PALKA: A System for Lexical Knowledge Acquisition *

Jun-Tae Kim and Dan I. Moldovan

Department of Electrical Engineering-Systems
University of Southern California
Los Angeles, CA 90089-2562

Abstract

In *memory-based* natural language processing, semantic phrasal patterns constitute a main knowledge source for recognizing input sentences. Although the memory-based parsing approach has many advantages, one significant problem is that a very large number of semantic phrasal patterns is needed. Manual creation of patterns is unrealistic, and even for a small application domain, it is very time consuming. To solve the scalability problem, *automatic acquisition* of semantic patterns must be provided. In this paper, we present a practical approach to solve this problem. The PALKA (Parallel Automatic Linguistic Knowledge Acquisition) system acquires semantic patterns from a set of domain specific sample texts and their desired output representations. The acquired patterns are tuned further through generalizations and specializations of semantic constraints. This paper presents the PALKA system and its application to a set of news articles.

1 Introduction

In *memory-based parsing* or *pattern-based phrase recognition*, the parser interprets input sentences by using pre-defined memory structures encoding syntactic, semantic and contextual knowledge. By using such knowledge, or pre-defined memory, one can achieve fast and efficient text processing by directly mapping a surface linguistic pattern to its meaning without full syntactic analysis and without applying conversion rules from syntactic structure to semantic interpretation [14] [7] [11].

The memory-based parsing approach has many advantages, and has been successfully applied to the information extraction from natural language texts [5] [12] [15]. However, one significant problem of this approach is that the parser needs a very large number of semantic phrasal patterns and connections between them for any practical application. Manual creation of semantic patterns is unrealistic, and very time consuming even for a small application domain. To solve the scalability problem, an *automatic acquisition* of semantic patterns must be provided.

Recent approaches to acquisition of semantic patterns include extending the knowledge base of pattern-concept pairs by *direct teaching* [17], acquisition of phrasal lexicon by using the *context* while interacting with user [18], and acquisition of surface semantic patterns from text by using *syntax to semantic rules* which associate possible semantic interpretation to each syntactic pattern [16] [13]. These approaches rely either on an intensive user interaction or on knowledge sources which are difficult to provide in practical applications.

In this paper, we present a practical approach to the semantic pattern acquisition and describe an acquisition system prototype PALKA. The major goal of this system is to facilitate the construction of a large knowledge base of semantic patterns. In contrast to previous approaches, our approach emphasizes the practicality of the acquisition system, by allowing only a small amount of user interaction and by using the knowledge sources that are either available on-line or easily constructed for specific domains. PALKA acquires semantic patterns from a set of domain specific sample texts and their desired output representations. The acquired patterns are further tuned through a series of generalizations and specializations of semantic constraints.

The memory-based parser mentioned in this paper was used for the MUC-4 domain[1] [12]. The natural language processing system was implemented on a marker-

*This research has been funded by the National Science Foundation Grant No. MIP 9009109.

CIKM '93 - 11/93/D.C., USA
© 1993 ACM 0-89791-626-3/93/0011 ....$1.50

[1] The Fourth Message Understanding Conference sponsored by DARPA. The task of MUC-4 is to extract information on terrorist

