

Ontology-Based Word Sense Disambiguation by Using Semi-Automatically Constructed Ontology

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Abstract

This paper describes a method for disambiguating word senses by using semi-automatically constructed ontology. The ontology stores rich semantic constraints among 1,110 concepts, and enables a natural language processing system to resolve semantic ambiguities by making inferences with the concept network of the ontology. In order to acquire a reasonably practical ontology in limited time and with less manpower, we extend the existing Kadokawa thesaurus by inserting additional semantic relations into its hierarchy, which are classified as case relations and other semantic relations. The former can be obtained by converting valency information and case frames from previously-built electronic dictionaries used in machine translation. The latter can be acquired from concept co-occurrence information, which is extracted automatically from large corpora. In our practical machine translation system, our word sense disambiguation method achieved a 9.2% improvement over methods which do not use an ontology for Korean translation.

Keywords

word sense disambiguation, ontology construction, corpus analysis, concept association

1 Introduction

An ontology is a knowledge base with information about concepts existing in the world or domain, their properties, and how they relate to each other. Three principal reasons to use an ontology in machine translation (MT) are to enable source language analyzers and target language generators to share knowledge, to store semantic constraints, and to resolve semantic ambiguities by making inferences with the concept network of the ontology (Mahesh, 1996; Nirenburg *et al.*, 1992). An ontology is different from a thesaurus in that it contains only language independent information and many other semantic relations, as well as taxonomic relations.

In this paper, we propose to use the ontology to disambiguate word senses. All approaches to word sense disambiguation (WSD) make use of words in a sentence to mutually disambiguate each other. The distinctions between various approaches lie in the source and type of knowledge made by the lexical units in a sentence. Our WSD approach is a hybrid method, which combines the advantages of corpus-based and knowledge-based methods. We use the ontology as an external knowledge source and secured dictionary information as context information. First, we apply the previously-secured dictionary information to select the correct senses of some ambiguous words with high precision, and then use the ontology to disambiguate the remaining ambiguous words. In this paper, a semi-automatic LIP (language independent and practical) ontology construction method is also proposed briefly. In order to acquire reasonably practical ontology in limited time and with less manpower, we take full advantage of already existing knowledge resources and practical usages in corpora. First, we introduced the same number and grain size of concepts of the Kadokawa thesaurus (Ohno & Hamanishi, 1981) and its taxonomic hierarchy into the ontology. The second strategy is to extend the hierarchy of the Kadokawa thesaurus by inserting additional semantic relations into its hierarchy. The additional semantic relations can be classified as case

relations and other semantic relations. The former can be obtained by converting the established valency information in bilingual dictionaries of COBALT-J/K (Collocation-Based Language Translator from Japanese to Korean) (Park *et al.*, 1997) and COBALT-K/J (Collocation-Based Language Translator from Korean to Japanese) (Moon & Lee, 2000) MT systems, as well as from the case frames in SELK (Sejong Electronic Lexicon of Korean) (Hong & Pak, 2001). The latter can be acquired from concept co-occurrence information, which is extracted automatically from a corpus (Li *et al.*, 2000). The remainder of this paper is organized as follows. In the next section, we describe the principles of ontology design and the semi-automatic ontology construction methodology. The ontology learning phase is explained in Section 3. An ontology-based WSD algorithm is given in Section 4. Experimental results are presented and analyzed in Section 5. Finally, we conclude and indicate the direction of our future work in Section 6.

2 Ontology Construction

2.1 Design Principles

Although no formal principles exist to determine the structure or content of the ontology we are developing, we can suggest some principles underlying our methodology. Firstly, an ontology for natural language processing (NLP) must provide concepts for representing word meanings in the lexicon and store selectional constraints of concepts, which enable inferences using the network of an ontology (Onyshkevych, 1997). These inferences can assist in metaphor and metonymy processing, as well as word sense disambiguation. For these reasons, an ontology becomes an essential knowledge source for high quality NLP, although it is very difficult and time-consuming to define its concepts and semantic relations, and to obtain selectional constraints of concepts. Secondly, an ontology can be effortlessly shared by any application and in any domain (Gruber, 1993; Karp *et al.*, 1999; Kent,

1999). More than two different ontologies in a certain domain can produce a semantic mismatch problem between concepts. Further, if you wish to apply an existing ontology to a new application, it will often be necessary to convert the structure of the ontology to the new one. Thirdly, an ontology must support language independent features, because constructing ontologies for each language is inefficient. Fourthly, an ontology must have capabilities for users to easily understand, search, and browse.

