A Practical Chunker for Unrestricted Text

E. Stamatatos, N. Fakotakis, and G. Kokkinakis

Dept. of Electrical and Computer Engineering
University of Patras
26500 Rio, Greece
stamatatos@wcl.ee.upatras.gr

Abstract. In this paper we present a practical approach to text chunking for unrestricted Modern Greek text that is based on multiple-pass parsing. Two versions of this chunker are proposed: one based on a large lexicon and one based on minimal resources. In the latter case the morphological analysis is performed using exclusively two small lexicons containing closed-class words and common suffixes of the Modern Greek words. We give comparative performance results on the basis of a corpus of unrestricted text and show that very good results can be obtained by omitting the large and complicate resources. Moreover, the considerable time cost introduced by the use of the large lexicon indicates that the minimal-resources chunker is the best solution regarding a practical application that requires rapid response and less than perfect parsing results.

1 Introduction

Nowadays, there is a wealth of texts available in electronic form, in large databases. These databases include unrestricted texts of any length and complexity. Such texts usually contain headlines and other non-sentential fragments, dialects and colloquial forms, and plenty of words that are not part even of the largest machine-readable lexicon. On the other hand, they may be ill-formed, especially in the case of databases including electronic texts taken from optical character recognition tools.

In general, the goal of a parser is to assign appropriate labels to input texts. Many Natural Language Processing (NLP) applications (e.g., information extraction, information retrieval, etc.) require fast and robust parsing of large volumes of unrestricted text. In such applications obtaining less than perfect parsing results but rapidly is very important.

Special attention has to be paid on low-level tasks such as text segmentation, sentence boundary detection, and *text chunking* (or intrasentential phrase boundaries detection). A closer look to these tasks, that are prerequisite for the vast majority of NLP applications, proves that their insufficient solution may cause considerable losses of accuracy of a consequent, more complicate task, especially in the case of dealing with unrestricted text. A sufficient solution of a low-level problem has the following desiderata:

- *Minimal computational cost*: It is not efficient for a low-level task to demand excessive computational cost, or to be based on complicated, time-consuming and hard-to-build resources such as large lexicons containing at least thousands of lexical entries and large grammars consisting of hundreds of thousands of rules, etc. [1].
- *Use of non-specialized information*: A system performing a low-level task has to be based on easily available resources rather than specialized information that is not necessary to subsequent tasks.
- *Robustness*: The unknown word problem is substantial to parsers based on large lexicons. Some approaches use heuristics (e.g. the recognition of certain suffixes or the case of the first letter in order to identify proper names) or simply ignore all the unknown words and try to parse the remaining part of the text [2]. Recently, several systems utilize statistical methods in order to assign the most likely morpho-syntactic information to the words not found in the lexicon [3, 4].

In this paper we present a practical approach to text chunking for unrestricted Modern Greek text that is based on multiple-pass parsing, an alternative technique to the traditional left-to-right parsing. This technique has been applied mainly to statistical parsers in order to improve parsing results [5] as well as in speech processing as a way to reduce computation substantially, without an increase in error rate [6]. Specifically, two versions of the proposed chunker are presented regarding the morphological analysis of the words that compose the text:

- The first one is based on a large lexicon together with a keyword lexicon and unknown word guessing techniques (called hereafter the lexicon-based chunker), and
- The second one is based exclusively on a keyword lexicon and word-guessing techniques, in other words the large lexicon is omitted (called hereafter the minimal-resources chunker).

The next section deals with relevant work in text chunking. Section 3 describes the proposed approach in detail. Then, some comparative performance results of the two versions are given in section 4. Finally, the conclusions drawn by this study are given in section 5.

2 Relevant Work

The term *text chunking* refers to techniques used for dividing sentences into relatively simple syntactic structures, such as noun phrases and prepositional phrases. It has been proposed by Abney [7] as a useful precursor to full parsing.

