Estimating Speaking Rate in Spontaneous Speech from Z-scores of Pattern Durations

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ABSTRACT

We propose a novel method for estimating speech rate based on the durations of similar patterns as a first step in determining the relation between various speaking styles used in everyday conversation and speaker intentions or attitudes. Whereas most methods of determining speaking rate require manually obtained label information or linguistic knowledge, the proposed method uses patterns of speech-sound sequences that occur relatively frequently in dialogue speech, as detected from the speech waveform information alone. For use as an index of speaking rate, the method calculates the z-score of each pattern duration, relative to the distribution of the respective pattern groups. The method uses speech recognition to provide a rough classification of the speech sounds, i.e., as a phonetic typewriter, but without requiring accuracy of recognition in any meaningful linguistic terms. From a large body of natural dialogue speech data, it divides the label sequences obtained from the recognizer/classifier into variable length patterns according to maximum likelihood, and classifies all speech segments having the same pattern as a group. The validity of speech rate detection was evaluated.

1. INTRODUCTION

People commonly express their intentions or attitudes in the form of paralinguistic information encoded in the various speaking styles of everyday conversation [1]. Such paralinguistic information is readily processed by human beings, but automatic interpretation by computer processing is still very difficult. It needs a more rigorous elucidation of the relations between (a) speaking styles and (b) intentions or attitudes. For that purpose, collection and analysis of a large-scale natural-dialogue speech corpus is indispensable, but natural dialogue data has great variation in articulation styles and it can be both difficult and expensive to obtain accurate transcriptions manually. Although application of speech recognition technology has improved greatly in recent years, the recognition accuracy is still inadequate for natural dialogue speech data. Therefore a speaking style analysis method independent of text information is an important subgoal of our research.

Speech rate is an important variable in the speaking styles used for everyday conversation. [2, 3, 4, 5] Although there has been considerable previous work to try and specify speech rate by e.g., combinations of syllable rate and phone rate [6], there are inconsistencies arising from both acoustic and linguistic information under the influence of e.g., vowel prolongation, de-vocalization, etc. Speech rate is still difficult to specify by conventional parameters such as syllable tempo or phone duration unless an accurate transcription and segmentation is available.

We therefore propose a method which makes use of sequences of speech-sound patterns which occur five or more times in a speaker’s dialogue data, based on a large volume of speech information but without use of text information, and we measure speaking rate by means of the z-scores of these pattern durations relative to the distribution of its pattern group. This method allows us to analyze changes in speech rate with respect to speaker intentions or speaker state. The method allows us to work with untranscribed speech, processing not only the speech patterns demarcated by pauses, but also the patterns embedded in a sentence utterance.

In addition, this method of pattern extraction processing is efficient as a general preprocessor for speaking style analysis of large scale speech data, since it can provide a basic framework for extraction and analysis of any variable features of dialogue speech data, i.e., it is applicable not only to speech rate but also to various acoustic or prosodic features such as fundamental frequency, power, and voice quality, to enable an estimate of local settings normalised per speaker without access to a transcription or labels.

2. PATTERN EXTRACTION METHOD

Compared to the clean speech of laboratory or studio recordings, in dialogue speech, many utterances undergo extreme phonetic modification (e.g., prolongation of vowels or gemination of consonants, elision or deletion of sounds, etc.) and transcription is an expensive and time-consuming process, particularly if it is to be done at the phonetic level. Even if it is to be used as a word-level target for automated segmentation, the written transcription itself is not necessarily suitable as a specification of the speech sounds.

For example, although speech rate in Japanese is usually specified as a period of time divided by the number of mora (or syllables) it contains, when there is insertion or prolongation of vowels or gemination of consonants, for example, it becomes difficult to specify the number of mora.

Although application of speech recognition technology to dialogue speech data has improved considerably in recent years, many spontaneous speech utterances are not registered either in the lexical dictionary or the language model. Yet these non-verbal speech noises are common in dialogue data, and though they signal important affective information, they also serve as a cause of recognition errors.

It is of course possible to add such non-verbal speech items to the dictionary or language model from existing transcriptions, but we note that this type of dialogue speech is very dependent on speakers and speaker-hearer conditions, and there is no guarantee that we can obtain a sufficient lexical set only by increasing the amount of transcribed data.

On the other hand, if similar types of speech patterns can
be extracted or detected automatically from dialogue speech. the duration of these similar patterns can be directly compared, and we can make an estimate of speech rate change by sampling the patterns at (irregular) intervals throughout the speech.

