Hybrid Spoken Language Translation
Using Sentence Splitting Based on Syntax Structure

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Abstract

In this paper, we propose a hybrid spoken language translation method utilizing sentence segmentation. By portioning the sentence using the result of syntax analysis, we can utilize rule-based control of the integration of sub-translations translated by a suitable method for each segment.

We also report a preliminary experiment on translation quality of our prototype Japanese-to-English translation system. We confirmed that our method achieved a 13.4% advantage in NIST score for the individual RBMT method, and a 6.0% advantage for the individual EBMT method.

1 Introduction

There is a great deal of research on the machine translation, and each of them has achieved surely advantage. There are three typical approaches: Rule-based Machine Translation (RBMT), Example-based MT (EBMT) and Statistical MT (SMT).

RBMT uses many translation rules(Amano et al., 1987): parsing, transfer, generation rules, etc. One part of these rules is described abstractly to overcome various linguistic phenomena, and another part is elaborated concretely to acquire skillful translation. Abstract rules give robustness to a system, but sometimes become a cause of lack of fluency.

EBMT is an analogical method based on human-translated examples(Nagao, 1984). Those examples are directly used as a result or are partially replaced to be matched to an input sentence. So translation tends to be more natural than in the case of RBMT. However, since the domain covered strongly depends on the example database, robustness is often inferior to that of RBMT.

SMT generates translation on the basis of statistical models derived from the analysis of bilingual corpora. It can cut development cost dramatically compared with RBMT and generate a natural translation result for a suitable domain. But, in some cases, well-developed RBMT outputs a more suitable translation and covers a larger domain.

These strengths and weaknesses of each translation method are not only inherent properties but also complementary properties. We propose a new hybrid translation method based on this complementarity. A characteristic of our proposal is that it divides the input sentence into optimum units based on its syntactic structure generated by RBMT and selects the best translation method for each segment.

It is especially effective in translating spoken language that is often breaking off fragmental speech. We think the most suitable approach for spoken language translation (SLT) is to pack such speech fragments into significant groups and translate them by switching the translator.

In the following section, using Japanese-to-English translation as a motif, we describe a detailed method. Next, we report on our evaluation experiments. Then, we present a comparison of other relevant studies and conclude the paper with a discussion of future work.

2 Hybrid Translation Method

EBMT is a powerful tool when an input sentence is long or idiomatic. But the use of an example match-
For Japanese, we use a clause as such a segment. A Japanese clause is a small and significant unit consisting of at most one subject and one predicate. To estimate such a clause structure, we utilize the method proposed by (Kamatani et al., 2006). They proposed an analysis method that estimates clause structures by treating input utterances as a sequence of fragmental phrases, and evaluates validities combined with dependency preferences. It allows evaluation of all candidates efficiently and choosing of the totally optimum one.

According to their analysis, even spoken language can be analyzed by using a grammar developed on the basis of the following two assumptions. 1) One utterance often consists of fragmental phrases. 2) When some fragments are unified as a clause, its internal structure is quite grammatical. By using their method, we can evaluate all combinations of segments cyclopaedically in real time.

We develop an original grammar centered on a clause structure. A part of our grammar is shown in Figure 2. Figure 3 shows a parsing example by GLR parser working with our grammar. For purposes of illustration, the packed shared forest structure (Tomita, 1991) is somewhat simplified and a node has an identifier with its syntactic category. For instance, the node marked (a) has a syntax category “NP” denoting “Noun Phrase”. In the figure, the node (e) is shared by other nodes (f) and (g), and node (h) packs local ambiguity <h1> and <h2>.

This grammar includes some special treatments to classify a relation between segments. It is used to sensitively translate a relation between each segment. For instance, as shown in Figure 2, we handle a parenthetic expression as a dependency relation...
2.2 Sentence Splitting based on the Syntax

First, we introduce the following notations and functions to formulate our sentence splitting method.

