Robust Parsing of Spoken Dialogue Using Contextual Knowledge and Recognition Probabilities

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ABSTRACT

In this paper we describe the linguistic processor of a spoken dialogue system. The parser receives a word graph from the recognition module as its input. Its task is to find the best path through the graph. If no complete solution can be found, a robust mechanism for selecting multiple partial results is applied. We show how the information content rate of the results can be improved if the selection is based on an integrated quality score combining word recognition scores and context-dependent semantic predictions. Results of parsing word graphs with and without predictions are reported.

1. INTRODUCTION

The linguistic processing (LP) component of a spoken dialogue system (SDS) must be robust in order to deal with recognition errors and spontaneous speech phenomena.

In the following we describe our approach towards robustness. This LP was developed in the project SYSLID (SYntactic and Semantic LI nguistic P rocessing for Spoken D ialogue Systems). It is fully integrated into the Daimler-Benz SDS [3] for German train timetable inquiries. The architecture of this system is shown in Figure 1.

It has been pointed out in [5] that a robust parser which may deliver multiple partial results has to cope with the problem of deciding which partial results should be selected. The solution suggested in [5] relies on the assignment of a quality score to each partial solution generated during parsing by means of a scoring function which integrates acoustic, syntactic, and semantic quality measures.

In the present paper we give a more detailed description of the implementation of this approach combining probabilistic and symbolic knowledge. First, we will illustrate why both contextual knowledge and recognition scores are important for flexible robust parsing. Next, the processing of these knowledge sources in the parser is described. Finally, we evaluate this approach by comparing the information content rates of analysis results that were produced with and without semantic predictions.

2. CONTEXTUAL KNOWLEDGE AND RECOGNITION SCORE

The parser receives a word graph as its input. The nodes of the graph represent points in time and the edges are labelled with scored word hypotheses.

Figure 2 shows a simplified word graph that contains three alternative one-word sentence hypotheses. Scores are positive numbers which assign a (pseudo-)probability measure to a word hypothesis: The smaller the score the higher the probability, i.e., in the example graph the hypothesis [1 er 22.08 2] has the best score (22.08). If one adopts the traditional view that it is the task of the parser to find the best scoring interpretation, then we would expect the parser to deliver er (he) as solution.
Now let us assume the following dialogue context:

**user1**: Ich möchte morgen nach Ulm fahren.
I want to go to Ulm tomorrow.

**system1**: Sie wollen nach Ulm fahren?
You want to go to Ulm?

Being a yes-no question, the last system utterance generates the expectation that the interjections *ja* (yes) or *nein* (no) will be contained in the user reply. Analyzing the graph in Figure 2 with this dialogue context, it is much more likely that the hypothesis [1 ja 31.25 2] is the correct solution, although it has not the best score.

Contextual expectations are mapped onto semantic predictions which are passed down to the LP in our system (cf. Figure 3). The predictions are generated on the basis of the last system utterance in a way similar to the dynamic prediction mechanism described in [1]. One possible way of using these predictions is to filter out all results which are incompatible with the predictions. This strategy would have the desired effect in the above example, but lead to a very restricted dialogue, because all additional user information were eliminated by this rigid filter. For example, in the context above a user might be overinformative and instead of simply confirming might answer:

**user2**: Ja um zehn Uhr.
Yes at ten o’clock.

Therefore, we prefer a less rigid strategy: If the semantic content of a (partial) result agrees with a top-down prediction, the result has a high pragmatic relevance, otherwise low. Pragmatic relevance is expressed as a numerical value which can be used to calculate a quality score integrating scores of different processing levels. The basic idea thus is to increase the overall score for predicted hypotheses in order to compensate lower recognition scores.

Assume, for example, that the word graph in Figure 3 was generated as the recognizer output of analyzing utterance user2. In the context of a yes-no question we would like to increase the overall score of the predicted hypothesis *ja* in the first part of the utterance. But the overinformative second part of the utterance, *um zehn Uhr*, should still be acceptable as a parse result, although it may not correspond to context expectations. The dialogue component of our system is flexible enough to interpret such additional information (cf. [4]).

