Master Thesis

Context-Aware Coordination of Cascaded Machine Translations

Supervisor Professor Toru Ishida

Department of Social Informatics
Graduate School of Informatics
Kyoto University

Rie TANAKA

February 7, 2008

Context-Aware Coordination of Cascaded Machine Translations

Rie TANAKA

Abstract

Recently more and more people communicate through the Internet, and machine translators are used as communication tools between peoples who cannot speak their partners' mother language. Since English is a hub language of development of language resources like machine translators or bilingual dictionaries, combining multiple machine translators via English enables intercultural communication and collaboration between non-English languages.

To combine multiple machine translators, problems interfering communication sometimes occur. Cascaded machine translators often yield mistranslations due to inconsistency of word selections, even if all translators are combined correctly and each translation result is correct. This is because each translator considers each input sentence only. This phenomenon is a big problem for both multi-hop translation cascading multiple translators and machine translator-mediated communication. Then, coordination of cascaded machine translators is needed. For resolution of such problems, this research addresses following issues.

Making multilingual equivalent terms

In order to examine whether the sense of translated sentence is different from the one of the source sentence, equivalent terms of all languages is required. Equivalent terms between two languages is developed as bilingual dictionaries between lots of languages, while that of more than three languages is developed manually among parts of languages. Therefore this research aims to generate multilingual equivalent terms automatically from existing language resources.

Coordinating of translators by propagating context

Coordination of translators, that is, consistent word selections, can be realized by extracting context and propagating it to machine translators. Context is extracted from the source sentence or whole document including the source sentence. The sense of translated sentence is kept consistent by

selecting translated words which suit propagated context. Methods of extracting context are proposed in previous researches. This research assumes that the context is already extracted, and focuses on the coordination by propagating extracted context.

To solve these two issues, this research proposed following solutions.

Extending bilingual dictionaries to multilingual by combining them

This research proposed the method to obtain multilingual equivalent terms by combining multiple bilingual dictionaries. Relations between words and translated words are represented as a graph, and equivalent terms are obtained by using the structure of it. If simply combining multiple dictionaries, there are some cases where multiple terms which do not share the same sense are also obtained. Such error can be prevented by considering the structure of the graph.

Coordinating word selections using multilingual equivalent terms

This research proposed a method to coordinate cascaded machine translators so as to select translated words based on the context which was propagated using multilingual equivalent terms. Each context extracted from the sentence is represented in each language, and machine translators can understand propagated context by referring multilingual equivalent terms. In one implementation of this idea, I showed an algorithm of coordination in which information of word selections was used as a context.

Finally, I actually generated equivalent terms in three languages (called tri-lingual dictionary) by proposed method, and implemented coordination of existing machine translators which I could not modify the inner systems. Coordination was realized by a simple way, in which the words having different sense from the source sentence were detected from translated sentence, and replaced by other words in tri-lingual dictionary. I evaluated the quality of Japanese-German-Japanese translation (often called back translation) and showed improvement of quality was possible by such simple implementation.

文脈を用いた機械翻訳連携

田仲 理恵

内容梗概

近年，インターネットを介してコミュニケーションをとる人々の数が増加し，コミュニケーションに使用される言語が多様化している．そのような中では英語を標準言語として用いることが難しくなってきており，互いの言語を話すことができない人々のコミュニケーションの手段として，機械翻訳が用いられるようになってきている．あらゆる言語からあらゆる言語への翻訳を可能にするためにすべての言語対の間の機械翻訳を開発することは不可能であり，複数の機械翻訳を連携させて使用することが必要である．機械翻訳やその他辞書などの言語資源の開発の中心は英語であり，いずれかの言語と英語間の言語資源は数多く開発されているため，英語をハブとして機械翻訳を繋ぎ合わせることで，直接の機械翻訳が存在しない言語間での対話が可能になり，言語を超えたコミュニケーションの可能性が広がる．

複数の機械翻訳を連結するためには，まずは入出力データの整合性を取るなど接続部分の問題がある．しかし，形式を揃えて連結することができても，ただ繋ぎ合わせるだけではコミュニケーションを阻害する問題が発生することが明らかになっている．個々の機械翻訳は他の機械翻訳が行った文脈解析等の処理を考慮しないため，個々の翻訳結果は正しくても，最初の入力文の意味が途中で変化してしまう危険性がある．この性質は，複数の機械翻訳を連携してマルチホップ翻訳を実現する場合に問題となる．また，機械翻訳を介して対話を行う場合にも，内容が毎回変わってしまうなどの問題が生じ，内容の確認や合意形成が難しくなる．この問題を解決するために，本研究では下記の 2 つの課題に取り組む．

多言語の同義語データを作成する

連結する機械翻訳全体の連携を行うためには，多言語における同義語の情報が必要となる．各言語において作成される訳文の意味が変わっていないかを判断するためには，扱う言語全体における同義語の情報が必要となるためである．二言語間の同義語データは，対訳辞書という形で多くの言語において作成されているが，多言語については，一部の言語間で人手により作成されたデータが存在するだけである．よって，既存の言語資源を用

いて，多言語の同義語データを自動生成することを目標とする．

文脈を伝播することで連携を行う

翻訳対象の文章，または翻訳対象の文章を含むテキスト全体から文脈を検出し，それを機械翻訳に伝播していくことによって連携を実現する．機械翻訳は，受け取った入力文に加えて伝播された文脈情報を参照し，文脈に合わない訳語を選択しないようにすることで訳文の意味を保つことができる．文脈の検出方法は多数研究されており，本研究では何らかの方法で文脈が検出されている場合に，それを機械翻訳に伝播して連携を行うことを目標とする．

以上の課題に対して，下記のような手法を提案した．

対訳辞書を組み合わせて多言語に拡張する

対訳辞書における単語と訳語の関係を，二言語における同義語情報とみなし，複数の対訳辞書を組み合わせることで多言語の同義語を取得する手法を提案した．複数の対訳辞書をただ組み合わせるだけでは，共通の意味の存在しない単語集合が取得されることがあるため，単語と単語間の対訳関係をグラフで表し，グラフの構造を利用して獲得を行うという方法を取った．

多言語の同義語情報により訳語選択を制御する

作成した多言語の同義語データを用い，伝播された文脈に基づいて訳語を選択するように機械翻訳を制御する手法を提案した．検出される文脈情報は言語固有のものであり，文脈に適した同義語を選択して訳語選択に用いることで，文脈の伝播を行う．このアイデアの実現として，文章の文脈情報として訳語選択情報を用いたアルゴリズムを示した．

最後に，提案手法を用いて三言語での同義語データを作成し，既存の機械翻訳を用いて連携を実装した．内部に手を加えることができない機械翻訳に対し，出力された訳文中から入力文と意味が異なる訳語を検出して置き換えを行うという単純な実装方法に対しても，ただつなぎ合わせるだけでは有効な結果が得られなかった折り返し翻訳において大幅な改善が行えることを示した．

Context-Aware Coordination of Cascaded Machine Translations

Contents

Chapter 1 Introduction

Recently more and more people communicate with each other through the Internet. As a variety of languages are used by the user of the Internet, it is getting difficult to use English as standard language. In such situation, machine translators are used as a tool of communication between peoples who cannot speak their partners' mother language. However, it is impossible to develop machine translators of between every two languages. To cover all pairs among n languages, the development of $n(n-1)$ direct machine translators is needed, but it is costly impossible.

Combining multiple machine translators to achieve translations between languages in which direct translator does not exist is a practical solution in such situation. Since English is a hub language of development of machine translator or other resources and they are developed between English and non-English language, translation among various languages can be possible by using English as an intermediate language. It also increases the chance of intercultural communication without language barriers. Especially combination of translators via English is essential to translate Asian languages into European languages except for English. Moreover, in fact, the development of machine translators between Asian languages is not sufficient, and even for Asian languages, combination of translators via English is required.

According to increase of language resources like machine translators or bilingual dictionaries, the Language Grid Project [1] practices activities about application and coordination of them for the purpose of overcoming the language and cultural barriers and realizing worldwide intercultural collaboration. As a part of activity, in a junior high school where many foreign students study with Japanese students, communication between Japanese teachers and foreign students in Japanese language class and between Japanese teachers and parents of foreign students are supported by machine translators and collaboration tools. Japanese-Portuguese translation for Brazilian student is needed in that school, and it is realized by combining Japanese-English and English-Portuguese translators, because there are few direct translators between Japanese and Portuguese. To understand the issues of communication with machine translators, Intercultural Collaboration Experiment was conducted where people having different mother languages performed a collaborative task through machine translators. The impact of machine translators toward communication has already been analyzed and it came out that problems interfering communication occur when multiple translators were combined [2].

To combine multiple machine translators, there are problems about consistency of input and output data type of each translator, at first. However, cascaded machine translators often yield mistranslations even if all machine translators are combined correctly. Since how each machine translator analyzes and selects translated words toward the input sentence is not considered by other translators, the sense of translated sentence can change on the way of cascaded translations. Such change is caused by inconsistent word selections. As a result of analysis in [2], there are two phenomena which cause mistranslation: *asymmetry* and *inconsistency* of word selections. In machine translation-mediated communication, echoing of statement is disrupted by asymmetries and making referring expressions of the same thing is disrupted by inconsistencies. This means that confirmation or agreement is difficult to achieve. Moreover, such problem is not limited in communication. When translating sentences by multi-hop translation cascading multiple translations, we can not get correct translation results because the sense of translated words may change.

For resolution of such problems caused by inconsistent word selections in combining multiple machine translators in cascaded form, this research addresses following issues.

Making multilingual equivalent terms

In order to examine whether the sense of translated sentence is different from the one of the source sentence, equivalent terms of all languages is required. Equivalent terms between two languages is developed as bilingual dictionaries between lots of languages, while that of more than three languages is developed manually among parts of languages. Therefore this research aims to generate multilingual equivalent terms automatically from existing language resources.

Coordination by propagating context

Coordination of translators, that is, consistent word selections, can be realized by extracting context and propagating it to machine translators. Context is extracted from the source sentence or whole document including the source sentence. The sense of translated sentence is kept consistent by selecting translated words which suit propagated context. Methods of extracting context are proposed in previous researches. This research assumes that the context is already extracted, and focuses on the coordination by propagating extracted context.

In previous researches, machine translators are developed in the area of natural language processing. Most research focused on translation between two languages. For example, methods to improve quality of translation of one translator or to generate interlinguas which can be used by all languages commonly were proposed. However, in the situation of combining translators, raising quality of each translator is not necessarily sufficient. On the other hand, method of extracting context from the sentence was proposed to analyze the document or to improve translation between two languages. This research is in the middle position among those researches and realizes correct translation result of target language by coordinating translations with propagating extracted context.

The remainder of this paper is as follows. First, in Chapter 2, this paper explains the examples of problems occurring in cascaded translations, and shows overview of proposed solution. In Chapter 3, this paper refers related works. And the next, this paper explains the method of generation of multilingual dictionary as a solution of the first research issue in Chapter 4, and the algorithm of coordination of machine translators and an example of execution as a solution of the second research issue in Chapter 5. Finally this paper reports the result of implementation and evaluation of proposed method, and discusses it in Chapter 6, and concludes in Chapter 7.

Chapter 2 Context-Aware Coordination

2.1 Issues in Composite Machine Translation Services

Problems occurring in cascaded machine translators are classified into three categories: inconsistency, asymmetry and intransitivity of word selections. *Inconsistency of word selections* is the phenomenon in which translated words of the same source word vary in different sentences. *Asymmetry of word selections* is the phenomenon in which the back translated word is different from the source word. *Intransitivity of word selections* is the phenomenon in which the word sense drifts across the cascade of machine translators. Figure 1 shows examples of the problems common in composite machine translation services. All sentences are presented in English in this paper; original Japanese and German sentences are shown in parentheses.

