PAPER Translation Repair Method for Improving Accuracy of Translated Sentences

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SUMMARY In this study, we have developed a translation repair method to automatically improve the accuracy of translations. Machine translation (MT) supports multilingual communication; however, it cannot achieve high accuracy. MT creates only one translated sentence; therefore, it is difficult to improve the accuracy of translated sentences. Our method creates multiple translations by adding personal pronouns to the source sentence and by using a word dictionary and a parallel corpus. In addition, it selects an accurate translation from among the multiple translations using the results of a Web search. As a result, the translation repair method improved the accuracy of translated sentences, and its accuracy is greater than that of MT.

key words: machine translation, translation repair, Web search, multilingual

1. Introduction

Increasing globalization has led to increased interactions among people who speak different native languages. However, it is difficult for a person to learn many languages. At the same time, people cannot communicate with each other in their respective native languages; as a result, a language barrier likely exists when they attempt to communicate with each other, and this hampers effective communication [1]– [3]. Therefore, several studies have attempted to develop systems that can be used to overcome this language barrier. For example, Language Grid [4], [5] is an infrastructure that combines machine translation (MT) engines, parallel corpora, and so on.

MT has shown promise for application in multilingual communication. For example, an MT-based intercultural communication support system has been studied [6], [7]. MT-based approaches can automatically create translation sentences. However, MT cannot achieve a high level of accuracy in such applications. For the same reason, MT is also unsuitable for use in fields that require high accuracy. To overcome these problems, parallel corpora whose accuracy is guaranteed have been developed [8]–[10]. In addition, an approach called translation repair has been proposed, in which the translation accuracy is improved by a human translator [11]. However, the accuracy of manual translation repair strongly depends on the individual translator.

In this study, we propose a translation repair method for a specialized field that provides more accurate translation results compared to existing MT-based approaches. This method includes two sub-methods: one creates translation candidates and the other selects accurate translations. The former increases the number of candidates, and the latter selects an accurate translation from among these candidates. Our proposed method uses MT, a parallel corpus, a word dictionary, and a Web search engine. We use it for translation from Japanese to English.

We apply this method to parallel texts (PTs). PTs form a multilingual corpus that is used to translate example sentences into multiple languages; they can support accurate multilingual communication. PTs have often been used in fields that require high accuracy [8]–[10]. In addition, a sharing project of PTs created by professionals and translators for specialized fields has been initiated [12]. We aim to reduce the burden of translators by applying our proposed method to the creation of PTs.

2. Related Works

Studies related to MT have already been discussed in the previous section.

The "TATOEBA project" collects PTs [13]. Its corpus is based on the "TANAKA corpus" [14]. This project has a database of Japanese, English, Chinese, German, and other languages. Yoshino et al. collected PTs in the medical field [12]. However, it is difficult to collect multilingual PTs without burdening translators. Our proposed method automatically creates PTs to reduce this burden. We check the translation accuracy through translators and reduce the frequency with which they have to create PTs.

The World Wide Web contains a large number of words and sentences written in many languages. Chen et al. studied the automatic extraction of PTs on the Web [15]. Nagata et al. studied the use of the Web as a translation dictionary [16]. Both these studies used the Web as a multilingual dictionary. Our study uses the Web to determine the accuracy of translation pairs based on the number of search results for a given translation candidate.

3. Translation Repair Method

This section explains our proposed translation repair method

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Fig. 2 Sub-method for creating translation candidates.

for creating accurate translation sentences. Thus far, MT has typically been used to automatically create translations; however, it creates only one translation. Our proposed method creates multiple accurate translations using two submethods (Fig. 1).

The first sub-method creates multiple translation candidates to increase the number of accurate candidates. It also adds personal pronouns to the source sentence, using a word dictionary, a parallel corpus, and MT. The second submethod selects an accurate translation from among these candidates. It uses a Web search engine.

3.1 Sub-Method for Creating Translation Candidates

The sub-method for creating translation candidates is used to increase the number of accurate translations. Candidates are created using the following five approaches: (1) MT, (2) Pron, (3) Word, (4) Pron+Word, and (5) PT (Fig. 2).

TC (1), MT:

In this approach, candidates are created using MT. TC (1) serves as a baseline because it is identical to existing MT-based approaches. We compare the result of TC (1) with that of our method.

