Phone Boundary Annotation in Conversational Speech

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Abstract
Phone-aligned spoken corpora are indispensable language resources for quantitative linguistic analyses and automatic speech systems. However, producing this type of data resources is not an easy task due to high costs of time and man power as well as difficulties of applying valid annotation criteria and achieving reliable inter-labeler’s consistency. Among different types of spoken corpora, conversational speech that is often filled with extreme reduction and varying pronunciation variants is particularly challenging. By adopting a combined verification procedure, we obtained reasonably good annotation results. Preliminary phone boundaries that were automatically generated by a phone aligner were provided to human labelers for verifying. Instead of making use of the visualization of acoustic cues, the labelers should solely rely on their perceptual judgments to locate a position that best separates two adjacent phones. Impressionistic judgments in cases of reduction and segment deletion were helpful and necessary, as they balanced subtle nuance caused by differences in perception.

Keywords: Inter-pausing unit, reduced words, forced alignment, human verification

1. Introduction
Spoken corpora with signal-aligned phone boundary annotation are indispensable language resources for quantitative speech analyses and automatic speech systems. Well-annotated spoken corpora in various languages have proved to be useful for studying pronunciation variants and developing automatic speech systems, for instance the Switchboard Corpus, the Buckeye Corpus, the Spoken Dutch Corpus, and the Corpus of Spontaneous Japanese (Greenberg et al., 1996; Pitt et al., 2005; Raymond et al., 2002; Oostdijk, 2000; Maekawa, 2003). Moreover, knowledge about speech variability has successfully improved recognition error rates of ASR systems (Liu, 2004; Tsai et al., 2007). This type of phone-aligned data was also used for evaluating the performance of automatic segmentation systems (Wang et al., 2008). However, the problem with producing phone-aligned spoken corpora lies not only in the high cost of time and man power, if the labeling is purely done by hand. It is also difficult to assess the applicability and granularity of annotation criteria and to achieve high inter-labeler’s consistency. In the case of automatic processing such as applying a recognizer or an aligner to produce boundary alignment, the equivalence to human perceptual judgment is often doubtful. In particular, the thresholds for recognizing segment deletion based on acoustic features, which are adopted by system developers, may not always correspond to those set and shared by human (Wester et al., 2001).

This is the main reason why we adopted a combined verification approach to construct phone boundary annotation for a conversational speech corpus. Phone boundaries that were automatically generated by an aligner were verified by human labelers. The labelers did not exactly label the phone boundary, but to give judgments whether the separation of two adjacent phones is perceptually acceptable for them. New boundaries were only assigned, when the labelers disagreed with the original locations and were in the opinion that the new ones can better separate the two adjacent phones.

The organization of this paper is as follows. Section 2 describes the dataset and the annotation procedure. The principles and results of the verification experiment are presented in section 3, followed by a general discussion and conclusion.

2. Automatic forced alignment
2.1 Dataset
The 42-hour Taiwan Mandarin Conversational Corpus (the TMC Corpus)¹ has been constructed at the Institute of Linguistics, Academia Sinica (Tseng, 2013) accounting for three different corpus scenario settings (free conversation, task-oriented and map task dialogues). The TMC Corpus contains 500K orthographically transcribed Chinese words. Speaker turn boundaries are annotated in PRAAT format by the transcribers (Boersma & Weenink, 2012). A dataset of 3.5 hours of speech extracted from the TMC Corpus was used for the present study. It consists of 702 long speaker turns produced by 7 male and 9 female speakers. Boundaries of syllables and individual instances listed in Table 1 are annotated in PRAAT, which are used later as cues for segmenting the original speech data into

¹ Details about the TMC Corpus please refer to the official website http://mmc.sinica.edu.tw.
inter-pausing units.

| Types                               | Total |
|-------------------------------------|-------|
| Ordinary syllables                  | 52,314|
| Silence                             | 1,465 |
| Speech-like paralinguistic sounds:  |       |
| laughing while speaking             | 1,408 |
| Noise-like paralinguistic sounds:   |       |
| inhaling, breathing, coughing, etc. | 3,108 |
| Syllable fragments                  | 601   |
| Foreign words                       | 57    |
| Fillers (with one or more than one syllables) | 428 |
| Discourse particles (originated from Mandarin Chinese or other Chinese dialects) | 1,410 |
| Total                               | 60,791|

Table 1: Data overview.