Figure 1 (a) is an example of inconsistency of word selection. The English word "paper" is translated to Japanese word "paper (kami)" in Case 1, while the same word is translated into "thesis (ronbun)" in Case 2. If this phenomenon occurs in the situation like inputting a sequence of sentence of the same context in machine translation-mediated chat, it becomes difficult to continue the interaction. Figure 1 (b) is an example of asymmetry in communication between Japanese user and English user. First, the Japanese word "party (pathi)," which means a social gathering, is translated into English correctly. Next, an English user echoes the word "party" but it is translated into the Japanese word "political party (tou)," because the English word "party" is a polysemous word. In a similar example, in the Japanese-German back translation cascading Japanese-English, English-German, German-English and English-Japanese machine translators, the Japanese word "octopus (tako)" has been back translated into "squid (ika)". This phenomenon is caused by the mediated German word "Tintenfisch (cephalopods)" obtained by English-German translator, a species of animal including both meaning of octopus and squid. Since "octopus" and "squid" is completely different in Japanese, even in mediated English, it is a very obvious error in daily conversation. Finally, intransitivity of word selection is displayed in Figure 1 (c). The Japanese word "fault (ketten)," which means

⟨Case 1⟩

Source sentence (English): I distribute this paper.

⇒ Translated sentence (Japanese): I distribute this paper.

(watashi ha kono kami wo haihu suru.)

⟨Case 2⟩

Source sentence (English): Please write your name in this paper.

⇒ Translated sentence (Japanese): Please write your name in this thesis.

(douzo, kono ronbun no naka de namae wo kaki nasai.)

(a) Inconsistency in English-Japanese translation

Japanese user (Japanese): We had a party in our club yesterday.

(kinou, kurabu de pa-thi ga ari mashita.)

⇒ Translated sentence (English): There was a party in our club yesterday.

English user (English): How was the party?

⇒ Translated sentence (Japanese): How was the political party?

(tou ha doudatta ka?)

(b) Asymmetry in Japanese-English and English-Japanese translation

Source sentence (Japanese): Her fault is a big problem.

(kanojo no ketten ha ookina mondai da.)

⇒ Translated sentence (English): Her fault is a big problem.

⇒ Translated sentence (German): Her responsibility is a big problem.

(Ihre Schuld ist ein großes Problem.)

(c) Drifting translated word in Japanese-English-German translation

Figure 1: Examples of cascaded machine translations

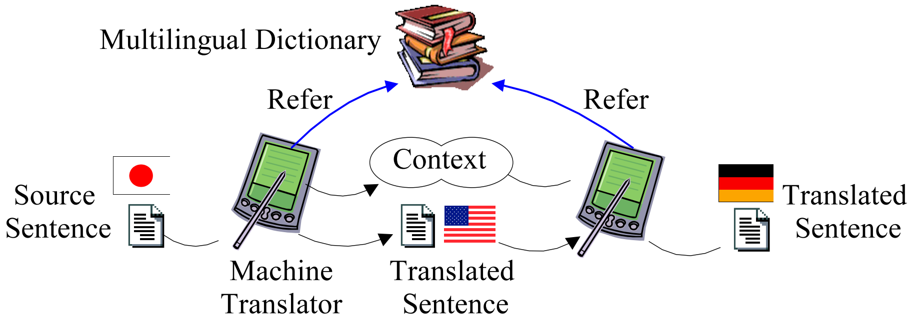
a character weakness, is translated into English correctly, but mistranslated to the German word "responsibility (Schuld)." This is because the intermediate English word "fault" has several meanings including weakness and responsibility and the English-German translator selected the translated word corresponding to the meaning of responsibility. The German word "responsibility (Schuld)" does not have a meaning of weakness and the sense of translated sentence is different from the one of source Japanese sentence.

In all examples, each translation is correct, but the translation result is considered as error when comparing with the source sentence. Though (a) and (b) are examples of interaction, the whole problems are put together to a problem of word selection: they are caused because of inconsistent word selection of polysemous word included in source sentence or intermediate translated sentence. For example, in example in (c), if the English-German translator knew the word "fault" was selected corresponding to the meaning of weakness, it would not have selected the word "responsibility (Schuld)" as a translated word.

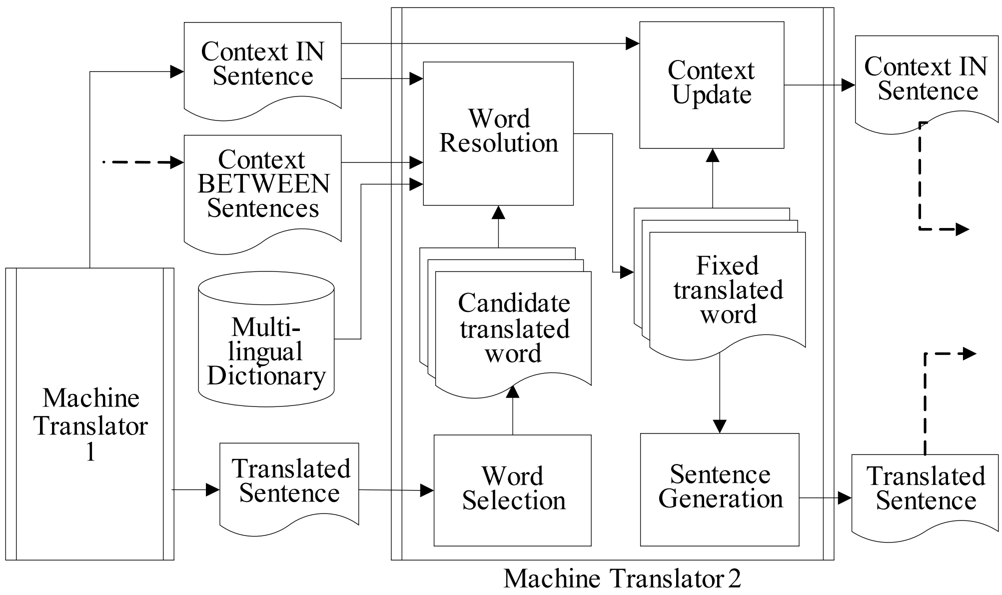
2.2 Solution with Context

For the purpose of preventing above errors, I propose the method to coordinate machine translators with propagated context so that they select translated words consistently. I call this "Context-aware coordination." Figure 2 (a) is an overview of coordination and (b) is more detailed processes. Machine translators outputting only translated sentences are changed so as to output both translated sentences and context as shown in (a). Machine translators receive the propagated context from prior translators and select proper translated words by referring context with multilingual dictionary. A multilingual dictionary is an extension of general bilingual dictionaries between two languages and it is a set of multilingual equivalent terms. In each entry of multilingual dictionary, each word is obtained from each language. When looking some word in some language up in multilingual dictionary, equivalent terms in other languages are obtained.

The context propagated through machine translators is described in each language and translators can understand the context by referring equivalent terms in multilingual dictionary. A lot of methods to extract the context from one sentence or whole document have already been proposed. This research assumes that the context can be extracted by some method. In terms of consistent word selections, the simplest context is information of word selections, that is,



(a) Overview of Context-Aware Coordination



(b) Detailed Processes of Coordination

Figure 2: Context-Aware Coordination

which translated word was selected corresponding to the source word. In each entry of multilingual dictionary which includes the source word, each word in each language has a same meaning as the source word, and it should be used as a translated word. Then consistent word selections are realized by propagating entries including the source word. In this case, a subset of multilingual dictionary is used as a context. If more advanced context, like that considering whole meaning of the source sentence or whole document including the source sentence, is available, multilingual dictionary is used as subsidiary information.

Figure 2 (b) details the processes of coordination. It shows how the second machine translator generates the translated sentence referring input sentence and propagated context. At first, the translator prepares candidates of translated words of each word in input sentence by "Word Selection" component and fixes which words to be used as translated words by "Word Resolution" component. The propagated context "Context IN Sentence" and multilingual dictionary is used in this process and words which are not semantically drifting are selected. The expression "semantically drifting" means that the sense of translated word has changed from the original sense of source word. When fixing words, "Context BETWEEN Sentences" is also used in addition to "Context IN Sentences." This means a context outside the source sentence. In case of translating one of the sequential sentences in chat or document, word selection considering the whole sentences is required. Moreover, information of term frequency of words or priority of word selection in the translator is also included in "Context BETWEEN Sentences." If "Context BETWEEN Sentences" is used, the words matching context of surrounding sentences or frequently used or which are most plausible for the machine translator are selected. After the translated words are fixed, the translated sentence is generated by "Sentence Generation" component. At the same time, the context is updated using generated translated sentence by "Context Update" component and propagated to the next translator with generated sentence.

In Figure 2 (b), all processes from receiving input and generating output are shown as one "machine translator." There are several ways of implementation of this system. For example, whether we can change the codes of machine translator or not depends on each machine translator. If we can, coordination is realized by adding parts to analyze propagated context and updating context to the inner system of machine translators. If we use the context extracted by some method separately from the analyzer of the translator, a part for processing such extraction is added similarly. In case we can not change codes, consistent word selection is realized by replacing the words in translated sentence which are semantically drifting with the correct words. Machine translators are considered as black boxes receiving input sentences and outputting translated sentences. A component for replacement is added outside the translator and wrapped whole system of translator and additional parts is viewed as "machine translator" in Figure 2 (b). In Chapter 5, the latter case we can not change the code is taken and algorithm for coordination outside the machine translators is shown at first. The modified algorithm so as to be used in the case we can change the codes is shown after that.

Chapter 3 Related Works

3.1 Related Works of Multilingual Translation

There have been a lot of researches focusing on the extension of machine translators between two languages to multilingual in addition to the researches focusing on improvement of the quality of each translation. Interlingua approach like [3] is one of them. Such approach is based on the idea of designing interlingua which can represent the meanings of each language and realizing multilingual translation by changing the sentence in source language to interlingua and changing it to the sentence of each target language. However, it is difficult to obtain high quality of translation through interlingua because it has to be designed so as to cover all grammatical forms or idioms of all languages. If focusing on only the quality of translation, developing all machine translators between all languages has higher possibility of realization.

Approaches using English as the hub language, as I described in Chapter 1, are other way of realization of multilingual translation or translation between two languages which do not have direct translators. However, there exist some problems in communication through such translators. As one solution of those problems, the method to annotate the mediated English sentences in the language called Linguistic Annotation Language is proposed [4]. Kanayama and Watanabe [4] solve two types of problems: information loss and error accumulation. Information loss is the phenomenon in which a part of information or meanings of source sentence is lost in translated sentence in target language when mediated English sentence includes polysemous words. For example, in the Japanese-French translation mediating English, both Japanese word "financial bank (ginkou)" and "river bank (teibou)" are translated to the same English word "bank", and it does not translated to French correctly. Error accumulation is the phenomenon in which if errors such as parsing errors occur in each translator, the translation precision of the whole system has become lower than that of each translator.

Those problems can be solved by annotating mediated English sentence. For the purpose of solving information loss, the source words in source sentence are annotated to the translated words in English sentence. In translation from English to target language, equivalence between the annotated source word and the target word in target language is judged by using bilingual dictionary from source language to target language. For the purpose of solving error accumulation, the source language information and structural information are annotated. Such information is referred by translator from English to target language in parsing English sentence. Kanayama and Watanabe [4] reported the result of experiment in which they applied their method to Japanese-English-French multi-hop translation and evaluated translation quality of 214 Japanese sentences which could be translated to English correctly. As a result, problematic word selections occurred in 23 sentences and 17 sentences out of that were translated correctly.