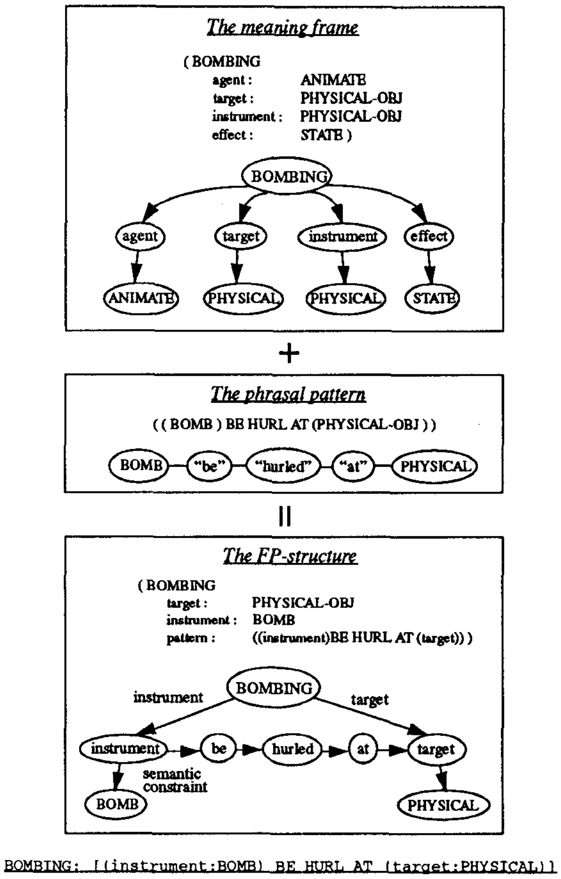

Figure 1: The frame-phrasal pattern representation

passing parallel computer called SNAP [11]. Parallel processing methods are also used to implement the acquisition system. Since our acquisition method is closely related to the parser, we use the example sentences and target representations from the MUC-4 corpus to describe PALKA. However, PALKA can be easily adapted to other domains if appropriate knowledge sources are provided.

2 The Acquisition Task

The task of acquisition system is to build a knowledge base of semantic phrasal patterns by using a relatively small number of domain text examples and their desired output representations. In this section, we present the representation of semantic patterns and the basic approach to the acquisition task.

2.1 Representation of semantic patterns

In memory-based parsing, linguistic knowledge is represented as a network of semantic phrasal patterns. A semantic phrasal pattern is a pair of a meaning frame

incidents from news articles.

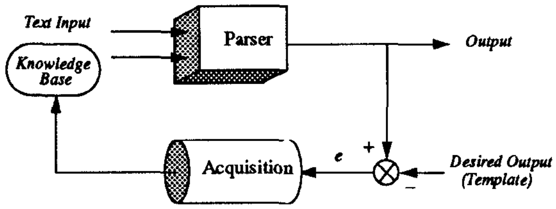

Figure 2: Conceptual diagram of acquisition as a feedback to the parser

and a phrasal pattern, which is called the *FP-structure* (Frame-Phrasal pattern structure) [6]. The knowledge base is organized as a network of FP-structures and a concept hierarchy.

Figure 1 shows an example of an FP-structure. A semantic frame is represented by a set of slots and their semantic constraints on fillers. A phrasal pattern is an ordered combination of concepts and lexical entries. A phrasal pattern of an FP-structure maps a surface linguistic pattern to the root concept of a frame that represents the meaning of that phrase. To combine a phrasal pattern and a meaning frame, each slot of the frame is linked to the corresponding element in the phrasal pattern. The input words are connected to each element in the FP-structure through the *isa* hierarchy of concepts. This representation is similar to the *pattern-concept pair* presented in [17], except that the concept is represented as a frame, and each slot of the frame is mapped to an element in the phrasal pattern.

As one can see in the example, the meaning of the phrase - or the category of the event - cannot be simply recognized by the main verb. There can be many different domain dependent expressions for the BOMBING event, and such patterns can only be acquired by looking at actual domain corpus.

Our parser is based on *marker-passing* paradigm [11]. The parsing algorithm consists of repeated applications of top-down expectations and bottom-up activations. When an input word is read, a bottom up activation is propagated from the lexical entry through the concept hierarchy. If an expected element receives an activation from its constraint, it is verified, and the expectation moves to the next element. Parsing succeeds if all elements in a pattern are verified. When the parsing succeeds, an instance of the FP-structure is generated as a result of recognition. More details of the parsing procedure can be found in [11].

2.2 Basic approach to the acquisition

Acquisition as a feedback to the parser

In our approach to the semantic knowledge acquisition, the acquisition process performs as a *feedback* to the parser. Depending on the current status of the