To support these principles, we chose the ontology markup language (OML) (Kent, 1999) as the ontology representation language of our ontology, which is based on Extensible Markup Language (XML) and conceptual graphs (Sowa, 1984). Since XML has a well-established syntax, it is reasonably simple to parse, and XML will be widely used, because it has many software tools for parsing and manipulating, and a human readable representation. We intend to leave room for improvement by adopting the semantics of conceptual graphs, because the present design of our LIP ontology is for the specific purpose of disambiguating word senses. In future, however, we must extend its structure and content to build an interlingual meaning representation during semantic analysis in machine translation. Sowa's conceptual graphs is a widely-used knowledge representation language, consisting of logic structures with a graph notation and several features integrated from semantic net and frame representation.

2.2 Two Strategies

Many ontologies are developed for purely theoretical purposes and are seldom constructed as a computational resource, because they are difficult to construct with limited time and manpower resources. To overcome these difficulties, we developed two strategies. First, we introduced the same number and grain size of concepts of the Kadokawa thesaurus and its taxonomic hierarchy into the LIP ontology. The thesaurus has 1,110 Kadokawa semantic categories and a 4-level hierarchy as a taxonomic relation (see Figure 1). This approach is a moderate shortcut to construct a practical ontology and easily enables us to utilize its results, since some resources are readily available, such as bilingual dictionaries of COBALT-J/K and COBALT-K/J. In these bilingual dictionaries, nominal and verbal words are already annotated with concept codes from the Kadokawa thesaurus. By using the same sense inventories of these MT systems, we can easily apply and evaluate our LIP ontology without additional lexicographic works. In addition, the Kadokawa thesaurus proved to be useful for providing a fundamental foundation to build lexical disambiguation knowledge in COBALT-J/K and COBALT-K/J MT systems (Li *et al.*, 2000). The second strategy to construct a practical ontology is to extend the hierarchy of the Kadokawa thesaurus by inserting additional semantic relations into its hierarchy. The additional semantic relations can be classified as case relations and other semantic relations. Thus far, case relations have been occasionally used to disambiguate lexical ambiguities in the form of valency information and case frame, but other semantic relations have not, because of the problem of discriminating them from each other, making them difficult to recognize. We define a total of

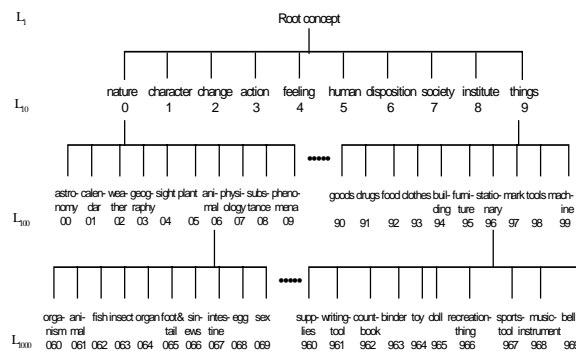


Figure 1: Concept hierarchy of the Kadokawa Thesaurus

30 semantic relation types for WSD by referring mainly to the SELK and the Mikrokosmos ontology (Mahesh, 1996), as shown in Table 1.

Types of Semantic Relation	Relation Lists
Taxonomic relation	is-a
Case relation	agent, theme, experiencer, accompanier, instrument, location, source, destination, reason, appraisee, criterion, degree, recipient
Other semantic relation	has-member, has-element, contains, material-of, headed-by, operated-by, controls, owner-of, represents, symbol-of, name-of, producer-of, composer-of, inventor-of, make, measured-in

Table 1: Semantic relation types in the LIP ontology

These semantic relation types cannot express all possible semantic relations existing among concepts, but experimental results demonstrated their usefulness for WSD. There are two approaches to obtain these additional semantic relations, which will be inserted into the LIP ontology. The first imports relevant semantic information from existing dictionary resources. The other applies the semi-automatic corpus analysis method (Li *et al.*, 2000). Both approaches are explained in Section 2.2.1 and 2.2.2, respectively. Figure 2 displays the overall constructing flow of the LIP ontology.

First, we build an initial LIP ontology by importing the existing Kadokawa thesaurus. Each concept inserted into the initial ontology has a Kadokawa code, a Korean name, an English name, a timestamp, and a concept definition. Although concept codes can be uniquely identified by the Kadokawa concept codes, their Korean and English names are inserted for the ontology developer's readability and convenience.