### 3. AN INTEGRATED QUALITY SCORE FOR CHART EDGES

We use a chart-based island parser implemented in Prolog which looks for the best scored, grammatically correct sentence hypothesis in the graph. It performs an agenda-driven heuristic search (cf. [5]). The chart of the parser is initialized with the word hypotheses of the input graph. The linguistic knowledge base of the parser is a highly lexicalized Unification Categorial Grammar (UCG) represented in DATR (cf. [2]). In UCG, syntactic and semantic structures are represented and constructed in an integrated way. Example (1) shows the lexical entry of *ja*, which has the syntactic category *part* (particle) and the semantic type *dm* marker (dialogue manager marker).

\[
\begin{array}{l}
mor : [ \text{form} : \text{ja} ] \\
syn : [ \text{head} : [ \text{major} : \text{part} ] ] \\
sem : [ \text{type} : \text{dm}\_\text{marker}, \text{value} : \text{yes} ]
\end{array}
\]  

(1)

Semantic predictions are provided from the dialogue manager in a format compatible with the semantic representations of lexical entries, e.g., the dialogue context “yes-no question” generates the prediction list shown in (2).

\[
\begin{array}{l}
[ \text{type} : \text{dm}\_\text{marker}, \text{value} : \text{yes} ] \\
[ \text{type} : \text{dm}\_\text{marker}, \text{value} : \text{no} ]
\end{array}
\]

(2)

The semantic attribute-value pairs of both lexical entries and predictions are compiled into Prolog terms with the same program. Thus, agreement of a chart edge with semantic predictions can be checked with standard Prolog unification.

The predictions are used by the parser in two ways: First, they serve as *seed definitions* for the island parser, which can thus start its search from pragmatically relevant islands. Second, the predictions
contribute to the integrated quality score which is assigned to each partial result during parsing. In order to integrate the symbolic contextual knowledge with the numerical recognition score we use a function \( pr(E) \) which maps the agreement with a prediction onto a numerical value.\(^1\) In our current experiments we use the following heuristic weightings: \( pr(E) = 4 \) if the semantic type of a chart edge \( E \) unifies with one of the top-down predictions, otherwise \( pr(E) = 1 \).

The computation of the integrated quality score \( QS \) of an edge \( E \) is defined as follows:

\[
QS(E) = \frac{Q_a(E)}{sc(E) \times pr(E)}
\]

where \( Q_a \) denotes the acoustic quality, \( sc \) the value for syntactic completeness,\(^2\) and \( pr \) the value for pragmatic relevance. The interpretation of \( QS \) is like that of the recognition score, i.e., the smaller the better.

The acoustic quality \( Q_a \) is given by:

\[
Q_a(E) = \frac{s f(E)}{\text{length}(E)}
\]

The \( shortfall \) function \( s f(E) \) (cf. [9, p. 298]) for a given edge \( E(i, j) \) that covers a segment from node \( i \) to node \( j \) is given by

\[
s f(E) = \text{Maxseg} - \text{maxseg}(i, j) + RS(E)
\]

where \( \text{Maxseg} \) is the maximum total score of the whole graph, \( \text{maxseg}(i, j) \) is the maximum score of the segment \( i \) to \( j \), and \( RS(E) \) is the recognition score. For example, the \( shortfall \) of the hypothesis \([1 ja 31.25 2]\) in Figure 3 is \( 110.21 - 22.08 + 31.25 = 119.38 \), which reflects the fact that a complete solution including this hypothesis is 9.17 points worse than the best scoring path \([\text{er um zehn uhr}]\).

The \( RS \) of an combined edge \( CE \), which was composed of two edges \( E_1 \) and \( E_2 \), is defined as the sum of \( E_1 \) and \( E_2 \).

Given these definitions, we can now illustrate the effect of semantic predictions on parsing the word graph in Figure 3. Assume the graph is parsed as an answer to a yes-no question, i.e., the prediction list given in \([\text{er um zehn uhr}]\) is used. Only one hypothesis, \( ja \), unifies with one of the predictions, \([\text{type: dm marker, value: yes}]\), i.e., \( pr(ja) = 4 \). Thus, its quality score is \( \frac{119.38}{76} = 29.84 \), whereas the scores of the alternative hypotheses spanning from node 1 to 2 stay equal to the acoustic quality due to \( pr(E) = 1 \). Let us further assume that the grammar allows building a prepositional time phrase \( \text{um zehn uhr} \). Since no time expression is predicted, the overall quality score of this phrase is equal to the acoustic quality \( Q_a \), i.e., \( \frac{110.21 - 22.08 + 88.76}{3} = 36.74 \).

