Japanese/English Cross-Language Information Retrieval:

Exploration of Query Translation and Transliteration

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Abstract

Cross-language information retrieval (CLIR), where queries and documents are in different languages, has of late become one of the major topics within the information retrieval community. This paper proposes a Japanese/English CLIR system, where we combine a query translation and retrieval modules. We currently target the retrieval of technical documents, and therefore the performance of our system is highly dependent on the quality of the translation of technical terms. However, the technical term translation is still problematic in that technical terms are often compound words, and thus new terms are progressively created by combining existing base words. In addition, Japanese often represents loanwords based on its special phonogram. Consequently, existing dictionaries find it difficult to achieve sufficient coverage. To counter the first problem, we produce a Japanese/English dictionary for base words, and translate compound words on a word-by-word basis. We also use a probabilistic method to resolve translation ambiguity. For the second problem, we use a transliteration method, which corresponds words unlisted in the base word dictionary to their phonetic equivalents in the target language. We evaluate our system using a test collection for CLIR, and show that both the compound word translation and transliteration methods improve the system performance.
1. Introduction

Cross-language information retrieval (CLIR) is the retrieval process where the user presents queries in one language to retrieve documents in another language. One of the traditional research references for CLIR dates back to the 1960s (Mongar, 1969). In the 1970s, Salton (1970; 1972) empirically showed that CLIR using a hand-crafted bilingual thesaurus is comparable with monolingual information retrieval in performance. The 1990s witnessed a growing number of machine readable texts in various languages, including those accessible via the World Wide Web, but each content is usually provided in a limited number of languages. Thus, it is feasible that users are interested in retrieving information across languages. Possible users of CLIR are given below:

- users who are able to read documents in foreign languages, but have difficulty formulating foreign queries,
- users who find it difficult to retrieve/read relevant documents, but need the information, for the purpose of which the use of machine translation (MT) systems for the limited number of documents retrieved through CLIR is computationally more efficient rather than translating the entire collection,
- users who know foreign keywords/phrases, and want to read documents associated with them, in their native language.

In fact, CLIR has of late become one of the major topics within the information retrieval (IR), natural language processing (NLP) and artificial intelligence (AI) communities, and numerous CLIR systems have variously been proposed (AAAI, 1997; ACM, 1996-1998; NIST, 1992-1998). Note that CLIR can be seen as a subtask of multi-lingual information retrieval (MLIR), which also includes the following cases:

- identify the query language (based on, for example, character codes), and search a multilingual collection for documents in the query language,
- retrieve documents, in which each document is in more than one language,
- retrieve documents using a query in more than one language (Fung et al., 1999).

However, these above cases are beyond the scope of this paper. It should also be noted that while CLIR is not necessarily limited to IR within two languages, we consistently use the term “bilingual,” keeping the potential applicability of CLIR to more than two languages in mind, because the variety of languages used is not the central issue of this paper.

Since by definition queries and documents are in different languages, CLIR needs a translation process along with the conventional monolingual retrieval process. For this purpose, existing CLIR systems adopt various techniques explored in NLP research. In brief, dictionaries, corpora, thesauri and MT systems are used to translate queries and/or documents. However, due to the rudimentary nature of existing translation methods, CLIR still finds it difficult to achieve the performance of monolingual IR. Roughly speaking, recent experiments showed that the average precision of CLIR is 50-75% of that obtained with monolingual IR (Schäuble and Sheridan, 1997), which stimulates us to further explore this exciting research area.
In this paper, we propose a Japanese/English bidirectional CLIR system targeting technical documents, which has been less explored than that for newspaper articles in past CLIR literature. Our research is partly motivated by the NACSIS test collection for (CL)IR systems, which consists of Japanese queries and Japanese/English abstracts collected from technical papers ([Kando et al., 1999] [1]). We will elaborate on the NACSIS collection in Section 5.1. As can be predicted, the performance of our CLIR system strongly depends on the quality of the translation of technical terms, which are often unlisted in general dictionaries.

Pirkola ([1998]), for example, used a subset of the TREC collection related to health topics, and showed that a combination of general and domain specific (i.e., medical) dictionaries improves the CLIR performance obtained with only a general dictionary. This result shows the potential contribution of technical term translation to CLIR. At the same time, it should be noted that even domain specific dictionaries do not exhaustively list possible technical terms. For example, the EDR technical terminology dictionary ([Japan Electronic Dictionary Research Institute, 1995b]), which consists of approximately 120,000 Japanese-English translations related to the information processing field, lacks recent terms like “jouhou chuushatsu (information extraction).” We classify problems associated with technical term translation as given below:

- technical terms are often compound words, which can be progressively created simply by combining multiple existing morphemes (“base words”), and therefore it is not entirely satisfactory or feasible to exhaustively enumerate newly emerging terms in dictionaries,

- Japanese often represents loanwords (i.e., technical terms and proper nouns imported from foreign languages) using its special phonetic alphabet (or phonogram) called “katakana,” with which new words can be spelled out,

- English technical terms are often abbreviated, which can be used as “Japanese” words.

To counter the first problem, we propose a compound word translation method, which selects appropriate translations based on the probability of occurrence of each combination of base words in the target language (see Section 4.2). Note that technical compound words sometimes include general words, such as “AI chess” and “digital watermark.” In this paper, we do not rigorously define general words, by which we mean words that are contained in existing general dictionaries but rarely in technical term dictionaries. For the second problem, we propose a “transliteration” method, which identifies phonetic equivalents in the target language (see Section 4.3). Finally, to resolve the third problem, we enhance our bilingual dictionary with multiples of each abbreviation and its complete form (e.g., “IR” and “information retrieval”) extracted from English corpora (see Section 4.4). Note that although a number of methods targeting those above problems have been explored in past research, no attempt has been made to integrate them in the context of CLIR.

Section 2 surveys past research on CLIR, and clarifies our focus and approach. Section 3 overviews our CLIR system, and Section 4 elaborates on the translation method aimed to resolve the above problems associated with technical term translation. Section 5 then evaluates the performance of our CLIR system using the NACSIS collection.

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http://www.rd.nacsis.ac.jp/~ntcadm/index-en.html
2. Past Research on CLIR

2.1. Retrieval Methodologies

Figure 1 classifies existing CLIR approaches in terms of retrieval methodology. The top level three categories correspond to the different titles of the following items.

**Query translation approach**  This approach translates queries into document languages using bilingual dictionaries or/and corpora, prior to the retrieval process. Since the retrieval process is fundamentally the same as performed in monolingual IR, the translation module can easily be combined with existing IR engines. This category can be further subdivided into the following three methods.

The first subcategory can be called dictionary-based methods. Hull and Grefenstette (1996) used a bilingual dictionary to derive all possible translation candidates of query terms, which are used for the subsequent retrieval. Their method is easy to implement, but potentially retrieves irrelevant documents and decreases the time efficiency. To resolve this problem, Hull (1997) combined translation candidates for each query term with the “OR” operator, and used the weighted boolean method to assign an importance degree to each translation candidate.

Pirkola (1998) also used structured queries, where each term is combined with different types of operators. Ballesteros and Croft (1997) enhanced the dictionary-based translation using the “local context analysis” (Xu and Croft, 1996) and phrase-based translation. Dorr and Oard (1998) evaluated the effectiveness of a semantic structure of a query in the query translation. As far as their comparative experiments were concerned, the use of semantic structures was not as effective as MT/dictionary-based query translation methods.