2.2 Phone boundary annotation: The procedure

As discussed in the introduction session, both automatic generation and human labeling have advantages and disadvantages. The procedure we suggest in this paper tries to reduce the cost and to raise the level of agreement in the sense of human perception. The procedure is illustrated in Figure 1. Since we chose long speaker turns, a pre-segmentation of the sound files into smaller units was necessary. Silent pauses, speech-like and noise-like paralinguistic sounds that were marked in our dataset were used as segmentation cues to obtain inter-pausing units (IPU) (Bigi & Hirst, 2012; Schuppler et al., 2011).

IPUs that did not contain Mandarin Chinese at all, but dialects spoken in Taiwan, were excluded from our final dataset. As a result, 5,276 IPUs were used for the phone boundary verification experiment. The average length of IPUs is 10.4 syllables, approximately equivalent to seven words in Mandarin Chinese. Making use of the sound and the transcript, we first ran the automatic phone aligner to obtain an initial version of phone boundaries. Subsequently, the boundaries were verified by human labelers. After a satisfactory rate of boundary deviation between the labelers was achieved, the final dataset was automatically derived from the verified boundaries with no human intervention.

2.3 Phone set

Acoustic models trained and decoded in continuous speech recognition systems developed for Mandarin Chinese are often based on INITIAL and FINAL components (Tsai et al., 2007). INITIAL and FINAL correspond to onset and rhyme in phonological terms. That is, a FINAL may consist of a nucleus and a coda consonant, implying a higher level than the level of phones. If the acoustic information is learned or trained from this level, it would not be possible to account for pronunciation variant in extremely reduced words such as those with a deleted nucleus, but the coda is present. Thus, we decided to use phone as the decoding unit. Previous corpus-based study on syllable contraction in Mandarin conversational speech showed that the reduction of multi-syllabic sequences resembles a spectrum of reduced phonetic representations with syllable merger as its target form (Tseng, 2005). Applying the general contraction rules, a considerable number of pronunciation variants involving (at least) disyllabic words that are reduced to different degrees should be predictable based on the canonical form. Ranging from consonant deletion, nuclei merging, to syllable merger, these pronunciation variants that are often found in conversational speech, cannot be properly taken into account, if only INITIAL and FINAL are distinguished for syllables.

Conventionally, a Mandarin Chinese syllable has the form of CGVX with C denoting a consonant onset, G a glide, V a vowel, and X a consonant coda (Duanmu, 2000; Ho, 1996). A set of 22 consonants presented in terms of the place of articulation in Table 2 can occupy the onset position, except for /ŋ/. Only the nasals /n/ and /ŋ/ can appear in coda position. Our inventory set also contains two glides /j/ and /w/, and 15 vowels including monophthongs and diphthongs /i, u, y, a, o, ɹ, e, ɹ, aɪ, ai, au, ou, ye/.

![Figure 1: A combined annotation procedure.](image)

Table 2: Mandarin consonants.

| Bilabial     | p | b | m |
|--------------|---|---|---|
| Labiodental  | f |   |   |
| Dent-alveolar| t | t̂ | n  |
| Alveolar     | s | ts | t̂s |
| Retroflex    | ʂ | tʂ | t̂s |
| Alveolo-palatal | c | tc | t̂c |
| Velar        | x | k | k̂ |

2.4 Training a phone aligner

To construct the phone aligner, we first built acoustic models for individual phones found in ordinary syllables. For the other instance types listed in Table 1, we built acoustic models for each of them, except for fillers and discourse particles, because their phonetic representations can be categorized into distinct types systematically. For fillers, we accounted for three different acoustic models.
by considering the nasality and the length in syllables: two filler types for monosyllabic instances, one with and one without a nasal coda, and one type for multi-syllabic fillers irrespective of the presence of a final coda. Four acoustic models were trained for discourse particles. One was applied to high frequency particles; one to particles originated from a Chinese dialect (Southern Min) that is dominantly spoken in Taiwan; and two to Mandarin Chinese particles that were grouped together according to the degree of similarity in syllable structure.