Above method is the same as our method in terms of addressing problematic word selections. However, it is limited to multi-hop translation between two languages. In addition, in case where the source word has multiple meanings or classification of concepts of target language is more detailed than that of source language, it is impossible to judge whether the translated word is correct or not by only referring information of source language. Our method prepares information of multilingual equivalent terms in advance and uses all context information obtained from sentences of all mediated languages. Context information indicates that by which senses the translated words were selected. That enables resolution of word sense even if the source word has several senses.

3.2 Related Works of Multilingual Dictionary

Development of EuroWordNet [9] is one of the researches of multilingual dictionary. WordNet [8] is English lexical database developed by hand, in which English words are classified to groups of synonymous words, called *synset*, and definition of them and relations with other synsets are also described. EuroWordNet is developed from WordNet in several languages by combining equivalent synsets of each language. It is available as multilingual dictionary. If there exists such dictionary, we can use it in context propagation. However, it does not exist among all languages. The other method of automatic generation of multilingual dictionary is required as described in following section.

One of the other approaches of developing dictionaries, method of automatic extraction of concept or mappings between concepts is proposed [5]. Tokunaga and Tanaka [5] aim to automatically develop machine readable bilingual dictionaries so as to analyze source sentences at the conceptual level. By proposed method, the set of conceptual items, the mapping relation between the surface words and the conceptual items, and the correspondence between the conceptual items of the source language and that of the target language are obtained by a pair of bilingual dictionaries between two languages (in the case of Japanese and English, Japanese-English and English-Japanese dictionary). Since there are two types of concepts, that is, the concepts which are unique to a language and the concepts which are universal over languages, this method extracts and maps them. When looking up a bilingual dictionary, there are several word senses corresponding to each headword and translated words are described corresponding to each word sense. Conceptual items are obtained by viewing word senses as concepts. Similarly, relations between headwords and word senses are obtained as mapping relations between the surface words and conceptual items. Correspondences between concepts are obtained by representing dictionary by a graph. In the graph, words and word senses are represented as vertices and mapping relations between words and word senses are represented as direct edges. If the graph contains a cyclic route through two words and two word senses, the word senses included such route are considered as representing the same concepts.

In the area of analyzing mapping relations between data which is distributed in a network, the method of calculating correctness of mappings by using the structure of the network is proposed [6]. This research focused on the situation where there is a network including multiple databases which schemas are unique to a database, that is, which have local schemas not global schema. Between neighboring schemas of neighboring databases, each two attributes indicating the same information are mapped with each other, and correctness of such mappings of attributes is calculated. Each database has only mapping information of attributes toward the schema of neighboring databases and does not have global information. In such network, it is aimed to obtain answers from multiple databases by sending a query to one of them and propagating it through whole network. The correctness of each mapping of attributes is required to propagate a query correctly.

In the proposed method, correctness of mappings is calculated based on the shape of the route formed by mappings. Assuming that there is a cyclic route which passes some databases and going back to the starting database, each attribute of the first query is changed according to the mapping obtained by following the route one after another. If the attribute is changed to the original attribute when it returns back to the starting database, that is, if there is a loop constructed by the mapping of the attributes, all mappings applied to the attribute are considered as correct mappings. For example, assume that an attribute $art/creator$ of the schema of the first database D_1 is mapped to the attribute $Creator$ of the schema of the second database D_2, and the attribute $Creator$ is mapped to the attribute $Auther$ of the schema of the third database D_3. If there is a mapping between the attribute $Auther$ of the schema of D_3 and the attribute $art/creator$ of the schema of D_1, three mappings which form a cyclic route are considered as correct and attributes $art/creator$, $Creator$ and $Auther$ are considered as representing the same information.

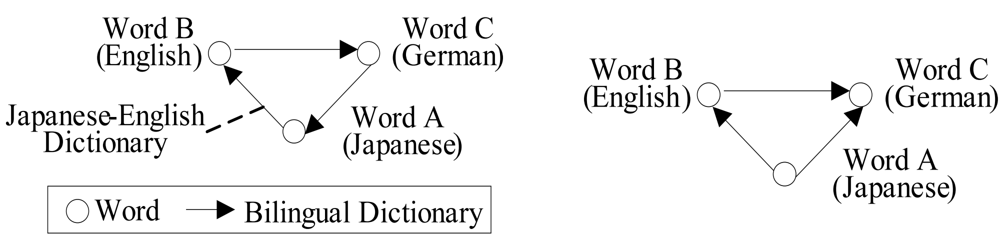
The basic idea of Cudre-Mauroux et al. [6] is similar to Tokunaga and Tanaka [5] in terms of judging equivalence of data based on the structure of the network or graph, although more detailed calculation algorithm using factor graph [7] and some evaluated values is proposed in Cudre-Mauroux et al. [6]. This research refers those works and proposes a method to obtain multilingual equivalent terms by using the structure of a graph which is generated by multiple bilingual dictionaries and representing relations of translation.

Chapter 4 Automatic Generation of Multilingual Dictionary

This section denotes a method of automatic generation of multilingual dictionary which is used in propagating context. At first, I explain the method of generation of tri-lingual dictionary, a set of tri-lingual equivalent terms among three languages (a *triple* hereafter), by combining several generic bilingual dictionaries. After that I show an idea of extension from the tri-lingual dictionary to multilingual dictionary among four or more languages.

4.1 Generation of Tri-lingual Dictionary

I extend ideas of previous research, which uses the structure of networks of some kind of data, and represent a mapping of words in different languages as a graph: a word is represented as a vertex and a mapping in bilingual dictionaries is represented as a directed edge. If the graph contains a triangle, the three words are considered to be equivalent terms. Figure 3 shows examples. Since a bilingual dictionary has a direction from source language to target language, all edges between words have directions. There are two types of triangles: *loop* and *transition*. The loop-type triangle (Figure 3 (a)) is obtained by starting from a source language, looking up dictionaries three times to return to the source language. The transition-type triangle (Figure 3 (b)) is obtained by starting from a source language, and looking up dictionaries to find transitive and direct routes between source and target languages.



(a) Loop-type Triangle

(b) Transition-type Triangle

Figure 3: Two types of triangles

To generate triples from loop-type triangles, either language is allocated as a starting language, and bilingual dictionaries are looked up according to the order in loop. If allocating Japanese as a starting language as shown in Figure 3 (a), a Japanese word (source word) is looked up in the Japanese-English dictionary. Then, one of the obtained English words is looked up in the English-German dictionary and one of the obtained German words is looked up in the German-Japanese dictionary. Three words which are looked up are considered as a triple if the source word is included in a set of Japanese words obtained from German-Japanese dictionary. As for transition-type triangle, the language of word from which has two edges pointing out is considered as a starting language, and after looking up dictionaries similarly, a tuple of three words of vertices of a triangle are generated as a triple.

Algorithm 1-1 shows an algorithm to generate triples from loop-type triangle and Algorithm 1-2 shows the one from transition-type triangle. These algorithms assume to use bilingual dictionaries with word senses. Dictionary with word senses is a dictionary in which multiple word senses are described corresponding to each headword and translated words are described corresponding to each word sense. Let one word sense (h, W), in which h is a headword and W is a set of translated word. (h, W) represents one of the senses which the headword h has. I define a set of such sense as a bilingual dictionary.

In Algorithm 1-1, generation of triples is started from headwords in the dictionary from language 1 to 2. A set of all translated words in language 2 WS_2 corresponding to the headword w_1 is obtained from that dictionary (line 12). There are multiple pairs (h_1, W_2) in which a headword h_1 is equal to w_1, and a set of all translated word corresponding to w_1 is obtained by merging the set W_2 in such pairs. After line 13, a set of all translated words in language 3 (WS_3) corresponding to the word w_2 in WS_2 is obtained from dictionary from language 2 to 3, and a set of all translated words in language 1 (WS_1) corresponding to the word w_3 in WS_3 is obtained from dictionary from language 3 to 1. If the source word w_1, which is the starting word of looking up dictionaries, is included in WS_1, a tuple of three words $\{w_1, w_2, w_3\}$ is obtained as a triple.

Algorithm 1-2 is similar. As for transition-type triangle, a set of all translated

Algorithm 1-1 GET-LOOP-TYPE-TRIPLE($D_{1,2}, D_{2,3}, D_{3,1}$) **return** T

```
w_1, w_2, w_3 /* A word in language 1, language 2, and language 3 */
WS_1, WS_2, WS_3 /* A set of words in language 1, language 2, and
                    language 3 */
(h_1, W_2) /* A word sense of h_1; h_1 is a word in language 1 and W_2 is
              a set of words in language 2 */
(h_2, W_3) /* A word sense of h_2; h_2 is a word in language 2 and W_3 is
              a set ofwords in language 3 */
(h_3, W_1) /* A word sense of h_3; h_3 is a word in language 3 and W_1 is
              a set of words in language 1 */
D_{1,2} = {(h_1, W_2)} /* A bilingual dictionary is a set of word senses (h_1, W_2);
                          h_1 is a headword and W_2 is a set of translated
                          words of h_1 */
D_{2,3} = {(h_2, W_3)} /* A bilingual dictionary is a set of word senses (h_2, W_3);
                          h_2 is a headword and W_3 is a set of translated
                          words of h_2 */
D_{3,1} = {(h_3, W_1)} /* A bilingual dictionary is a set of word senses (h_3, W_1);
                          h_3 is a headword and W_1 is a set of translated
                          words of h_3 */
T /* A set of triples of equivalent words in language 1, language 2, and
     language 3 */
T ← φ
for each w_1 in all headwords of D_{1,2} do
    WS_2 ← ∪{W_2 of tuple (h_1, W_2)|(h_1, W_2) ∈ D_{1,2}, h_1 = w_1}
    for each w_2 in WS_2 do
        WS_3 ← ∪{W_3 of tuple (h_2, W_3)|(h_2, W_3) ∈ D_{2,3}, h_2 = w_2}
        for each w_3 in WS_3 do
            WS_1 ← ∪{W_1 of tuple (h_3, W_1)|(h_3, W_1) ∈ D_{3,1}, h_3 = w_3}
            if w_1 ∈ WS_1 then
                T ← T ∪ {{w_1, w_2, w_3}}
            end if
        end loop
    end loop
end loop
return T
```

Algorithm 1-2 GET-TRANSITION-TYPE-TRIPLE($D_{1,2}, D_{1,3}, D_{2,3}$) **return** T

w_1, w_2, w_3 /* A word in language 1, language 2, and language 3 */

WS_1, WS_2, WS_3 /* A set of words in language 1, language 2, and language 3 */

WS'_3 /* A set of words in language 3 */

(h_1, W_2) /* A word sense of h_1; h_1 is a word in language 1 and W_2 is a set of words in language 2 */

(h_1, W_3) /* A word sense of h_1; h_1 is a word in language 1 and W_3 is a set of words in language 3 */

(h_2, W_3) /* A word sense of h_2; h_2 is a word in language 2 and W_3 is a set of words in language 3 */

$D_{1,2} = \{(h_1, W_2)\}$ /* A bilingual dictionary is a set of word senses (h_1, W_2); h_1 is a headword and W_2 is a set of translated words of h_1 */

$D_{1,3} = \{(h_1, W_3)\}$ /* A bilingual dictionary is a set of word senses (h_1, W_3); h_1 is a headword and W_3 is a set of translated words of h_1 */

$D_{2,3} = \{(h_2, W_3)\}$ /* A bilingual dictionary is a set of word senses (h_2, W_3); h_2 is a headword and W_3 is a set of translated words of h_2 */

T /* A set of triples of equivalent words in language 1, language 2, and language 3 */

$T \leftarrow \phi$

for each w_1 **in** all headwords of $D_{1,2}$ **do**

  $WS_2 \leftarrow \cup\{W_2 \text{ of tuple } (h_1, W_2) | (h_1, W_2) \in D_{1,2}, h_1 = w_1\}$

  $WS_3 \leftarrow \cup\{W_3 \text{ of tuple } (h_1, W_3) | (h_1, W_3) \in D_{1,3}, h_1 = w_1\}$

  for each w_2 **in** WS_2 **do**

    $WS'_3 \leftarrow \cup\{W_3 \text{ of tuple } (h_2, W_3) | (h_2, W_3) \in D_{2,3}, h_2 = w_2\}$

    for each w_3 **in** WS_3 **do**

      if $w_3 \in WS'_3$ **then**

        $T \leftarrow T \cup \{\{w_1, w_2, w_3\}\}$

      end if

    end loop

  end loop

end loop

return T

words in language 2 (WS_2) and language 3 (WS_3) corresponding to starting word w_1 are obtained at first (lines 13-14). A set WS'_3 is obtained corresponding to the word w_2 in WS_2. After that, the words which are included in both WS_3 and WS'_3, where WS_3 and WS'_3 are obtained from different dictionaries, are searched, and a tuple of w_1, w_2 and the commonly included word is obtained as a triple (lines 17-20).