- The parser derives a syntax forest \( f \) with a set of nodes \( N_f \) for one input sentence.
- One syntax forest can be divided into each individual syntax tree \( t \in f \) and its nodes set \( N_t \subseteq N_f \).
- Each node has one syntax category \( c \in C \).
- \( \text{Cat}(n) \) gives a syntactic category of a node \( n \in N_f \).
- \( \text{Prt}(n) \) gives a set of nodes in a partial forest structure dominated by a node \( n \in N_f \).
- \( \text{Trees}(n) \) gives a set of nodes in trees including a node \( n \in N_f \).

Our hybrid method enumerates two types of splitting candidates. They are “basic segment” and “pairing segment” which are defined as follows.

**Basic segment candidates**:

\[
S_b = \{ \text{seg}|\text{seg} = \text{Prt}(n) \mid \text{Cat}(n) \in C_s \}
\]

Where \( C_s \subseteq C \) is a set of syntactic categories predefined to elect the splitting candidate. For Japanese analysis, we use syntactic category “C” and “SC” shown in a Figure 2.

Here we call this type of segment a “basic segment”, and the root node of the segment a “dominator node”. In the following explanation, we express a basic segment by using a notation “(n)”. That means a basic segment dominated by a dominator node \( n \in N_f \).

**Pairing segment candidates**:

\[
S_p = \{ \text{seg}|\text{seg} = \text{Trees}(n_j) \cap \{ \text{Prt}(n_i) - \text{Prt}(n_j) \} \mid \text{Prt}(n_i), \text{Prt}(n_j) \in S_b \\
\quad \land \text{Prt}(n_j) \subseteq \text{Prt}(n_i) \}
\]

When any given two nodes are dominator nodes of a basic segment and one node has a structure dominated by the other node as its substructure, the remainder structure of the two syntactic structures will be chosen as a segment. This structural subtraction stands on a supposition that even if the meaningfully complete segment is removed from another segment, the remainder is understood correctly.

Here we call a segment of this type a “pairing segment”, the root node of the remaining segment a “dominator node”, and the root node of a deleted substructure an “exclusive node”. In the following explanation, we express a basic segment by using a notation “\((n_1, n_2)\)”. That means a paring segment derived from a dominator node \( n_1 \in N_f \) and an exclusive node \( n_2 \in N_f \).

Figure 3 shows an example of sentence splitting. Here, we assume that the nodes marked \( b, c, d, e, f \) and \( h \) satisfy the condition as a dominator node of a basic segment. For example, the node \( b \) dominates a syntax structure for the partial input morphemes “サイズが大きいので/Because the size is large.” that can be regarded as a basic segment \((b)\). In the figure, spans of each basic segment are indicated by black arrows.

All pairs of two dominator nodes of enumerated basic segments are checked to ascertain whether each of them satisfies a condition of a paring segment. In the example presented in Figure 3, we can consider 5 pairs that satisfy the condition for paring segments: \((f, h), (h, b), (f, c), (h, c)\) and \((h, e)\). For example, the segmented morphemes “私はやめます/I quit buying it.” are found for a pair of the node \( h \) and \( e \). In the figure, the spans of morphemes for each basic segment are indicated as white arrows. Clearly, even a discontinuous sequence of input morphemes is detected as a segment.
2.3 Choose Optimum Split

We introduce two additional functions to describe a way to find optimum splitting.

- $M_{rp}(seg)$ gives a set of morphemes expressed by one segment $(seg)$.
  - If $seg \in S_b$, $M_{rp}(seg)$ gives a sequence of morphemes dominated by $b$.
  - If $seg \in S_p$, $M_{rp}(n_i, n_j)$ gives a relative complement of morphemes dominated by $n_i$ and $n_j$.
- $Root(seg)$ gives a dominator node of a basic segment and a paring segment.