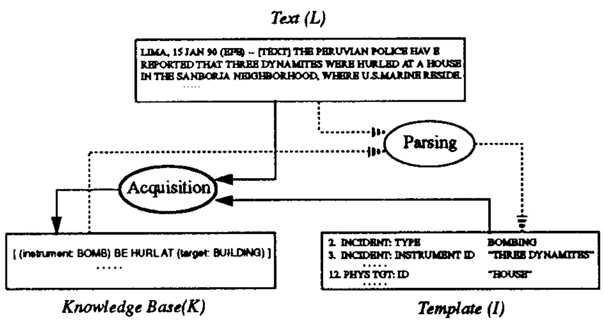

Figure 3: Knowledge acquisition as a reverse process of parsing

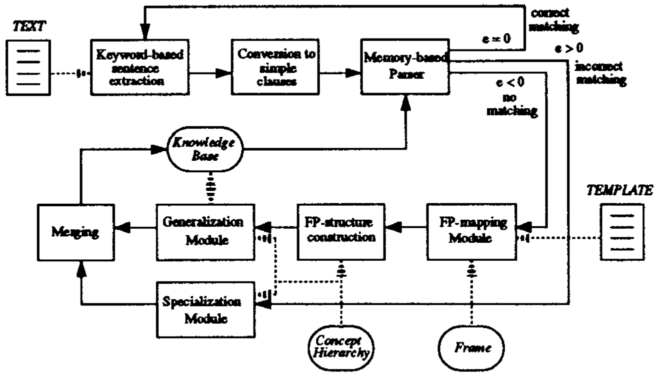

Figure 4: The functional structure of PALKA

knowledge base, the parser may produce one of the following results: (1) Correct interpretation, (2) No interpretation, or (3) Incorrect interpretation. Examples of each case and corresponding actions by the acquisition system are as follows:

- *Case 1:* Correct interpretation (*parser output = desired output*).
  1. Pattern: Appropriate
  2. Action: None

- *Case 2:* No interpretation (*parser output* $= \emptyset$, *desired output* $\neq \emptyset$).
  1. Pattern: BOMBING: [(instrument: DYNAMITE) EXPLODE] (or None)
  2. Sentence: *"A powerful bomb exploded in front of the building"*
  3. Interpretation: None
  4. Action: Create a new pattern and generalize it

- *Case 3:* Incorrect interpretation (*parser output* $\neq \emptyset$, *desired output* $= \emptyset$).
  1. Pattern: BOMBING: [(instrument: THING) EXPLODE]
  2. Sentence: *"The foreign debt crisis exploded in Andean countries"*
  3. Interpretation: BOMBING-EVENT, instrument = "foreign debt crisis"
  4. Action: Specialize the pattern

In case 2, the parser produces no interpretation since the semantic constraint DYNAMITE is too specific to be matched by the input sentence. In this case, a new pattern is created from the input sentence, and generalized with previous patterns. In case 3, the input sentence is misinterpreted as a BOMBING event since the semantic constraint is overgeneralized as THING. In this case, the semantic constraint is specialized to an appropriate level.

Figure 2 shows the concept of acquisition feedback (This is only a *conceptual* diagram, so several knowledge sources are omitted). Through the acquisition process described above, the system creates a consistent and semantically correct knowledge base.

Acquisition as a reverse process of parsing

When new knowledge is needed, the creation of a semantic pattern is regarded as a reverse process of parsing. Parsing process is to extract information (I) contained in natural language text (L) by using semantic knowledge (K). The acquisition process is to extract necessary semantic knowledge (K) from language (L) by using the information (I) which is available. So, the relationship between parsing and acquisition can be represented as follows:

$$\text{Parsing: } (L, K) \rightarrow I$$
$$\text{Acquisition: } (L, I) \rightarrow K$$

The relationship between parsing and acquisition is shown in Figure 3. In our system, the MUC-4 corpus of news articles is used as L, and the desired output of each article (*template*)[2] is used as I. From L and I, the system generates knowledge base K, which is a collection of domain dependent semantic patterns.

3 Knowledge Acquisition with PALKA

PALKA is an automatic semantic pattern acquisition tool. It acquires domain dependent semantic patterns for a given frame. The phrasal patterns (collocational information) are acquired from texts, and mappings to the frame (semantic information) are acquired from templates. Figure 4 shows the functional structure of the PALKA system. For a given frame definition, the acquisition system selects candidate sentences which may have relevancy, and converts them into simple clauses. After trial parsing, the user determines the

[2] Currently, 1400 news articles on terrorist domain and their corresponding templates are available on line.

correctness of parsing output. If there is no output for relevant sentence ($e < 0$), a new FP-structure is created through *FP-mapping*, *FP-structure construction*, and *generalization*. If the output is incorrect ($e > 0$), the matched pattern in the knowledge base is modified through *specialization*. In this section, the acquisition procedure is described in detail with examples.

