate of the current stretch. The second speech rate measure is the duration of the following phone (which, in most cases, is a vowel). This measure is independent of the duration of the target phone. It represents an even more local speed measure than the local stretch speed, however, it should be noted that because it

[1] Since the speaker identity variable is inherently correlated with other speaker-background factors such as gender and age, there is no need to test the interaction between them.

only measures the duration of one segment after the target phone, it is also more susceptible to non-rate-related factors, such as intrinsic vowel duration.

A two-factor ANOVA testing the effects of local stretch speed measure and duration of the following phone, as well as their interaction, on VOT shows that both of them, but not so much the interaction, have significant effects on the release duration (see Table VIII below). Altogether they account for 12.99% of the variability in VOT. A similar ANOVA on the speed measures' effects on closure duration shows that basically only the local stretch speed has an effect on closure, but not the duration of the following phone nor their interaction. Altogether they can account for 4.9% of the variability in closure duration (while local stretch speed alone can account for 4.8%).

	df	de	F	p
local stretch speed	1	10165	915.79	<0.001
duration of following phone	1	10165	598.69	<0.001
interaction	1	10165	6.87	0.008

Table VIIIa ANOVA on the effects of two speed measures and their interaction on VOT; df = degree of freedom; de = degree of error

	df	de	F	p
local stretch speed	1	10165	517.71	<0.001
duration of following phone	1	10165	10.24	=0.001
interaction	1	10165	1.68	0.194

Table VIIIb ANOVA on the effects of two speed measures and their interaction on closure duration; df = degree of freedom; de = degree of error

3.2.4 Factors of phonetic context

In order to study the effects of phonetic context, the two neighboring phones of the target phone are coded for category (C for consonant, V of single vowel, O of diphthong and nasalized vowels, <N> for non-linguistic noise). Since this whole section only concentrates on word-initial voiceless stops in non-utterance-initial location, by definition none of the target cases immediately follow a sound of category <N>. Besides, most of them precede a vowel sound and none of them immediately precede a sound of category <N>, which is not surprising since they are all word-initial. Table VIIII gives a general count of neighboring phones by category.

	C	V	O	<N>
preceding phone	5528	4596	45	0
following phone	670	9375	124	0

Table VIIII Counts of preceding phones and following phones by category

The ANOVA results on the effects of both the preceding phone category and the following phone category and their interaction on VOT are shown in Table Xa and test results on their effects on closure duration are shown in Table Xb.

	df	de	F	p
preceding phone cat.	2	10161	55.74	<0.001
following phone cat.	2	10161	13.21	<0.001
interaction	3	10161	1.95	0.118

Table Xa ANOVA on the effects of phonetic context factors on VOT

	df	de	F	p
preceding phone cat.	2	10161	372.35	<0.001
following phone cat.	2	10161	1.51	0.22
interaction	3	10161	0.57	0.63

Table Xb ANOVA on the effects of phonetic context factors on closure duration

Both variables but not their interaction have an effect on VOT; but only preceding phone category has an effect on closure duration, not following phone category nor their interaction. Altogether they account for 1.3% of the variability in VOT, and 6.8% of the variability in closure duration.

3.2.5 Word frequency

In addition to the factors discussed so far, we also tested the effects of word frequency on release and closure duration. The frequency of a word is calculated as the number of tokens of that word divided by the total number of target cases (i.e. tokens) of the same speaker. Therefore, all tokens of the same word will have the same frequency value within the speaker, but might differ across speakers. Figure 16 shows the distribution of frequency values in all speakers' data.