The second subcategory, corpus-based methods, uses translations extracted from bilingual corpora, for the query translation (Carbonell et al., 1997). In this paper, “(bilingual) aligned corpora” generally refer to a pair of two language corpora aligned to each other on a word, sentence, paragraph or document basis. Given such resources, corpus-based methods are expected to acquire domain specific translations unlisted in existing dictionaries. In fact, Carbonell et al. (1997) empirically showed that their corpus-based query translation method outperformed a dictionary-based method. Their comparative evaluation also showed that the corpus-based translation method outperformed GVSM/LSI-based methods (see the following “Interlingual representation approach” item for details of GVSM and LSI). Note that for the purpose of corpus-based translation methods, a number of translation extraction techniques explored in NLP research (Fung, 1995; Kajii and Aizono, 1996; Smadja et al., 1996) are applicable.

Finally, hybrid methods use corpora to resolve the translation ambiguity inherent in bilingual dictionaries. Unlike the corpus-based translation methods described above, which rely on bilingual corpora, Ballesteros and Croft (1998) and Chen et al. (1994) independently used a monolingual corpus for the disambiguation, and therefore the implementation cost is less. In practice, their method selects the combination of translation candidates that frequently co-occur in the target language corpus. On the other hand, bilingual corpora are also applicable to hybrid methods. Okumura et al. (1998) and Yamabana et al. (1996) independently used the same disambiguation method, in that they consider word frequencies in both the source and target
languages, obtained from a bilingual aligned corpus. Nie et al. (1999) automatically collected parallel texts in French and English from the World Wide Web, to train a probabilistic query translation model, and suggested its feasibility for CLIR.

Davis and Ogden (1997) used a bilingual aligned corpus as the document collection for training retrieval. They first derive possible translation candidates using a dictionary. Then, training retrieval trials are performed on the bilingual corpus, in which the source and translated queries are used to retrieve source and target documents, respectively. Finally, they select translations which retrieved documents aligned to those retrieved with the source query. Note that this method provides a salient contrast to other query translation methods, in which translation is performed independently from the retrieval module.

Chen et al. (1999) addressed the disambiguation of polysemy in the target language, along with the translation disambiguation, specifically in the case where a source query term corresponds to a small number of translations, but some of these translations are associated with a large number of word senses, the polysemous disambiguation is more crucial than the resolution of translation ambiguity. To counter this problem, source query terms are expanded with words that frequently co-occur, which are expected to restrict the meaning of polysemous words in the target language documents.

**Document translation approach** This approach translates documents into query languages, prior to the retrieval. In most cases, existing MT systems are used to translate all the documents in a given collection (Gachot et al., 1996; Kwon et al., 1998; Oard, 1998). Otherwise, a dictionary-based method is used to translate only index terms (Aone et al., 1997). It is feasible that when compared with short queries, documents contain a significantly higher volume of information for the translation. In fact, Oard (1998) showed that the document translation method using an MT system outperformed several types of dictionary-based query translation methods.

However, McCarley (1999) showed that the relative superiority between query and document translation approaches varied depending on the source and target language pair. He also showed that a hybrid system (it should not be confused with one described in the “Query translation approach” item above), where the relevance degree of each document (i.e., the “score”) is the mean of those obtained with query and document translation systems, outperformed systems based on either query or document translation approach. However, generally speaking, the full translation on large-scale collections can be prohibitive.

**Interlingual representation approach** The basis of this approach is to project both queries and documents in a language-independent (conceptual) space. In other words, as Salton (1971), Salton and Ballerini (1996) identified, the interlingual representation approach is based on query expansion methods proposed for monolingual IR. This category can be subdivided into thesaurus-based methods and variants of the vector space model (VSM) (Salton and McGill, 1983).

Salton (1971, 1972) applied hand-crafted English/French and English/German thesauri to the SMART system (Salton, 1971), and demonstrated that a CLIR version of the SMART system is comparable to the monolingual version in performance. The International Road Research Documentation scheme (Mongar, 1969) used a trilingual thesaurus associated with English, German and French. Gilarranz et al. (1997)
and Gonzalo et al. (1998) used the EuroWordNet multilingual thesaurus (Vossen, 1998). Unlike these above methods relying on manual thesaurus construction, Sheridan and Ballerini (1996) used a multilingual thesaurus automatically produced from an aligned corpus.

The generalized vector space model (GVSM) (Wong et al., 1985) and latent semantic indexing (LSI) (Deerwester et al., 1990), which were originally proposed as variants of the vector space model for monolingual IR, project both queries and documents into a language-independent vector space, and therefore these methods can be applicable to CLIR. While Dumais et al. (1996) explored an LSI-based CLIR, Carbonell et al. (1997) empirically showed that GVSM outperformed LSI in terms of CLIR. Note that like thesaurus-based methods, GVSM/LSI-based methods require aligned corpora.

![Classification of CLIR retrieval methods](image)

Figure 1: Classification of CLIR retrieval methods (the method we adopt is underlined)

### 2.2. Presentation Methodologies

In the case of CLIR, retrieved documents are not always written in the user’s native language. Therefore, presentation methodology of retrieval results is a more crucial task than in monolingual IR. It is desirable to present smaller-sized contents with less noise, in other words, precision is often given more importance than recall for CLIR systems. Note that effective presentation is also crucial when a user and system interactively retrieve relevant documents, as performed in relevance feedback (Salton and McGill, 1983).

However, a surprisingly small number of references addressing this issue can be found in past research literature. Aone et al. (1997) presented only keywords frequently appearing in retrieved documents, rather than entire documents. Note that since most CLIR systems use frequency information associated with index terms like “term frequency (TF)” and “inverse document frequency (IDF)” (Salton and McGill, 1983) for the retrieval, frequently appearing keywords can be identified without an excessive additional computational cost. Experiments independently conducted by Oard and Resnik (1993) and Suzuki et al. (1998) showed that even a simple translation of keywords (such as using all possible translations defined in a dictionary) improved on the efficiency for users to find relevant foreign documents from the whole retrieval result. Suzuki et al. (1999) more extensively investigated the user’s retrieval efficiency (i.e., the time efficiency and accuracy with which human subjects find relevant foreign documents) by comparing different presentation
methods, in which the following contents were independently presented to the user:

1. keywords without translation,

2. keywords translated with the first entry defined in a dictionary,

3. keywords translated through the hybrid method (see the “Query translation approach” item in Section 2.2),

4. documents summarized (by an existing summarization software) and manually translated.

Their comparative experiments showed that the third content was most effective in terms of the retrieval efficiency.

For monolingual IR, automatic summarization methods based on the user’s focus/query have recently been explored. Mani and Bloedorn (1998) used machine learning techniques to produce document summarization rules based on the user’s focus (i.e., query). Tombros and Sanderson (1998) showed experimental results, in which presenting the fragment of each retrieved document containing query terms improved on the retrieval efficiency of human subjects. Applicability of these methods to CLIR needs to be further explored.