First, we classify the syntactic categories $c \in C_s$. $C_{sc} \subseteq C_s$ includes categories given to nodes whose substructures can be translated independently. The other categories $c \in C_s$ are classified into $C_c$. That means $C_c = C_s - C_{sc}$. For Japanese analysis, we use a classification $C_c = \{"cm"\}, C_{sc} = \{"SC"\}$. Therefore, each segment in $S_b$ and $S_p$ can be classified into two types.

$$S_c = \{seg | seg \in S_b \cup S_p, \text{s.t. } \text{Cat}(Root(seg)) \in C_c\}$$

We calculate a combination of segments as the optimum split with the following two strategies. The first strategy chooses as many optimum segments to be briefly evaluated by syntax, it leads to assure quality. Because we can consider these segments without evaluating a confidence score of each partial EBMT result and calculating the total score of the translation for a whole utterance. Accordingly, it does not assure that the split sequence can generate the best translation result.

Another choosing method is to consider all the pairs of EBMT results and calculate the total confidence scores. But there is trade-off between calculation cost and translation precision, and such a constitutively produced confidence score does not always assure quality. Because we can consider these segments to be briefly evaluated by syntax, it leads to the local maximum at least. For these reasons, we only use this strategy.

In the example described in Figure 3, basic segments $(b)$ and $(c)$, and a paring segment $(h, e)$ are selected as an optimum combination that gives the best division of the utterance (Figure 4).

2.4 Embedding partial EBMT results

The segments composing the optimum splitting $Opt_{sc} \cup Opt_c$ are individually translated by EBMT. Then, the EBMT result with sufficient confidence score is used as a partial translation.

\[
\begin{align*}
\land & \left[ \left( \bigcup_{a_k \in Opt_{sc}} \bigcup_{a_i \in A_p} a_k \cap \bigcup_{a_i \in A_p} a_i \right) = \emptyset \right] \\
\land & \left[ \exists N_i \left( \bigcup_{a_i \in Opt_{sc}} \text{Root}(a_i) \subseteq N_i \right) \cup \left( \bigcup_{a_i \in A_p} \text{Root}(a_i) \subseteq N_i \right) \right]
\end{align*}
\]

A set $Split_c$ represents possible segment combinations for a partial input sentence that is not covered by $Opt_{sc}$.

\[
Opt_c = \arg\max_{A_p \in Split_c, seg_i \in A_p} |M_{rp}(seg_i)|
\]

These two strategies extract just one combination of segments without evaluating a confidence score of each partial EBMT result and calculating the total score of the translation for a whole utterance. Accordingly, it does not assure that the split sequence can generate the best translation result.

![Figure 4: Optimum Splitting](image-url)
We utilize an EBMT method proposed by (Wu et al., 2005). They improved quality and example coverage of a translation memory system by taking advantage of sentence-level matching, subsentential matching and pattern-based MT methods.

Their proposed method also includes input sentence splitting as a subsentential matching. But segments are estimated statistically and the whole sentence is translated by a single EBMT method. We use a translation result generated by the sentence-level matching method to embed, because we want to acquire a partial translation of as high quality as possible and evaluate individual performances.

We also used the confidence score of EBMT by using sentence similarity defined by them and trigram language model (\( F(T) \)) of a target language.

\[
F(T) = \left( \prod_{i=1}^{||T||} p(t_i|t_{i-2}, t_{i-1}) \right)^{-\frac{1}{||T||}} \tag{1}
\]

where the \( T \) is a target sentence and the \( t_i \) is a morpheme in it.

\[
Score = \beta_1 \cdot Sim(X, Y) + \beta_2 \cdot F(T) \tag{2}
\]

where \( Sim(X, Y) \) is similarity between an input utterance \( X \) and a source sentence \( Y \) of an example pair, \( \beta_1 \) and \( \beta_2 \) are weights which are experimentally given, and \( 0 \leq Score \leq 1.0 \). The detailed definition of \( Sim(X, Y) \) is given in their paper.