Example 1 (Triples generated from loop-type triangle starting from the Japanese word "sky/heaven/midair (sora)")

Take an example of a loop-type triangle starting from the Japanese word "sky/heaven/midair (sora)". Figure 4 shows words and their mappings in each bilingual dictionary. When looking the starting word in a Japanese-English dictionary, "sky," "air," "heaven" and other words are obtained as translated words. When looking "sky" up in an English-German dictionary, German words "sky/heaven (Himmel)," "sky/heaven (Firmament)" and other words are obtained. When looking "sky/heaven (Himmel)" up in a German-Japanese dictionary, Japanese words "sky/heaven/midair (sora)," "sky/heaven (ten)" and other words are obtained, and a tuple {sky/heaven/midair (sora), sky, sky/heaven (Himmel)} is taken as a triple, because the starting word is included in Japanese words which are finally obtained. By continuing this process, in addition to the triple {sky/heaven/midair (sora), sky, sky/heaven (Himmel)}, {sky/heaven/midair (sora), air, midair (Luft)}, {sky/heaven/midair (sora), heaven, sky/heaven (Himmel)} and {sky/heaven/midair (sora), heaven, sky/heaven (Firmament)} are also obtained. Since the Japanese word "sky/heaven/midair

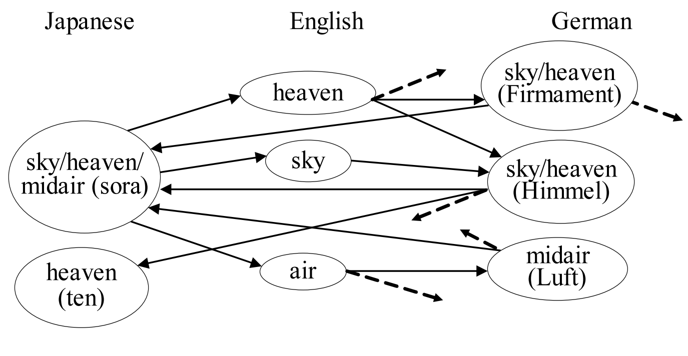


Figure 4: Example of a loop-type triangle representing "sky"

(sora)" has several meanings, the senses of triples are somewhat different with each other.

4.2 Correctness of Obtained Triples

If there are three words sharing the same sense and their relations of equivalence are written in bilingual dictionaries, they can be got as a triple without fail. If all pairs of two words are equivalent each other, all pairs of vertices of words have one or more edges in the graph and three words always form a triangle.

However, it is not necessary the case that three words in a triple share the same sense. One of the examples is shown in Figure 5. Parenthetic words are word senses $S_1, S_2, S_3, ...$ each word has. When word A has word sense S_1 and S_2, word B has word sense S_2 and S_3 and word C has word sense S_3 and S_1, there is no sense shared by three words even if they are considered as a triple.

Assume that each word in a triple has n senses with uniform distribution. Estimation of probability that there are some shared senses among three words can be calculated as follow: when each word is represented by a set of n vertices of n senses and two senses corresponded in bilingual dictionaries are combined, a triple is considered as sharing the same sense only if there are one or more set of three vertices combined each other. For simplicity, there is no case where one vertex is combined with two or more vertices in the same language, and edges combining each vertex do not have direction. In a graph representing a triple, each pair of sets of n vertices always has one or more edges. There are a lot of ways combining three sets of n vertices. However, an edge represents that the two word senses are equal, and if word sense A is equal to word sense B and word sense B equal to word sense C, word sense A and C are always equal. Therefore there are only two types of routes formed by three edges: closed route

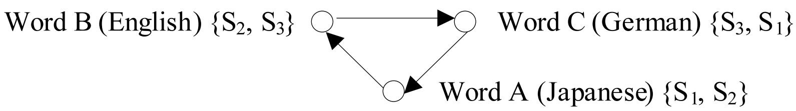
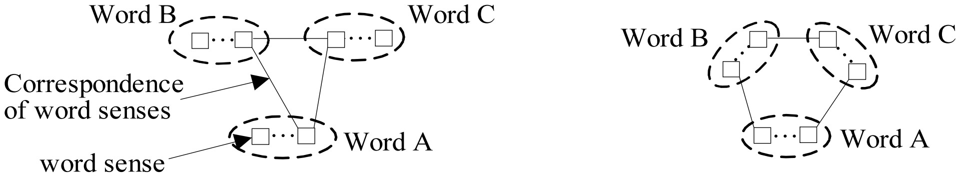


Figure 5: The case where there is no shared sense in a triple



(a) Closed route (b) Opened route

Figure 6: Two types of routes combining word senses

shown in Figure 6 (a) and opened route shown in Figure 6 (b).For preparation of calculation, the number of cases where three sets of n vertices have no opened route and closed route, represented as $NoRoute(n)$, is calculated as below.

$$NoRoute(n) = 3\sum_{i=1}^{n}\left\{({}_nP_i)^2 \times (\sum_{j=0}^{n-i} P_j \times_n P_j)\right\} + 1$$

The number of cases where three sets of n vertices have one or more closed route, represented as $Close(n)$, and the number of cases where they have one or more opened route only, represented as $Open(n)$ are calculated as below.

$$\begin{aligned} &Open(n) \\ &= ({}_nP_2)^3 \times NoRoute(n-2) + ({}_nP_4)^3 \times NoRoute(n-4) + ... \\ &= \begin{cases} \sum_{i=1}^{\frac{n}{2}-1}\left\{({}_nP_{2i})^3 \times NoRoute(n-2i)\right\} + ({}_nP_n)^3 & (n = 2k, k \geq 1) \\ \sum_{i=1}^{\frac{n-1}{2}-1}\left\{({}_nP_{2i})^3 \times NoRoute(n-2i)\right\} + ({}_nP_{n-1})^3 & (n = 2k+1, k \geq 1) \end{cases} \end{aligned}$$

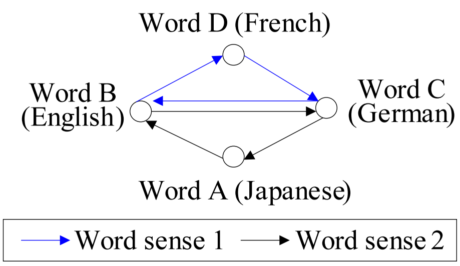
$$\begin{aligned} &Close(n) \\ &= ({}_nP_1)^3 \times (Open(n-1) + NoRoute(n-1)) + ... \\ &= \sum_{i=1}^{n-1}\left\{({}_nP_i)^3 \times (Open(n-i) + NoRoute(n-i)\right\} + ({}_nP_n)^3 \\ &Common(n) = \frac{Close(n)}{Close(n) + Open(n)} \qquad (*) \end{aligned}$$

By calculating with formula (*),$Common(2) = 0.83$, $Common(3) = 0.91$, $Common(6) = 0.99$ and the probability comes closer to 1 as n is getting bigger. In practice, term frequencies of n senses are not equal and there exist some biases like that probabilities of existence of edges combining typical word senses are higher than that of other edges. Actual probability of which three words do NOT share the same sense is vanishingly low.

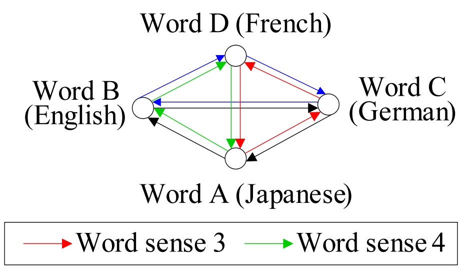
4.3 Extension to Four or More Languages

To extend the above method to four or more languages, combining triples generated in each three languages is better than generating tuples of four or more languages from loop-type route or transition-type route. This is because the probability of which a tuple does not have a shared sense is getting higher as the number of languages increases. The word senses can be changed on the way of looking up dictionaries. For example, in case of Japanese, English, German and French words, we first obtain Japanese-English-German triples and English-German-French triples. The quadruple is generated by combining two triples whose English and German words are the same.

Probability of no shared sense still remains even if generating quadruples from triples. In above example of Japanese, English, German and French, there is no shared sense if a sense of the Japanese-English-German triple is different from that of the English-German-French triple (Figure 7 (a). Four triangles can exist among four words at most and a quadruple of no shared sense has been generated from four triangles (Figure 7 (b). However, since the probability of no shared sense is getting lower as the number of triangles existing among four words increases, there is room for improvement, like by giving tuples some evaluated values according to the number of triangles existing. This issue is our future work.



(a)



(b)

Figure 7: The case where there is no shared sense in a quadruple

Chapter 5 Coordination of Cascaded Machine Translators

5.1 Algorithms for Coordination outside Machine Translators

This section explains algorithms for coordination of machine translators, by which machine translators propagate context and generate proper translated sentences with multilingual dictionary which has already existed. Although the previous section showed an algorithm for three languages, the following algorithms do not depend on the number of languages. In this section, I show the algorithm outside machine translators.

5.1.1 Whole Process of Coordination

A main algorithm of coordinating cascaded translation in n language is shown in Algorithm 2-1 and from Algorithm 2-2 to Algorithm 2-5 show sub functions called in main algorithm. These algorithms assume that machine translators can not be changed and realize the coordination shown in Figure 2 with regarding them as black boxes. They are simplest implementation using only information of word selection as context in the sentence.

COORDINATE-TRANSLATORS, in Algorithm 2-1, coordinates a set of n machine translators MT. Let i-th machine translator MT_i which inputs source sentence s_i and outputs translated sentence t_i. The sentence s_{i+1}, which is modified the output t_i so as not to semantically drift, is an input of the next translator MT_{i+1}. This algorithm repeats the same processes from MT_1 to MT_n and outputs s_{n+1} as the final result in the target language.