2.3. Evaluation Methodologies

From a scientific point of view, performance evaluation is invaluable for CLIR. In most cases, the evaluation of CLIR is the same as performed for monolingual IR. That is, each system conducts a retrieval trial using a test collection consisting of predefined queries and documents in different languages, and then the performance is evaluated based on the precision and recall. Several experiments used test collections for monolingual IR in which either queries or documents were translated, prior to the evaluation. However, as Sakai et al. (1999) empirically showed, the CLIR performance varies depending on the quality of the translation of collections, and thus it is desirable to carefully produce test collections for CLIR. The production of test collections usually involves collecting documents, producing queries and relevance assessment for each query. However, since relevance assessment is expensive, especially for large-scale collections (even in the case where the pooling method (Voorhees, 1998) is used to reduce the number of candidates of relevant documents), Carbonell et al. (1997) first translated queries into the document language, and used as (pseudo) relevant documents those retrieved with the translated queries. In other words, this evaluation method investigates the extent to which CLIR maintains the performance of monolingual IR.

For the evaluation of presentation methods, human subjects are often used to investigate the retrieval efficiency, as described in Section 2.2. However, evaluation methods involving human interactions are problematic, because human subjects are in a way trained through repetitive retrieval trials for different systems, which can potentially bias the result. On the other hand, in the case where each subject uses a single system, difference of subjects affects the result. To minimize this bias, multiple subjects are usually classified based on, for example, their literacy in terms of the target language, and those falling into the same cluster are virtually regarded as the same person. However, this issue still remains an open question, and needs to be further explored.
2.4. Our Focus and Approach

Through discussions in the above three sections, we identified the following points which should be taken into consideration for our research.

For translation methodology, the query translation approach is preferable in terms of implementation cost, because this approach can simply be combined with existing IR engines. On the other hand, other approaches can be prohibitive, because (a) the document translation approach conducts the full translation on the entire collection, and (b) the interlingual representation approach requires alignment of bilingual thesauri/corpora. In fact, we do not have Japanese-English thesauri/corpora with sufficient volume of alignment information at present. One may argue that the NACSIS collection, which is a large-scale Japanese-English aligned corpora, can be used for the translation. However, note that bilingual corpora for the translation must not be obtained from the test collection used for the evaluation, because in real world usage one of the two language documents in the collection is usually missing. In other words, CLIR has little necessity for bilingual aligned document collections, in that the user can retrieve documents in the query language, without the translation process.

However, at the same time we concede that each approach is worth further exploration, and in this paper we do not pretend to draw any premature conclusions regarding the relative merits of different approaches. To sum up, we focus mainly on translating sequences of content words included in queries, rather than the entire collection. Among different methods following the query translation approach, we adopt the hybrid method using a monolingual corpus. In other words, our translation method is relatively similar to that proposed by Ballesteros and Croft et al. (1998) and Chen et al. (1999). However, unlike their cases, we integrate word-based translation and transliteration methods within the query translation.

For presentation methodology, we use keywords translated using the hybrid translation method, which were proven to be effective in comparative experiments by Suzuki et al. (1999) (in the case where retrieved documents are not in the user’s native language). Note that for the purpose of the translation of keywords, we can use exactly the same method as performed for the query translation, because both queries and keywords usually consist of one or more content words.

Finally, for the evaluation of our CLIR system we use the NACSIS collection (Kando et al., 1999). Since in this collection relevance assessment is performed between Japanese queries and Japanese/English documents, we can easily evaluate our system in terms of Japanese-English CLIR. On the other hand, the evaluation of English-Japanese CLIR is beyond the scope of this paper, because as discussed in Section 2.3 the production of English queries has to be carefully conducted, and is thus expensive. Besides this, in this paper we do not evaluate our system in terms of presentation methodology, because experiments using human subjects is also expensive and still problematic. These remaining issues need to be further explored.

3. System Overview

Figure 2 depicts the overall design of our CLIR system, in which we combine a translator with an IR engine for monolingual retrieval. In the following, we briefly explain the retrieval process based on this figure.

First, the translator processes a query in the source language (query in S) to output the translation
For this purpose, the translator uses a dictionary to derive possible translation candidates and a collocation to resolve the translation ambiguity. Note that a user can utilize more than one translation candidate, because multiple translations are often appropriate for a single query. By the collocation, we mean bi-gram statistics associated with content words extracted from NACSIS documents. Since our system is bidirectional between Japanese and English, we tokenize documents with different methods, depending on their language. For English documents, the tokenization involves eliminating stopwords and identifying root forms for inflected content words. For this purpose, we use WordNet (Fellbaum, 1998), which contains a stopword list and correspondences between inflected words and their root form. On the other hand, we segment Japanese documents into lexical units using the ChaSen morphological analyzer (Matsumoto et al., 1997), which has commonly been used for much Japanese NLP research, and extract content words based on their part-of-speech information.

Second, the IR engine searches the NACSIS collection for documents (docs in T) relevant to the translated query, and sorts them according to the degree of relevance, in descending order. Our IR engine is currently a simple implementation of the vector space model, in which the similarity between the query and each document (i.e., the degree of relevance of each document) is computed as the cosine of the angle between their associated vectors. We used the notion of TF-IDF for term weighting. Among a number of variations of term weighting methods (Salton and Buckley, 1988; Zobel and Moffat, 1998), we tentatively implemented two alternative types of TF (term frequency) and one type of IDF (inverse document frequency), as shown in Equation (1).

\[
\begin{align*}
    TF &= f_{t,d} \quad \text{(standard formulation)} \\
    TF &= 1 + \log(f_{t,d}) \quad \text{(logarithmic formulation)} \\
    IDF &= \log(\frac{N}{n_t}) 
\end{align*}
\]

Here, \( f_{t,d} \) denotes the frequency that term \( t \) appears in document \( d \), and \( n_t \) denotes the number of documents containing term \( t \). \( N \) is the total number of documents in the collection. The second TF type diminishes the effect of \( f_{d,t} \), and consequently IDF affects the similarity computation more. We shall call the first and second TF types “standard” and “logarithmic” formulations, respectively. For the indexing process, we first tokenize documents as explained above (i.e., we use WordNet and ChaSen for English and Japanese documents, respectively), and then conduct the word-based indexing. That is, we use each content word as a single indexing term. Since our focus in this paper is the query translation rather than the retrieval process, we do not explore other IR techniques, including query expansion and relevance feedback.

Finally, in the case where retrieved documents are not in the user’s native language, we extract keywords from retrieved documents, and translate them into the source language using the translator (KWs in S). Unlike existing presentation methods, where keywords are words frequently appearing in each document (Aone et al., 1997; Suzuki et al., 1998; Suzuki et al., 1999), we tentatively use author keywords. In the NACSIS collection, each document contains roughly 3-5 single/compound keywords provided by the author(s) of the document. In addition, since the NACSIS documents are relatively short abstracts (instead of entire papers), it is not entirely satisfactory to rely on the word frequency information. Note that even in the case where
retrieved documents are in the user’s native language, presenting author keywords is expected to improve the retrieval efficiency. For future enhancement, we optionally use an MT system to translate entire documents retrieved (or only documents identified as relevant using author keywords) into the user’s native language (docs in S). We currently use the Transer Japanese/English MT system, which combines a general dictionary consisting of 230,000 entries, and a computer terminology dictionary consisting of 100,000 entries. Note that the translation of the limited number of retrieved documents is less expensive than that of the whole collection, as performed in the document translation approach (see Section 2.1).