EBMT results with sufficient confidence scores will be elected and embedded as a partial translation of the whole utterance. Two embedding styles are defined and switched by the segment kind.

**Basic segment :**
1. Delete the syntactic structure that has the dominator node as a root node and depends on only the morphemes in this segment.
2. Add a special terminal node that denotes the EBMT translation result. The new terminal node will be unified to a parent node of the dominator node. If the dominator node already has other nodes, the order of these nodes follows the order of input morphemes.

**Pairing segment :**
1. Move the exclusive node to the dominator node as a new parent node. If the dominator node already has other nodes, the order of these nodes follows the order of input morphemes.

Figure 5: Embedding EBMT Result to the Tree(1)

Figure 6: Embedding EBMT Result to the Tree(2)

2. Delete the syntactic structure that has the dominator node as a root node and depends on only the morphemes in this segment.
3. Add a special terminal node that denotes the EBMT result. The new terminal node will be unified to a parent node of the dominator node. If the dominator node already has other nodes, the order of these nodes follows the order of morphemes in the input sentence.

We define these processes so as to regard them as one of the transfers in the RBMT system. So, even after embedding, the syntax tree keeps translatability by RBMT.

Now, we assume that a paring segment \((h, e)\) gets the EBMT result “I just can’t by it” with a sufficient confidence score, and a basic segment \((b)\) also acquires the EBMT result “It’s so big for me”. Figure 5 and Figure 6 show examples of the embedding process. The order in which segments are embedded is unrestricted.

### 2.5 Integration and Generation

Even after embedding an example to a syntax structure, it keeps its characteristics as a syntax tree. So,
it is only necessary to develop new rules that handle such a partially translated structure. It is quite a natural task for RBMT.

3 Experiment

3.1 Experimental Settings

We evaluate three systems: individual EBMT (Wu et al., 2005) and RBMT, and hybrid SLT system. The performance of EBMT and RBMT can be a baseline for our proposed hybrid method. Here, we use only the sentence-level matched EBMT result with confidence $Score \geq 0.6$ in equation (2) for the hybrid SLT system. The result of EBMT is just to choose a translation with the highest confidence score, regardless of its absolute value. On the other hand, we allow subsentential matched translation result as a result of individual EBMT. Introducing a subsentential matching as a result makes it possible to compare the splitting method between the statistical method and ours.

Because we don’t have enough bilingual travel domain corpora that we can use freely, we developed 123,819 Japanese-English translation pairs as an example base of EBMT. We prepare two types of test set aside from examples. One is a set of balanced travel domain sentences, and the other is a set of relatively long sentences. As mentioned in section 2, since our hybrid method divides an input sentence into several parts, it works only for the sentences that have a certain level of length.

For evaluation, we use NIST score (Doddington, 2002) and BLEU score (Papineni et al., 2002). Each sentence in the test set has one translation reference.

3.2 Evaluation Result

The evaluation result for the balanced test set is shown in Table 2. Since the DB for the same travel domain is used, both NIST and BLEU score higher for EBMT than for RBMT. Moreover, the Hybrid SLT method scored higher than each individual translation method. This result proves the effect of our method. The result of hybrid MT consists of 622 sentences by individual EBMT, 363 sentences by individual RBMT, and 15 sentences by composing partial EBMT and RBMT results.

The evaluation result for long sentences is shown in Table 3. The hybrid method outputs the 44 translations by EBMT, the 125 translations by RBMT, and the 31 translations composed by both EBMT and RBMT.

As an input sentence gets longer, it becomes harder to find an example translation matching it, and more complex to parse it. Both EBMT and RBMT get lower scores than the balanced test set. The score of the hybrid SLT is also reduced, but it is still higher than that of the individual MT method. This result highlights the advantage of our method.

Table 4 shows some translation results for the second test set, which are translated by composing the partial results of EBMT and RBMT. Three translation results are shown in the table. The row labeled “Ref.” means the translation reference that was translated manually and used for the evaluation. And there are three translation results generated by each method for each source sentence (Src.).