TC (2), Pron:

In this approach, a personal pronoun – "私は (I)," "あ なたは (you)," or "私の (my)" – is added to a source sentence to create accurate translation candidates. This is because sentences in Japanese often omit the subject; this may reduce the accuracy of MT.

TC (3), Word:

In this approach, English words in text translated by MT are replaced with a noun and a compound noun from a word dictionary. This is because the proposed method aims to accurately translate sentences in a specialized field – we believe that sentences in a given field tend to use similar expressions and words.

As shown in Fig. 2, the word dictionary contains word pairs such as "介護サービス-care service." This approach replaces "nursing service" with "care service." In other words, the Japanese word indicated by a wavy line is translated into the English one indicated by a wavy line. Such a replacement is carried out as follows. (i) If a source sentence includes a word from the word dictionary, the source sentence and the word is translated by MT. (ii) The translated word is replaced with an English word from the word dictionary if the translated sentence contains the translated word. (iii) If the translated sentence does not contain the translated word, the word in the source sentence is indicated as one that cannot be translated and the corresponding word in the translated sentence is replaced with a word from the word dictionary.

TC (4), Pron+Word:

This approach applies TC (3) to a sentence translated using TC (2).

TC (5): PT

In this approach, a new English sentence is created using PTs. A pair of a Japanese and an English sentence without noun(s) at the beginning (in Japanese) and ending (in English) of the sentence, respectively, are created. These fragments are called "shard sentences." The Japanese noun(s) at the beginning of the sentence are translated if a Japanese source sentence includes the Japanese shard sentence. Then, the translated noun(s) are incorporated into the English shard sentence.

As shown in Fig. 2, PT includes shard sentences such as "を受けたいです" and "I'd like to have." Moreover, a Japanese source sentence includes a fragment such as "を受けたいです." This fragment does not contain nouns at the beginning of the sentence. Then, the noun "介護サービス" is translated to obtain "nursing service," and this is incorporated into the shard sentence "I'd like to have." The sentence thus obtained is used as the translation candidate.

After this sub-method creates the translation candidates, it deletes some of the candidates based on the following conditions.

- The translation candidate is identical to another candidate.
- 2. The translation candidate includes Japanese characters (each having a 2 byte size).
- 3. A sentence in which a preposition and an objective[†] are added to TC (1) and TC (3) is respectively equivalent to TC (2) and TC (4). TC (2)/TC (4) is thus deleted.

As shown in Fig. 2, this sub-method creates 10 translation candidates. Then, 2 are deleted based on the above conditions, with the result that 8 are finally provided.

3.2 Sub-method for selecting accurate translations

The sub-method for judging and selecting accurate translations involves the following two steps.

Step 1, Web search engine:

Figure 3 shows how an accurate translation is selected using a Web search engine. First, translation candidates are searched – with exact words^{††} – using the Web search engine, and the number of search results is recorded. The candidate with the maximum number of results is selected as being the accurate one. If multiple candidates have the maximum number of results, they are selected as being the accurate ones. If zero search results are obtained for all candidates, this step is unable to select an accurate translation.



Fig.3 Sub-method for selecting accurate translation. The first step judges an accurate translation based on the number of search results.

Step 2, MT:

If step 1 is unable to select an accurate translation, an accurate translation is selected using MT. In other words, TC (1) (Sect. 3.1) is used for selection.

This sub-method uses these steps to select a translation candidate that is most likely to be accurate.

4. Trial Experiment

4.1 Creating $D1_{all}$ Data Set

In this study, we used 4,570 Japanese sentences and 2,449 English sentences from TackPad [12]. This data includes Japanese - English PTs for 2,457 sentences and 2,138 Japanese sentences that have not yet been translated to English sentences^{$\dagger\dagger\dagger$}.

First, we randomly selected 100 Japanese sentences that do not include parentheses from the set of untranslated sentences as source sentences. Using the first sub-method described above, we obtained 372 English translation candidates – on average, 3.7 translation candidates were created per source sentence (minimum, 2 sentences; maximum, 9 sentences). We define this data set as $D1_{all}$. The set of 2,457 PTs was used as the word dictionary and parallel corpus. J-Server of the Language Grid was used for MT [4], [5].

Next, six translators evaluated the 372 translation candidates and rated them numerically as follows: 1, None; 2, Little; 3, Much; 4, Most; and 5, All.

We used Walker et al.'s adequacy evaluation to evaluate the meaning comparison of multiple languages [17]. In this study, if the average evaluation rating was less than 4, which was difficult to achieve, we judged the candidate as being inaccurate.