3.1 The knowledge Source

Two major knowledge sources are the *text* and the *template*. A *text* is a set of natural language sentences describing domain specific events. The domain currently used is concerned with terrorist events in Latin America, and the text is a set of news articles. PALKA uses the text to acquire phrasal patterns. A *template* is a desired output representation of a sample text which is generated by hand. It contains all the information that should be extracted from the text. PALKA uses the templates to map a phrasal pattern to a corresponding frame. When templates are not available, PALKA acquires the mapping information through the user interaction. Other knowledge sources used by PALKA are:

- The *frame definition* represents the type of information to be extracted from the domain texts. The frame definition of BOMBING is described in the next section.
- The *concept hierarchy* contains general classification of objects, events and states, and domain specific concepts. It is used to specify a semantic constraint of each element in an FP-structure. It is also used for generalization and specialization of patterns.
- The *dictionary* maps an input word to one or more concepts in the concept hierarchy. For example, "dynamite" is mapped to concept BOMB, and "house" is mapped to concept BUILDING, which is linked to concept PHYSICAL-OBJECT through *isa* relations.

3.2 Frame definition and sentence extraction

The acquisition of semantic patterns is performed for one frame at a time. For example, the system first acquires all the patterns for BOMBING event frame, and then for KILLING frame, and so on. In what follows, the acquisition procedure in PALKA is described by using the BOMBING frame example. The BOMBING frame is defined as:

```
(BOMBING
      isa:         (TERRORIST-ACTION)
      keyword:     (bomb bombing dynamite explode explosion ...)
      agent:       (ANIMATE)
      target:      (PHYSICAL-OBJECT)
      instrument:  (PHYSICAL-OBJECT)
      effect:      (STATE))
```

The first slot *isa* points to a more general frame in the knowledge base to which this frame is connected. In the second slot *keyword*, several keywords are specified. Relevant sentences are extracted from the sample texts by using these keywords. The other 4 slots - *agent*, *target*, *effect*, and *instrument* - indicate the types of information used in this domain. For each slot, a semantic constraint is specified. By using the keyword *"dynamite"*, the following sentence is extracted from the text, as a possible relevant one.

THE PERUVIAN POLICE HAVE REPORTED THAT THREE DYNAMITES WERE HURLED AT A HOUSE IN THE SANBORJA NEIGHBORHOOD, WHERE U.S. MARINE RESIDE.

3.3 Conversion to simple clauses

The original text consists of complex sentences which contain relative clauses, nominal clauses, conjunctive clauses, etc. Since semantic patterns are acquired from simple clauses, it is necessary to convert a complex sentence to a set of simple clauses. A simple phrasal parser converts the extracted sentence into simple clauses through the following steps.

Step 1: Grouping words
The phrasal parser groups words based on each word's syntactic category and ordering rules for noun-groups and verb-groups. Basic syntactic disambiguation of word category is performed at this stage. The result of grouping words for the example sentence is:

```
[THE PERUVIAN POLICE]noun-group
[HAVE REPORTED]verb-group
[THAT]rel-pronoun
[THREE DYNAMITES]noun-group
[WERE HURLED]verb-group
[AT]preposition
[A HOUSE]noun-group
[IN]preposition
[THE SANBORJA NEIGHBORHOOD]noun-group
[,]punctuation
[WHERE]rel-pronoun
[U.S. MARINE]noun-group
[RESIDE]verb-group
[.]punctuation
```

Step 2: Simplification and decomposition
After grouping is performed, the phrasal parser first simplifies the sentence by eliminating several unnecessary elements such as determiners, adverbs, quotations, brackets, and so on. Then it converts the simplified sentence into several simple clauses by using several conversion rules. The conversion rules include separation of relative clause, nominal clause, and conjunctive clause. The following three simple clauses are the results of the phrasal parsing.

