A Metric to Classify Style of Spoken Speech

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Abstract

The ability to classify spoken speech based on the style of speaking is an important problem. With the advent of BPO’s in recent times, specifically those that cater to a population other than the local population, it has become necessary for BPO’s to identify people with certain style of speaking (American, British etc). Today BPO’s employ accent analysts to identify people having the required style of speaking. This process while involving human bias, it is becoming increasingly infeasible because of the high attrition rate in the BPO industry. In this paper, we propose a new metric, which robustly and accurately helps classify spoken speech based on the style of speaking. The role of the proposed metric is substantiated by using it to classify real speech data collected from over seventy different people working in a BPO. We compare the performance of the metric against human experts who independently carried out the classification process. Experimental results show that the performance of the system using the novel metric performs better than two different human expert.

1 Introduction

BPO’s (Business Process Outsourcing) centers are increasingly finding their way because of the increased quality consciousness, particularly in the service industry segment. Development in the area of telecommunications make it feasible for the BPO’s to be located in regions which it is servicing other than the local population. In addition socio-economic reasons justify the geographical location of BPO’s anywhere without the people being serviced being aware of it. This has led to a spate of BPO’s cropping up in developing countries where there exists a large population that can speak the language of the people not necessarily in the same style. For this reason, there is no definite recruitment qualification that one should possess to join a BPO, except that, one be able to speak in the style

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of the population that the BPO services. The increase in number of BPO’s and the no specific qualification requirement, leads to a situation of total influx, people are always on the move (high attrition). This leads to the requirement of a constant recruitment process at the BPO’s. Today, BPO’s with no exception, employ accent analyst to select candidates. The accent analyst judges the suitability of a candidate by analyzing the speaking style of the candidate. The process of recruitment is time consuming (on an average only about 7% of the candidates appearing for the interview are selected) and is prone to human bias. There is a need for an automatic system that can measure the candidates speaking style or more precisely, classify the candidates speaking style as being suitable (good), trainable (average) or unsuitable (bad).

Often one is able to make out the speakers background (American, British, Indian etc) by just listening to the spoken speech of the person. In addition, one is also able to tell if the person is speaking well or not, even in the absence of knowledge of the language being spoken. Thus, it is possible for a human to categorize speakers based of their speaking style by listening to their speech. A trained human is able to perform this task of classification better because he is aware of the nuances of what to be on the lookout for which identifies a well spoken speech. An ideal system\(^1\) would be the one that has the ability to classify people based on their speaking style by looking at their free-spoken speech. While work is on at the Cognitive Systems Research Laboratory of Tata Infotech, the development of such a system is still premature.

In this paper, we propose a system that can be used to classify people based on their speaking style\(^2\). The heart of the system is the use of a new metric, which captures the speaking style of a person. Further, we describe the construction and use of such a metric. In this paper, we aim at developing a system that is able to categorize the speaking style of a person by analyzing predetermined set of words and sentences\(^3\).

## 2 Metric to Classify spoken speech

The speaking style and articulatory capability of spoken speech can be assessed automatically by comparing the test samples with ideal samples using a metric,

\[
\mathcal{D} \overset{\text{def}}{=} (\mathcal{D}_{ij}, \mathcal{I}_p_{ij}, \mathcal{I}_r_{ij})
\]

The metric \(\mathcal{D}\) is suitable for comparing two spoken words or sentences, \(i\) and \(j\). Note that the metric \(\mathcal{D}\) captures both the articulatory(\(\mathcal{D}_{ij}\)) and the intonation (\(\mathcal{I}_p_{ij}\) and \(\mathcal{I}_r_{ij}\)) capability of the speaker, both of which together characterise the speaking style of the spoken speech. While \(\mathcal{D}_{ij}\) captures the closeness of the content of the two spoken words or sentences, \(\mathcal{I}_p_{ij}\) and \(\mathcal{I}_r_{ij}\) capture the closeness in terms of intonation or the style of the

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\(^1\)Essentially the system would be built by first analyzing and deriving rules by listening to spoken speech samples. These rules would enable development of the system to determine the quality of speech.

\(^2\)To assist BPO recruitment process.

\(^3\)The speaker would be asked to speak a carefully selected list of words and sentences, which would be used by the system to analyze the style of speaking.
speaking. Note that \( I_{P_{ij}} \) depends on the parameter *pitch* while the measure \( I_{R_{ij}} \) depends on the *stress* of the spoken speech.