In Section 4, we will explain the translator in Figure 2, which involves compound word translation and transliteration methods. While our translation method is applicable to both queries and keywords in documents, in the following we shall call it the query translation method without loss of generality.

Figure 2: The overall design of our CLIR system (S and T denote the source and target languages, respectively)

4. Query Translation Method

4.1. Overview

Given a query in the source language, tokenization is first performed as for target documents, that is, we use WordNet and ChaSen for English and Japanese queries, respectively (see Section 3). We then discard stopwords and extract only content words. Here, “content words” refer to both single and compound words. Let us take the following English query as an example:

improvement or proposal of data mining methods.

For this query, we discard “or” and “of,” to extract “improvement,” “proposal” and “data mining methods.” Thereafter, we translate each extracted content word on a word-by-word basis, maintaining the word order.

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3 Developed by NOVA, Inc.
in the source language. A preliminary study showed that approximately 95% of compound technical terms
defined in a bilingual dictionary (Ferber, 1989) maintain the same word order in both Japanese and English.
Note that we currently do not consider relation (e.g., syntactic relation) between content words, and thus
each content word is translated independently. In brief, our translation method consists of the following two
phases:

(1) derive all possible translations for base words,

(2) resolve translation ambiguity using the collocation associated with base word translations.

While phase (2) is the same for both Japanese-English and English-Japanese translations, phase (1) differs
depending on the source language. In the case of English-Japanese translation, we simply consult our
bilingual dictionary for each base word. However, transliteration is performed whenever base words unlisted
in the dictionary are found.

On the other hand, in the case of Japanese-English translation, we consider all possible segmentations of
the input word, by consulting the dictionary, because Japanese compound words lack lexical segmentation.
Then, we select such segmentations that consist of the minimal number of base words. This segmentation
method parallels that for the Japanese compound noun analysis (Kobayashi et al., 1994). During the
segmentation process, the dictionary derives all possible translations for base words. At the same time,
transliteration is performed only when _katakana_ words unlisted in the base word dictionary are found.

### 4.2. Compound Word Translation

This section explains our compound word translation method based on a probabilistic model, focusing
mainly on the resolution of translation ambiguity. After deriving possible translations for base words (by
way of either consulting the base word dictionary or performing transliteration), we can formally represent
the source compound word $S$ and one translation candidate $T$ as below.

\[
S = s_1, s_2, \ldots, s_n
\]

\[
T = t_1, t_2, \ldots, t_n
\]

Here, $s_i$ denotes an $i$-th base word, and $t_i$ denotes a translation candidate of $s_i$. Our task, i.e., to select
the $T$ which maximizes $P(T|S)$, is transformed into Equation (2) through use of the Bayesian theorem, as
performed in the statistical machine translation (Brown et al., 1993).

\[
\arg \max_T P(T|S) = \arg \max_T P(S|T) \cdot P(T) \tag{2}
\]

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4For Japanese query terms used in our evaluation (see Section 1), the average number of possible segmentations was 4.9.
In practice, in the case where the user utilizes more than one translation, $T$'s with greater probabilities are selected. We approximate $P(S|T)$ and $P(T)$ using statistics associated with base words, as in Equation (3).

$$P(S|T) \approx \prod_{i=1}^{n} P(s_i|t_i)$$

$$P(T) \approx \prod_{i=1}^{n-1} P(t_{i+1}|t_i)$$

One may notice that this approximation is analogous to that for the statistical part-of-speech tagging, where $s_i$ and $t_i$ in Equation (3) correspond to a word and one of its part-of-speech candidates, respectively (Church and Mercer, 1993). Here, we estimate $P(t_{i+1}|t_i)$ using the word-based bi-gram statistics extracted from target language documents (i.e., the collocation in Figure 2). Before elaborating on the estimation of $P(s_i|t_i)$ we explain the way to produce our bilingual dictionary for base words, because $P(s_i|t_i)$ is estimated using this dictionary.

For our dictionary production, we used the EDR technical terminology dictionary (Japan Electronic Dictionary Research Institute, 1995b), which includes approximately 120,000 Japanese-English translations related to the information processing field. Since most of the entries are compound words, we need to segment Japanese compound words, and correlate Japanese-English translations on a word-by-word basis. However, the complexity of segmenting Japanese words becomes much greater as the number of component base words increases. In consideration of these factors, we first extracted 59,533 English words consisting of only two base words, and their Japanese translations. We then developed simple heuristics to segment Japanese compound words into two substrings. Our heuristics relies mainly on Japanese character types, i.e., “kanji,” “katakana,” “hiragana,” alphabets and other characters like numerals. Note that kanji (or Chinese character) is the Japanese idiogram, and katakana and hiragana are phonograms.

In brief, we segment each Japanese word at the boundary of different character types (or at the leftmost boundary for words containing more than one character type boundary). Although this method is relatively simple, a preliminary study showed that we can almost correctly segment words that are in one of the following forms: “CK,” “CA,” “AK” and “KA.” Here, “C,” “K” and “A” denote kanji, katakana and alphabet character sequences, respectively. For other combinations of character types, we identified one or more cases in which our segmentation method incorrectly performed.

On the other hand, in the case where a given Japanese word consists of a single character type, we segment the word at the middle (or at the left-side of the middle character for words consisting of an odd number of characters). Note that roughly 90% of Japanese words consisting of four kanji characters can be correctly segmented at the middle (Kobayashi et al., 1994). However, in the case where resultant substrings begin/end with characters that do not appear at the beginning/end of words (for example, Japanese words rarely begin with a long vowel), we shift the segmentation position to the right.

Tsuji and Kageura (1997) used the HMM to segment Japanese compound words in an English-Japanese bilingual dictionary. Their method can also segment words consisting of more than two base words, and reportedly achieved an accuracy of roughly 80-90%, whereas our segmentation method is applicable only to
those consisting of two base words. However, while the HMM-based segmentation is expected to improve the quality of our dictionary production, in this paper we tentatively show that our heuristics-based method is effective for CLIR despite its simple implementation, by way of experiments (see Section 5).

As a result, we obtained 24,439 Japanese and 7,910 English base words. We randomly sampled 600 compound words, and confirmed that 95% of those words were correctly segmented. Figure 3 shows a fragment of the EDR dictionary (after segmenting Japanese words), and Figure 4 shows a base word dictionary produced from entries in Figure 3. Figure 4 contains Japanese variants, such as memori/memorii for the English word “memory.” We can easily produce a Japanese-English base word dictionary from Figure 3, using the same procedure.

During the dictionary production, we also count the correspondence frequency for each combination of $s_i$ and $t_i$, in order to estimate $P(s_i|t_i)$. In Figure 4, for example, the Japanese base word “soukan” corresponds once to “associative,” and twice to “correlation.” Thus, we can derive Equation (4).

$$
P(\text{associative} | \text{soukan}) = \frac{1}{3}$$

$$
P(\text{correlation} | \text{soukan}) = \frac{2}{3}$$

However, in the case where $s_i$ is transliterated into $t_i$, we replace $P(s_i|t_i)$ with a probabilistic score computed by our transliteration method (see Section 4.3).