2.2.1 Computational Dictionary Utilization

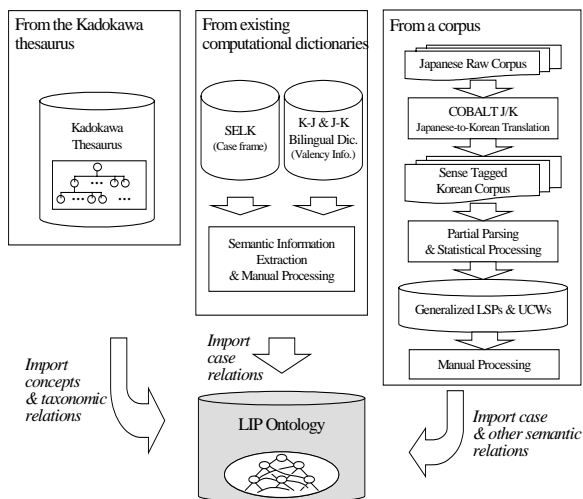


Figure 2: Overall constructing flow of the LIP ontology

Case relations between concepts can be primarily derived from semantic information in the SELK and the bilingual dictionaries of MT systems, which are COBALT-J/K and COBALT-K/J. The ultimate goal of the SELK project is to compile an electronic lexical database which harmonizes linguistic validity, psychological reality and computational efficiency. This will result in an exhaustive representation of Korean linguistic knowledge used by a native speaker of contemporary Korean. The SELK project has been developed on a theoretically neutral basis, with no partiality to any particular theoretical framework. SELK is composed of various sub-dictionaries, with each sub-dictionary corresponding to the dictionary of a word category, such as a noun dictionary, a verb dictionary, etc. (Hong & Pak, 2001)

We obtained 7,526 case frames from verb and adjective sub-dictionaries in the SELK, which contain 3,848 entries. Automatically converting lexical words in the case frame into the Kadokawa concept codes by using COBALT-K/J, we extracted a total of 6,224 case relation instances.

The bilingual dictionaries, which contain 20,580 verb and adjective entries, have 16,567 instances of valency information. Semi-automatically converting syntactic relations into semantic relations by using specific rules and human intuition, we generated 15,956 case relation instances. The specific rules are inferred from training samples, which are explained in Section 3. These obtained instances may overlap each other, but all instances are inserted only once into the initial LIP ontology.

2.2.2 Corpus Analysis

For the automatic construction of a sense-tagged corpus, we used the COBALT-J/K, which is a high-quality practical MT system developed by POSTECH in 1996. The system has been used successfully in full operation at POSCO (Pohang Iron and Steel Company), Korea, to translate patent materials on iron and steel subjects. We performed a slight modification on COBALT-J/K so that it can produce Korean translations from Japanese texts with all nominal and verbal words tagged with the specific concept codes of the Kadokawa thesaurus. As a result, a Korean sense-tagged corpus, which has two hundred and fifty thousand sentences, can be obtained from Japanese

texts. Unlike English, the Korean language has almost no syntactic constraints on word order as long as a verb appears in the final position. So we defined 12 local syntactic patterns (LSPs) using syntactically related words in a sentence, such as “noun + *i/ka*¹ + verb,” “noun + *ul/lul* + verb,” “noun + *ey* + noun,” etc. Frequently co-occurring words in a sentence may have no syntactic relations to homographs but may control their meaning. Such words are retrieved as unordered co-occurring words (UCWs). Example of UCWs for *nwun* with the sense ‘eye’ are *koyangi* (061: cat), *mosup* (110, 620: appearance), and *saram* (507: human); and examples of UCWs for *nwun* with the sense ‘snow’ are *yengha* (126: below zero) and *san* (032: mountain).

Case relations are obtained from LSPs and other semantic relations are acquired from UCWs. The LSPs and UCWs can be extracted by partial parsing and scanning. To select the most probable concept types, Shannon’s entropy model is adopted to define the noise of a concept type to discriminate the homograph. Although it processes for concept type discrimination, many co-occurring concept types, which must be further selected, remain in each LSP and UCW. The Kadokawa concept codes are used for the purpose of concept generalization of words in LSPs and UCWs. All words in LSPs and UCWs are annotated with the three-digit concept codes in the Kadokawa thesaurus. For each word senses of a homograph, the frequency of concept codes in LSPs and UCWs shows a very different distribution. So we performed concept generalization by using the different distribution. Finally, manual processing was performed to generate the ontological relation instances from the generalized LSPs and UCWs. The results obtained include approximately about 3,701 case relations and 1,650 other semantic relations from 9,245 LSPs and UCWs with their frequencies. Table 2 presents some samples of ontological relation instances. The obtained instances are inserted into the initial LIP ontology.