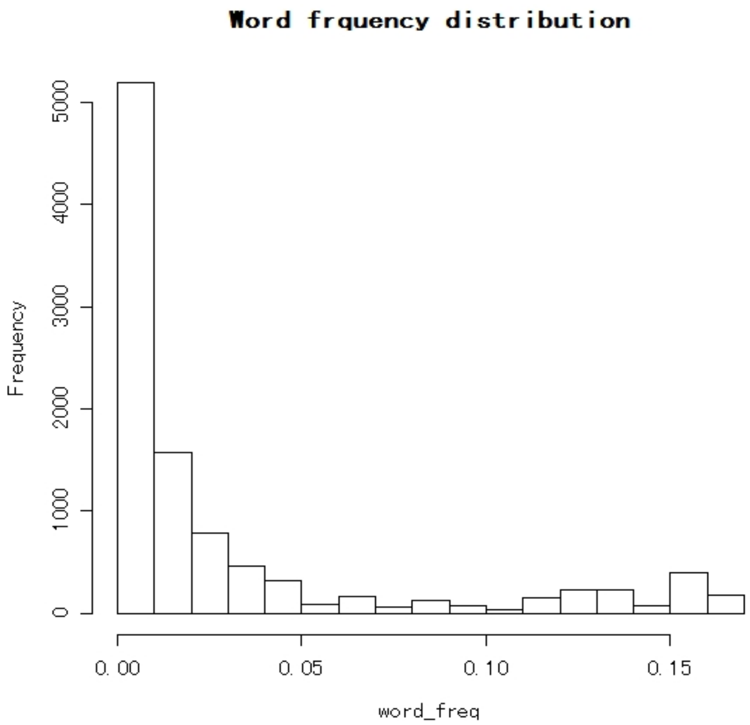


Figure 16 Distribution of word frequency values

As shown in the above figure, the distribution of word frequency values roughly follows the inverse function, with most word tokens accumulated in the low-frequency bins and only a few in the high-frequency bins. Notice that the above figure plots the frequency variable of each token, and if the word has a high frequency in the data set, there are also more tokens of it in the set by definition. That is why there appears to be an increase along the vertical direction near the right end of the horizontal axis.

This frequency variable has also been shown to have an effect on VOT and closure duration (Fosler-Lussier and Morgan 2000). In our study, as shown in the figure, the frequency distribution of words in real speech is anything but balanced. In fact, in all the speakers, the most frequent word in their target set is the word "to" (frequency ranging from 8% to 13% across speakers), without exception. If some words occur extremely often, it is possible that they become the target of certain changes in production, for instance, acceleration, phone reduction and coarticulation. Therefore if the frequency variable is shown to have an effect on duration values like closure and release in stops, it can be a sign of the presence of these processes.

An ANOVA on word frequency's effect on VOT shows there to be a significant effect of word frequency on VOT ($F(1,10167) = 547.67$, $p<0.001$). This variable alone accounts for 5% of the variability in VOT. The ANOVA on word frequency and closure duration shows that there, too, is also a significant effect of word frequency on closure ($F(1,10167) = 306.88$, $p<0.001$). The word frequency variable accounts for 2.92% of the variability in closure duration.

3.2.5 Overall correlation with variance in duration values

For both closure and release duration values, a multi-variable linear regression is performed on all the factors that are shown in previous subsections to have significant effects. The variables that are used in each regression model (Model A for VOT and Model B for closure duration), together with a summary of statistics, are listed below.

Model A:

formula: VOT ~ phone type + speaker + local stretch speed + duration of following phone + preceding phone category + following phone category + word frequency
adjusted R square: 26.06%
$F(27,10141) = 134.1$
$p<0.001$

Model B:

formula: closure ~ phone type + speaker + local stretch speed + preceding phone category + word frequency
adjusted R square: 20.72%
$F(24,10144)=111.7$
$p<0.001$

In other words, we are only able to account for about 26% of the variability in release duration and 20% of the variability in closure duration in the data, after taking into account all factors that have been so far examined and shown to be correlated with closure or release duration. The proportion of variability accounted for is much lower than what has been shown in previous studies, using similar factors. (Among others, Allen et al. 2003 claims that 80% of the variability in VOT can be accounted for by speaking rate, measured in the duration of the following vowel+coda.)

As seen from the two models above, VOT and closure have different predictors. The duration and category of the following phone are not significantly correlated with closure duration (duration: p=0.001; category: p=0.22. cf. section 3.2.3 and 3.2.4). In fact, if we compare the effects of each single factor on VOT and on closure duration (Figure 17), we find interesting differences between VOT and closure duration.

