A Trainable Approach for Multi-Lingual Speech-To-Speech Translation System

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ABSTRACT
This paper presents a statistical speech-to-speech machine translation (MT) system for limited domain applications using a cascaded approach. This architecture allows for the creation of multilingual applications. In this paper, the system architecture and its components, including the speech recognition, parsing, information extraction, translation, natural language generation (NLG) and text-to-speech (TTS) components are described. We have implemented the described system for translating speech between Mandarin and English language pair in an air travel application domain. We are current porting the system to the military domain. Encouraging experimental results have been observed and are presented.

Keywords
speech-to-speech translation, statistical natural language understanding based translation, statistical natural language generation

1. INTRODUCTION
Commerce and travel have created an ever increasing need for translation between languages. Recently, progress in the fields of speech and language processing have begun to allow the creation of automated systems to accomplish this task. However, the technical challenges of creating a useful speech-to-speech translation device pushes against the limitations of current technologies such as speech recognition, natural language understanding, machine translation, natural language generation, and text-to-speech synthesis. In this paper, we present a speech translation system employing a statistical framework appropriate for use in language restricted domains. In our cascaded approach, the recognition results obtained in the speaker’s language are analyzed and then, through a series of distinct abstract representations, corresponding sentences are generated in the language of the listener.

Compared to other speech translation systems [1], [2], [3], [4] developed by other researchers, our system has several distinguished features. First, all the components in our system, including parser and language generation, are statistics based, and therefore are trainable from speech or text corpus. No handcrafted rules, grammars, or templates are needed. This makes our system flexible, scalable, and robust as the application domain changes. We have built the system for the air travel domain and are currently porting it to the military domain to verify the robustness. Another feature is that our translation is based on the understanding of the meaning of the sentence. It avoids the literal translation and the correct grammar assumption of the transcribed text from the input speech, as it most likely includes recognition errors, and emphasizes meaning preservation. When the automatic transcribed speech script is parsed, the statistical parser focuses on the meaningful phrases and automatically ignores irrelevant portions or out-of-domain concepts in the script. Another innovative characteristic of our system is that we are trying to use the natural language understanding component to help the speech recognizer, as we believe the language structure and conversation structure can be utilized to improve speech recognition performance.

This paper is organized as follows: In Sec. 2, we describe the system architecture and its components, including the speech recognition, parsing, information extraction, translation, natural language generation (NLG) and text-to-speech (TTS) components. Sec. 3 presents the evaluation results and discussions and Sec. 4 contains concluding remarks.

2. SYSTEM OVERVIEW
Figure 1 shows the architecture of our speech translation system. The input speech is recognized through an automatic speech recognizer and parsed by a statistical natural language understanding (NLU) model. An information extraction component is responsible for analyzing the semantic tree that was obtained from the NLU, and extracting two kinds of information from the tree. The first kind of information is a language independent “interlingua” representation. This, combined with a canonical representation of the language dependent attributes instantiated within the semantic model, is sent to a natural language generation (NLG) engine to render in the target language. Both types of information are translated using distinct models, with the specific attributes of items, such as times and dates, using conventional techniques familiar to the machine translation community. The interlingua translation, however, takes place at a semantic level and can result in considerable surface changes in the final result. Finally, when a text representation of the utterance in the target language is completed, a text-to-speech synthesizer is used to produce spoken output.

For a cascaded approach to machine translation to work, the hierarchical information represented in the semantic tree for a sentence...
must be invariant across translations, at least in the application domain of interest. This invariance has been validated, in part, by work involving translation between English and certain European languages [4]. A more complete test of this assumption would require dissimilar languages that have quite different phrase order conventions, such as Chinese and English, as in the work presented here. Part of the design of our system is reflected in the annotation of the training corpus, which forms the embodiment of a particular interlingua style.

Figure 2: Example for Chinese sentence - The Semantic Tree Representation

The sentence, including speech actions, for example. The semantic concept representation, along with the class constituents, captures the information contained in the parsed sentence. This representation allows direct phrase translation to be applied to the class constituents, but a more general conceptual translation should occur at the second level. Thus this design should allow for the rearrangements that occur when concepts are presented in different order in different languages.