A parser for Modern Greek texts is presented in [8]. This parser is able to mark the type of clauses contained in long sentences as well as to identify the phrases included in these clauses, based on a set of keywords and a set of heuristic rules. An accuracy of 84% is reported (this percentage increases to 96% after the use of some enhanced heuristics). This approach requires complete morphological analysis of every word included in the text. Moreover, when the text contains unknown words or extremely complicated syntax it fails to return any useful information.

A language-independent system for parsing unrestricted text based on Constraint Grammar formalism is presented in [1]. It is able to accurately disambiguate morphologically and syntactically any piece of text. However, it requires a very large master lexicon and some domain-specific lexicons used during morphological analysis as well as a large grammar containing thousands of rules.

On the other hand, shallow parsers provide analyses that are less complete than the output of conventional parsers. A shallow parser typically identifies some phrasal constitutes, such as noun phrases, without indicating their internal structure and their function in the sentence [9].

A text chunker using transformation-based learning is described by Rashaw and Marcus [10]. This approach has achieved recall and precision rates of roughly 92% for simple noun phrase chunks and 88% for somewhat more complex chunks that partition the sentence. Moreover, a stochastic approach to text chunking using Markov models is described by Skut and Brants [11]. However, both of these approaches require a part-of-speech tagger of high accuracy.

LEXTER [12] is a surface-syntactic analyzer that extracts maximal-length noun phrases from French texts for terminology applications. It is claimed that 95% of all maximal length noun phrases is recognized correctly, but no precision results are mentioned. Another maximal-length noun phrase extractor is *NPTool* [13]. This tool is based on a handcrafted lexicon and two finite state parsers, one noun phrase hostile and one noun phrase friendly. The combination of these parsers produces a list of acceptable noun phrases that can be used for terminological purposes. The reported recall and precision results are 98.5-100% and 95-98% respectively, evaluated against a 20,000-word corpus including texts from different domains. An efficient partial parser that combines enhanced part-of-speech tags, called *supertags*, with a lightweight dependency analyzer is presented by Srinivas [14]. The reported recall and precision rates for noun chunking are 93% and 91.8% respectively.

Last but not least, *FASTUS* described in [2], is a system for extracting information from English texts which works as a cascaded, non-deterministic automaton. This system initially tries to recognize basic noun and verb phrases, by using a finite-state grammar, and then identifies complex phrases by combining the simple ones. Unknown or otherwise unanalyzed words are ignored in subsequent processing unless they occur in a context that indicates they could be names. The comparison of *FASTUS* to more sophisticated systems show that one can go a long way with simple techniques and achieve very good parsing results very fast [15].

3 System Description

Our solution attempts to take advantage of some linguistic characteristics of Modern Greek in order to minimize the required resources. Particularly:

- Modern Greek is a quasi-free word order language. Thus, the sequence of the chunks may be changed without affecting the meaning of the sentence.

- Its morphology is extremely rich including a wealth of inflectional categories identified generally by word suffixes. It is worth noting that Sgarbas and his colleagues [16] propose 99 inflectional categories in order to cover the nouns of Modern Greek.
- Modern Greek verbs usually have characteristic endings different from all other inflectional parts-of-speech.
- The use of articles and particles usually indicating the start of noun and verb phrases respectively is very common, even in front of proper names. The identification of the beginning of simple phrases is therefore relatively easy.

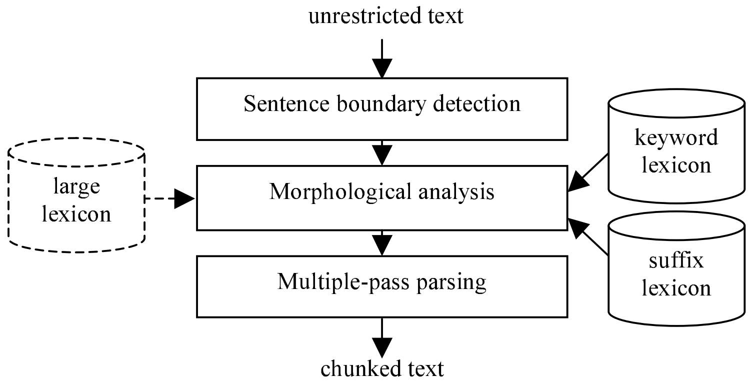

Fig. 1. Overview of the proposed text chunker. The large lexicon may be included (lexicon-based chunker) or omitted (minimal-resources chunker).