4.2 Results and Discussion of First Sub-Method

Table 1 shows the results of the sub-method for creating

[†]{for/to/about/with/on/at/from} {you/me}

^{††}In the case of the Google Search engine, the phrase is enclosed in double quotes.

^{†††}The number of Japanese - English PTs exceeds the number of English sentences because PTs may have many-to-many combinations.

| Table 1 | Accuracy result of translation candidates, D1 _{all} . |
|---------|--|
|---------|--|

| | Т | F | Sum | Rate | Source |
|--------|----|-----|-----|-------|--------|
| TC (1) | 37 | 63 | 100 | 37.0% | 100 |
| TC (2) | 39 | 180 | 219 | 17.8% | 99 |
| TC (3) | 8 | 8 | 16 | 50.0% | 16 |
| TC (4) | 6 | 23 | 29 | 20.7% | 15 |
| TC (5) | 6 | 2 | 8 | 75.0% | 4 |
| Sum | 96 | 276 | 372 | 25.8% | 100 |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

"Source" indicates the number of source sentences used to create translation candidates. If multiple candidates are created from a source, the number under "Source" differs from that under "Sum."

 Table 2
 Examples of created translation candidates.

| | Translation candidates | Accurate |
|--------|-----------------------------------|----------|
| TC (1) | A pulse is measured. | F |
| TC (2) | I measure a pulse. | Т |
| TC (2) | You measure a pulse. | F |
| TC (2) | My pulse is measured. | F |
| TC (5) | Let me take your pulse. | Т |
| TC (5) | We are going to check your pulse. | Т |

Source sentence is "脈拍を測ります (I will feel your pulse)."

"T" and "F" indicate accurate and inaccurate translation candidates, respectively.

translation candidates. 63 translation candidates created by TC (1) were judged inaccurate. However, more translation candidates were created using TC (2)-(5). TC (2) created more accurate candidates than did TC (1), but with low accuracy rate. TC (3) and TC (5) created candidates with higher accuracy rate. Table 2 shows an example of created translation candidates. In Table 2, TC (1) (by MT) failed in the translation, whereas TC (2) and TC (5) created accurate translations.

In $D1_{all}$, we investigated the number of source sentences that could be used to create accurate translation candidates. 56 out of 100 source sentences were found to be used to create accurate translation candidates. As shown in Table 1, MT created 37 accurate translation candidates. Therefore, the translation candidates created from the remaining 19 source sentences were inaccurate according to TC (1) and accurate according to TC (2)-(5). The submethod for creating translation candidates created 56/37 = 1.51 times the number of accurate translation candidates than did MT. Therefore, we conclude that this sub-method can be effectively used to create more accurate translation candidates.

Please note that our method may not create accurate translation candidates if a source sentence omits the explanation required for translation. For example, the sub-method did not create accurate translation candidates from " $\sub{5}$ $\cancel{5}$ $\cancel{5}$

 Table 3
 Accuracy result of translation candidates, $D1_{part}$.

| | Т | F | Sum | Rate |
|------------|----|-----|-----|-------|
| TC (1) | 32 | 19 | 51 | 62.7% |
| TC (2)-(5) | 53 | 104 | 157 | 33.8% |
| Sum | 85 | 123 | 208 | 40.9% |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

"TC (2)-(5)" indicates the sum of TC (2) through TC (5).

 Table 4
 Result of selection sub-method and translation repair method for accurate PT.

| | | Т | F | Sum | Rate |
|--------------------|---------------|----|----|-----|-------|
| D1 _{part} | MT (baseline) | 32 | 19 | 51 | 62.7% |
| | PMT | 39 | 13 | 52 | 75.0% |
| | PLS | 41 | 13 | 54 | 75.9% |
| D1 _{all} | MT (baseline) | 37 | 63 | 100 | 37.0% |
| | PMT | 44 | 58 | 102 | 43.1% |
| | PLS | 46 | 64 | 110 | 41.8% |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

4.3 Results and Discussion of Second Sub-Method

The second sub-method selects accurate translations from among the candidates. It uses a part of $D1_{all}$, $D1_{part}$, in which all accurate translation sentences (5 source sentences) and all inaccurate ones (44 source sentences) based on source sentences are removed. $D1_{part}$ includes 51 source sentences and 208 translation candidates.