## 3 Problem Formulation

### 3.1 Selection of Ideals

The reference speech samples are analysed qualitatively and assigned a quantitative measure based on the metric (triplet) discussed in Section 2. Consider the reference speech data is collected for \( W \) predefined words (or sentences) from \( G \) classification groups (example, Very Good, Good, Average, Bad, Very Bad) of people. Assume that each group \( G \) has \( N_G \) number of persons in it. Selection of ideals is based on initially segregating the spoken speech samples into \( W \) predefined words (or sentences) and a set of \( G \) groups (or categories) of spoken style categories. For each \( w \in W \) and \( g \in G \), determine \( \overline{D}_{wg} \), the average over all the utterence by different number \((N_G)\) of person. This produces a set of measurements which represents all the words and groups namely, \( \{\overline{D}_{ij}\}_{i=1,j=1}^{W,G} \) using the pseudo code described in Algorithm 1.

\[
\text{Algorithm 1} \text{ Computing the metric } \overline{D}_{ij} \text{ for the reference speech data.} \\
\text{for } i = 1: W \text{ do} \\
\quad \text{for } j = 1: G \text{ do} \\
\quad \quad \text{for } k = 1: N_G \text{ do} \\
\quad \quad \quad \text{for } l = 1: N_G \text{ do} \\
\quad \quad \quad \quad \text{Calculate } D_{ij}^{kl} \\
\quad \quad \end{array}
\end{align*}

\[
\overline{D}_{ij} = \frac{D_{ij}^{kl}}{(N_G)^2}
\]

end for
end for
end for

A reference speech sample \( R_{ij} \) is chosen for each word \( i = 1, \ldots W \) and for each group \( j = i = 1, \ldots G \) if the variation within each word-group category is *not larger* than a predefined threshold. Else several (in the worst case all) reference speech samples in the word-group category are chosen. The estimation of \( \overline{D}_{ij} \) helps in identifying \( R_{ij} \) for each word-group category. In essence, \( R_{ij} \)'s (one or several) are the *chosen representatives* of all the speech samples in the \( i^{th} \) word and \( j^{th} \) group category.

*Note that for each word \( i \) and each group \( j \) there is a reference speech sample set \( R_{ij} \) (in the extreme case, this \( R_{ij} \) could be multiple files encompassing all the reference speech files in that word-group category) and a score \( \overline{D}_{ij} \).*
3.2 Classification based on Ideals

Given a test speech sample \( t \), and \( G \) category groups, the problem is one of tagging the given test speech sample \( t \) to one of the groups \( G \) based on the closeness of the test speech sample to all the ideals in all the \( G \) groups, using either the \( L^1 \), \( L^2 \) or the \( L^\infty \) metric. In all our experiments we use \( L^2 \) norm.

It is assumed that the content of the test speech sample \( t \) is known (meaning that the word or the sentence that has been spoke is known) and is \( x \). Now, we compare the test speech sample with the reference speech samples \( R_{xj} \) for \( j = i, \cdots, G \) and calculate the triplet scores \( T_j = (D_{ij}, P_{ij}, R_{ij}) \). Note that \( T_j \) is obtained by comparing the test sample \( t \) with all the ideals in all the \( G \) groups and then choosing the minimum \( T_j \). The test speech sample, \( t \), is classified as belonging to the group \( g \) if the following criteria

\[
D_{tg} \leq D_{tj} \\
P_{tg} \geq P_{tj} \\
R_{tg} \geq R_{tj}
\]

is satisfied \( \forall j = 1, \cdots, G \) and \( j \neq g \).

4 Experimental Results

A set of 20 words and 10 sentences were selected in consultation with phoneticians and accent training experts. The set consisted of words and sentences which were very commonly prone to pronunciation error and in some cases the words were tongue twisters. The choice of the set is deemed to be capable of assessing the development of articulation of a person. Data was collected from a set of 20 people in each category (very good, good, average, bad and very bad speaking style). All person were asked to speak the predetermined set of 20 words and 10 sentences on the telephone using an IVR application custom built for collecting data. The speech data was tagged separately by two accent experts into one of the five (very good, good, average, bad, very bad) categories. Table 1 gives the agreement between two human accent experts. Total agreement is when both the human experts categorised the same speech sample as belonging to the same category (example, both the experts say that the speech sample is good) and 1-step agreement corresponds to the the human experts differing on their categorization by a distance of 1 category (example, one expert say that the speech sample is good while the other says that the speech sample is very good or average).

For purpose of experimentation to evaluate our system, we divided the speech data into 3 parts. We used data 2 parts of the data corresponding to each of the 5 categories to select the ideals and used the other 1 part to test the performance of the system. The overall performance of the system for classifying spoken speech is tabulated in Table 2. The performance of the automated system is much better than the performance between two human experts. Notice that the performance of the human expert - system (see Table 2) is better than the expert-expert (see Table 1) performance.
Table 1: Agreement between two human experts.

|                  | Expert 1 - Expert 2 |
|------------------|---------------------|
| Total Agreement  | 26 %                |
| 1-step Agreement | 45 %                |

Table 2: Agreement between the system and the two human experts.

|                  | Expert 1 - System | Expert 2 - System |
|------------------|-------------------|-------------------|
| Total Agreement  | 56 %              | 47 %              |
| 1-step Agreement | 100 %             | 90 %              |

5 Conclusions

With increase in BPO’s there is a need for automatic speaking style analyser. Speaking style analysis by human experts is bound to be biased by cues that might not necessarily be associated with the speaking style and the judgement of the speaking style is dependent on the human expert. To overcome this bias that may be associated with human expert in analysing a person for his speaking style we have developed a system to automatically analyse the speaking style of a person. We proposed a metric which captures both the articulatory capability and the intonation of the speaker, both of which jointly characterise the speaking style of the person. Experimental results show that the performance of the system far exceeds the performance between two independent human experts.