1. [PERUVIAN POLICE] [HAVE REPORTED] [IT]
2. [THREE DYNAMITES] [WERE HURLED] [AT] [HOUSE]

[IN] [SANBORJA NEIGHBORHOOD]
3. [U.S. MARINE] [RESIDE] [IN]
[SANBORJA NEIGHBORHOOD]

Based on the keywords specified in the BOMBING frame, only the second clause is selected for further processing. To describe the *FP mapping module* and the *FP-structure construction*, we assume that the output of the memory-based parser of clause 2 is NIL (i.e., $e < 0$).

3.4 FP mapping module

At this point, the definition of the BOMBING frame is available (the *meaning frame*), and the simple clause pattern was extracted (the *phrasal pattern*). To construct an FP-structure from these, links between the frame slots and the phrasal pattern elements should be established. There are two different modes of operation to find out the mapping according to the availability of templates.

1) Automatic mapping mode: If the templates are available[3], PALKA finds out the mapping by using the information in the corresponding template (Figure 3 shows a part of the template for our example.) Each slot of the frame definition corresponds to one or more slots in the template. For example, the *target* slot of the frame corresponds to the PHYS TGT: slot and HUM TGT: slot of the template. For each slot of the frame, the system searches through the template to pick up fillers for that slot. Then each element in the phrasal pattern is compared with the fillers collected. If an element is matched with the filler, then a link between the corresponding slot and the matched element is made.

2) Interactive mapping mode: In case the templates are not available, PALKA first finds out candidates for each slot by using the general semantic constraint specified for each slot in the frame definition, and then establish the mapping through the user interaction. For example, the general semantic constraint of the *target* slot is PHYSICAL-OBJECT, and so the candidate elements for *target* slot are the "three dynamites" and "house", since their semantic categories are under the concept PHYSICAL-OBJECT in the concept hierarchy. The candidates for each slot are presented to the user, and user selects one for each slot.

The following mapping is obtained after the FP mapping procedure. The *agent* and *effect* slots are not linked, since either 1) no elements are matched to the fillers of corresponding slots in the template or 2) no candidates which satisfy the semantic constraint are found.

[THREE (instrument: DYNAMITES)] [WERE HURLED] [AT]
[(target: HOUSE)] [IN] [SANBORJA NEIGHBORHOOD]

[3] Also, a semantically tagged texts can be used to provide necessary mapping information.

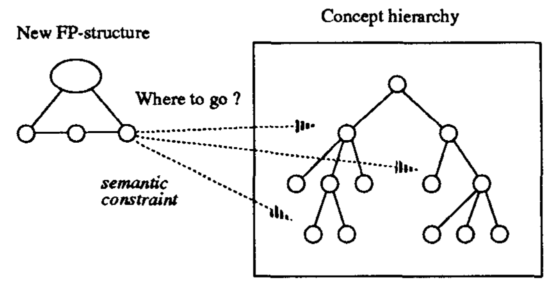

Figure 5: The generalization problem

3.5 FP-structure construction

After all the links are established, PALKA constructs an FP-structure based on the mapping information. The basic strategy for constructing an FP-structure is to include the mapped elements and the main verb, and discard the unmapped elements. Some basic rules for FP-structure construction are as follows:

rule 1. All mapped elements are replaced by their semantic categories.

rule 2. If a mapped element in noun group is a head noun, the whole group is replaced by that element. If it is not, the remaining elements are included too.

rule 3. All unmapped prepositional phrases are discarded.

rule 4. An unmapped noun group is also included after replaced by the semantic category of its head noun, if it is not a part of a prepositional phrase.

rule 5. All verbs are replaced by their root forms and all auxiliary verbs except the be-verb in passive form are discarded.

By applying rules 1 and 2, the noun groups "THREE DYNAMITES" and "HOUSE" are replaced respectively by the concepts BOMB and BUILDING. After applying rules 3 and 5, the prepositional phrase "IN SANBORJA NEIGHBORHOOD" is discarded, and the verb group "WERE HURLED" is replace by BE HURL. The final form of the FP-structure acquired from the example sentence is as follows:

```
(BOMBING
    target:     (BUILDING)
    instrument: (BOMB)
    pattern:    ((instrument) BE HURL AT (target)))
```

3.6 Generalization and Specialization

The next step after the FP-structure construction is the generalization of the acquired pattern. The goal of generalization is to determine an optimal level of generalization for each element's semantic constraint in the phrasal pattern. Figure 5 shows this problem. The semantic constraint of each element is given by a concept or a disjunction of concepts in the concept hierarchy.