Multilingual dictionary is represented by a set of n-tuples, equivalent terms in n languages. A subset of multilingual dictionary T_i is propagated as the context of the source sentence. T_i, which is propagated to i-th translation, is a set of n-tuples which includes previous translated words. When one n-tuple in T_i is represented as $(w_1, ..., w_i, w_{i+1}, ..., w_n)$, w_1 to w_i are included in previous input sentences s_1 to s_i, and they show that which words were used as translated words previously corresponding to the source word w_1. w_{i+1} to w_n are equivalent terms of words used previously, and shows which words should be used in the

Algorithm 2-1 COORDINATE-TRANSLATORS(MT, s_1) **return** s_{n+1}

MT /* An ordered list of cascaded machine translators combined ($M_T = \{MT_1, MT_2, ..., MT_n\}$) */
s_i /* Original input sentence of MT_i */
t_i /* Output sentence of $MT_i(t_i \neq s_{i+1})$ */
$MT_i = \{(s_i, t_i)\}$ /* A machine translator; a set of pairs of input sentence s_i and output sentence t_i */
o_i /* A word in sentence s_i */
c_{i+1} /* A word in sentence t_i */
(h_i, W_{i+1}) /* A concept of h_i; h_i is a word in source language of MT_i and W_{i+1} is a set of words in target language of MT_i */
$D_{i,i+1} = \{(h_i, W_{i+1})\}$ /* A bilingual dictionary, whose source and target languages are the same as ones of MT_i; A set of word senses (h_i, W_{i+1}); h_i is a headword and W_{i+1} is a set of translated words of h_i */
T_i /* A set of possible n-tuples $(w_1, w_2, ..., w_n)$, where w_k is included in $s_k(k \leq i)$; All n-tuples are registered in n-Lingual Dictionary */
P_i /* A set of pairs (o_i, c_{i+1}), where $o_i \in s_i$ and $c_{i+1} \in t_i$ of MT_i */
Q_i /* A set of pairs (o_i, m_{i+1}), where $o_i \in s_i$ and m_{i+1} is modified translated word of o_i */
$T_1 \leftarrow \{(w_1, w_2, ..., w_n) | w_1 \in s_1\}$
for each MT_i **in** MT **do**
    $t_i \leftarrow MT_i(s_i)$
    $P_i \leftarrow$ GET-WORD-PAIRS-USED-BY-MT($s_i, t_i, D_{i,i+1}$)
    $Q_i \leftarrow$ CREATE-WORD-PAIRS-TO-BE-USED(P_i, T_i)
    if $Q_i \neq P_i$ **then**
        $s_{i+1} \leftarrow$ MODIFY-TRANSLATED-SENTENCE(t_i, P_i, Q_i)
    else
        $s_{i+1} \leftarrow t_i$
    end if
    $T_{i+1} \leftarrow$ SELECT-POSSIBLE-N-TUPLES(T_i, Q_i)
end loop
return s_{i+1}

future translations. By referring such T_i and selecting words in T_i as translated words, multilingual translation is achieved without change of sense of sentence.

Procedures shown in lines 14 to 22 correspond to processing of one machine translator in Figure 2 (b). The translated sentence before modification t_i is generated from MT_i (line 14), and pairs P_i of source word in source sentence s_i and translated word in translated sentence t_i are generated by GET-WORD-PAIRS-USED-BY-MT algorithm (line 15, shown in Algorithm 2-2). These procedures correspond to "Word Selection" component. Next, words which senses are semantically drifting are detected by referring the context T_i and are replaced with words in T_i by CREATE-WORD-PAIRS-TO-BE-USED algorithm (line 16, shown in Algorithm 2-3). The pairs of source word and replaced translated word are represented as Q_i. This procedure corresponds to "Word Resolution" component. If there are replaced words, translated sentence t_i is modified and outputted as the next input sentence s_{i+1} by MODIFY-TRANSLATED-SENTENCE algorithm (line 18, shown in Algorithm 2-4). This procedure corresponds to "Sentence Generation" component. Finally, context T_i is updated by SELECT-POSSIBLE-N-TUPLES algorithm (line 22, shown in Algorithm 2-5). This procedure corresponds to "Context Update" component. Following subsections show sub algorithms in detail.

In Figure 2 (b), "Candidate translated word" is outputted from the "Word Selection" component. In those algorithms by which coordination is realized outside machine translators, one translated word selected by machine translator is output toward one source word from GET-WORD-PAIRS-USED-BY-MT algorithm. In the algorithms by which coordination is realized inside, described later, multiple translated words which machine translator possesses toward one source word are output in the literal sense of "candidate."

Algorithm 2-2 GET-WORD-PAIRS-USED-BY-MT($s_i, t_i, D_{i,i+1}$) **return** P_i

s_i /* Original input sentence of MT_i */
t_i /* Output sentence of $MT_i(t_i \neq s_{i+1})$ */
o_i /* A word in sentence s_i */
c_{i+1} /* A word in sentence t_i */
WS_{i+1} /* A set of words in target language of MT_i */
(h_i, W_{i+1}) /* A concept of h_i; h_i is a word in source language of MT_i and W_{i+1} is a set of words in target language of MT_i */
$D_{i,i+1} = \{(h_i, W_{i+1})\}$ /* A bilingual dictionary, whose source and target languages are the same as ones of MT_i; A set of word senses (h_i, W_{i+1}); h_i is a headword and W_{i+1} is a set of translated words of h_i */
P_i /* A set of pairs (o_i, c_{i+1}), where $o_i \in s_i$ and $c_{i+1} \in t_i$ of MT_i */
$P_i \leftarrow \phi$
for each o_i **in** s_i **do**
 $WS_{i+1} \leftarrow \cup\{W_{i+1}$ of tuple $(h_i, W_{i+1}) | (h_i, W_{i+1}) \in D_{i,i+1}, h_i = o_i\}$
 for each c_{i+1} **in** t_i **do**
  if $c_{i+1} \in WS_{i+1}$ **then**
   $P_i \leftarrow P_i \cup \{(o_i, c_{i+1})\}$
   break
  end if
 end loop
end loop
return P_i

5.1.2 Getting Pairs of Source Word and Translated Word

Algorithm 2-2 matches source words in s_i with translated words in t_i generated by MT_i, that is, detects which word is selected as a translated word corresponding to the source word. Bilingual dictionary is used for matching, which definition is as same as that in Chapter 4. Matching is done by looking each word in s_i up in the bilingual dictionary and examining whether obtained translated words is included in t_i. Take an example of source Japanese sentence s_i = "Her fault is a big problem (kanojo no ketten ha ookina mondai da)" and translated English sentence t_i = "Her fault is a big problem." Matching of the source word "fault (ketten)" is made by looking it up in a Japanese-English dictionary and comparing obtained translated words "fault," "defect" and "shortcoming" with t_i. Since translated word "fault" is included in t_i, a pair (fault (ketten), fault) is obtained. t_i is represented as a set of words in Algorithm 2-2 and can be got by using morphological analysis, for instance. If more advanced matching system which has the same function as this algorithm is available, it can be used as GET-WORD-PAIRS-USED-BY-MT function in Algorithm 2-1 instead.

5.1.3 Detecting Semantic Drifting and Modifying

Algorithm 2-3 detects words which senses is semantically drifted from P_i and modifies it. As previous explanation, information of which words were selected as translated words previously and which words are to be selected as translated words in the future is preserved in T_i. In the pair (o_i, c_{i+1}) of source word o_i and translated word c_{i+1}, c_{i+1} is judged as semantically drifting if it is not included in any n-tuples of T_i that include o_i. The word to be replaced is selected from n-tuples including o_i. There are several ways of selection. If the context outside the source sentence is available, which is shown as "Context BETWEEN Sentences" in Figure 2, the n-tuple which matches the context is selected. If term frequency of the general words is available, the n-tuple including the word frequently used is selected. If there is information of term frequency or priority of word selection that each machine translator possesses in inner system, it is also used. If none of the above information is used, that means there is no information except for the context in the source sentence, one n-tuple is selected randomly.

In the judgment of semantic drifting in this algorithm, only information including multilingual dictionary is used, and words which are not included in it are considered as impossible to judge and maintain. In addition, this assumes that quality of each machine translators is high and basically relies on the word selection of each translator. Since the translated word is selected by some analysis process, like syntax analysis or analysis of relation to surrounding words, this algorithm modifies words only if the selected word is not included in possessing n-tuples. When the context outside the sentence is available, whether it should be used in priority to word selections of machine translators is a complex and difficult problem. At this moment, the information of context outside the

Algorithm 2-3 CREATE-WORD-PAIRS-TO-BE-USED(P_i, T_i) **return** Q_i

s_i /* Original input sentence of MT_i */
t_i /* Output sentence of $MT_i (t_i \neq s_{i+1})$ */
o_i /* A word in sentence s_i */
c_{i+1} /* A word in sentence t_i */
T_i /* A set of possible n-tuples $(w_1, w_2, ..., w_n)$,
        where w_k is included in $s_k (k \leq i)$;
P_i /* A set of pairs (o_i, c_{i+1}), where $o_i \in s_i$ and $c_{i+1} \in t_i$ of MT_i */
Q_i /* A set of pairs (o_i, m_{i+1}), where $o_i \in s_i$ and m_{i+1} is modified
        translated word of o_i */
$Q_i \leftarrow \phi$
for each pair (o_i, c_{i+1}) **in** P_i **do**
    for each n-tuple $(w_1, w_2, ..., w_n)$ **in** T_i **do**
        if $o_i = w_i$ and $c_{i+1} = w_{i+1}$ **then**
            $Q_i \leftarrow Q_i \cup \{(o_i, c_{i+1})\}$
            break
        end if
    end loop
    if $(o_i, c_{i+1}) \notin Q_i$ **then**
        $m_{i+1} \leftarrow i$+1th word in n-tuple selected from
                $\{(w_1, w_2, ..., w_n) | o_i = w_i, (w_1, w_2, ..., w_n) \in T_i\}$
        $Q_i \leftarrow Q_i \cup \{(o_i, m_{i+1})\}$
    end if
end loop
return Q_i

sentence is used only as the subsidiary information.

5.1.4 Modifying Translated Sentence

Algorithm 2-4 modifies translated sentence t_i by replacement with pairs P_i of source word and translated word and pairs Q_i of source word and modified translated word. A word to be replaced is the translated word c_{i+1} in the pair (o_i, c_{i+1}) which is not included in Q_i. The pair (o_i, m_{i+1}) including the same source word o_i is obtained from Q_i and the word c_{i+1} in t_i is replaced with the modified word m_{i+1} of the obtained pair.

Algorithm 2-4

MODIFY-TRANSLATED-SENTENCE(t_i, P_i, Q_i) **return** s_{i+1}

```
s_i, s_{i+1} /* Original input sentence of MT_i and MT_{i+1} */
t_i /* Output sentence of MT_i(t_i ≠ s_{i+1}) */
o_i, o'_i /* A word in sentence s_i */
c_{i+1} /* A word in sentence t_i */
m_{i+1} /* A modified translated word of o_i */
P_i /* A set of pairs (o_i, c_{i+1}), where o_i ∈ s_i and c_{i+1} ∈ t_i of MT_i */
Q_i /* A set of pairs (o_i, m_{i+1}), where o_i ∈ s_i and m_{i+1} is modified
        translated word of o_i */
for each pair (o_i, c_{i+1}) in P_i do
    if (o_i, c_{i+1}) ∉ Q_i then
        for each pair (o'_i, m_{i+1}) in Q_i do
            if o'_i = o_i then
                t_i ← replace c_{i+1} in t_i by m_{i+1}
                break
            end if
        end loop
    end if
end loop
s_{i+1} ← t_i
return s_{i+1}
```

5.1.5 Updating Context

Algorithm 2-5 updates context T_i to T_{i+1} by using words in modified translated sentence. T_i and modified pairs Q_i are given. This algorithm narrows down T_i to T_{i+1} so that each n-tuple in T_{i+1} includes words selected in the prior (first to i-th) translations. In T_i, more than two n-tuples including the same k-th word ($1 \leq k \leq i$) can exist with different $i+1$th words. n-tuples which includes the translated word m_{i+1} of the pair (o_i, m_{i+1}) in Q_i as the $i+1$th word is also included in T_{i+1}.