Table 3 shows the accuracy result of $D1_{part}$. The minimum number of translation candidates in $D1_{part}$ per source sentence was 2 (1 accurate and 1 inaccurate sentence), and the maximum number was 9 (6 accurate and 3 inaccurate sentences). The minimum accuracy rate of translation candidates in $D1_{part}$ per source sentence was 12.5% (1 accurate and 7 inaccurate sentences), and the maximum was 75% (3 accurate and 1 inaccurate sentence).

Table 4 shows the result of the second sub-method for $D1_{part}$ and $D1_{all}$. We used $D1_{part}$ to evaluate the submethod and $D1_{all}$ to evaluate the translation repair method. We found a strong negative correlation (-0.80) between the accurate translation candidates and the length of English sentences. Therefore, instead of MT in Step 2 of the second sub-method, we selected sentences with the minimum length as being accurate. In this study, we defined a submethod called Priority to Machine Translation (PMT) to use MT after the Web search engine. We also defined a submethod called Priority to Length of Sentence (PLS) to use sentences with the minimum length after the Web search engine. PMT is equivalent to the second sub-method described in Sect. 3.2. PLS replaces Step 2 in Sect. 3.2 with a method to select the sentence with minimum length.

As shown for $D1_{part}$ in Table 4, the accuracy rates of PMT and PLS were respectively 12.3 and 13.1 points greater than that of MT. Therefore, we conclude that this sub-method can be effectively used to select more accurate

| Ш | тс | Translation Candidates | Accur | SP | Step 1 | Step 2 | |
|-------|----|---|-------|--------|--------|--------|-----|
| ID IC | | Translation Calificates | Accui | JK | Supr | PMT | PLS |
| | 1 | Blood was vomited. | F | 1,030 | | | |
| 5 | 2 | I vomited blood. | Т | 29,900 | * | | |
| 5 | 2 | You vomited blood. | Т | 4,260 | | | |
| | 2 | My blood was vomited. | F | 0 | | | |
| 90 | 1 | How should it be done to make the pimple mark thin? | F | 0 | _ | * | |
| | 3 | How should it be done to make the acne mark thin? | F | 0 | - | | |
| | 4 | How should I do to make the acne mark thin? | Т | 0 | _ | | * |

Table 5Example of sub-methods for selecting accurate translations.

Source sentences are "血を吐いた (I vomited blood)" and "にきび跡を薄 くするにはどうすればいいでしょうか (How should I do to heal the acne scar?)."

"T" and "F" indicate accurate and inaccurate translation candidates, respectively.

"SR" indicates the number of search results.

translations.

As shown for $D1_{all}$ in Table 4, the accuracy rates of PMT and PLS were respectively 6.1 and 4.8 points greater than that of MT. Therefore, we conclude that the translation repair method can be effectively used to create more accurate translations. Table 5 shows examples of sub-method for selecting accurate translations. In ID 5 of Table 5, the sub-method of selecting accurate translations selected the accurate translation candidate. In ID 90 of Table 5, all the search results were zero. In Step 2, although the PMT selected an inaccurate translation candidate, the PLS selected accurate one.

Please note that our method may not select accurate translation candidates even if translation candidates include accurate candidates; our sub-method uses monolingual texts, and not multilingual text pairs. For example, TC (1) of Table 2 is inaccurate. Nevertheless this sentence has the most number of search results in Table 2. (The number of search results are 31,700, 241, 1,490, 4, 28,500, and 2 sequentially, from the top of Table 2.)

5. Evaluation Experiment and Discussion

As described above, the evaluation of the translation repair method showed that it is useful for creating more accurate translations. However, we discussed only specific data sets and MT-based approach. Below, we discuss some new data sets and different MT-based approaches to demonstrate the wide applicability of our proposed method.

5.1 Creating *D2*_{all} Data Set

First, we randomly selected 100 Japanese sentences from TackPad to create a new data set of source sentences. These source sentences differed from those in $D1_{all}$. Then, we applied the sub-method for creating translation candidates to these sentences. In this evaluation, we separately tested J-Server (Sect. 4.1) and Google Translate. The former uses a

| Fable 6 | Accuracy resu | ilt of translation | candidates, D2 _{al} | , using J-Serve |
|---------|---------------|--------------------|------------------------------|-----------------|
| | | | | |

| $D2_{all}$ | Т | F | Sum | Rate | Source |
|------------|-----|-----|-----|-------|--------|
| TC (1) | 45 | 54 | 99 | 45.5% | 99 |
| TC (2) | 48 | 265 | 313 | 15.3% | 99 |
| TC (3) | 3 | 3 | 6 | 50.0% | 6 |
| TC (4) | 4 | 15 | 19 | 21.1% | 6 |
| TC (5) | 1 | 10 | 11 | 9.1% | 4 |
| Sum | 101 | 347 | 448 | 22.5% | 100 |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

"Source" indicates the number of source sentences used to create translation candidates. If multiple candidates are created from a source, the number under "Source" differs from that under "Sum."