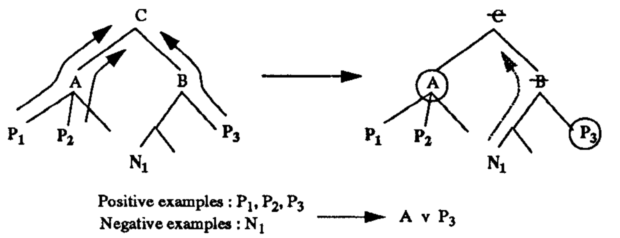

Figure 6: Inductive determination of semantic constraint

It determines the coverage of the phrasal pattern. As mentioned in Section 2.2, if the constraint is given too specific, it may miss a sentence, and if it is given too general, it may be matched incorrectly.

Since the semantic category of a newly created pattern is determined to be the most specific one, it should be generalized if possible. The acquired FP-structure is compared with existing ones for further generalization. Whenever two FP-structures with the same phrasal patterns are generated, their semantic constraints are generalized. When an overgeneralized pattern is found (incorrect matching), the corresponding semantic constraint is specialized.

In PALKA, the inductive learning method [8] [10] is applied to the generalization of semantic constraints. For induction, the semantic constraint of a newly created pattern is used as a positive example, and the semantic constraint of an incorrectly matched pattern is used as a negative example.

While sentences are processed, the PALKA keeps lists of example semantic constraints for each FP-structure. When a positive example is encountered, the example concept is added to the positive list (P). When a negative example is encountered, the example concept is added to the negative list (N). The generalization is performed at the end of the acquisition process by using those positive and negative example lists.

The generalization is to detect the ***most general concepts*** among the ***consistent concepts*** which subsume the positive examples and do not subsume the negative examples. Let $Sup(S)$ be a set of all subsumers (parents) of the concepts in the set S, CS be a set of consistent semantic constraints, and $MGCS$ be a disjunction of most general concepts among CS. Then, $Sup(P)$ is the set of all hypotheses for consistent semantic constraint, and among them, $Sup(N)$ must be eliminated since they produce incorrect interpretations. Therefore, the set $Sup(P)-Sup(N)$ represents the set of consistent semantic constraint CS. The most general concepts are selected from CS, and combined with disjunctions to form the final semantic constraint. The most general concepts in a set are the concepts which do not have their subsumers in the set.

frame	sentence extracted	patterns acquired	generalization	specialization	FP-structure created	average creation
BOMBING	220	89	22	5	67	30.5 %
KILLING	601	108	71	12	37	6.2 %

Figure 7: Result of the acquisition from 500 MUC4 texts

Figure 6 shows an example of generalization procedure. P_1, P_2, and P_3 are positive examples, and N_1 is a negative example. In this example, the $Sup(P)$ and $Sup(N)$ are:

$$Sup(P) = Sup(\{P_1, P_2, P_3\}) = \{C, A, B, P_1, P_2, P_3\}$$
$$Sup(N) = Sup(\{N_1\}) = \{C, B, N_1\}$$

Therefore, the consistent constraint set is:

$$CS = Sup(P) - Sup(N) = \{A, P_1, P_2, P_3\}$$

Since A and P_3 are the most general concepts, the semantic constraint is determined as:

$$\textit{Result semantic constraint} = MGCS = (A \vee P_3).$$

In case there were no negative examples (no specialization occur), a semantic constraint is generalized to the highest level concept in the concept hierarchy according to above procedure. There are two possible ways to prevent this: 1) Select the most specific concept among those which subsume ***all*** the positive examples. 2) Put limitations to the maximum generalizable level.

In our example, the semantic constraint of the ***instrument*** slot is generalized from BOMB to EXPLOSIVE, and the ***target*** slot is generalized from BUILDING to PHYSICAL-OBJECT by using the method 1).