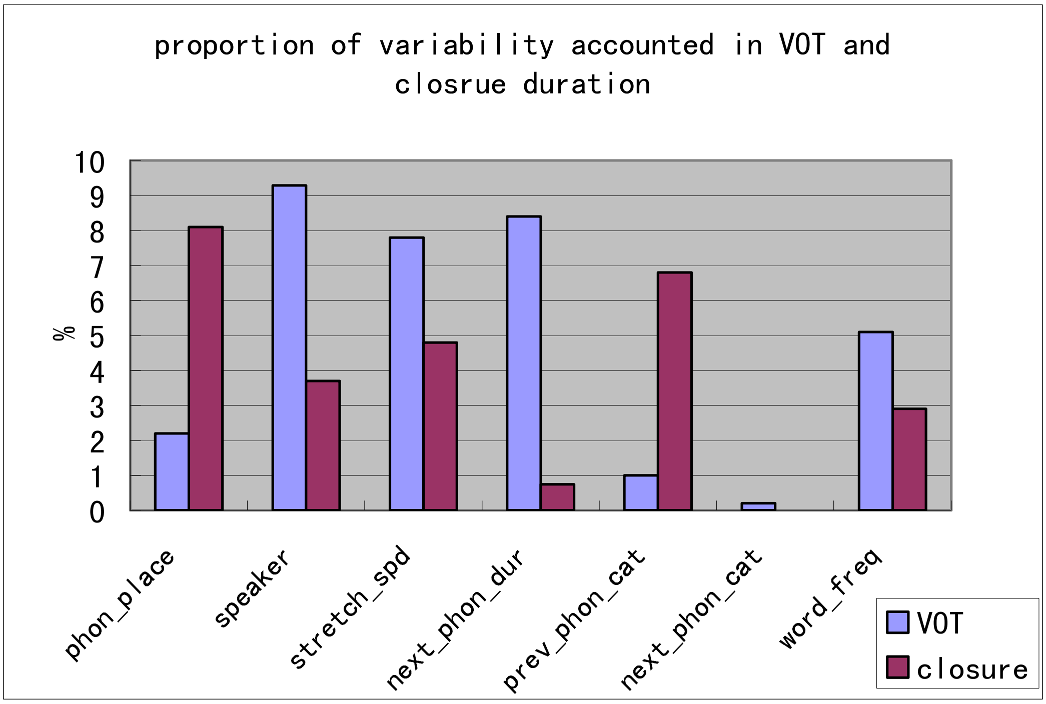


Figure 17

As shown in the above figure, the best predictors for VOT are very different from the best predictors for closure duration. For instance, speed (both two measures) and speaker identity are the best predictors for VOT (the two speed measures account for 7.8%, 8.4% of the variability separately, and 12.99% when they are combined; speaker identity accounts for 9.29% of the variability in VOT), but they only account a small amount of the variability in closure duration (4.8% and 0.7% from the two speed measures separately and 4.9% when they are combined; speaker identity accounts for 3.7% of the variability in closure duration). On the other hand, the best predictors for closure duration – place of phone production (a.k.a. phone type) and the category of previous phone – account for 8.1% and 6.8% (respectively) of the variability in closure but only 2.2% and 1.3% in VOT. Word frequency also has a noticeable difference in explaining the variability of the two (5% in VOT and 2.92% in closure).

When put together, all the pieces suggest that closure duration is most sensitive to a very local environment, i.e. the current phone and the previous phone (not even the following phone since that's already separated by the release). VOT, on the contrary, is more susceptible to global and therefore more general factors, such as speaker differences, speaking rate, word forms, etc. This sheds light on the direction for future study in search of the sources of the remaining 80% variability: for studying closure duration, more variables with respect to the current and the previous phone need to be examined; for studying VOT, more variables with a global domain (at least as big as a syllable or a word) need to be taken into account.

4. Discussion

This paper mainly discusses two issues. The first is a methodology question: how to automatically extract phonetically important information (such as VOT and closure duration in voiceless stops) from a large-scale speech corpus? The second one is a linguistic question: how is closure and release duration distributed over speaker and context in spontaneous connected speech, and what factors vary with the variation in closure and release duration?

4.1 On the methodology

Our take on the first one is to further develop the similarity score approach, which was first proposed and tested in Johnson 2006, and implement a burst detector program that makes use of the calculated scores. The scoring approach is, in its very heart, just a simple measure of how similar one piece of acoustic information is to another on the spectrogram. But together with Mel spectral templates developed for a set of steady-state phones of the speaker, one is able to measure how similar a piece of acoustic data is to, say, the typical [a], or the typical [f] of the same speaker. Therefore the method itself is in essence speaker-independent.

In this study, we have developed an algorithm that recognizes certain patterns in the score vectors and uses that to determine the point of release in voiceless stops. We find that a two-dimensional score vector (<silence> score plus <sh> score) is already adequate to represent the pattern of release in stops and such a pattern is robust enough across a wide range of context in uncontrolled spontaneous speech. The pattern recognition algorithm works confidently on average around 90% of the time (average rejection rate among the 19 speakers is 13.13%); the optimal error in theory is 2.5ms due to the 5ms step size in scores and the mean error is estimated to be around 3-5ms (error is around 3.22ms in the two training cases, and within 5ms in the test with 50 examples across speaker). As discussed before, a large portion of the error comes from residuals of the two rejections rules (e.g. spurious releases) and unusual multiply-released stops.