 Table 7
 Accuracy result of translation candidates, D2_{all}, using Google Translate.

| $D2_{all}$ | Т | F | Sum | Rate | Source |
|------------|----|-----|-----|-------|--------|
| TC (1) | 25 | 73 | 98 | 25.5% | 98 |
| TC (2) | 36 | 298 | 334 | 10.8% | 98 |
| TC (3) | 2 | 2 | 4 | 50.0% | 4 |
| TC (4) | 2 | 14 | 16 | 12.5% | 4 |
| TC (5) | 5 | 9 | 14 | 35.7% | 5 |
| Sum | 70 | 396 | 466 | 15.0% | 100 |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

"Source" indicates the number of source sentences used to create translation candidates. If multiple candidates are created from a source, the number under "Source" differs from that under "Sum."

rule-based translation model, whereas the latter uses a statistical translation model. We used the same word dictionary, parallel corpus, and Web search engine as those mentioned in Sect. 4.1. However, with regard to TC (2), the personal pronoun "bccc (your)" was added to the existing list.

Five translators evaluated the new translation candidate pairs using the same ratings as those mentioned in Sect. 4.1. The selection criterion was also the same. The obtained data set was defined as $D2_{all}$.

5.2 Results and Discussion of First Sub-Method Using New Data

Tables 6 and 7 show the results for $D2_{all}$ using J-Server and Google Translate, respectively. The respective number of source sentences is 99 and 98 – the difference is because this sub-method deletes sentences containing Japanese characters.

A comparison of Tables 6 and 1 for TC (1) shows that the accuracy rate of MT in $D2_{all}$ was 8.5 points greater than that in $D1_{all}$. Moreover, a comparison of Tables 6, 7, and 1 for TC (2) shows that it created more accurate translation candidates in $D2_{all}$ as in the case of $D1_{all}$. Similarly, TC (3) created translation candidates with high accuracy rate for $D2_{all}$ as in the case of $D1_{all}$.

However, a comparison of Tables 6 and 7 for TC (5) shows that the number of accurate translation candidates in $D2_{all}$ was lesser than that in $D1_{all}$. TC (5) uses only the degree of similarity of sentence structures. It may create inaccurate translation candidates if there are PTs of no lit-

 Table 8
 Accuracy result of translation candidates, D2_{part}.

| D2 _{part} | | Т | F | Sum | Rate |
|--------------------|------------|----|-----|-----|-------|
| J-Server | TC (1) | 43 | 12 | 55 | 78.2% |
| | TC (2)-(5) | 52 | 151 | 203 | 25.6% |
| | Sum | 95 | 163 | 258 | 36.8% |
| Google | TC (1) | 25 | 16 | 41 | 61.0% |
| | TC (2)-(5) | 45 | 117 | 162 | 27.8% |
| | Sum | 70 | 133 | 203 | 34.5% |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

"TC (2)-(5)" indicates the sum of TC (2) through TC (5).

eral translation or having multiple meanings. For example, TC (5) creates an inaccurate translation candidate when it translates "みぞおちが痛いです (I have a pain in my pit of the stomach)" using PT "頭が痛いです -I have a headache." The shard sentence "が痛いです (have a pain)" corresponds to the Japanese source sentences. The shard sentence "I have a" does not imply "pain." However, TC (5) creates inaccurate translation candidates such as "I have a pit of the stomach."

We believe that translated text from the parallel corpus is not a literal translation (for example, "I have a pain in my head."). We conclude that TC (5) should contribute toward creating accurate translation candidates, although its accuracy rate is low.

We investigated the number of source sentences for which this sub-method created multiple accurate translation sentences. In the results of $D2_{all}$ using J-Server (Table 6), accurate candidates were created from 57 out of 99 source sentences. TC (1) created 45 accurate candidates. Therefore, the translation candidates created from the remaining 12 source sentences were inaccurate according to TC (1) and accurate according to TC (2)-(5). The sub-method for creating translation candidates created 57/45 = 1.27 times the number of accurate translation candidates than did MT.