2.3 Attribute Translation

Only the named attributes at the leaf nodes in the semantic tree need to be translated in the traditional sense of word-for-word translation. This is currently performed using language to language dictionaries. In cases where phrases or words may be ambiguous, a semantic tag specific phrase translation dictionary is created. That is, a phrase or word may have different translations when considered generally, but usually not within a specific semantic context. Our sets of Chinese-to-English and English-to-Chinese tag-dependent dictionaries were created semi-automatically from general Chinese-to-English and Chinese-to-English dictionaries which were subsequently audited to remove erroneous translations.

2.4 Automatic Speech Recognition and Synthesis

The English and Mandarin speech recognizers were developed for large vocabulary (over 64K words) continuous dictation speech. The baseline speaker-independent systems are trained on over 200 hours of speech collected from over 2000 speakers for each language [7]. The English recognizer uses an alphabet of 52 phones, while the Mandarin system uses 162 phones, including some tone-dependent phones [8]. Each phone is modeled with a 3-state left-to-right HMM. Both systems have approximately 3000 context-dependent states modeled using 40K Gaussian distributions. The acoustic front-end uses a 24-dimension cepstral feature vector and transformed using LDA.

To improve the recognition accuracy, a LM trained for the DARPA Communicator [9] air travel task was substituted for the general English LM. Unfortunately, for Mandarin system, we do not have a similar domain specific LM; therefore the general dictation Chinese LM is used.

One distinguished feature our system has is that our speech recognizer is coupled with the NLU analyzer, rather than separated as in other systems [2, 10, 1]. The NLU classer and parser results are sent back to the recognizer in order to activate a dialog-state-dependent LM [9], or a turn-based LM [11], to further improve the recognition accuracy. This is motivated by the fact that task ori-
mented conversations often have clear conversation structures which can help to limit the search space for speech recognition. We are also exploring the use of semantic classer and parser information for a better LM that utilizes the language structure.

For speech synthesis, a trainable, phrase-splicing and variable substitution system [12] is used to synthesize Mandarin or English speech from the translated Chinese or English sentence. Because of the fact that sometimes the translation output is in the form of mixed input and output languages, for example, when there are untranslatable names of locations, our text-to-speech system has the unusual ability to generate speech across language boundaries seamlessly.

2.5 Statistical Natural Language Generation

The high level semantic translation is accomplished by natural language generation of the semantic representation in the target language. More specifically, statistical NLG is used to discover the preferred concept ordering and to assign the lexical form of a grammatical sentence in the target language. Our statistical NLG models [13] are directly learned from a training corpus, using no manually designed grammars or knowledge base.

This work uses a maximum entropy [14] probability model extended from the "NLG2" model described in [13], [15]. It uses a conditional distribution over \( V \cup \{ \text{STOP} \} \) for the current symbol to be generated, where \( V \) is the vocabulary of all possible symbols and \( \{ \text{STOP} \} \) is an artificial symbol to mark the end of an independent generation. In this context, \( \text{symbols} \) refer to the introduction of semantic concepts or individual target words into the output word sequence. Output begins with a particular sentence type, as identified in the parsed input. Examples of the sentence type in the air travel domain include Query, Action, Book and Define. By including the sentence or phrase type in our generation scheme, we can narrow the probability space. The details of the NLG model training and search are in [15].

3. EVALUATION

Defining a useful performance metric for a language to language translation system is a challenging problem in itself. One such metric, \textit{Bleu} [16], recently proposed by our colleagues for use in text-to-text machine translation was used for evaluation. The \textit{Bleu} metric requires human translated scripts as reference, and for our tests, the modified unigram precision (MUP) measure was used. However, the domain specific translation task with spoken word input has many characteristics that present particular challenges. One issue relates to the problem of spontaneous speech recognition, errors due to disfluencies are considered beyond the scope of this paper.

Because the algorithm presented here is trained on a domain-specific corpus, the system is more likely to insert domain-specific words such as words pertaining to flights and booking (in our example) even in the case where these words were not spoken explicitly. For this reason, we have also compared the performance against the online \textit{Babel Fish} system [17]. More complete evaluation requires human judges and, for illustration, we include two examples of translations in Fig 3.

4. CONCLUSIONS

The new statistical translation model presented in this paper shows great promise due to its ability to build semantic representations of spoken phrases and to allow general transformations on these representations when creating statements in the target language. This ability has been demonstrated by choosing the highly dissimilar language pair, English and Chinese. In addition, because the presented translation system is based on statistical models trained using corpora, developing translations systems for new languages should require only a fraction of the effort normally invested in building language to language translation systems.

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6. REFERENCES