4.2 On the linguistic question

As for the second question, most of the previous research involving VOT and closure duration in stops was about well-controlled laboratory experiments, typically involving reading of word lists or short paragraphs. The biggest advantage of these studies is that many factors can be carefully controlled and unambiguously recorded. However, these can be disadvantages, too, since they no longer reflect the features of natural speech, and whatever conclusion is achieved cannot be applied in a wider context.

In this study, we used predicted values for VOT and closure duration in word-initial voiceless stops in 19 speakers' data from the Buckeye Corpus, and studied their correlation with a number of factors. As discussed in the result session, all the factors we've investigated, which are also factors that have been studied a lot in previous literature, only account for up to 26% of the variability in VOT and around 20% of the variability in closure duration. Specifically, our data clearly show that gender and age, whose effect on VOT has been asserted in a number of studies (Koenig 2000, Ryalls et al. 1997, Whiteside and Marshall 2001, Robert et al. 2005, among others), only account for no more than 1% of the variability in both VOT and closure duration. (But it should be noted that the division between younger and older speaker groups in our study is by under thirty and over forty, while in most of other studies, the age gap between the two groups is much bigger.)

Speaking rate, which, according to Allen et al. (2003), accounts for 80% of the variability in VOT, in our data only accounts for 13% of the variability in VOT and 4.5% of the variability in closure, even if the rate measure employed in their study, the duration of the following vowel, is very similar to one of the two rate measures we use in our study.

Place of articulation doesn't account for much variability in VOT either (2.2%). As a matter of fact, the widely-recognized rule of velars having the longest VOTs and alveolars the shortest is not strictly followed in one third of the speakers. But place of articulation has a more significant effect on closure duration (8.1% of variability).

We also tested the word frequency variable. Our preliminary results show that it could have a significant effect on both VOT and closure duration.

Last but not least, our study also shows the different patterns of VOT and closure duration in terms of both mean value distribution and correlate factors. VOT is shown to have higher correlation with global variables while closure duration is mostly only sensitive to the local setting (i.e. the previous phone and the current plosive). Though this suggestion needs to be examined more thoroughly, it certainly points to a promising direction for future study on the topic of VOT and closure duration in English stops.

Appendix I Rejection details in all speakers

	F01	F02	F03	F04	F05	F06	F07	F08	F09	F10
N	674	572	777	900	1243	490	231	449	699	412
Rsil	2	1	0	0	4	0	0	1	0	0
Rsh	1	1	1	0	1	0	0	0	0	0
R1	46	48	207	28	75	24	4	29	21	14
R2	12	30	29	33	48	31	3	18	15	18
Ngood	613	492	540	839	1115	435	224	401	663	380
R%	9.05	13.98	30.5	6.77	9.64	11.22	3.03	10.69	5.15	7.76

	M01	M02	M03	M04	M05	M06	M07	M08	M09
N	564	1027	784	865	724	512	636	618	718
Rsil	0	0	0	1	0	0	0	0	0
Rsh	0	1	0	0	2	0	1	0	1
R1	31	94	7	48	93	53	3	54	7
R2	12	128	39	27	98	21	12	44	20
Ngood	521	804	738	789	531	438	663	520	690
R%	7.62	21.71	5.86	8.78	26.65	14.45	2.51	15.85	3.89

N = the total number of target cases
Rsil = the number of cases where no decreasing period is found in <silence> score
Rsh = the number of cases where no increasing period is found in <sh> score
R1 = the number of cases rejected by the first rejection rule
R2 = the number of cases rejected by the second rejection rule
Ngood = the number of remaining cases after all rejection
R% = 1- Ngood /N, the rejection rate

Rejection is applied in the above sequence.

Appendix II Speakers' average speaking rate and their relative rank in the group

	Average speaking rate	rank
F01	5. 8552	3
F02	5. 1846	10
F03	5. 7704	4
F04	5. 3442	8
F05	5. 3042	9
F06	4. 5032	16
F07	4. 0218	19
F08	4. 8831	12
F09	5. 3513	7
F10	4. 3584	18
M01	4. 4421	17
M02	5. 889	2
M03	4. 8757	13
M04	4. 6359	14
M05	5. 6882	5
M06	4. 6359	15
M07	5. 6137	6
M08	6. 4345	1
M09	5. 1081	11

Average speaking rate = total number of syllables produced / total amount of time (in s)
rank: the fastest (highest averaging speaking rate) is ranked 1, and the lowest speed is ranked 19.

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