An overview of the proposed system is given in figure 1. Initially, the input text is segmented into sentences using a sentence boundary detector trained for Modern Greek [17]. Then, each word of the sentence is analysed morphologically as described in the next subsection. The chunk boundaries are identified by applying multiple passes to the input text as described in subsection 3.2.

3.1 Morphological Analysis

The morphological analysis of the words is performed based on a hierarchical procedure. Initially, in both versions of the chunker (i.e., minimal resources and lexicon-based) the keyword lexicon is used to identify the most common words. In more detail, this lexicon contains 432 keywords (or closed-class words) including articles, particles, prepositions, pronouns, numerals, and some special adverbs. The entries in this lexicon are of the following format (i.e., Prolog predicates):

keyword(WORD, INITIAL, DESCRIPTIONS)

where *WORD* is the keyword, *INITIAL* indicates whether it indicates the beginning of a noun phrase, a verb phrase or a prepositional phrase, and *DESCRIPTIONS* is a list of morphological descriptions. The keyword lexicon was constructed manually.

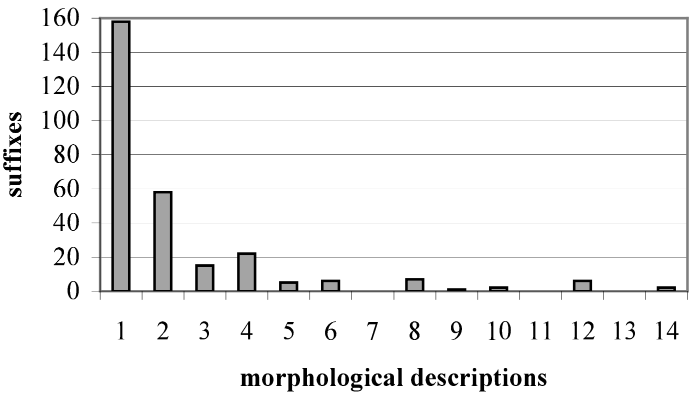

Fig. 2. Number of suffixes per morphological descriptions to which they correspond.

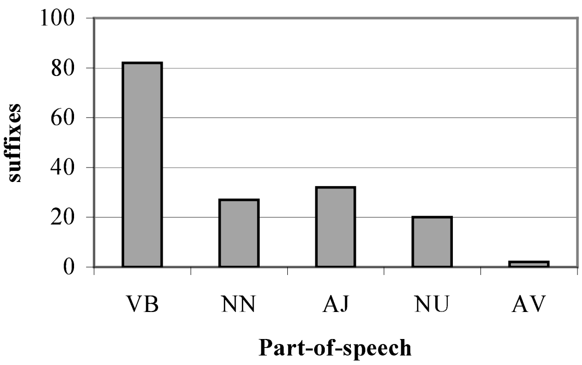

Fig. 3. Suffixes with one morphological description per part-of-speech. The abbreviations *VB, NN, AJ, NU*, and *AV* stand for verbs, nouns, adjectives, numerals, and adverbs, respectively.

However, any large lexicon that covers closed-class words can be used for the extraction of a keyword lexicon.

For the words not found in the keyword lexicon, the lexicon-based chunker uses a large lemma lexicon. This already existing lexicon was developed in the framework of a PC-KIMMO-based morphological analyzer for Modern Greek [16] and contains 30,000 lemmas covering nouns, adjectives, verbs, and adverbs. The combination of the PC-KIMMO-based analyzer and the lemma lexicon is able to give non-deterministic morphological descriptions for any word-form of the covered lemmas.