As a result, 51 tri-states acoustic models were used for training our aligner with the HTK toolkit (Young et al., 2006). The models, facilitated by the already annotated syllable boundaries, were trained at a frame shift of 5ms and a window length of 15ms, where for each frame, 13 MFCCs (the mel-scaled cepstral coefficients C0-C12) and their first and second order derivatives (39 features) were calculated. For the current phone aligner, fundamental frequency is not taken into account, although pitch-related features may play an important role in understanding and processing Chinese lexical tones. With a frame shift of 5ms and no skipping three emitting states of models, the phones will be assigned a minimum length of 15ms within manually pre-determined syllables. For the verification experiment, the results of applying 5,276 IPUs of data to our phone aligner were converted to a PRAAT readable format (Boersma & Weenink, 2012) with the transcript information on one tier and the aligned phone boundaries on the other, as illustrated in Figure 2.

3. Human verification of boundaries

The 3.5-hour speech dataset contains in total 133,339 phones. We used 10% for the training phase and 90% for the evaluation phase. The summary in terms of phone categories is given in Table 3. Six labelers with prior experiences with speech data annotation were grouped into three pairs (A, B, and C). We ran a training phase to acquaint our labelers with the verification criteria. The training data was divided into three subsets. Each subset was verified by two labelers in the same group, i.e. all data were examined by two labelers. Mutual discussion among labelers was allowed in the training phase to achieve a common consensus. The threshold we set for a satisfactory inter-labeler’s consistency was that 85% of the verified phone boundaries should not deviate more than 20ms within each pair of labelers. The labelers did not start with the actual experiment until they achieved the consistency threshold. In the evaluation phase, no discussion was allowed. The entire experiment period including the training and evaluation phases last three months.

| Phone categories    | Occurrences |
|---------------------|-------------|
| Monophthongs        | 39,097      |
| Nasals              | 17,951      |
| Glides              | 15,369      |
| Plosives            | 14,685      |
| Diphthongs          | 13,218      |
| Retroflex           | 9,021       |
| Affricates          | 7,351       |
| Filler+para. sounds | 7,067       |
| Approximant         | 3,095       |
| Fricatives          | 2,995       |
| Lateral             | 2,080       |
| Particles           | 1,410       |
| Total               | 133,339     |

Table 3: Phones in the dataset

3.1 Phone boundary verification

3.1.1. Separation of two adjacent phones

The essential, but also the most difficult, issue for labeling phone boundaries in natural speech is the transition from one phone to the other. No concrete rule was instructed to the labelers how they should deal with the inter-segmental transition. They should only rely on their perceptual judgments to decide on a location that best separates two adjacent phones. Thus, visualized acoustic cues such as pitch, spectrogram and intensity information were not provided to the labelers. They made their decisions based on the listening only. On the one hand, the perceptual judgment of the labelers served as additional modification to the acoustically based alignment result. On the other hand, as our data have been verified by two labelers, the perceptual discrepancy between the labelers is regarded as a kind of balance of individual perceptual differences.

3.1.2. Allophones

When words were correctly transcribed in the text, but the labelers with a sensitive hearing perceived allophonic differences, they should ignore the allophonic variation, as it does not affect the word meaning. On the one hand, it was not the goal of this study to do narrow transcription. On the other hand, it would be difficult to keep up a high inter-labeler consistency rate, if allophonic differences in the dataset are to be considered consistently.

3.1.3. Marking deletion

What should the labelers do, if phones that should appear in the canonical form are not heard in the speech? In this case, the words were correctly transcribed, but some of the phones were audibly not present. This is a known, difficult problem labelers are often encountered with,
when they are to determine phone boundaries in natural, continuous speech such as conversational speech. To preserve all phone labels generated by the forced aligner for later automatic processing and result analysis, as well as to reduce the effort of locating a boundary for non-existing phones, we designed a function in PRAAT to help labelers mark deletion. If a phone was absent for labelers, they were instructed to use the **Deletion** function that automatically minimize absent phones to an interval of 5ms, as shown in the very bottom of the menu in Figure 2. Using this function, the deletion is annotated without spending unnecessary time for determining the extremely difficult boundaries.