One may argue that $P(s_i|t_i)$ should be estimated based on real world usage, i.e., bilingual corpora. However, such resources are generally expensive to obtain, and we do not have Japanese-English corpora with sufficient volume of alignment information at present (see Section 2.4 for more discussion).

| English          | Japanese                  |
|------------------|---------------------------|
| CCD memory       | CCD memorii              |
| IC memory        | IC memori                |
| associative learning | soukan gakushuu    |
| associative memory | renso memori           |
| associative record | ketsugou rekoodo |
| correlation function | soukan kansuu    |
| error detection  | ayamari kenshutsu       |
| factor correlation | inshi soukan    |
| hybrid IC        | haiburiddo shuusekikairo|

Figure 3: A fragment of the EDR technical terminology dictionary

### 4.3. Transliteration

This section explains our transliteration method, which identifies phonetic equivalent translations for words unlisted in the base word dictionary.

Figure 5 shows example correspondences between English and (romanized) katakana words, where we insert hyphens between each katakana character for enhanced readability. The basis of our transliteration method is analogous to that for compound word translation described in Section 4.2. The formula for the
source word $S$ and one transliteration candidate $T$ are represented as below.

$$S = s_1, s_2, \ldots, s_n$$

$$T = t_1, t_2, \ldots, t_n$$

Here, unlike the case of compound word translation, $s_i$ and $t_i$ denote $i$-th “symbols” (which consist of one or more letters), respectively. To derive possible $s_i$’s and $t_i$’s, we consider all possible segmentations of the source word $S$, by consulting a dictionary for symbols, namely the “transliteration dictionary.” Then, we select such segmentations that consist of the minimal number of symbols. Note that unlike the case of compound word translation, the segmentation is performed for both Japanese-English and English-Japanese transliterations.

| English     | Japanese                |
|-------------|-------------------------|
| CCD         | CCD                     |
| IC          | IC, shuusekikairo       |
| associative | soukan, rensou, ketsugou|
| correlation | soukan                  |
| detection   | kenshutsu               |
| error       | ayamari                 |
| factor      | inshi                   |
| function    | kansuu                  |
| hybrid      | haiburiddo              |
| learning    | gakushuu                |
| memory      | memori, memorii         |
| record      | rekoodo                 |

Figure 4: A fragment of an English-Japanese base word dictionary produced from Figure 3

| English     | Japanese                |
|-------------|-------------------------|
| system      | shi-su-te-mu            |
| mining      | ma-i-ni-n-gu            |
| data        | dekta                   |
| network     | ne-tto-wa-ku            |
| text        | te-ki-su-to             |
| collocation | ko-ro-ke-i-sho-n        |

Figure 5: Example correspondences between English and (romanized) Japanese *katakana* words

Thereafter, we resolve the transliteration ambiguity based on the a probabilistic model similar to that for the compound word translation. To put it more precisely, we compute $P(T|S)$ for each $T$ using Equation (2), and select $T$’s with greater probabilities. Note that $T$’s must be correct words (that are indexed in the NACSIS document collection). However, Equation (3), which approximates $P(T)$ by combining $P(t_i)$’s for substrings of $T$, potentially assigns positive possibility values for incorrect (unindexed) words.

In view of this problem, we estimate $P(T)$ as the probability that $T$ occurs in the document collection, and consequently the probability for unindexed words becomes zero. In practice, during the segmentation
process we simply discard such $T$’s that are unindexed in the document collection, so that we can enhance the computation for $P(T|S)$’s. On the other hand, we approximate $P(S|T)$ as in Equation (3), and estimate $P(s_i|t_i)$ based on the correspondence frequency for each combination of $s_i$ and $t_i$ in the transliteration dictionary.

The crucial content here is the way to produce the transliteration dictionary, because such dictionaries have rarely been published. For the purpose of dictionary production, we used approximately 35,000 *katakana* Japanese words and their English translations collected from the EDR technical terminology dictionary ([Japan Electronic Dictionary Research Institute, 1995b](#)) and bilingual dictionary ([Japan Electronic Dictionary Research Institute, 1995a](#)). To illustrate our dictionary production method, we consider Figure 5 again. Looking at this figure, one may notice that the first letter in each *katakana* character tends to be contained in its corresponding English word. However, there are a few exceptions. A typical case is that since Japanese has no distinction between “L” and “R” sounds, the two English sounds collapse into the same Japanese sound. In addition, a single English letter may correspond to multiple *katakana* characters, such as “x” to “ki-su” in “&text, te-ki-su-to.” To sum up, English and romanized *katakana* words are not exactly identical, but similar to each other.

We first manually defined the similarity between the English letter $e$ and the first romanized letter for each *katakana* character $j$, as shown in Table 1. In this table, “phonetically similar” letters refer to a certain pair of letters, such as “L” and “R,” for which we identified approximately twenty pairs of letters. We then consider the similarity for any possible combination of letters in English and romanized *katakana* words, which can be represented as a matrix, as shown in Figure 6. This figure shows the similarity between letters in “&text, te-ki-su-to.” We put a dummy letter “$,” which has a positive similarity only to itself, at the end of both English and *katakana* words.

One may notice that matching plausible symbols can be seen as finding the path which maximizes the total similarity from the first to last letters. The best path can efficiently be found by, for example, Dijkstra’s algorithm ([Dijkstra, 1959](#)). From Figure 6, we can derive the following correspondences: “&te, te,” “&x, ki-su” and “&t, to.” In practice, to exclude noisy correspondences, we used only English-Japanese translations whose total similarity from the first to last letters is above a predefined threshold. The resultant transliteration dictionary contains 432 Japanese and 1018 English symbols, from which we estimated $P(s_i|t_i)$.

| Condition                          | Similarity |
|-----------------------------------|------------|
| $e$ and $j$ are identical          | 3          |
| $e$ and $j$ are phonetically similar | 2          |
| both $e$ and $j$ are vowels or consonants | 1          |
| otherwise                          | 0          |

To evaluate our transliteration method, we extracted Japanese *katakana* words (excluding compound words) and their English translations from an English-Japanese dictionary ([Nichigai Associates, 1996](#)). We
then discarded Japanese/English pairs that were not phonetically equivalent to each other, and were listed in the EDR dictionaries. For the resultant 248 pairs, the accuracy of our transliteration method was 65.3%.

Thus, our transliteration method is less accurate than the word-based translation. For example, the katakana word “re-ji-su-ta (register/resistor)” is transliterated into “resister,” “resistor” and “register,” with the probability score in descending order. Note that Japanese seldom represents “resister” as “re-ji-su-ta” (whereas it can be theoretically correct when this word is written in katakana characters), because “resister” corresponds to more appropriate translations in kanji characters. However, the compound word translation is expected to select appropriate transliteration candidates. For example, “re-ji-su-ta” in the compound word “re-ji-su-ta tensou gengo (register transfer language)” is successfully translated, given a set of base words “tensou (transfer)” and “gengo (language)” as a context.