In the case of the lexicon-based chunker, the words not covered by this lexicon are analyzed using a guessing procedure based on the word suffixes. In the case of the minimal-resources chunker the words not found in the keyword lexicon are analyzed by this guessing procedure. Specifically, the suffix lexicon contains 282 suffixes that cover the vast majority of Modern Greek words. These suffixes were taken mainly from the already existing PC-KIMMO-based morphological description of Modern Greek [16]. The entries in this lexicon are of the following format (i.e., Prolog predicates):

suffix(SUFFIX, DESCRIPTIONS)

where *DESCRIPTIONS* is a list of morphological descriptions assigned to each word according to its *SUFFIX*. The maximal length suffix that matches the input word is selected.

Figure 2 shows the number of suffixes (vertical axis) in connection to the number of morphological descriptions that they assign (horizontal axis). Over 56% (158 out of 282) of the total suffixes assign only one morphological description to the words they match. Approximately 52% (82 out of 158) of these deterministic suffixes correspond to verbs as depicted in figure 3.

If a word suffix does not match to any of the entries of the suffix lexicon (usually foreign names or archaic words) then no morphological description is assigned, and this word is marked as a special word. However, it is not ignored in subsequent analysis. Additionally, a flag that indicates a possible proper name is assigned to every word based on the case of its first letter.

3.2 Multiple-Pass Parsing

The goal of our chunker is the identification of the boundaries of the main phrases (i.e., chunks) included in each sentence without analyzing their internal structure or their function in the sentence. Nevertheless, simple morphological disambiguation is performed, by applying selectional restrictions (e.g., number, case and gender agreement within noun phrases).

In particular, the detected chunks may be noun phrases (NPs), prepositional phrases (PPs), verb phrases (VPs), and adverbial phrases (APs). In addition, two chunks are usually connected by a sequence of conjunctions (CONs).

The identification of chunk boundaries is performed via multiple-passes on the input sentence. Each pass analyzes a part of the sentence, based on the results of the previous passes, and the remaining part is kept for subsequent passes. In general, the first passes try to detect simple cases that are easily recognizable, while the last passes deal with more complicated ones. Moreover, the last passes are less accurate than the initial ones due to the high degree of ambiguity they have to resolve. Cases that are not covered by the disambiguation rules remain unanalyzed. The presented approach utilizes five passes. The function of each one is described below.

- **Pass 1:** Simple NPs, PPs, and VPs are detected based on the recognition of phrase initial keywords, and the application of simple, empirically derived rules. For instance, this pass may detect the following chunks:

Example	Detected chunk
την αναγκαία γνώση και ευαισθησία (the necessary knowledge and sensitivity)	*NP*

ο 20ος αιώνας (the 20th century)	*NP*
της κ. Ελένης Παπαδοπούλου (of Mrs. Heleni Papadopoulou)	*NP*
οι αραιοκατηκημένες και γεωλογικά σχεδόν απομονωμένες περιοχές (the thinly populated and geologically almost isolated areas)	*NP*
με πολλή δύναμη (with great power)	*PP*
με συγκριτικά ελάχιστο κόστος (with comparetively minimum cost)	*PP*
δεν έχουν περάσει (they haven't passed)	*VP*
αναρωτήθηκα (I wondered)	*VP*
να δώσεις (to give)	*VP*

- **Pass 2:** Simple NPs at genitive case that usually follow other NPs as well as simple PPs are detected. Thus, this pass may detect the following chunks:

Example	Detected chunk
NP[*την χρήση*] *δορυφορικών συστημάτων* (NP[the usage] of satellite systems)	*NP*
με NP[*τον κ. Μπιλ Σμιθ*] (with NP[Mr. Bill Smith])	*PP*
από NP[*το περιπολικό*] (from NP[the cruiser])	*PP*
για NP[*τον μηχανικό*] (for NP[the engineer])	*PP*

Note, that in the above examples the chunks included in brackets (NP[*την χρήση*], NP[*τον μηχανικό*]) have been detected by the previous pass.