The examples shown in Figure 3a-c are three variants of the disyllabic word *ranhou* /ʐən xou/ (‘then’). Figure 3a shows an instance of *ranhou* with all phones present. In Figure 3b, the coda nasal /n/ was marked as deleted by the labelers, whereas Figure 3c shows both the nasal coda of the first syllable and the onset of the second syllable are not present.

3.2 Experiment results

3.2.1. Verification results

The verification results of three labeler pairs are shown in Table 4. In each of the three pairs, more than 90% of the phone boundaries assigned by the two labelers deviated from each other with an interval less than 20ms. In the calculation of deviation, we compared the ending boundary of each phone. The deviation in the evaluation phase was reduced compared to that in the training phase. Furthermore, to closely observe the verification results, Figure 4 summarizes the results in terms of boundary deviation at a time step of 5ms. The results are similarly distributed across the three pairs, suggesting a successful training phase and a good inter-labelers’ consistency.

![](image1)

**Figure 3a:** No deletion in *ranhou* /ʐən xou/.

![](image2)

**Figure 3b:** Deletion of /n/ in *ranhou* /ʐən xou/.

![](image3)

**Figure 3c:** Deletion of /n/ and /x/ in *ranhou* /ʐən xou/.

3.2.2. Phones with severe deviation

Table 5 lists the results of phone categories that caused deviations larger than 20ms. Glides /j, w/, monophthongs /a, ə/, and the lateral /l/ were more problematic than the other phone categories. These phone categories caused a large boundary discrepancy between the labellers in more than 10% of the phones. Contrastively, fricatives, plosives, and affricates were less problematic with regard to boundary annotation. One possible reason for this result may lie in different transition types of phone categories. While the transition in sonorants is continuous and non-abrupt, fricatives, plosives, and affricates are more clearly presented in acoustic configuration that leads to a more successful alignment of the phone aligner.

![](image4)

**Figure 4:** Phone boundary deviation.

### Table 4: Labelers’ consistency.

| Labelers | Training set | Evaluation set |
|----------|--------------|----------------|
|          | phones < 20ms | phones < 20ms  |
| Pair A   | 4,832 87.75%  | 47,057 92.95%  |
| Pair B   | 4,541 90.71%  | 44,497 92.16%  |
| Pair C   | 4,609 86.90%  | 26,665 93.68%  |
| Total    | 13,982 88.43% | 118,219 92.82% |

### Table 5: Phone categories Phones (>20ms deviation)

| Phone categories | Phones (>20ms deviation) |
|------------------|--------------------------|
| Glides           | 1,821 (11.85%)           |
| Monophthongs     | 4,162 (10.65%)           |
| Lateral          | 219 (10.53%)             |
| Approximant      | 240 (7.75%)              |
| Diphthongs       | 912 (6.9%)               |
| Nasals           | 1,184 (6.6%)             |
| Retroflex        | 547 (6.06%)              |
3.2.3. Phones marked as deleted

Table 6 lists the occurrences of phone categories that were marked deleted by at least one labeler, with information about the percentages in the overall data. As a result, 3,690 phones in our dataset were marked as not present (deleted), making up 2.8% of the overall data. Among the 3,690 phones, only about 20% were not audible for both labelers, suggesting that the thresholds each person sets for phone deletion vary individually. It was more likely for the approximant /x/, the lateral /l/, and the glides /j, w/ to be marked deleted. For the nasal /n/, 445 out of the 497 deleted occurrences are located in coda position. Only 52 occurrences of the deleted /n/ are in onset position. Among 536 deleted monophthongs, 214 were Schwa.

| Phone categories       | Deletion No. (% in dataset) |
|------------------------|-----------------------------|
| Glides                 | 881 (5.73%)                 |
| Nasals                 | 578 (3.22%)                 |
| Monophthongs           | 536 (3.17%)                 |
| Plosives               | 441 (3.00%)                 |
| Approximant            | 313 (10.11%)                |
| Retroflex              | 301 (3.34%)                 |
| Affricates             | 206 (2.80%)                 |
| Fillers+para. sounds   | 160 (2.26%)                 |
| Lateral                | 113 (5.43%)                 |
| Fricatives             | 94 (3.14%)                  |
| Diphthongs             | 65 (0.49%)                  |
| Particles              | 2 (0.14%)                   |
| Total                  | 3,690 (2.8%)                |

Table 6: Phone omission.