Therefore, we propose a method for extracting similar speech patterns automatically, based on acoustic information, as a component technology for the analysis of speaking style and other prosodic features that slowly change throughout the course of an utterance.

2.3. Pattern grouping
The start time and end time are assigned to each speech pattern by post-processing of the recognizer output, and the $z$-scores of these segment durations are calculated for all tokens in each pattern group.

3. EXPERIMENTS
In order to check the validity of the proposed method, an evaluation experiment was conducted using a subset of the same dialogue speech corpus. The validity was evaluated by comparing the patterns obtained by the proposed method (henceforth, ‘recognition patterns’) without the use of a transcription, and the equivalent patterns obtained from a phonemic segmentation based on the transcribed text (henceforth, ‘transcription patterns’) which we assume to be more accurate since they are more expensive to obtain. If the same result is obtained for recognition patterns and transcription patterns, it can be said that the validity of the proposed method is high.

3.1. Corpus
A section of the spontaneous dialogue speech corpus from the JST/CREST-ESP project [1, 12, 13, 14] was used as the speech material. This corpus has the following features:

- Spontaneous dialogue speech over the telephone, recorded using high-quality head-mounted microphone connected to local disc at 44.1kHz.
- A young adult female speaker of Japanese.
- Data recorded over period of 2 years (more than 250 hours of speech data).
- Each dialogue lasts between 6 and 30 minutes.
- Includes various inter-personal relationships (parents, husband, children, relatives, friends, others).

We used 145,152 utterances from 792 dialogues for the training. Each utterance was determined from a manual transcription and defined as a ‘minimal meaningful speech unit’. Processing was performed with the proposed method, based only on speech waveform information alone, and no transcribed text or other information relating to the utterance content was used except for evaluation.

3.2. Phonemic segmentation as evaluation criterion
For the evaluation, we used similar patterns determined from the phoneme sequence output by a speech recognition engine (Julius [9]) used in alignment mode and fed with a hand-made transcription of each utterance in place of a grammar module.

As mentioned above, we used the VI-train command of the Multigram Package [11] to provide the dictionary of label-sequence patterns and the unit sequences. The settings of HMMs for phonemic segmentation and configuration of pattern extraction were as described in section 2.

Because the manually transcribed text is in Japanese orthography (and therefore mixes Chinese kanji characters with the phonetic kana alphabet) we used the public-domain Japanese morphological analyzer ChaSen [15] to produce a sequence of phonemic characters representing the text as a basis for the automatic segmentation.

3.3. Preleminary experiment
The number of labels making up the multigram dictionary codebook varied in the range of 1 $\leq N \leq 6$. No patterns longer than 6 occurring more than 50 times were extracted.
We found that there were many more fragmentary patterns of 3 phonemes for the recognition patterns, than for the transcription patterns. Moreover, the patterns incorporating 3 labels or fewer correspond to very many speech segments and may be greatly influenced by neighboring phonemes, so the variation of these segments will be great when compared with others of the ‘same’ pattern. On the other hand, patterns of 5 labels correspond to a smaller number of speech segments of a specific type, and the influence of surrounding phoneme variations can be considered to be comparatively small, so we limited our evaluation to only the changes of speech rate observed within the 5-label patterns.

3.4. Evaluation measure

In this section, we verify the validity of the pattern extraction results by the proposed method and confirm the speech rate estimation (based on z-scores of pattern durations in the group distributions of each pattern) by comparison with the case of transcription patterns.

First, if there is any overlap between speech segments corresponding to the recognition pattern and segments corresponding to the transcription patterns, then we judge the recognition pattern to be sufficiently aligned or correct. Next, the validity of the proposed method is evaluated at these well-aligned points.

For the correspondingly aligned data, the agreement between the pattern duration z-scores from recognition patterns and those from transcription patterns was checked. To the extent that both z-scores correspond, the possibility that speech rate can be appropriately measured by the proposed method is confirmed.

Furthermore, correlation between the proposed method and a conventional speech rate which used transcription was confirmed for all extracted patterns, for there were some recognition patterns which had no transcription pattern counterparts due to mis-recognition.

4. RESULTS AND DISCUSSION

4.1. Reliability of speech segment extraction

Table 1 shows the ten most frequent patterns of multigram code-words of length 5. Many include silence symbols (/sp/ or /q/) from the recognizer, but we selected the interjection /naNka/ for further manual inspection.