- **Pass 3:** Remaining pronouns either are appended to adjacent NPs or forming new NPs, and verbal predicates are detected. For example, this pass may detect the following chunks:

Example	Detected chunk
VP[*είναι*] *σημαντικά αλλά περίπλοκα* (VP[they are] important but complicated)	*VP*
όλα NP[*τα κλειδιά*] (all NP[the keys])	*NP*
NP[*η μητέρα*] *μας* (our NP[mother])	*NP*
αυτό (this)	*NP*

Note that the chunks included in brackets have been detected by previous passes.

- **Pass 4:** CONs, APs, as well as NPs with no initial keywords are detected in the remaining words. Moreover, PPs are formed based on NPs that have been detected in pass 3. For instance, this pass may detect the following chunks:

Example	Detected chunk
αν και (although)	*CON*

σχεδόν τελείως (almost completely)	*AP*
εθνικό έργο (national project)	*NP*
ζωή και ελπίδα (life and hope)	*NP*
σε NP[*όλες τις περιπτώσεις*] (in NP[all the instances])	*PP*

- **Pass 5:** In this pass, the simple phrases are combined in order to form more complex ones. Moreover, complex APs are detected. Thus, this pass is able to detect chunks like the following:

Example	Detected chunk
NP[*η ανάπτυξη*] NP[*της νέας τεχνολογίας*]	*NP*
(NP[the development] NP[of the new technology])	
PP[*με τα μάτια*] NP[*της καρδιάς*]	*PP*
PP[with the eyes] NP[of the heart]	
πολύ AP[*προσεκτικά*] (very AP[carefully])	*AP*
VP[*τρέχει*] VP[*να σωθεί*]	*VP*
(VP[he runs] VP[to be saved])	

Note that punctuation marks are included in the parsing procedure and treated as special symbols. It must be stressed that we tried to separate the identification of simple phrases from more complex ones since many applications require the identification of simple rather than complex phrases. An example analysis of the analysis of a sample text is given in the appendix at the end of the document.

4 Performance

The presented text chunker has been tested using a corpus of roughly 200,000 words which includes texts downloaded from the website of the Modern Greek newspaper entitled "TO BHMA" (the tribune).[1] These texts cover the majority of the genres found in a newspaper including news reportage, editorials, articles, letters to the editor, sports review, etc.

The entire corpus was analyzed using both the lexicon-based and the minimal-resources chunker and then one human judge manually evaluated its output. Comparative results in terms of recall and precision are given in table 1. As regards the minimal-resources chunker, the low recall of APs is caused by the similarity of the suffixes of the majority of Modern Greek adverbs to the suffixes of adjectives. The low precision of NPs is caused mainly by the analysis of remaining words that took place in the fourth pass.

On the average, the recall of the lexicon-based approach is considerably higher, especially in the case of NPs and APs. On the other hand, the precision results are lower. This is due to the fact that the lexicon is not able to provide all the possible morphological descriptions for some words. Additionally, the words remained

[1] http://tovima.dolnet.gr

unanalyzed using the lexicon-based system are 20% less in comparison with the minimal-resources chunker (i.e., 2.9% and 3.6% of the total words respectively). However, the parsing time cost of the lexicon-based approach is approximately 50% higher than the corresponding one of the minimal resources approach and this is very crucial for an application that requires analysis of large volumes of text very fast.

Table 1. Comparative performance of the two chunkers.

	Lexicon-based		Minimal-resources	
Chunk	Recall (%)	Precision (%)	Recall (%)	Precision (%)
NPs	94.46	85.58	91.18	88.72
PPs	93.96	99.12	93.35	99.36
VPs	93.63	97.57	91.32	98.19
Aps	85.28	96.90	72.47	96.27
Overall	*93.05*	*92.35*	*89.55*	*94.45*
Time cost (words / sec)	238		514	
Unanalyzed words (%)	2.9		3.6	

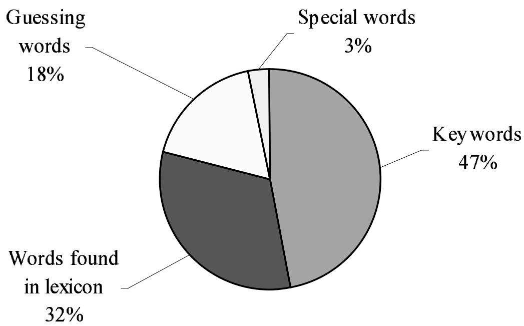

Fig. 4. The analysis of the test corpus by the lexicon-based approach.