4 Related Work

In the spoken language domain, research is often focused on determining the end of an utterance and subsentence punctuation predication, such as (Matusov et al., 2007). Such approaches are useful for

| Table 2: Evaluation for Japanese-to-English Translation of the Balanced Sentences Set |
|---|---|---|
| System | NIST | BLEU |
| EBMT | 4.9372 | 0.2403 |
| RBMT | 4.4644 | 0.1885 |
| Hybrid MT | 5.0474 | 0.2511 |

| Table 3: Evaluation for Japanese-to-English Translation of the Relatively Long Sentences Set |
|---|---|---|
| System | NIST | BLEU |
| EBMT | 3.8798 | 0.1351 |
| RBMT | 3.8191 | 0.1252 |
| Hybrid MT | 4.1127 | 0.1597 |

| Table 1: Test set specification |
|---|---|---|
| | Number of Sentences | Japanese Source | English Reference |
| Balanced | 1000 | 4.9372 | 0.2403 |
| Long Sentence | 200 | 4.4644 | 0.1885 |
Table 4: Sample Japanese-to-English translations

| 1 | Src. | ご迷惑でなければ、座席を少し前 | Ref. | If it’s not much trouble, can I put my seat back a little? |
|---|------|-----------------------------|-----|----------------------------------------------------------|
|   |      | っていていいですか？        | EBMT| Annoying, may I lower my seat a little?                  |
|   |      |                             | RBMT| As long as it is not troublesome, may I push down a little seat? |
|   |      |                             | Hybrid| If it’s not too much trouble, I may push down a little seat. |

| 2 | Src. | 問の部屋の人があまりに騒がないので、部屋を替えても下さない | Ref. | Please change my room because the people next door are noisy. |
|---|------|-----------------------------------------------------------|-----|---------------------------------------------------------------|
|   |      |                                                           | EBMT| Many people next door room noisy, to give room.               |
|   |      |                                                           | RBMT| The person of the next room is noisy. Please change the room. |
|   |      |                                                           | Hybrid| People room next door is so noisy. Would you me a different room? |

| 3 | Src. | 食事の時間になったら起きてもらうかもしれませんか？ | Ref. | Would you wake me up at meal time, please? |
|---|------|---------------------------------------------|-----|----------------------------------------|
|   |      |                                             | EBMT| Trains wake be dinner at the same time?   |
|   |      |                                             | RBMT| Would you start, if the time of a meal comes? |
|   |      |                                             | Hybrid| If the time of a meal comes Excuse me, let me wake. |

5 Future Work

Our hybrid SLT method utilizes a Japanese clause as a unit to switch translation methods. A Japanese clause is small enough to understand a meaning, but it seems a rather big structure to increase a chance of applying EBMT. In particular, some short utterances do not fully benefit from our method, because a simple sentence usually consists of just one clause.

For the next step, we are studying use of a phrase. But it is more difficult to embed a phrase translation than a clause translation, since a phrase exhibits diverse behavior and other dependent are usually needed in order to determine translation. Among such segments that are somewhat awkward as units, a noun phrase is comparatively easy to handle.

While we are expanding coverage of the hybrid method, we are also examining a method of calculating the confidence score for each EBMT result and the final translation. For the first step, we have to evaluate using a monolingual language model translation for the whole utterance and check whether it gets a corresponding bless in calculation cost.
6 Conclusion

In this paper, we propose a hybrid spoken language translation (SLT) method which divides input sentence into some parts and translates them by switching RBMT and EBMT for each part. A characteristic of our method is that it splits an utterance based on its syntactic structure.

We also report fundamental experimental results. In the evaluation for balanced test set, our method achieves a 13.0% advantage in NIST score for the individual RBMT method and a 2.2% advantage for the baseline EBMT method. For long sentences, our hybrid method achieves a 6.0% advantage for the conventional EBMT and RBMT systems.

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