In the results of $D2_{all}$ using Google Translate (Table 7), accurate candidates were created from 41 out of 98 source sentences. TC (1) created 25 accurate candidates. Therefore, the translation candidates created from the remaining 16 source sentences were inaccurate according to TC (1) and accurate according to TC (2)-(5). The sub-method for creating translation candidates created 41/25 = 1.64 times the number of accurate translation candidates than did MT.

Using J-Server, less accurate translation candidates were created in $D2_{all}$ than in $D1_{all}$. However, using Google Translate, the reverse was true. Therefore, we believe that this sub-method increases more translation accuracy when the translation accuracy of MT is low.

5.3 Results and Discussion of Second Sub-Method Using New Data

The second sub-method uses a part of $D2_{all}$, in a manner similar to that mentioned in Sect. 4.3. In $D2_{part}$, all accurate translation sentences (J-Server: 2 source sentences) and all inaccurate ones (J-Server: 43 source sentences, Google

Result of selection sub-method for accurate PT using D2_{part}.

| $D2_{part}$ | | Т | F | Sum | Rate |
|-------------|---------------|----|----|-----|-------|
| | MT (baseline) | 43 | 12 | 55 | 78.2% |
| J-Server | PMT | 45 | 10 | 55 | 81.8% |
| | PLS | 48 | 9 | 57 | 84.2% |
| Google | MT (baseline) | 25 | 16 | 41 | 61.0% |
| | PMT | 23 | 19 | 42 | 54.8% |
| | PLS | 22 | 22 | 44 | 50.0% |

The data represent the number of sentences.

Table 9

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

Table 10Result of translation repair method for accurate PT using $D2_{all}$.

| $D2_{all}$ | | Т | F | Sum | Rate |
|------------|---------------|----|----|-----|-------|
| J-Server | MT (baseline) | 45 | 54 | 99 | 45.5% |
| | PMT | 47 | 52 | 99 | 47.5% |
| | PLS | 50 | 53 | 103 | 48.5% |
| Google | MT (baseline) | 25 | 73 | 98 | 25.5% |
| | PMT | 23 | 76 | 99 | 23.2% |
| | PLS | 22 | 82 | 104 | 21.2% |

The data represent the number of sentences.

"T" and "F" indicate the number of accurate and inaccurate translation candidates, respectively.

Translate: 59 source sentences) based on source sentences are removed. Table 8 shows the accuracy result for $D2_{part}$.

Table 9 shows the result of the second sub-method for $D2_{part}$. For J-Server, the accuracy rates of PMT and PLS were respectively 3.6 and 6.0 points greater than that of MT. However, for Google Translate, the accuracy rates of PMT and PLS decreased compared to that of MT.

Table 10 shows the result of the second sub-method for $D2_{all}$. Here, we evaluate the translation repair method. For J-Server, the accuracy rates of PMT and PLS were respectively 2.0 and 3.0 points greater than that of MT. However, for Google Translate, the accuracy rates of PMT and PLS decreased compared to that of MT.

The result for $D2_{all}$ shows that the translation repair method using J-Server was able to create accurate translations, although the accuracy rate of $D2_{all}$ was lesser than that of D1_{all}. However, this method using Google Translate was unable to create accurate translations. We attribute this problem to the fact that Google Translate is based on a statistical translation model that is based on existing sentences on the Web. Therefore, the grammar of translated sentences tends to be accurate. For example, Google Translate translates a sentence such as "眠りが浅いです (I sleep badly)" to "The sleeper." When it translates the sentence with "watashi-wa (I)" added, the translated text is "I sleep lightly," which is accurate. However, the respective number of search results is 37,000,000 and 22,600, as a result of which the sub-method finally selects the former. Moreover, this sub-method uses the result of the Google Search engine. The statistical data used in Google Translate may also be collected using this engine. Therefore, we conclude that it will be necessary to develop another method for Google Translate in order to increase its accuracy.

6. Conclusions

In this study, we have proposed a translation repair method to accurately translate sentences from Japanese to English. This method can increase the translation accuracy using MT, a parallel corpus, a word dictionary, and a Web search engine.