An overview of the morphological analysis results of the entire corpus using the lexicon-based parser is given in figure 4. Approximately 47% of the total words were included in the keyword lexicon. The lexicon succeeded to provide information for 32% of the total words. It has also to be noted that the lexicon provided an average of 1.9 morphological descriptions per word. On the other hand, the application of the guessing procedure to these very same words (i.e., 32% of the total words) for comparative purposes provided an average of 3.6 morphological descriptions per word. The guessing procedure was applied to 18% of the total words while 3% of the total words did not match any of the entries of the suffix lexicon (i.e., special words).

5 Conclusion

We presented a text chunker for unrestricted Modern Greek text. We proposed two versions of this chunker: one based on a large lexicon and one based on minimal resources. In the latter case the morphological analysis is performed using exclusively two small lexicons containing closed-class words and common suffixes of the Modern Greek words. The comparison of these two systems shows that very good results can be obtained by omitting the large and complicate resources. Moreover, the considerable time cost introduced by the use of complicate resources indicates that the minimal-resources chunker is the best solution regarding a practical NLP application that requires rapid response and less than perfect parsing results.

The presented text chunker takes advantage of some characteristics of Modern Greek that facilitate the recognition of simple phrases. Nevertheless, we strongly believe that similar methods can be applied to other natural languages with similar characteristics (i.e., morphological complexty, mandatory use of articles, particles, etc.). For example, Italian and Spanish are most likely to benefit by our approach.

The proposed system is currently modified in order to be adopted to the specific requirements of three national research projects: (i) MITOS[2], a system for information retrieval and extraction from financial spot news, (ii) DILOS[3], a bilingual electronic dictionary of economic terms with references to frequencies and terms in text corpora, and (iii) DIKTIS[4], a dialogue system for information extraction from medical text corpora. In each of these cases, we attempt to take advantage of the special characteristics of the domain-specific text corpora (e.g., financial spot news, medical prescriptions, etc.) that have to be analyzed for improving the performance. The minimal-resources chunker has also be utilized for the extraction of stylistic measures that have been used in the framework of an authorship attribution system [18].

References

1. Karlsson, F., A. Voutilainen, J. Heikkila, and A. Anttila (1995). *A Language-Independent System for Parsing Unrestricted Text.* Mouton de Gruyter.
2. Hobbs, J., D. Appelt, J. Bear, D. Israel, M. Kameyama, M. Stickel, and M. Tyson (1996). FASTUS: a Cascaded Finite-State Transducer for Extracting Information from Natural-Language Text. In E. Roche and Y. Schabes (eds) *Finite State Devices for Natural Language Processing.* Cambridge MA: MIT Press.
3. Dermatas, E. and G. Kokkinakis (1995). Automatic Stochastic Tagging of Natural Language Texts. *Computational Linguistics*, 21(2), pp. 137-164.
4. Mikheev, A. (1997). Automatic Rule Induction for Unknown Word Guessing. *Computational Linguistics*, 23(3), pp. 405-423.
5. Goodman, J. (1997). Global Thresholding and Multiple-Pass Parsing. In *Proc. of the Second Conference on Empirical Methods in Natural Language Processing*, pp. 11-25.
6. Schwartz, R, L. Nguyen, and J. Makhoul (1996). Multiple-Pass Search Strategies. In C. Lee, F. Soong, and K. Paliwal (eds) *Automatic Speech and Speaker Recognition: Advanced Topics*, Kluwer Academic Publishers, pp. 429-456.