3.7 Experimental Results

The PALKA prototype is implemented using C on SUN workstation. A preliminary experiments have been performed with 500 MUC-4 texts to acquire FP-structures for the BOMBING frame and the KILLING frame. Each text contains approximately 14 sentences on average. The time spent for the acquisition was about 5 hours including manual post-processing such as minor corrections of the phrasal pattern form. Although only two frames and 500 texts were used in this experiment, the time to create semantic patterns is significantly reduced compared with manual creation.

Figure 7 shows the total number of sentences extracted for each frame from 500 texts, number of new FP-structure acquired, number of generalization and specialization performed, number of final FP-structure, and the average number of FP-structure created per sentence. The result shows that 30 % of processed sentence produced a new FP-structure for BOMBING frame, but only 6 % of the sentence produced a new one

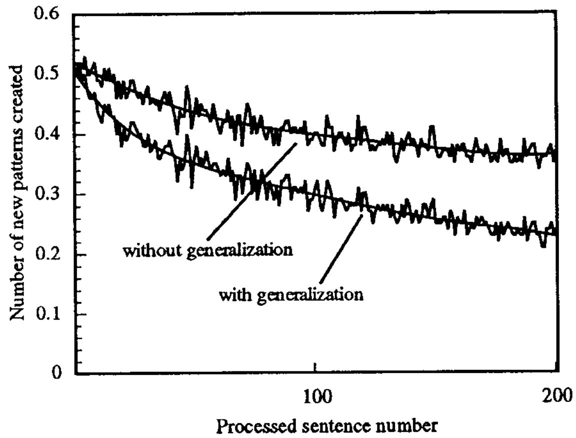

Figure 8: Average number of patterns created for BOMBING frame

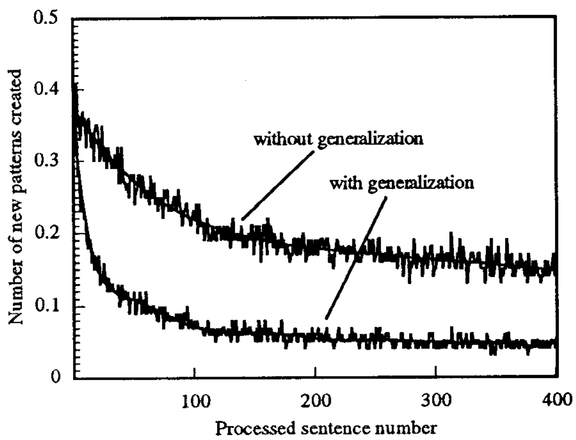

Figure 9: Average number of patterns created for KILLING frame

for KILLING frame. This shows that a relatively small number of different expressions is used to describe the KILLING event in this domain. As an example, the pattern "((target) BE KILL)" was found 97 times during the acquisition process.

A basic assumption of our approach to semantic pattern acquisition is that only a finite number of expressions are frequently used in a specific domain to represent a specific event. In other words, the patterns acquired from a relatively small number of sample texts can cover a much larger number of texts from the same domain. The growth of the knowledge base eventually becomes saturated.

Figure 8 and 9 show the changes of acquisition rates for BOMBING and KILLING frames while processing 500 texts. Since the acquisition rate varies depending on the order of sentences processed, 100 experiments were performed with random re-ordering of sentences and the results are averaged. In Figure 8, the acquisition rate decreases but not saturated yet. This is because 1) there were only 200 related sentence examples found, and 2) as mentioned earlier, relatively large number of expressions are used to describe the BOMBING event. More example sentences are needed to reach to the saturation. In Figure 9, the acquisition rate for KILLING frame is almost saturated when 200 sentence examples are processed (only 2/3 of total processing is shown.) In both cases, it is clear that the acquisition rate strictly decreases, which means that the size of the knowledge base approaches the saturation point. Also, in both experiment, the effect of generalization on the acquisition rate is clearly shown. With generalization, the acquisition rate decreases more rapidly, because some of the patterns are not actually created but generalized with others.