Algorithm 2-5 SELECT-POSSIBLE-N-TUPLES(T_i, Q_i) **return** T_{i+1}

s_i /* Original input sentence of MT_i */
t_i /* Output sentence of $MT_i(t_i \neq s_{i+1})$ */
o_i /* A word in sentence s_i */
m_{i+1} /* A modified translated word of o_i */
T_i /* A set of possible n-tuples $(w_1, w_2, ..., w_n)$,
    where w_k is included in $s_k(k \leq i)$
Q_i /* A set of pairs (o_i, m_{i+1}), where $o_i \in s_i$ and m_{i+1} is modified
    translated word of o_i */
$T_{i+1} \leftarrow \phi$
for each pair (o_i, m_{i+1}) **in** Q_i **do**
    $T_{i+1} \leftarrow T_{i+1} \cup \{(w_1, w_2, ..., w_n) | w_i = o_i$ and
        $w_{i+1} = m_{i+1}, (w_1, w_2, ..., w_n) \in T_i\}$
end loop
return T_{i+1}

5.2 Algorithms for Coordination inside Machine Translators

Algorithms using existing machine translators with no change and realizing coordination outside the translators are shown in 5.1. Those algorithms can apply to the case where we can change the inner system of translators. If we can change them so that they receive context T_i in Algorithm 2-1 and select translated words from T_i in priority to other words, the coordination is realized by only adding context update component. Procedures from line 13 to 23 in Algorithm 2-1 would be changed as Algorithm 2-1-2. Unlike Algorithm 2-1, the translated sentence s_{i+1} generated by machine translator is correct sentence with no semantic drifting. Procedure in line 3 in Algorithm 2-1-2 corresponds procedures of sentence generation, CREATE-WORD-PAIRS-TO-BE-USED and MODIFY-TRANSLATED-SENTENCE in Algorithm 2-1. This algorithm shows the case where only the part of word selection in translators are changed and which word is selected corresponding to the source word is detected by GET-WORD-PAIRS-USED-BY-MT, like Algorithm 2-1. If translators could be changed so that they output the selected translated words in addition to the translated

Algorithm 2-1-2

COORDINATE-TRANSLATORS-INSIDE(MT, s_1) **return** s_{n+1}

1: $T_1 \leftarrow \{(w_1, w_2, ..., w_n) | w_1 \in s_1\}$
2: **for each** MT_i **in** MT **do**
3: $\quad s_{i+1} \leftarrow MT_i(s_i)$
4: $\quad P_i \leftarrow$ GET-WORD-PAIRS-USED-BY-MT($s_i, s_{i+1}, D_{i,i+1}$)
5: $\quad T_{i+1} \leftarrow$ SELECT-POSSIBLE-N-TUPLES(T_i, P_i)
6: **end loop**
7: **return** s_{i+1}

sentence, coordination algorithm would be simpler by merging procedures in line 3 and 4.

In Algorithm 2-1-2, procedures of generation of translated sentence and pairs of source and translated word correspond to "Word Selection," "Word Resolution" and "Sentence Generation" component in Figure 2. At final procedure in line 5 corresponds to "Context Update" component. In this way, coordination can be realized with both changeable and unchangeable machine translators.

5.3 Example of Coordinated Translation

Example 2 (Coordination of translation of sentence in Figure 1 (c))

Now I take an example of coordinated translation with algorithms shown in 5.1 using an example sentence shown in Figure 1 (c). For simplicity, only information for word selection T_i is used as context information and tri-lingual dictionary of Japanese, English and German generated by method shown in Chapter 4 is used as an implementation of multilingual dictionary. In addition, replacement of translated words is limited to noun words. Figure 8 shows the coordination process by using component of Figure 2 (b). This figure mainly shows that the second English-German translator generates translated sentence by referring propagated context from the first Japanese-English translator.

1) Preparation

For preparation, Japanese-English-German triples including words in source Japanese sentence "Her fault is a big problem (kanojo no ketten ha ookina mondai da)" are picked up from tri-lingual dictionary and preserved as T_1. Triples including the noun word "fault (ketten)" or "problem (mondai)" are picked up. T_1 is transferred to Japanese-English translator with the source sentence.

2) Japanese-English translation

First, source Japanese sentence s_1 = "Her fault is a big problem (kanojo no ketten ha ookina mondai da.)" is translated by MT_1. After English sentence t_1 = "Her fault is a big problem" is obtained, pairs of source words in s_1 and translated words in t_1 are generated by GET-WORD-PAIRS-USED-BY-MT. $P_1 = \{$(fault (ketten), fault), (problem (mondai), problem)$\}$ is obtained here. Whether translated words in pair P_1 is included in T_1 is investigated and modified if not included by CREATE-WORD-PAIRS-TO-BE-USED. Since T_1 contains all triples including "fault (ketten)" or "problem (mondai)", triples including both "fault (ketten)" and "fault" or "problem (mondai)" and "problem" must be contained in T_1. If not so, "fault (ketten)" and "fault" do not share the same meaning, or bilingual dictionaries used in making tri-lingual dictionary are incomplete, and it is impossible to maintain the word selection of "fault (ketten)". Assume that expected triples are included in T_1. Then modification is not executed and t_1 is sent to the next without any change. Finally, T_1 is updated using fixed translated words by SELECT-POSSIBLE-N-TUPLES. Since Q_1 is equal to $P_1 = \{$(fault (ketten), fault), (problem (mondai), problem)$\}$, triples of T_1 which includes both "fault (ketten)" and "fault" or "problem (mondai)" and "problem" are to be included in T_2. Assume that T_2 is $\{$(fault (ketten), fault, fault (Fehler)), (fault (ketten), fault, fault (Mangel)), (problem (mondai), problem, problem (Problem))$\}$. T_2 is propagated to English-German translator with $s_2 = t_1$.

3)English-German translation

Similarly as Japanese-English translation, the source sentence s_2 = "Her fault is a big problem." is translated, the German sentence t_2 = "Her responsibility is a big problem (Ihre Schuld ist ein großes Problem)" is got and pairs of source word and translated word are obtained by GET-WORD-

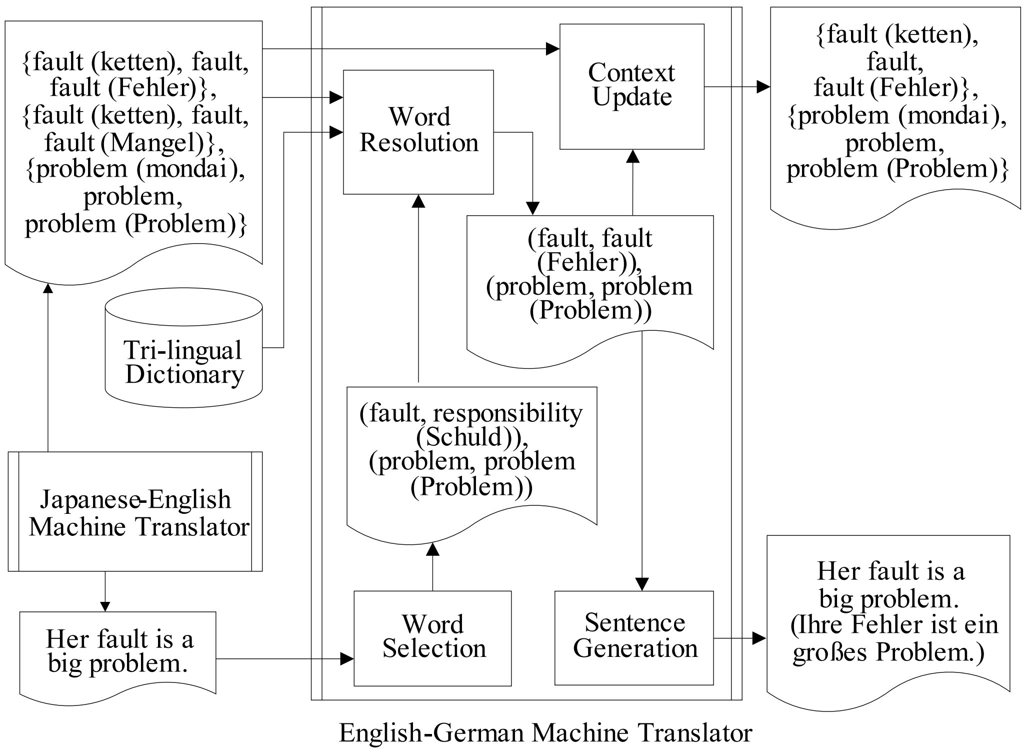


Figure 8: Example of Coordinated Translation

PAIRS-USED-BY-MT. The pairs P_2 is {(fault, responsibility (Schuld)), (problem, problem (Problem))}. In the procedure of CREATE-WORD-PAIRS-TO-BE-USED, the word "responsibility (Schuld)" is considered as semantically drifted, because there is no triple in T_2 that includes both "fault" and "responsibility (Schuld)", while a triple including both "problem" and "problem (Problem)" is in T_2. Therefore either one of triples that include the source word in that pair "fault", that is, triples (fault (ketten), fault, fault (Fehler)) and (fault (ketten), fault, fault (Mangel)), is selected, and the word "responsibility (Schuld)" is replaced by the word of selected triple. If the former is selected, the modified pair is (fault, fault (Fehler)). Then Q_2 would be {(fault, fault (Fehler)), (problem, problem (Problem))}. Next, by MODIFY-TRANSLATED-SENTENCE, the word "responsibility (Schuld)" in t_2, included in the pair (fault, responsibility (Schuld)) which is included in not Q_2 but P_2, is replaced by the word "fault (Fehler)", modified translated word in Q_2. Output sentence s_3 would be " Her fault is a big problem (Ihre Fehler ist ein großes Problem)". Finally, T_2 is narrowed down moreover by SELECT-POSSIBLE-N-TUPLES and T_3 would be $\{$(fault (ketten), fault, fault (Fehler)), (problem (mondai), problem, problem (Problem))$\}$.

Chapter 6 Implementation and Evaluation

I made Japanese-English-German triples according to the algorithm shown in Chapter 4, and implemented coordination of cascaded translation shown in Chapter 5 in Japanese, English and German with triples. I then conducted a preliminary evaluation of the quality of Japanese-German back translation using the cascade of Japanese-English, English-German, German-English and English-Japanese translations. Next, I also conducted evaluation of the one of Japanese-German multi-hop translation using the cascade of Japanese-English and English-German translation to examine whether semantically drifting of words were solved in German sentence. For simplicity, I limited the part-of-speech of triples and modification to noun words.

As evaluations of algorithms to generate triples, I analyzed (1) distribution of numbers of word senses of words included in generated triples to ensure that they could contribute the improvement of word selections of polysemous words, and (2) how well triples could cover arbitrary Japanese documents. As evaluations of algorithms to coordinate translators, whether the quality of translated sentence generated with coordination was significantly different from the one without coordination was evaluated.

6.1 Generation of Triples and Analysis

Table 1 shows the kind of dictionaries used, the numbers of their headwords and the number of triples obtained from them. Triples were generated from two types of triangles, loop-type triangle and transition-type triangle. Languages and directions of dictionaries were the same as Figure 3 and starting language was Japanese. The numbers of triples collected were 15,627 for loop-type, 13,757 for transition-type, and in total 21,914 without overlaps.

6.1.1 Distribution of Word Senses

Table 2 and Table 3 show the distribution of word senses of words included in obtained triples and classified triples according to the combination of word senses. All dictionaries shown in Table 1 (a) had data of word senses with each headword and analysis was based on the word senses obtained from them.