---

[2] EPET II – 2-1.3-102

[3] EPET II – 98LE-12

[4] EPET II – 98LE-24

7. Abney, S. (1991). Parsing by Chunks. In Berwick, Abney, and Tenny (eds), *Principle-based Parsing.* Kluwer Academic Publishers.
8. Michos S., F. Fakotakis, and G. Kokkinakis (1995). A Novel and Efficient Method for Parsing Unrestricted Texts of Quasi-Free Word Order Languages. *Int. Journal on Artificial Intelligence Tools*, 4(3). World Scientific, pp. 301-321.
9. Church, K. (1988). A Stochastic Parts Program and Noun Phrase Parser for Unrestricted Text. In *Proc. of Second Conference on Applied Natural Language Processing*, pp. 136-143.
10. Ramshaw, L. and Marcus M. (1995). Text Chunking Using Transformation-based Learning. In *Proc. of ACL Third Workshop on Very Large Corpora.* pp. 82-94.
11. Skut, W. and Brants T. (1998). Chunk Tagger: Statistical Recognition of Noun Phrases. In *ESSLLI-98 Workshop on Automated Acquisition of Syntax and Parsing.*
12. Bourigault, D. (1992). Surface Grammatical Analysis for the Extraction of Terminological Noun Phrases. In *Proc. of the Fifteenth Int. Conference on Computational Linguistics*, 3, pp. 977-981.
13. Voutilainen, A. (1993). NPtool, a Detector of English Noun Phrases. In *Proc. of the Workshop on Very Large Corpora: Academic and Industrial Perspectives,* Ohio State University, pp. 48-57.
14. Srinivas, B. (1997). Performance Evaluation of Supertagging for Partial Parsing. In *Proc. of the Fifth International Workshop on Parsing Technologies.*
15. Sundheim, B. (ed.) (1995). *Proceedings of the 6th Message Understanding Conference (MUC-6).* Columbia, Advanced Research Projects Agency, Information Technology Office, Maryland.
16. Sgarbas, K., N. Fakotakis and G. Kokkinakis (1995). A PC-KIMMO-based Morphological Description of Modern Greek. *Literary and Linguistic Computing*, 10(3), Oxford University Press, New York, pp. 189-201.
17. Stamatatos, E., N. Fakotakis, and G. Kokkinakis (1999). Automatic Extraction of Rules for Sentence Boundary Disambiguation. In *Proc. of the Workshop in Machine Learning in Human Language Technology, Advance Course on Artificial Intelligence (ACAI'99),* pp. 88-92.
18. Stamatatos, E., N. Fakotakis, and G. Kokkinakis (1999). Automatic Authorship Attribution. In *Proc. of the 9th Conf. of the European Chapter of the Association for Computational Linguistics (EACL'99),* pp. 158-164.

Appendix: Analysis of a Sample Text

In order to illustrate the parsing procedure using the multiple passes, we give an analysis example of a sample text The chunks detected in each pass are shown in boldface. The sentence boundaries are indicated by the symbol #. Note that the word *Σύμφωνα* (i.e., according) remains unanalyzed since its suffix may indicate a noun, an adjective, or an adverb and the context do not solve this ambiguity. The minimal-resources chunker was used to analyze this sample text. Note also that the rough English translation aims mostly at helping the reader to understand the syntactic complexities of the text.

Sample text (and rough English translation):
Το άλλο, τραγικό θύμα (the other tragic victim) αυτής της ιστορίας (of this story), η 25άχρονη (the 25-years-old) Αμαλία Παπαδοπούλου (Amalia Papadopoulou), συνεχίζει (keeps) να δίνει (on giving) από την εντατική μονάδα (from the emergency unit) του Ερυθρού Σταυρού (of the Red Cross), τον αγώνα της (her fight) να κρατηθεί στη ζωή (for staying alive). Σύμφωνα με το σημερινό ιατρικό ανακοινωθέν (according to today's medical bulletin), οι θεράποντες ιατροί (the attendant doctors), διαπιστώνουν (ascertain) μικρή βελτίωση (slight improvement) της κατάστασης (of the situation), η οποία (which) ωστόσο (however) παραμένει (remains) ιδιαιτέρως κρίσιμη (particularly crucial).