Finally, we devote a little more space to compare our transliteration method and other related works. Chen et al. (1998) proposed a Chinese-English transliteration method. Given a (romanized) source word, their methods compute the similarity between the source word and each target word listed in the dictionary. In brief, the more letters two words share in common, the more similar they are. In other words, unlike our case, their methods disregard the order of letters in source and target words, which potentially degrades the transliteration accuracy. In addition, since for each source word the similarity is computed between all the target words (or words that share at least one common letter with the source word), the similarity computation can be prohibitive. Lee and Choi (1997) explored English-Korean transliteration, where they automatically produced a transliteration model from a word-aligned corpus. In brief, they first consider all possible English-Korean symbol correspondences for each word alignment. Then, iterative estimation is performed to select such symbol correspondences that maximize transliteration accuracy on training data. However, when compared with our symbol alignment method, their iterative estimation method is computationally expensive. Knight and Graehl (1998) proposed a Japanese-English transliteration method based on the mapping probability between English and Japanese katakana sounds. However, while their method needs a large-scale phoneme inventory, we use a simpler approach using surface mapping between

Figure 6: An example matrix for English-Japanese symbol matching (arrows denote the best path)
English and katakana characters, as defined in our transliteration dictionary. Note that none of those above methods has been evaluated in the context of CLIR. Empirical comparison of different transliteration methods needs to be further explored.

### 4.4. Further Enhancement of Translation

This section explains two additional methods to enhance the query translation.

First, we can enhance our base word dictionary with general words, because technical compound words sometimes include general words, as discussed in Section 1. Note that in Section 4.2 we produced our base word dictionary from the EDR technical terminology dictionary. Thus, we used the EDR bilingual dictionary ([Japan Electronic Dictionary Research Institute, 1995a](#)), which consists of approximately 370,000 Japanese-English translations aimed at general usage. However, unlike in the case of technical terms, it is not feasible to segment general compound words, such as “hot dog,” into base words. Thus, we simply extracted 162,751 Japanese and 67,136 English single words (i.e., words that consist of a single base word) from this dictionary. In addition, to minimize the degree of translation ambiguity, we use general translations only when (a) base words unlisted in our technical term dictionary are found, and (b) our transliteration method fails to output any candidates for those unlisted base words.

Second, in Section 1 we also identified that English technical terms are often abbreviated, such as “IR” and “NLP,” and they can be used as Japanese words. One solution would be to output those abbreviated words as they are, for both Japanese-English and English-Japanese translations. On the other hand, it is expected that we can improve the recall by using complete forms along with their abbreviated forms. To realize this notion, we extracted 7,307 tuples of each abbreviation and its complete form from the NACSIS English document collection, using simple heuristics. Our heuristics relies on the assumption that either abbreviations or complete forms often appear in parentheses headed by their counterparts, as shown below:

- Natural Language Processing (NLP),
- cross-language information retrieval (CLIR),
- MRDs (machine readable dictionaries).

While the first example is the most straightforward, in the second and third examples we disregard a hyphen and lowercase letter (i.e., “s” in “MRDs”), respectively. In practice, we can easily extract such tuples using the regular expression pattern matching. Figure 7 shows example tuples of abbreviations and complete forms extracted from the NACSIS collection. In this figure, the column “Frequency” denotes the frequency that each tuple appears in the collection, with which we can optionally set a cut-off threshold for multiple complete forms corresponding to a single abbreviation (e.g., “information retrieval,” “isoprene rubber” and “insulin receptor” for “IR”).

### 5. Evaluation

#### 5.1. Methodology

We investigated the performance of our system in terms of Japanese-English CLIR, based on the TREC-type evaluation methodology. That is, the system outputs 1,000 top documents, and the TREC evaluation
| Abbreviation | Complete form       | Frequency |
|--------------|---------------------|-----------|
| IR           | information retrieval | 3         |
| IR           | isoprene rubber      | 1         |
| IR           | insulin receptor     | 1         |
| MT           | machine translation  | 11        |
| MT           | mobile telephone     | 3         |
| NLP          | natural language processing | 8 |

Figure 7: Example abbreviations and their complete forms

software was used to plot recall-precision curves and calculate non-interpolated average precision values.

For the purpose of our evaluation, we used a preliminary version of the NACSIS test collection (Kando et al., 1999). This collection includes approximately 330,000 documents (in either a combination of English and Japanese or either of the languages individually), collected from technical papers published by 65 Japanese associations for various fields. Each document consists of the document ID, title, name(s) of author(s), name/date of conference, hosting organization, abstract and keywords, from which we used titles, abstracts and keywords for the indexing. We used as target documents approximately 187,000 entries where abstracts are in both English and Japanese.

This collection also includes 21 Japanese queries. Each query consists of the query ID, title of the topic, description, narrative and list of synonyms, from which we used only the description. In general, most topics are related to electronic, information and control engineering. Figure 8 shows example descriptions (translated into English by one of the authors).

In the NACSIS collection, relevance assessment was performed based on the pooling method (Voorhees, 1998). That is, candidates for relevant documents were first obtained with multiple retrieval systems. Thereafter, for each candidate document, human expert(s) assigned one of three ranks of relevance, i.e., “relevant,” “partially relevant” and “irrelevant.” The average number of candidate documents for each query is 4,400, among which the number of relevant and partially relevant documents are 144 and 13, respectively. In our evaluation, we did not regard partially relevant documents as relevant ones, because (a) the result did not significantly change depending on whether we regarded partially relevant as relevant or not, and (b) interpretation of partially relevant is not fully clear to the authors.

Since the NACSIS collection does not contain English queries, we cannot estimate a baseline for Japanese-English CLIR performance based on English-English IR. Instead, we used a Japanese-Japanese IR system.

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5The official version of the NACSIS collection includes 39 Japanese queries and the same document set as in the preliminary version we used. NACSIS (National Center for Science Information Systems, Japan) held a TREC-type (CL)IR contest workshop in August 1999, and participants, including the authors of this paper, were provided with the whole document set and 21 queries for training. These 21 queries are included in the final package of the test collection. See [http://www.rd.nacsis.ac.jp/~ntcadm/workshop/work-en.html](http://www.rd.nacsis.ac.jp/~ntcadm/workshop/work-en.html) for details.

6In the NACSIS workshop, each participant can submit more than one retrieval result using different systems. However, at least one result must be gained with only the description field.
which uses as documents Japanese titles/abstracts/keywords comparable to English fields in the NACSIS collection. One may argue that we can manually translate Japanese queries into English. However, as discussed in Section 2.3, the CLIR performance varies depending on the quality of translation, and thus we avoided an arbitrary evaluation.

| ID   | Description                                           |
|------|-------------------------------------------------------|
| 0005 | dimension reduction for clustering                    |
| 0006 | intelligent information retrieval using agent functions |
| 0019 | syntactic analysis methods for Japanese sentences     |
| 0024 | machine translation systems                           |

Figure 8: Example query descriptions in the NACSIS collection

5.2. Quantitative Comparison

We compared the following query translation methods:

- all possible translations derived from the (original) EDR technical terminology dictionary (Japan Electronic Dictionary Research Institute, 1995b) are used for query terms, which can be seen as a lower bound method of this comparative experiment (“EDR”),
- all possible base word translations derived from our base word dictionary are used (“ALL”),
- k-best translations selected by our compound word translation method are used, where transliteration is not used (“CWT”),
- transliteration is performed for unlisted katakana words in CWT above, which represents the overall query translation method we proposed in this paper (“TRL”).