3.3 Final dataset

For producing the final dataset, the middle position of the boundaries assigned by the labelers was calculated and taken as the final phone boundary with no further human intervention.

4. Discussion

Utilizing our phone-aligned dataset, a wide range of research works concerning conversational speech is possible. For instance, deleted phones in reduced spoken words are normally judged and identified by phonetically trained experts, often with a focus on phone sequencing instead of the contextual information such as the perception of spoken words. As we have marked deleted phones in the experiment, we are able to identify what kinds of words are more likely to be reduced by observing words in which at least one phone was marked deleted. Reduced words with omitted segments normally also cause obvious difficulties for automatic speech systems to recognize or to align. Besides, location relative to the position in the IPUs also provides contextual information about the surface form of words and possibly also the discourse structure associated with these words.

Table 7 lists ten words that have the highest percentage rates of deletion in our dataset. In the TMC Corpus, these words are among the top 100 most frequent words (Tseng, 2013). As shown in Table 7, different preferences for IPU positions are found. It is more likely for yinwei (because) and ranhou (then) to be reduced in IPU initial position. Dui tends to be reduced in both IPU initial and medial positions, but less likely in IPU final position. The rest of words are more likely to be reduced, when they are in IPU medial position. Concerning the deleted phones, we found some systematic distributions. When a word contains glides, it is usually the glide that is deleted, e.g. wo, women, jiu, and dui. In the case of disyllabic words, it is usually the onset of the second syllable that is deleted, e.g. ranhou, xianzai, and shihou. But for disyllabic words with a plural suffix, the preference for segment deletion differs. The Schwa and the coda of the second syllable (the suffix) tend to be deleted and the bilabial nasal onset of the suffix tends to be preserved. For monosyllabic words like dui and de, though both with a plosive onset consonant, the reduction forms are quite different. De is a structural particle that is usually preceded by a head, while dui is a preposition that is usually followed by a head, or a predicate that has a function of acknowledgement. The frequently reduced segment in de is the onset (the onset is in the juncture between the head and de), but the glide in dui. These preliminary observations with regard to deletion point out the interrelationship between reduction degree, IPU position (i.e. position in a spoken discourse), and the phonological property of segments. To closely study reduced forms in different IPU positions, we are currently conducting a free phone decoding experiment to automatically generate phone sequences for individual words and then select the prototypical pronunciation variants. Phonological and phonetic rules of segment deletion will be compared in a systematic way.

| Word variants | IPU initial | IPU medial | IPU final | No. in dataset | Total deletion |
|---------------|-------------|-------------|-----------|----------------|----------------|
| lamen (they)  | 10 (77%)    | 6           | 165       | 56%            |
| ranhou (then) | 93 (28%)    | 66 (20%)    | 328       | 51%            |
| yinwei (because) | 91 (32%) | 39 (14%)    | 287       | 49%            |
| jiu (then, so) | 9 (63%)     | 25 (8%)     | 226       | 34%            |
| shihou (time) | 0 (69%)     | 8 (229)     | 229       | 34%            |
| xianzai (now) | 14 (78%)    | 6 (433)     | 433       | 23%            |
| dui (for, yes) | 48 (9%)     | 48 (9%)     | 509       | 20%            |
| de (structure part.) | 0 | 104 (17%) | 598 | 18% |
| women (we) | 49 (184) | 7 (1,460) | 1,460 | 16% |
| wo (I)      | 11 (61)     | 8 (1,362)   | 1,362     | 6%             |
| Total       | 325         | 789         | 5,597     | 21%            |

Table 7: Deletion in different prosodic positions.

5. Conclusion

While expert opinions on fine details may play a decisive role in phonetic analysis, it is also important to make available large-scale well-annotated spoken language resources. Phonetic representations of spoken words may
largely deviate from their canonical forms in conversational speech. By adopting a combined procedure of automatic phone alignment and perceptual verification, we constructed a phone-aligned dataset of conversational speech with relatively low cost of human power, but relatively high annotation quality.

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