Pass 1:
NP[Το άλλο , τραγικό θύμα] αυτής **NP[της ιστορίας]** , **NP[η 25άχρονη Αμαλία]** Παπαδοπούλου , **VP[συνεχίζει]** **VP[να δίνει]** από **NP[την εντατική μονάδα]** **NP[του Ερυθρού Σταυρού]** , **NP[τον αγώνα]** της **VP[να κρατηθεί]** σε **NP[τη ζωή]** . # Σύμφωνα με **NP[το σημερινό ιατρικό ανακοινωθέν]** , **NP[οι θεράποντες ιατροί]** , **VP[διαπιστώνουν]** μικρή βελτίωση **NP[της κατάστασης]** , **NP[η οποία]** ωστόσο **VP[παραμένει]** ιδιαιτέρως κρίσιμη . #

Pass 2:
NP[Το άλλο , τραγικό θύμα] αυτής NP[της ιστορίας] , NP[η 25άχρονη Αμαλία] **NP[Παπαδοπούλου]** , VP[συνεχίζει] VP[να δίνει] **PP[από την εντατική μονάδα]** NP[του Ερυθρού Σταυρού] , NP[τον αγώνα] της VP[να κρατηθεί] **PP[στη ζωή]** . # Σύμφωνα **PP[με το σημερινό ιατρικό ανακοινωθέν]** , NP[οι θεράποντες ιατροί] , VP[διαπιστώνουν] μικρή βελτίωση NP[της κατάστασης] , NP[η οποία] ωστόσο VP[παραμένει] ιδιαιτέρως κρίσιμη . #

Pass 3:
NP[Το άλλο , τραγικό θύμα] **NP[αυτής της ιστορίας]** , NP[η 25άχρονη Αμαλία] NP[Παπαδοπούλου] , VP[συνεχίζει] VP[να δίνει] PP[από την εντατική μονάδα] NP[του Ερυθρού Σταυρού] , **NP[τον αγώνα της]** VP[να κρατηθεί] PP[στη ζωή] . # Σύμφωνα PP[με το σημερινό ιατρικό ανακοινωθέν] , NP[οι θεράποντες ιατροί] , VP[διαπιστώνουν] μικρή βελτίωση NP[της κατάστασης] , NP[η οποία] ωστόσο **VP[παραμένει ιδιαιτέρως κρίσιμη]** . #

Pass 4:
NP[Το άλλο , τραγικό θύμα] NP[αυτής της ιστορίας] , NP[η 25άχρονη Αμαλία] NP[Παπαδοπούλου] , VP[συνεχίζει] VP[να δίνει] PP[από την εντατική μονάδα] NP[του Ερυθρού Σταυρού] , NP[τον αγώνα της] VP[να κρατηθεί] PP[στη ζωή] . # Σύμφωνα PP[με το σημερινό ιατρικό ανακοινωθέν] , NP[οι θεράποντες ιατροί] , VP[διαπιστώνουν] **NP[μικρή βελτίωση]** NP[της κατάστασης] , NP[η οποία] **CON[ωστόσο]** VP[παραμένει ιδιαιτέρως κρίσιμη] . #

Pass 5:
NP[Το άλλο , τραγικό θύμα αυτής της ιστορίας] , **NP[η 25άχρονη Αμαλία Παπαδοπούλου]** , **VP[συνεχίζει να δίνει]** **PP[από την εντατική μονάδα του Ερυθρού Σταυρού]** , NP[τον αγώνα της] VP[να κρατηθεί] PP[στη ζωή] . # Σύμφωνα PP[με το σημερινό ιατρικό ανακοινωθέν] , NP[οι θεράποντες ιατροί] , VP[διαπιστώνουν] **NP[μικρή βελτίωση της κατάστασης]** , NP[η οποία] CON[ωστόσο] VP[παραμένει ιδιαιτέρως κρίσιμη] . #