One may notice that both EDR and ALL correspond to the dictionary-based method, and CWT and TRL correspond to the hybrid method described in Section 2.1. In the case of EDR, compound words unlisted in the EDR dictionary were manually segmented so that substrings (shorter compound words or base words) could be translated. There was almost no translation ambiguity in the case of EDR. In addition, preliminary experiments showed that disambiguation degraded the retrieval performance for EDR. In CWT and TRL, k is a parametric constant, for which we set $k = 1$. Through preliminary experiments, we achieved the best performance when we set $k = 1$. By increasing the value of $k$, we theoretically gain a query expansion effect, because multiple translations semantically related are used as query terms. However, in our case, additional translations were rather noisy with respect to the retrieval performance. Note that in this experiment, we did not use the general and abbreviation dictionaries. We will discuss the effect of those dictionaries in Section 4.4.

Table 2 shows the non-interpolated average precision values, averaged over the 21 queries, for different combinations of query translation and retrieval methods. It is worth comparing the effectiveness of query translation methods with different retrieval methods, because advanced retrieval methods potentially overcome the rudimentary nature of query translation methods, and therefore may overshadow the difference of
query translation methods in CLIR performance. In consideration of this problem, as described in Section 3, we adopted two alternative term weighting methods, i.e., the standard and logarithmic formulations. In addition, we used as the IR engine in Figure 2 the SMART system (Salton, 1971), where the augmented TF-IDF term weighting method (“ATC”) was used for both queries and documents. This makes it easy for other researchers to rigorously compare their query translation methods with ours within the same evaluation environment, because the SMART system is available to the public.

In Table 2, J-J refers to the baseline performance, that is, the result obtained by the Japanese-Japanese IR system. Note that the performance of J-J using the SMART system is not available because this system is not implemented for the retrieval of Japanese documents. The column “# of Terms” denotes the average number of query terms used for the retrieval, where the number of terms used in ALL was approximately seven times as great as those of other methods. Suggestions can be derived from these results as follows.

Table 2: Non-interpolated average precision values, averaged over the 21 queries, for different combinations of query translation and retrieval methods

| # of Terms | Retrieval Method | Standard TF | Logarithmic TF | SMART |
|------------|-----------------|-------------|----------------|-------|
| J-J        | 4.0             | 0.2085      | 0.2443         | —     |
| TRL        | 4.0             | 0.2427      | 0.2911         | 0.3147|
| CWT        | 3.9             | 0.2324      | 0.2680         | 0.2770|
| ALL        | 21              | 0.1971      | 0.2271         | 0.2106|
| EDR        | 4.1             | 0.1785      | 0.2173         | 0.2477|

First, the relative superiority between EDR and ALL varies depending on the retrieval method. Since neither case resolved the translation ambiguity, the difference in performance for the two translation methods is reduced solely to the difference between the two dictionaries. Therefore, the base word dictionary we produced was effective when combined with the standard and logarithmic TF formulations. However, the translation disambiguation as performed in CWT improved the performance of ALL, and consequently CWT outperformed EDR irrespective of the retrieval method. To sum up, our compound word translation method was more effective than the use of an existing dictionary, in terms of CLIR performance.

Second, by comparing results of CWT and TRL, one can see that our transliteration method further improved the performance of the compound word translation relying solely on the base word dictionary, irrespective of the retrieval method. Since TRL represents the overall performance of our system, it is worth comparing TRL and EDR (i.e., a lower bound method) more carefully. Thus, we used the paired t-test for statistical testing, which investigates whether the difference in performance is meaningful or simply due to chance (Hull, 1993; Keen, 1992). We found that the average precision values of TRL and EDR are significantly different (at the 5% level), for any of the three retrieval methods.

Third, the performance was generally improved as a more sophisticated retrieval method was used, for all of the translation methods excepting ALL. In other words, enhancements of the query translation and IR engine independently improved on the performance of our CLIR system. Note that the difference between the SMART system and the other two methods is due to more than one factor, including stemming and term
weighting methods. This suggests that our system may achieve a higher performance using other advanced IR techniques.

Finally, TRL and CWT outperformed J-J for any of the retrieval methods. However, these differences are partially attributed to the different properties inherent in Japanese and English IR. For example, the performance of Japanese IR is more strongly dependent on the indexing method than English IR, since Japanese lacks lexical segmentation. This issue needs to be further explored.

Figures 9-11 show recall-precision curves of different query translation methods, for different retrieval methods, respectively. In these figures, while the superiority of EDR and ALL in terms of precision varies depending on the recall, one can see that CWT outperformed EDR and ALL, and that TRL outperformed CWT, regardless of the recall. In Figures 9 and 10, J-J generally performed better at lower recall while any of four CLIR methods performs better at higher recall. As discussed above, possible rationales would include the difference between Japanese and English IR. To put it more precisely, in Japanese IR a word-based indexing method (as performed in our IR engine) fails to retrieve documents in which words are inappropriately segmented. In addition, the ChaSen morphological analyzer often incorrectly segments *katakana* words, which frequently appear in technical documents. Consequently this drawback leads to a poor recall in the case of J-J.

![Figure 9: Recall-precision curves using the standard TF](image)

Figure 9: Recall-precision curves using the standard TF
Figure 10: Recall-precision curves using the logarithmic TF

Figure 11: Recall-precision curves using the SMART system
5.3. Query-by-query Analysis

In this Section, we discuss reasons why our translation method was effective in CLIR performance, through a query-by-query analysis.

First, we compared EDR and CWT (see in Section 5.2), to investigate the effectiveness of our compound word translation method. For this purpose, we identified fragments of the NACSIS query that were correctly translated by CWT but not by EDR, as shown in Table 3. In this table, where we insert hyphens between each Japanese base word for enhanced readability, Japanese/English words unlisted in the EDR technical terminology dictionary are underlined. Note that as mentioned in Section 5.2, in these cases translations for remaining base words were used as query terms. However, in the case of the query 0019, the EDR dictionary lists a phrase translation, i.e., “kakariuke-kaiseki (analysis of dependence relation),” and thus “analysis,” “dependence” and “relation” were used as query terms (“of” was discarded as a stopword). One can see that except for the five cases asterisked, out of 18 cases, CWT outperformed EDR. Note that in the case of 0019, EDR conducted a phrase-based translation, while CWT conducted a word-based translation. The relative superiority between these two translation approaches varies depending on the retrieval method, and thus we cannot draw any conclusion regarding this point in this paper. In the case of the query 0006, although the translation in CWT was linguistically correct, we found that the English word “agent function” is rarely used in documents associated with agent research, and that “function” ended up degrading the retrieval performance. In the case of the query 0020, “loanword” would be a more appropriate translation for “gairaigo.” However, even when we used “loanword” for the retrieval, instead of “foreign” and “word,” the performance of EDR did not change.

| ID   | Japanese (Translation in CWT)                        | Change in Average Precision (EDR → CWT) |
|------|------------------------------------------------------|----------------------------------------|
| 0001 | jiritsu-idou-robotto (autonomous mobile robot)       | 0.2325 → 0.3667 0.2587 → 0.4058 0.2259 → 0.3441 |
| 0004 | bansho-gazou-rikai (document image understanding)    | 0.0011 → 0.2775 0.0091 → 0.3768 0.0217 → 0.2740 |
| 0006 | eejento-kinou (agent function)                       | 0.2008 → 0.1603* 0.2920 → 0.1997* 0.1430 → 0.1395* |
| 0016 | saidai-kyoutsuu-bubungurafu (greatest common subgraph)| 0.1615 → 0.5039 0.4661 → 0.6216 0.1295 → 0.4460 |
| 0019 | kakariuke-kaiseki (dependency analysis)              | 0.0794 → 0.3550 0.1383 → 0.4302 0.1852 → 0.1449* |
| 0020 | katakana-gairai-go (katakana foreign word)          | 0.4536 → 0.4568 0.2408 → 0.4674 0.9429 → 0.8769* |