Source Concept Code (Governor)	Semantic Relation	Destination Concept Code (Dependent)	Freq.
346 (question)	agent	543 (ruler)	35
743 (increase)	theme	171 (price)	72
344 (plan)	theme	419 (bill)	64
394 (construct)	theme	369 (business)	108
381 (exercise)	theme	449 (right)	21
719 (nation)	location	706 (city)	99
71 (group)	has-member	5 (person)	100
290 (bind)	reason	449 (authority)	12
⋮	⋮	⋮	⋮

Table 2: Samples of ontological relation instances

3 Ontology Learning

To use the LIP ontology in NLP applications, a scoring mechanism was required to determine whether the governor and dependent concepts satisfy their semantic constraints in the LIP ontology. Therefore, in order to measure concept association, we use an association ratio

¹ The Yale Romanization is used to represent Korean lexical words.

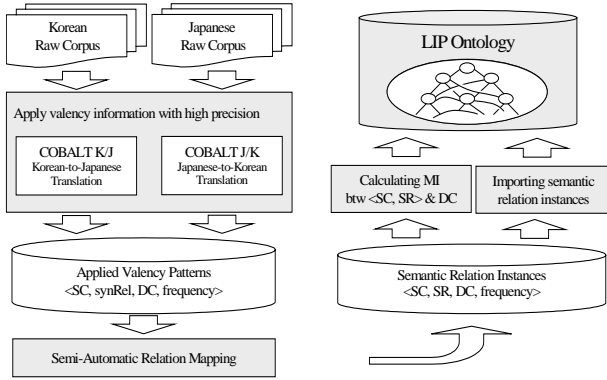


Figure 3: Construction flow of ontology training data

based on the information theoretic concept of mutual information (MI), which is a natural measure of the dependence between random variables (Church & Hanks, 1989). Resnik (1995) suggested a measure of semantic similarity in an IS-A taxonomy, based on the notion of information content. However, his method differs from ours in that we consider all semantic relations in the ontology, not taxonomy relations only. To implement this idea, *source concepts* (*SC*) and *semantic relations* (*SR*) are bound into one entity, since *SR* is mainly influenced by *SC*, not the *destination concepts* (*DC*). Therefore, if two entities, $\langle SC, SR \rangle$, and *DC* have probabilities $P(\langle SC, SR \rangle)$ and $P(DC)$, then their mutual information $I(\langle SC, SR \rangle, DC)$ is defined as:

$$I(\langle SC, SR \rangle, DC) = \log_2 \left(\frac{P(\langle SC, SR \rangle, DC)}{P(\langle SC, SR \rangle)P(DC)} + 1 \right)$$

The MI between concepts in the LIP ontology must be calculated before using the ontology as knowledge for disambiguating word senses. Figure 3 shows the construction process for training data in the form of $\langle SC$ (*governer*), *SR*, *DC* (*dependent*), *frequency* \rangle and the calculation of MI between the LIP ontology concepts. We performed a slight modification on COBALT-K/J and COBALT-J/K to enable them to produce sense-tagged valency information instances with the specific concept codes of the Kadokawa thesaurus. After producing the instances, we converted syntactic relations into semantic relations using the specific rules and human intuition. As a result, we extracted sufficient training data from the Korean raw corpus: KIBS (Korean Information Base System, '94-'97) is a large-scale corpus of 70 million words, and the Japanese raw corpus, which has eight hundred and ten thousand sentences. During this process, more specific semantic relation instances are obtained when compared with previous instances obtained in Section 2. Since such specific instances reflect the context of a practical situation, they are also imported into the LIP ontology. Table 3 shows the final number of semantic relations inserted into the LIP ontology.

4 WSD using the LIP Ontology

The LIP ontology is applicable to many fields. In this paper, we propose to use the ontology to disambiguate word senses. All approaches to WSD make use of words in a sentence to mutually disambiguate each other. The

Types	Number
Taxonomic relations	1,100
Case relations	112,746
Other semantic relations	2,093
Total	115,939