Table 1: Obtained triples

(a) Bilingual dictionaries used to obtain triples

Dictionary	Number of headwords
Genius Japanese-English dictionary	31,926 (noun)
Concise Japanese-German dictionary	38,487 (all words)
Oxford English-German dictionary	31,180 (noun)
Crown German-Japanese dictionary	34,255 (noun)

(b) Number of triples of each type

Type	Number of triples
Loop-type	15,627
Transition-type	13,757
Total (no overlaps)	21,914

(c) Number of words of each type of triples

Language	Number of words in loop-type triples	Number of words in transition-type triples
Japanese	9,080	7,290
English	7,003	5,492
German	7,507	5,748

Since a part of German words in Japanese-German dictionary was not included in German-Japanese dictionary as headwords, word senses of a part of German words in triples were unknown. In Table 3, the number of triples which included polysemous words, that is, triples which included one or more words having more than two word senses, was 12,522 (80 %) for loop-type and 11,196 (81 %) for transition-type. The number of triples in which all words had more than two senses, namely all words were polysemous words, was less than 10 % for both type. The number of triples which did not contain polysemous word was less than 20 % for both types. In Table 2, the ratio of words having only one sense was higher in Japanese. This means that each word existed according to the detailed meaning and the meanings of triples were different with each other in detail. Thus the probability of no shared sense, described in Chapter 4, was low actually, and it could be said that obtained triples were used to translations of

Table 2: Distribution of word senses of words of triples

(a) Loop-type triples

Number of concepts	Japanese		English		German	
	Number of words	Ratio	Number of words	Ratio	Number of words	Ratio
1	8508	0.937004	3488	0.498072	4361	0.580924
2	363	0.039978	1455	0.207768	1860	0.247769
3	92	0.010132	836	0.119377	713	0.094978
4	76	0.00837	483	0.06897	301	0.040096
5	18	0.001982	269	0.038412	130	0.017317
6	7	0.000771	154	0.021991	77	0.010257
7	5	0.000551	93	0.01328	37	0.004929
8	6	0.000661	65	0.009282	13	0.001732
9	2	0.00022	50	0.00714	5	0.000666
more than 10	3	0.00033	110	0.015708	10	0.001332
Total	9080	1	7003	1	7507	1

(b) Transition-type triples

Number of concepts	Japanese		English		German	
	Number of words	Ratio	Number of words	Ratio	Number of words	Ratio
1	6682	0.916598	2403	0.437546	2855	0.496695
2	391	0.053635	1181	0.21504	1406	0.244607
3	98	0.013443	771	0.140386	588	0.102296
4	73	0.010014	436	0.079388	256	0.044537
5	21	0.002881	244	0.044428	112	0.019485
6	10	0.001372	151	0.027495	71	0.012352
7	4	0.000549	90	0.016387	33	0.005741
8	5	0.000686	60	0.010925	11	0.001914
9	2	0.000274	49	0.008922	4	0.000696
more than 10	4	0.000549	107	0.019483	8	0.001392
unknown	0	0	0	0	404	0.070285
Total	7290	1	5492	1	5748	1

Table 3: Number of triples including polysemous word

(a) Loop-type triples

Number of concepts	Number of triples		Ratio
All words have more than 2 senses	1,136		0.072695
Japanese word had only 1 sense	6,297		
English word had only 1 sense	101		
German word had only 1 sense	244		
Japanese and English words had only 1 sense	1,566		
Japanese and German words had only 1 sense	3,094	Total	
English and German words had only 1 sense	84	11,386	0.728611
All words had only 1 sense	3,105		0.198695
Total	15,627		1

(b) Transition-type triples

Number of concepts	Number of triples		Ratio
All words have more than 2 senses	1,238		0.089991
Japanese word had only 1 sense	5,314		
English word had only 1 sense	143		
German word had only 1 sense	359		
Japanese and English words had only 1 sense	1,282		
Japanese and German words had only 1 sense	2,740	Total	
English and German words had only 1 sense	120	9,958	0.723850
All words had only 1 sense	2,064		0.150033
Number of senses of German word was unknown	497		0.036127
Total	13,757		1

polysemous words with high reliability.

I also analyzed how many words were included multiple triples. The result is shown in Table 4. The number of words included in only one triple was largest in Japanese, English and German words, and distributions of words showed similar tendency in three languages.

Table 4: Number of words included in multiple triples

Number of triples	Loop-type			Transition-type		
	Japanese	English	German	Japanese	English	German
1	5821	3890	4321	4194	2771	3067
2	1764	1420	1549	1602	1147	1189
3	716	606	641	695	525	510
4	344	345	361	357	341	293
5	199	237	200	196	185	182
6	102	145	122	91	139	132
7	56	98	75	62	98	93
8	26	60	64	43	61	60
9	23	49	46	23	52	51
more than 10	29	153	128	27	173	172
Total	9080	7003	7507	7290	5492	5749

6.1.2 Cover Ratio of Triples to Arbitrary Documents

I analyzed how well each type of triples could cover arbitrary Japanese documents based on the term frequency. I used term frequency of noun words and words of all part-of-speech in a Web corpus holding 470M sentences with 5000M Japanese words [10].

Firstly, I analyzed how many noun words which have high term frequency were included in triples, that is, how many noun words in that corpus could be translated with triples. The result is shown in Figure 9. Loop-type triples showed almost the same tendency as transition-type triples. Words were sorted in descending order of term frequency and ranked according to frequencies. How many words in each rank were included in triples is shown in the graph. Since there could exist two or more words having the same frequency (same rank), the ratio of words included in triples was calculated. I call this ratio the inclusion ratio of words in triples. In Figure 9, points of green color and pink color are samples of ratio. Lines of green color and red color show the inclusion ratio of all words appearing from rank 1 to the rank in triples. Blue line shows the ratio of words appearing from rank 1 to each rank toward all words appearing in that corpus. I call this ratio the cover ratio of documents. In both types

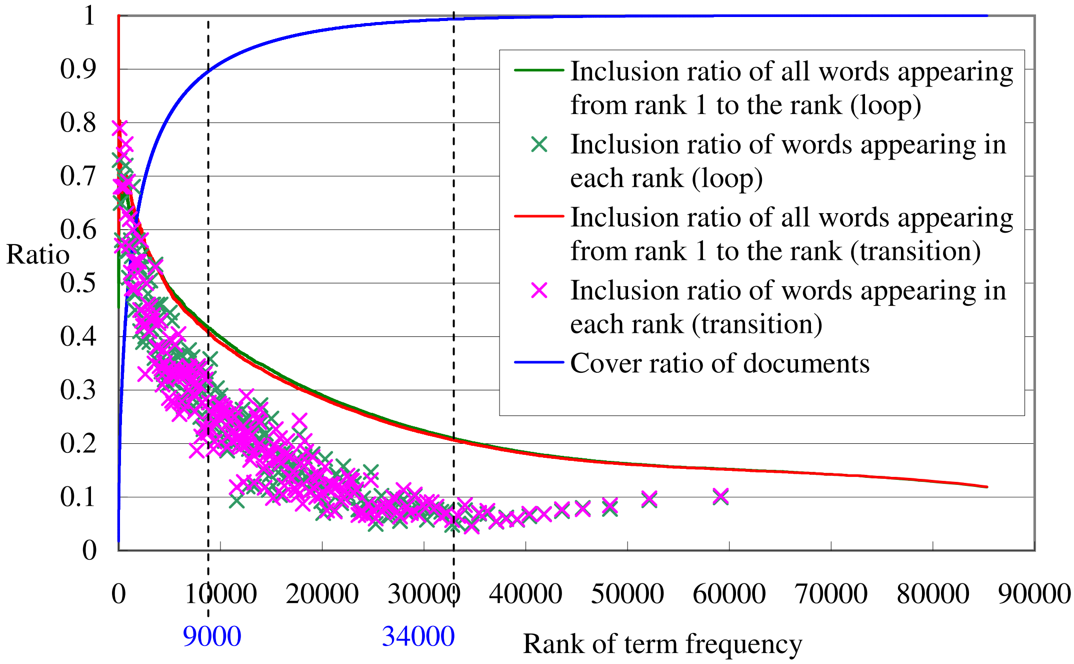


Figure 9: Inclusion ratio of words having high frequencies

of triples, words appearing from rank 1 to 9,000 could cover 90 % of all noun words, and 40 % of them (that is, 36 % of all words) were included by triples. Words appearing from rank 1 to 34,000 could cover almost all of all noun words, and 20 % of them were included in triples.

Secondly I calculated the cover ratio of documents by each type of triples. I sorted triples in descending order of term frequency of Japanese words they include, and analyzed how many triples could cover how much of all words. I call this ratio cover ratio of noun words by triples. Since triples were inefficient for coordinated translation if most of the documents were covered by only triples in which each number of word senses was one, that is, triples without polysemous word, I also calculated the cover ratio by such triples. Moreover, I calculated the ratio with term frequency of all part-of-speech in order to examine the effect to the all words included in arbitrary Japanese documents. I call this ratio cover ratio of documents by triples. The result is shown in Figure 10. Loop-type triples showed almost the same tendency as transition-type triples. Since the

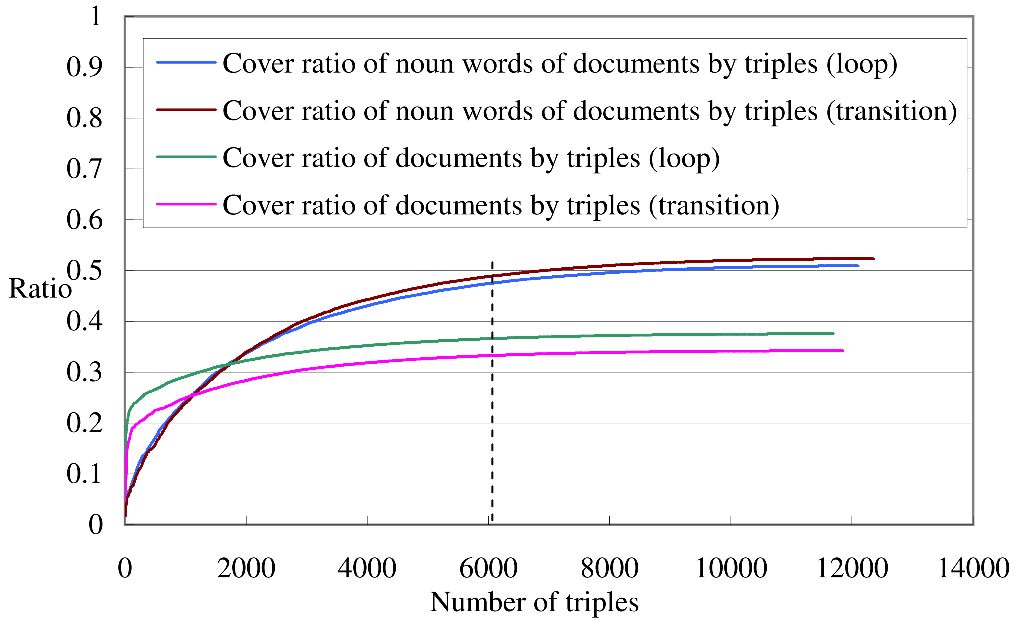


Figure 10: Cover ratio of documents

cover ratio by triples without polysemous word was very low, the graph does not contain this ratio. If we used triples in descending order of term frequency, 6,000 triples could cover 50 % of noun words and 38 % of all part-of-speech words. This means that a relatively small number of triples could cover frequently used noun words.

I analyzed similarly toward all 21,914 triples. The tendency or change of value of ratio was similar to that of each type of triples. If we used triples in descending order of term frequency, 6,000 triples could cover 50 % of noun words and 38 % of all part-of-speech words. If we used all triples, they could cover 58 % of noun words and 40 % of all part-of-speech. Those results mean that the effect of loop-type triples was as same as that of transition-type.