4 Conclusion

In this paper, a practical approach to the acquisition of semantic phrasal patterns and an implementation of the approach were presented. The semantic pattern is represented as a pair of a meaning frame and a phrasal pattern. The phrasal patterns (collocational information) are acquired from texts, and mappings to the frame (semantic information) are acquired from templates or from the user. The acquired semantic patterns are further tuned through generalizations and specializations of their semantic constraints. The experiments using PALKA with 500 MUC-4 domain texts demonstrates the feasibility of our approach. The time to construct knowledge bases of semantic patterns can be significantly reduced.

One limitation of our approach is that we acquire only semantic patterns for verb-oriented clauses. To provide more detailed information for each slot of the frame, semantic patterns for noun phrases should also be acquired. To do that, the use of other knowledge sources such as on-line dictionary are being considered for future work. This is also important when the desired output representation of the sample text is not available. Using on-line dictionary and tagged corpus can be a feasible solution. Also, in the current implementation, the relations between different semantic patterns are not investigated. Establishing such relations is desirable for both efficiency of representation and flexibility of interpretation. These possibilities are being considered for further improvements of the system.

References

[1] J. D. Becker, "The phrasal lexicon", *Bolt Beranek*

and Newman Inc. Report No. 3081, 1975.

[2] R. C. Berwick, *The Acquisition of Syntactic Knowledge*, The MIT press, 1985.

[3] R. J. Brachman and J. G. Schmolze, "An overview of the KL-ONE knowledge representation system", *Cognitive Science*, vol. 9, 1985.

[4] A. Hauptmann, "From syntax to meaning in natural language processing", *Proceedings of the 10th National Conference on Artificial Intelligence (AAAI-91)*, 1991.

[5] J. R. Hobbs, D. Appelt, M. Tyson, J. Bear and D. Israel, "FASTUS: System summary", *Proceedings of Fourth Message Understanding Conference (MUC-4)*, 1992.

[6] J.-T. Kim and D. Moldovan, "Acquisition of semantic patterns for infomation extraction from corpora", *Proceedings of Ninth Conference on AI applications*, 1993.

[7] H. Kitano, "ΦDM-Dialog. An experimental speech-to-speech dialog translation system", *IEEE Computer*, June, 1991.

[8] R. Michalski, "A theory and methodology of inductive learning", *Artificial Intelligence, Vol. 20*, 1983.

[9] M. Minsky, "A framework for representing knowledge", in *The Psychology of Computer Vision*, P. H. Winston (ed.), McGraw-Hill Book Co., New York, 1975.

[10] T. Mitchell, "Generalization as search", *Artificial Intelligence, Vol. 18*, 1982.

[11] D, Moldovan, W. Lee, C. Lin, and M. Chung, "SNAP: Parallel processing applied to AI", *IEEE Computer*, June, 1992.

[12] D. Moldovan, S. Cha, M. Chung, K. Hendrickson, J. Kim and S. Kowalski, "Description of the SNAP system used for MUC-4 ", *Proceedings of Fourth Message Understanding Conference (MUC-4)*, 1992.

[13] M. T. Pazienza and P. Velardi, "Methods for extracting knowledge from corpora", *Proceedings of the 5th Annual Workshop on Conceptual Structures*, 1990.

[14] C. K. Riesbeck and C. E. Martin, "Direct memory access parsing", *Report 354*, Dept. of Computer Science, Yale University, 1985.

[15] Ellen Riloff and Wendy Lehnert, "Automated dictionary construction for infomation extraction from text", *Proceedings of Ninth Conference on AI applications*, 1993.

[16] P. Velardi, M. T. Pazienza and S. Magrini, "Acquisition of semantic patterns from a natural corpus of texts", *ACM SIGART Newsletter*, No. 108, April 1989.

[17] R. Wilenski, Y. Arens and D. Chin, "Talking to UNIX in English: An overview of UC", *Communications of the ACM*, Vol. 27, No. 6, 1984.

[18] U. Zernik, *Strategies in Language Acquisitions: Learning Phrases from Examples in Context*, Ph.D Dissertation, Computer Science Dept., UCLA, 1987.

[19] U. Zernik (ed.), *Lexical Acquisition: Exploiting On-Line Resources to Build a Lexicon*, Lawrence Erlbaum Associates, NJ, 1991.