The contributions of this paper are as follows:

- 1. We have proposed a translation repair method to create accurate translations. This method includes two submethods: one creates translation candidates and the other selects accurate translations.
- 2. The sub-method for creating translation candidates increase the number of accurate translation candidates. We showed that this sub-method could create 1.3-1.6 times the number of accurate translation candidates than did MT. Moreover, we showed that it could create more accurate translation candidates with the addition of personal pronouns and the use of a word dictionary and a parallel corpus.
- 3. The sub-method for selecting accurate translations selects an accurate translation from among these candidates. We showed that this sub-method improved the accuracy rate of translations by 6-13 points compared to MT, which uses a rule-based translation model.

The future challenges are as follows:

- We intend to improve the sub-method for creating a greater number of translation candidates.
- We will develop a sub-method to select accurate translations for MT based on a statistical translation model.
- We will investigate the accuracy of Japanese-Chinese PTs and Japanese-Korean PTs.

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References

- Y. Takano and A. Noda, "A temporary decline of thinking ability during foreign language processing," J. Cross-Cultural Psychology, vol.24, pp.445–462, 1993.
- [2] M. Aiken, C. Hwang, J. Paolillo, and L. Lu, "A group decision support system for the Asian Pacific rim," J. International Information Management, vol.3, no.2, pp.1–13, 1994.
- [3] K.J. Kim and C.J. Bonk, "Cross-cultural comparisons of online collaboration," J. Computer Mediated Communication, vol.8, no.1, 2002.
- [4] T. Ishida, "Language Grid: An infrastructure for intercultural collaboration," IEEE/IPSJ Symposium on Applications and the Internet (SAINT-06), pp.96–100, 2006.
- [5] S. Sakai, M. Gotou, M. Tanaka, R. Inaba, Y. Murakami, T. Yoshino, Y. Hayashi, Y. Kitamura, Y. Mori, T. Takasaki, Y. Naya, A. Shigeno, S. Matsubara, and T. Ishida, "Language grid association: Action research on supporting the multicultural society," Proc. ICKS-08, pp.55–60, 2008.

- [6] T. Yoshino, K. Fujii, and T. Shigenobu, "Availability of Web information for intercultural communication," Proc. PRICAI 2008, pp.923–932, 2008.
- [7] M. Matsuda and Y. Kitamura, "Development of machine translation system for Japanese children," Proc. IWIC'09, pp.269–271, 2009.
- [8] M. Miyabe, K. Fujii, T. Shigenobu, and T. Yoshino, "Parallel-text based support system for intercultural communication at medical receptions," Proc. IWIC 2007, pp.132–143, 2007.
- [9] T. Fukushima, T. Yoshino, and A. Shigeno, "Development of multilingual interview-sheet composition system to support multilingual communication in medical field," Proc. KES 2011, Lecture Notes in Artificial Intelligence (LNAI), vol.6882, pp.31–40, 2011.
- [10] S. Hasegawa, K. Sato, S. Matsunuma, M. Miyao, and K. Okamoto, "Multilingual disaster information system: Information delivery using graphic text for mobile phones," AI & Society, pp.265–278, 2005.
- [11] M. Miyabe, T. Yoshino, and T. Shigenobu, "Effects of undertaking translation repair using back translation," Proc. IWIC'09, pp.33–40, 2009.
- [12] T. Yoshino, T. Fukushima, M. Miyabe, and A. Shigeno, "A Webbased multilingual parallel corpus collection system for the medical field," Proc. IWIC'09, pp.321–324, 2009.
- [13] F. Bond, E. Nichols, D.S. Appling, and M. Paul, "Improving statistical machine translation by paraphrasing the training data," Proc. IWSLT 2008, pp.150–157, 2008.
- [14] Y. Tanaka, "Compilation of a multilingual parallel corpus," Proc. PACLING 2001, pp.265–268, 2001.
- [15] J. Chen, R. Chau, and C.H. Yeh, "Discovering parallel text from the World Wide Web," Proc. ACSW Frontiers'04, pp.157–161, 2004.
- [16] M. Nagata, T. Saito, and K. Suzuki, "Using the web as a bilingual dictionary," Proc. workshop on Data-driven methods in machine translation, pp.1–8, 2001.
- [17] K. Walker, M. Bamba, D. Miller, X. Ma, C. Cieri, and G. Doddington, "Multiple-translation arabic (MTA) Part 1," Linguistic Data Consortium, Philadelphia, 2003.



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