6.2 Implementation and Evaluation of Coordinated Translation

6.2.1 Japanese-German Back Translation

I implemented coordination of Japanese-German back translation with all 21,914 triples and preliminarily evaluated the quality of translation. Evaluation was

Table 5: Change of evaluated values

(a) Number of sentences which evaluated values was changed

Change	Evaluator 1	Evaluator 2	Evaluator 3	Average
Got better	38	51	33	40.666667
Got worse	5	8	0	4.333333

(b) Change of average evaluated values

	Evaluator 1	Evaluator 2	Evaluator 3	Average
Average value of B	2.34	2.58	2.33	2.416666667
Average value of C	2.8	3.15	2.72	2.89
Change	+0.46	+0.57	+0.39	+0.473333333

(c) Ratio of improvement in each evaluated value of B (%)

Evaluated valued of B	Evaluator 1	Evaluator 2	Evaluator 3	Average
4	37.5	38.461538	25	33.653846
3	21.428571	37.142857	38.461538	32.344322
2	61.111111	58.620690	28	49.243934
1	47.727273	88.888889	42.424242	59.680135

done by comparing source Japanese sentences (A), back translated Japanese sentences generated without context-aware coordination (B), and the ones generated with coordination (C). I let three Japanese subjects evaluate the quality of translation: how much of the original meaning of A was expressed in B and C on a following five-point scale.

5: All

4: Most

3: Much

2: Little

1: None

Source Japanese sentences were selected from the Machine Translation Test Set provided by NTT Natural Language Research Group [11]. I translated sentences and randomly selected 100 samples, where the replacement of translated words had occurred one or more times during translation.

The result of evaluation is shown in Table 5. Table 5 (a) shows the number of sentences which evaluated value of B was different from that of C, and (b) shows the change of average of evaluated value. The quality of sentence was improved in 41 % of all sentences on average. However, the quality of 4 % of all sentences had got worse. In total, the quality of whole sentences with context-based coordination was raised by an average 0.47 points: 2.4 without coordination and 2.8 with coordination. In most of the sentences which evaluated values had got worse, the evaluated values of B were less than 3. The sentences which senses were different from the one of source sentences but had no error in terms of syntax or grammar had evaluated values more than 3. The sentences including errors of syntax or grammar in additional to the semantically drifting were ranked as 1 or 2. In brief, there was no bad influence on the sentences in which much of the meaning could be understood.

Table 5 (c) shows the ratio of improvement in each evaluated value. For example, in the result of evaluator 1, the quality of 37.5 % of sentences which were ranked 4 without coordination were improved. In total, 34 % with rank 4, 32 % with rank 3, 49 % with rank 2 and 60 % with rank 1 were improved. Furthermore, for the sentences which evaluated values with coordination were more than 4, improvement appeared in 34 % with rank 4, 32 % with rank 3, 15 % with rank 2 and 5 % with rank 1. This means that substantial improvement enough to change the degree of understanding of the meaning was appeared in sentences with rank more than 3. In brief, our method had effects toward sentences which contain not syntax errors but semantic errors only.

Finally I examined whether the change of evaluated values could be said as significant by test in statistics. Since population variances of a set of evaluated values of B (called data set B) and that of C (called data set C) were unknown and it could not be said both variances were equal with each other, I used Welch's test to examine whether there was a significance difference between population means of data set B and C. When I represent the number of data set B and C as n_B and n_C, average as X_B, X_C and deviation of samples as ${s_B}^2, {s_C}^2$. Then, t represented as follows:

(a) Example of improvement from evaluated value 4 to 5

Source sentence (Japanese; A): A truck was blocking the road.

(torakku ga michi wo husaide ita.)

⇒ Translated sentence B: A truck was blocking the method.

(torakku ha houhou wo samatageta.)

⇒ Translated sentence C: A truck was blocking the road.

(torakku haa michi wo samatageta.)

(b) Example of improvement from evaluated value 3 to 5

Source sentence (Japanese; A): The chief employs laborers.

(shachou ha roudousya wo tukau.)

⇒ Translated sentence B: The president employs laborers.

(daitouryou ha roudousya wo tukau.)

⇒ Translted sentence C: The chief employs laborers.

(shachou ha roudousya wo tukau.)

Figure 11: Effect of coordination

$$t = \frac{X_B - X_C}{\sqrt{\frac{{s_B}^2}{n_B} + \frac{{s_C}^2}{n_C}}}$$

is distributed according to the t distribution with following v degrees of freedom.

$$v = \frac{\left({s_B}^2/n_B + {s_C}^2/n_C\right)^2}{\frac{\left({s_B}^2/n_B\right)^2}{n_B - 1} + \frac{\left({s_C}^2/n_C\right)^2}{n_C - 1}}$$

The result of test was calculated by above formulas with data set B and C of each evaluator. There was significance difference with 98.5 % confidence level with evaluator 1 and 3, and almost 100 % confidence level with evaluator 2. It can be said our method could improve the quality of back translation in terms of statistics too.

Figure 11 shows examples of improvement. In example (a), Japanese word "road (michi)" is mistranslated to the word "method (houhou)." This mistranslation was caused by the mediated English word "way" and German word "road/method (Weg)", which have both meanings of road and method. Although mediated English sentence and German sentence can be interpret as same meaning as the source sentence, back translated Japanese sentence can not. Similarly, the Japanese word "chief (syachou)" which means the chief of a company is mistranslated to the word "president (daitouryou)" that means the chief of a country in example (b). This semantically drifting was caused by mediated English word "president" and German word "president (Presidnt)" similarly to example (a).

6.2.2 Japanese-German Multi-hop Translation

I implemented Japanese-German multi-hop translation and analyzed the quality in the same way as 6.2.1. I let three native German speakers evaluate the quality of translation by comparing the gold-standard German sentence which was generated manually (sentence A) and German sentence generated without coordination (sentence B) or German sentence with coordination (sentence C). I translated all of about 3,700 Japanese sentences included in the same test set [11] and used all sentences in which replacement of translated word occurred. The number of source sentences was about 400. The result was different from the one of Japanese-German back translation. The ratio of sentences which evaluated value were changed was low, and the number of sentences which evaluated values rose was almost the same as the number of sentences which the value got worse, that is, there did not appear remarkable improvement. Both the source sentence used in Japanese-German multi-hop translation and the ones used in back translation were got from the same population, and it can be said that this tendency also appeared in the intermediated German sentence of back translation in 6.2.1. Though proposed method was efficient for the back translation, it does not seem to have had a significant effect for the multi-hop translation.

There are some possible reasons of this result; since triples were not complete, words which were not to be replaced actually had been replaced and vice versa, or words which were unusually used were selected to replace, or some other reasons. However, the only thing to be said here is that proposed method is efficient for solution of asymmetry or inconsistency of word selections at the present moment. Investigating the detailed causes and improving algorithms so as to be efficient similarly to the intransitivity of word selections is our future work.

Chapter 7 Conclusion

This research focused on the situation where cascaded machine translators yield mistranslation even if result of each translator is correct. Since each translator translates input sentence without considering the other translators, the sense of translated sentence has changed because of inconsistent word selections. Those phenomena are big problems in multi-hop translation by cascading multiple machine translator or machine translator-mediated communication. To solve those problems and realize coordinated translation with consistent word selections, I proposed following two solutions.

Making multilingual equivalent terms

In order to examine whether the sense of translated sentence is different from the one of the source sentence, equivalent terms of all languages is required. Equivalent terms between two languages is developed as bilingual dictionaries between lots of languages, while that of more than three languages is developed manually among parts of languages. Therefore this research aims to generate multilingual equivalent terms automatically from existing language resources.

Coordination by propagating context

Coordination of translators, that is, consistent word selections, can be realized by extracting context and propagating it to machine translators. Context is extracted from the source sentence or whole document including the source sentence. The sense of translated sentence is kept consistent by selecting translated words which suit propagated context. Methods of extracting context are proposed in previous researches. This research assumes that the context is already extracted, and focuses on the coordination by propagating extracted context.

Finally, I actually generated data of equivalent terms in three languages by using proposed method. And I also implemented coordination of existing machine translators which I can not modify the inner system by simple way as follows. In our implementation, information about which words were selected as translated words is used as the context of translation. The words which senses are semantically drifting from the source words are detected from the translated sentence generated by machine translators and replaced by the words which are equivalent to the source words. As a result, in coordinated back translation cascading translator from source language to target language and the one from target language to source language, quality of translation was improved in comparison with back translation simply combining two translators.

As future works, I address extension of the method of generating tri-lingual dictionary to enable coordination of machine translators among more than three languages. Although we can get 4-tuples (quadruples) simply combining multiple 3-tuples (triples), as the number of languages increases, the possibility that generated tuple does not share the same meaning is getting higher. The method to generate more reliable multilingual dictionary is required. On the other hand, it is necessary to resolve causes or characteristics of multi-hop translation, in which remarkable improvement did not appears by applying proposed method. The future work is to examine whether this problem is resolved with the complete tri-lingual dictionary, other method of selecting 3-tuples from candidate tuples is needed, or other problems are hidden in other parts, and to resolve such problems.

Acknowledgments

The author would like to express sincere gratitude to the supervisor, Professor Toru Ishida at Kyoto University, for his continuous guidance, valuable advice, and helpful discussions.

The author would like to express her thanks to the advisers, Professor Hajime Kita at Department of Social Informatics, Kyoto University, Professor Tatsuya Kawahara at Department of Intelligence Science and Technology, Professor Sadao Kurohashi at Department of Intelligence Science and Technology, Assistant Professor Satoshi Oyama at Department of Social Informatics, Kyoto University, for spending precious time for valuable discussions and advice.

The author would like to express her thanks to Researcher Yohei Murakami at National Institute of Information and Communications Technology, for his valuable advice, and technical support.

Finally, the author would like to thank all members of Professor Ishida's laboratory for their various supports.

This research was mainly carried out in National Institute of Information and Communications Technology (NICT) during I was working as a technical staff, and was partially supported by Kyoto University Global COE Program: Informatics Education and Research Center for Knowledge-Circulating Society.

References

[1] Ishida, T.: Language Grid: An Infrastructure for Intercultural Collaboration. IEEE/IPSJ Symposium on Applications and the Internet (SAINT-06), pp. 96–100, keynote address, 2006.

[2] Yamashita, N and Ishida, T.: Effects of Machine Translation on Collaborative Work. *International Conference on Computer Supported Cooperative Work (CSCW-06)*, pp. 515–523, 2006.

[3] Deryle W. L., Alexander M. F. and John R. R. L. Large-scale machine translation: An interlingua approach. In *Seventh International Conference on Industrial and Engineering Applications of Artificial Intelligence and Expert Systems*, pp. 525–530, 1994.

[4] Kanayama, H., and Watanabe, H.: Multilingual Translation via Annotated Hub Language. *MT-Summit IX*, pp. 202–207, 2003.

[5] 徳永健伸, 田中穂積.: 対訳辞書からの概念項目の自動抽出. 人工知能学会誌, Vol. 6, No.2, pp. 228 – 235, 1991.

[6] Cudre-Mauroux, P., Aberer, K and Feher, A.: Probabilistic Message Passing in Peer Data Management Systems. *22nd International Conference on Data Engineering (ICDE'06)*, pp. 41, 2006.

[7] Kschischang, F., Frey, B. and Loeliger, H, A.: Factor graphs and the sum-product algorithm. *IEEE Transactions on Information Theory*, 47(2), 2001.

[8] Christiane Fellbaum. (ed.): *WordNet An Electronic Lexical Database*. The MIT Press, 1998. See: http://citeseer.ist.psu.edu/lin98review.html.

[9] Vossen, P. (ed.): *EuroWordNet: A Multilingual Database with Lexical Semantic Networks*. Dordrecht, Netherlands: Kluwer, 1998. See: http://www.hum.uva.nl/ ewn/.

[10] 河原大輔, 黒橋禎夫.: 高性能計算環境を用いたWebからの大規模格フレーム構築. 情報処理学会 自然言語処理研究会 171-12, pp.67–73, 2006.

[11] http://www.kecl.ntt.co.jp/mtg/resources/index.php