Table 3: Final ontological relation instances in the LIP ontology

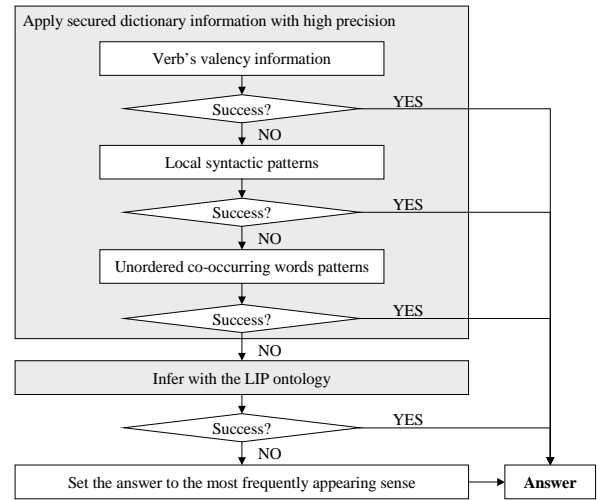


Figure 4: Proposed WSD algorithm

distinctions between various approaches lie in the source and type of knowledge made by the lexical units in a sentence.

Our WSD approach is a hybrid method, which combines the advantages of corpus-based and knowledge-based methods. We use the LIP ontology as an external knowledge source and secured dictionary information as context information. Figure 4 shows our overall WSD algorithm. First, we apply the previously-secured dictionary information to select the correct senses of some ambiguous words with high precision, and then use the LIP ontology to disambiguate the remaining ambiguous words.

The roles of the LIP ontology in WSD are as follows. First, if previously-secured information for a concept is not available in a dictionary, the ontology provides generalized semantic constraints for the concept. The generalized semantic constraints were made in the previous ontology-building and training phase by other semantic constraints, including the same concept code. Second, if direct semantic relation between concepts is not available in the LIP ontology, the ontology and its scoring mechanism provide a relaxation procedure, which approximates their semantic association. The following are detailed descriptions of the procedure for applying the LIP ontology to WSD work.

4.1 Locate the Least Weighted Path from One Ontology Concept to Other Concept

If MI is regarded as a weight between ontology concepts, the LIP ontology can be treated as a graph with weighted edges. All edge weights are non-negative and weights are

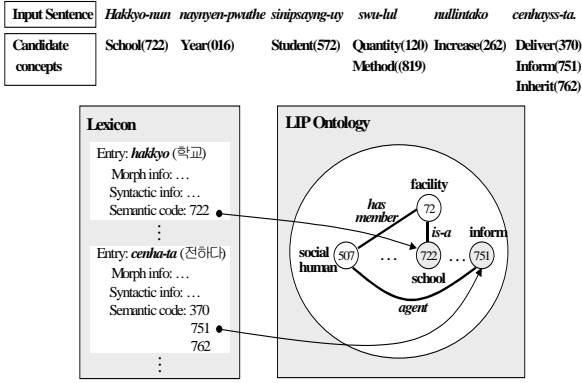


Figure 5: Example of the best path between the words “*hakkyo* (school)” and “*cenhata* (inform)” in the LIP ontology

converted into penalties by the formula below. c indicates a constant, maximum MI between concepts of the LIP ontology.

$$Pe(< SC, SR >, DC) = c - I(< SC, SR >, DC)$$

We use the formula below to locate the least weighted path from one concept to the other concept. The score function S is defined as:

$$S(C_i, C_j) = \begin{cases} 1 & \text{if } C_i = C_j, \\ \min_p (Pe(< C_i, R_p >, C_j)) & \text{if } C_i \neq C_j \text{ and } C_i \xrightarrow{R_p} C_j, \\ \min_{C_k \in \{C_i \rightarrow C_j\}} (S(C_i, C_k) + S(C_k, C_j)) & \text{if } C_i \neq C_j, \text{ and } C_k \xrightarrow{R_p} C_j. \end{cases}$$

Here C and R indicate concepts and semantic relations, respectively. By applying this formula, we can verify how well selectional constraints between concepts are satisfied. In addition, if there is no direct semantic relation between concepts, this formula provides a relaxation procedure, which enables it to approximate their semantic relations. This characteristic enables us to obtain hints toward resolving metaphor and metonymy expressions.

For example, the input sentence “*hakkyo-nun naynyen-pwuthe sinipsayng-uy swu-lul nullintako cenhayss-ta*” means “the school decided to increase the number of enrollment from the next year.” Figure 5 shows the best path between the words “*hakkyo* (school)” and “*cenhata* (inform)”, indicated in bold lines. In the case of selecting the correct sense among candidate senses of the word “*cenhayss-ta*”, there is no applicable dictionary information among candidate senses of other words. In addition direct semantic relations are not available in the generalized case frame between the word “*hakkyo*” and “*cenhata*,” so the score function provides the following relaxation process. The concept “school” is a “facility,” and the “facility” has “social human” as its members. The concept “inform” has “social human” as its agent.