Second, we compared CWT and TRL in Table 4, which uses the same basic notation as Table 3. The NACSIS query set contains 20 katakana base word types, among which “ma-i-ni-n-gu (mining)” and “ko-ro-ke-i-sho-n (collocation)” were unlisted in our base word dictionary. Unlike the previous case, transliteration generally improved on the performance. On the other hand, we concede that only three queries are not enough to justify the effectiveness of our transliteration method. In view of this problem, we assumed that every katakana word in the query is unlisted in our base word dictionary, and compared the following two extreme cases:

- every katakana word was untranslated (i.e., they were simply discarded from queries), which can be seen as a lower bound method in this comparison,
transliteration was applied to every \textit{katakana} word, instead of consulting the base word dictionary.

Both cases were combined into the CWT Section 5.2. Note that in the latter case, when a \textit{katakana} word is included in a compound word, transliteration candidates of the word are disambiguated through the compound word translation method, and thus noisy candidates are potentially discarded. It should also be noted that in the case where a compound word consists of solely \textit{katakana} words (e.g., \textit{deeta-mainingu} (data mining)), our method automatically segments it into base words, by transliterating all the possible substrings.

Table 5 shows the average precision values, averaged over the 21 queries, for those above cases. By comparing Tables 2 and 5, one can see that the performance was considerably degraded when we disregard every \textit{katakana} word, and that even when we applied transliteration to every \textit{katakana} word, the performance was greater than that of CWT and was quite comparable to that of TRL. Among the 20 \textit{katakana} base words, only “\textit{eejento} (agent)” was incorrectly transliterated into “eagent,” which was due to an insufficient volume of the transliteration dictionary.

Table 4: Query-by-query comparison between CWT and TRL

| ID | Japanese (Translation in TRL) | Change in Average Precision (CWT → TRL) |
|----|--------------------------------|---------------------------------------|
|    |                               | Standard TF | Logarithmic TF | SMART |
| 0008 | \textit{deeta-mainingu} (data mining) | 0.0018 → 0.0942 | 0.0299 → 0.3363 | 0.3156 → 0.7295 |
| 0012 | \textit{deeta-mainingu} (data mining) | 0.0018 → 0.1229 | 0.0003 → 0.1683 | 0.0000 → 0.0853 |
| 0015 | \textit{corokeishon} (collocation) | 0.0054 → 0.0084 | 0.0389 → 0.0485 | 0.0193 → 0.3114 |

Table 5: Non-interpolated average precision values, averaged over the 21 queries, for the evaluation of transliteration

| Retrieval Method | # of Terms | Standard TF | Logarithmic TF | SMART |
|------------------|------------|-------------|----------------|-------|
| discard every \textit{katakana} word | 2.8 | 0.1519 | 0.1840 | 0.1873 |
| transiterate every \textit{katakana} word | 4.0 | 0.2354 | 0.2786 | 0.3024 |

Finally, we discuss the effect of additional dictionaries, i.e., the general and abbreviation dictionaries. The NACSIS query set contains the general word “\textit{shimbun kiji} (newspaper article)” and abbreviation “\textit{LFG} (lexical functional grammar)” unlisted in our technical base word dictionary. The abbreviation dictionary lists the correct translation for “\textit{LFG}.” On the other hand, our general dictionary, which consists solely of single words, does not list the correct translation for “\textit{shimbun-kiji}.” Instead, the English word “story” was listed as the translation, which would be used in a particular context. Table 6, where basic notation is the same as Table 3, compares average precision values with/without these translations. From this table we cannot see any improvement with the additional dictionaries. However, when the correct translation was provided as in 0023 with “newspaper article,” the performance was improved disregarding the retrieval method. In addition, since we found only two cases where additional dictionaries could be applied, this issue needs to be further explored using more test queries.
Table 6: Query-by-query comparison for the general and abbreviation dictionaries

| ID   | Japanese (Translation)                  | Change in Average Precision |          |          |          |
|------|----------------------------------------|----------------------------|----------|----------|----------|
|      |                                        | Standard TF    | Logarithmic TF | SMART    |          |
| 0023 | shimbun-kiji (story)                   | 0.0003 → 0.0000* | 0.0000 → 0.0000 | 0.0000 → 0.0000 |          |
| 0023 | shimbun-kiji (newspaper article)       | 0.0003 → 0.0200  | 0.0000 → 0.0858 | 0.0000 → 0.1800 |          |
| 0025 | LFG (lexical functional grammar)       | 0.8000 → 0.5410* | 0.8000 → 0.6879* | 0.9452 → 0.8617* |          |

6. Conclusion

Reflecting the rapid growth in utilization of machine readable multilingual texts in the 1990s, cross-language information retrieval (CLIR), which was initiated in the 1960s, has variously been explored in order to facilitate retrieving information across languages. For this purpose, a number of CLIR systems have been developed in information retrieval, natural language processing and artificial intelligence research.

In this paper, we proposed a Japanese/English bidirectional CLIR system targeting technical documents, in that translation of technical terms is a crucial task. Since our research methodology must be contextualized in terms of past research literature, we surveyed existing CLIR systems, and classified them into three approaches: (a) translating queries into the document language, (b) translating documents into the query language, and (c) representing both queries and documents in a language-independent space. Among these approaches, we found that the first one, namely the query translation approach, is relatively inexpensive to implement. Therefore, following this approach, we combined query translation and monolingual retrieval modules.

However, a naive query translation method relying on existing bilingual dictionaries does not guarantee sufficient system performance, because new technical terms are progressively created by combining existing base words or by the Japanese *katakana* phonograms. To counter this problem, we proposed compound word translation and transliteration methods, and integrated them within one framework. Our methods involve the dictionary production and probabilistic resolution of translation/transliteration ambiguity, both of which are fully automated. To produce the dictionary used for the compound word translation, we extracted base word translations from the EDR technical terminology dictionary. On the other hand, we corresponded English and Japanese *katakana* words on a character basis, to produce the transliteration dictionary. For the disambiguation, we used word frequency statistics extracted from the document collection. We also produced a dictionary for abbreviated English technical terms, to enhance the translation.

From a scientific point of view, we investigated the performance of our CLIR system by way of the standardized IR evaluation method. For this purpose, we used the NACSIS test collection, which consists of Japanese queries and Japanese/English technical abstracts, and carried out Japanese-English CLIR evaluation. Our evaluation results showed that each individual method proposed, i.e., compound word translation and transliteration, improved on the baseline performance, and when used together the improvement was even greater, resulting in a performance comparable with Japanese-Japanese monolingual IR. We also showed that the enhancement of the retrieval module improved on our system performance, independently from the enhancement of the query translation module.
Future work will include improvement of each component in our system, and the effective presentation of retrieved documents using sophisticated summarization techniques.

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