Table 1: patterns of 5 phonemes, most frequent 10 patterns

<table>
<thead>
<tr>
<th>pattern</th>
<th>number of tokens</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;sp&gt;ru:Nq</td>
<td>162</td>
</tr>
<tr>
<td>&lt;sp&gt;nu:Nq</td>
<td>161</td>
</tr>
<tr>
<td>&lt;sp&gt;uu:Nq</td>
<td>152</td>
</tr>
<tr>
<td>kaqte</td>
<td>134</td>
</tr>
<tr>
<td>tokoa</td>
<td>133</td>
</tr>
<tr>
<td>toqte</td>
<td>118</td>
</tr>
<tr>
<td>naNka</td>
<td>116</td>
</tr>
<tr>
<td>&lt;sp&gt;mo:Nq</td>
<td>107</td>
</tr>
<tr>
<td>moqte</td>
<td>104</td>
</tr>
<tr>
<td>koqte</td>
<td>99</td>
</tr>
</tbody>
</table>

We found 116 speech segments corresponding to /naNka/ in both the transcription patterns and the recognition patterns. Of these, 81 were correctly aligned (Table 2).

Table 2: Result of listening test

<table>
<thead>
<tr>
<th>word including pattern</th>
<th>meaning in english</th>
<th>frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>naNka</td>
<td>interjection</td>
<td>96</td>
</tr>
<tr>
<td>naNka</td>
<td>how many times</td>
<td>16</td>
</tr>
<tr>
<td>naNka</td>
<td>question</td>
<td>2</td>
</tr>
<tr>
<td>naNka</td>
<td>etc.</td>
<td>1</td>
</tr>
<tr>
<td>naNka</td>
<td>something</td>
<td>1</td>
</tr>
<tr>
<td>total</td>
<td></td>
<td>116</td>
</tr>
</tbody>
</table>

4.2. Speech rate based on z-score of pattern duration

The larger the z-score of pattern duration, the slower the speaking rate of the corresponding speech segment can be assumed in the proposed method. Because both distributions of duration from the 116 recognition patterns and transcription patterns are similar to a log normal distribution, duration is computed as z-scores after being converted to logarithmic values. As a result, both distributions of duration patterns are close to normal distribution (Fig. 2)

![Figure 2: Duration z-scores of /naNka/, after log conversion](image)

As a result of the checks on the 81 correct data in the 116 segments automatically extracted by the proposed method, the duration z-scores appear equal to the duration z-score of the transcription patterns in general. So, it is thought appropriate to predict speech rate based on z-score of recognition patterns obtained by the proposed method (Fig. 3).

![Figure 3: Duration z-score of patterns](image)
The correlation between the proposed method and vowel-per-second rate \cite{16} is shown in Fig. 4.

\begin{center}
\begin{tabular}{ccc}
\hline
\textbf{group} & \textbf{correspondence formula} & \textbf{correlation} & \textbf{vowels} \\
\hline
a & $y = -0.5x + 1.8$ & -0.693 & 1 \\
b & $y = -1.0x + 5.5$ & -0.551 & 2 \\
c & $y = -2.0x + 8.0$ & -0.592 & 3 \\
\hline
\end{tabular}
\end{center}

5. CONCLUSION

We proposed a method for analyzing speaking rate based on the duration distribution of the estimated speech patterns, after automatically extracting sets of speech patterns which are not dependent on text information and which appear 50 times or more in a dialogue using only audio information, as the first step towards analyzing the various speaking styles encountered in a large-scale dialogue speech corpus. By this method, speech rate analysis can be considered as almost equivalent to the case where a transcribed text is used. We will make the proposed method more precise by reconsidering the structure of extracted patterns.

The pattern extraction technique of the proposed method is effective as a preprocessing technique for analyzing speaking styles based on a large amount of dialogue speech data, and provides a fundamental framework for extracting and analyzing the various features of paralinguistic information in speech. It is also applicable to the analysis of fundamental frequency, power, voice quality, etc.

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7. REFERENCES

\begin{enumerate}
\item \cite{1} Campbell, N. and Mokhtari, P.: “Voice Quality, the 4th prosodic dimension”, Proc. ICPhS 2003, pp.2414–2420 (2003).
\item \cite{5} Wood, S.: “What happens to vowels and consonants when we speak faster?”, Working Papers 9, Phonetics Laboratory Lund University, pp.8–39 (1973).
\item \cite{13} Campbell, N. and Mokhtari, P.: “DAT vs. MD”, Proc. ASJ Spring 1-P-27, pp.405–406 (2002).
\item \cite{14} Campbell, N.: “Labelling natural conversational speech data”, Proc. ASJ Fall 1-10-22, pp.273–274 (2002).
\item \cite{15} ChaSen, http://chasen.aist-nara.ac.jp/hiki/ChaSen/.
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