To locate the best path, the search mechanism of our LIP ontology applies the following heuristics. Firstly, a taxonomic relation must be treated as exceptional from

other semantic relations, because they inherently lack frequencies between parent and child concepts. So we experimentally assign a fixed weight to those edges. Secondly, the weight given to an edge is sensitive to the context of prior edges in the path. Therefore, our mechanism restricts the number of times that a particular relation can be traversed in one path. Thirdly, this mechanism avoids an excessive change in the gradient.

5 Experimental Evaluation

For experimental evaluation, eight ambiguous Korean nouns and four verbs were selected, along with a total of 604 test sentences in which one of the homographs appears. The test sentences were randomly selected from the KIBS. Out of several senses for each ambiguous word, we considered only two or three senses that are most frequently used in the corpus. We performed three experiments: The first experiment, BASE, is the case where the most frequently used senses are always taken as the senses of test words. The purpose of this experiment is to show a baseline in WSD work. The second, PTN, uses only secured dictionary information, such as the selectional restriction of verbs, local syntactic patterns, and unordered co-occurring words patterns in disambiguating word senses. This is a general method without an ontology. The third, LIP, shows the results of our WSD method using the LIP ontology. The experimental results are shown in Table 4. In these experiments, the LIP method achieved a 9.2% improvement over the PTN method for Korean analysis. The main reason for these results is that, in the absence of secured dictionary information about an ambiguous word, the ontology provides a generalized case frame (i.e. general semantic constraints) by the concept code of the word. In addition, when there is no direct semantic constraint between concepts, our search mechanism provides a relaxation procedure (see Figure 5). Therefore, the quality and usefulness of the LIP ontology were indirectly proved by these results.

6 Conclusion

In this paper we have proposed a semi-automatic construction method of the LIP ontology and a WSD algorithm using the ontology. The LIP ontology includes substantial semantic relations between concepts, and differs from many of the resources in that there is no language-dependent knowledge in the resource, which is a network of concepts, not words. Semantic relations of the LIP ontology are generated by considering two different languages, Korean and Japanese. In addition, we can easily apply the ontology without additional lexicographic works, since large-scale bilingual dictionaries have words already annotated with concept codes of the LIP ontology. Therefore, our LIP ontology is a language independent and practical knowledge base. Our ontology construction method requires manual processing, i.e., mapping from syntactic relations to semantic relations by specific rules and human intuition. However, this is necessary for building a high-quality semantic knowledge base. Our construction method is quite effective in comparison with other methods. The LIP ontology is applied to our WSD algorithm in the form of an ontological graph search. The search mechanism determines whether selectional constraints between concepts are satisfied or not, and

Homograph	Sense	BASE	PTN	LIP
<i>Pwuca</i>	father & child	76.9	69.2	86.0
	rich man			
<i>Kancang</i>	liver	67.3	87.8	91.8
	soy sauce			
<i>Kasa</i>	housework	48.1	88.5	96.1
	words of song			
<i>Kwutwu</i>	shoe	79.6	85.7	95.9
	word of mouth			
<i>Nwun</i>	eye	82.0	96.0	92.0
	snow			
<i>Yongki</i>	courage	62.0	74.0	82.0
	container			
<i>Kyengpi</i>	expenses	74.5	78.4	90.2
	defense			
<i>Kyeongki</i>	times	52.9	80.4	95.6
	match			
<i>Nayli-ta</i>	get off (a bus)	42.0	72.0	88.0
	draw (a decision)			
	fall (snow)			
<i>Seywu-ta</i>	make (a plan)	54.0	88.0	98.0
	build			
<i>Ssu-ta</i>	use	46.0	86.0	96.0
	write			
	put on (a hat)			
<i>Taywu-ta</i>	burn	50.0	86.0	92.0
	give someone a ride			
Average precision		61.3	82.7	91.9

Table 4: Experimental results of WSD (%)

includes a relaxation procedure, which enables concept pairs with no direct selectional restriction to approximate their semantic association. This characteristic enables us to obtain hints toward resolving metaphor and metonymy expressions. We plan further research on how to effectively divide the grain size of ontology concepts to best express the whole world knowledge, and how to utilize the LIP ontology in a full semantic analysis process.

Acknowledgements

The authors would like to thank the Ministry of Education of Korea for its financial support toward the Electrical and Computer Engineering Division at POSTECH through its BK21 program.

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