Under the assumption that the grammar does not contain a rule to combine \( ja \) and \( \text{um zehn uhr} \), the parser will terminate without having found a complete solution that spans the whole input. In this case, the robust mechanism of selecting multiple partial results is applied: Starting from the edge with the best quality score, the best scoring adjacent edges are collected recursively until a sequence of partial results spanning the whole utterance is found. In our example, the predicted result \( ja \) has got the best quality score during parsing. Since it is located at the beginning of the graph, no left-adjacent solutions have to be looked for. Among the right-adjacent edges \( um, uns, und, um zwei uhr \) and \( \text{um zehn uhr} \) the latter has the best score and is selected. Its end node marks the end of the graph, too. Thus a sequence of partial results through the graph was found and the LP hands over these results as Semantic Interface Language (SIL, cf. [6]) structures to the dialogue manager (cf. Figure 4). Examples (6) and (7) show the selected parsing results in SIL format.

\[
\begin{array}{l}
\text{id} : A \\
\text{syn} : \\
\quad \text{category} : \text{part} \\
\quad \text{string} : ja \\
\quad \text{score} : 29.84 \\
\text{sem} : \\
\quad \text{type} : \text{dm marker} \\
\quad \text{value} : yes
\end{array}
\]

\[
\begin{array}{l}
\text{id} : C \\
\text{syn} : \\
\quad \text{category} : \text{prep} \\
\quad \text{string} : \text{um zehn uhr} \\
\quad \text{score} : 36.74 \\
\text{sem} : \\
\quad \text{the hour} : [\text{id} : E \\
\quad \quad \text{type} : \text{hour} \\
\quad \quad \text{value} : 10]
\end{array}
\]

4. EVALUATION

The main task of a parser in a speech understanding system is to determine the meaning of the spoken utterance. It has been argued in [8] that the sentence understanding capabilities of a SDS are best judged by the information content (IC) metric. IC calculates the percentage of task-relevant information (TRI) contained in the parser output. This requires the annotation of each utterance with a series of
attribute-value pairs, where each attribute is a task-relevant concept (TRC). In the present domain of timetable inquiries, examples of TRCs are: source-city, goal-city, time, date, dm_marker. For example, the TRI of the utterance ja um 10 Uhr is [dm_marker:yes, time:10]. This reference annotation is called RTRI.

IC can then be calculated by comparing RTRI with the parser output. For that purpose the SIL structures produced by the parser are translated into attribute-value pairs compatible with the ones of RTRI, e.g., the structure shown in (3) is mapped to [time:10]. The output of this translation is called PTRI.

Performance of the robust parser is measured by the metric IC, which is calculated as a percentage using formula (8)

\[
IC = 100 \left( 1 - \frac{i + s + d}{\text{items}} \right)
\]

where items is the total number of items in RTRI and i, s, and d are the numbers of items inserted, substituted, and deleted in PTRI, respectively.

Assume, for example, that the word graph in Figure 3, whose RTRI is [dm_marker:yes, time:10], is parsed without predictions. This will produce two partial results, namely er and um 10 uhr. The SIL structure of the former cannot be mapped to a TRC. Thus PTRI is [time:10], i.e., \(d = 1\) because one of the RTRI items is deleted in PTRI. This yields an IC of 100 \((1 - \frac{1}{1}) = 50\%\).

The parser was tested in stand-alone mode on 50 word graphs generated by the Daimler-Benz word recognizer [3]. The graphs had a density of 4 edges per spoken word and a word accuracy rate of 73.3%.

To measure the impact of the predictions we first parsed the graphs without predictions. In the second setup, semantic predictions were handed over as an additional argument to the parser. The choice of the prediction was determined by the original dialogue context of the utterance.

The results are shown in the following table, where ic-pr and ic+pr are the IC rates without and with predictions, respectively, and t-pr and t+pr are the corresponding average parse times (in seconds) taken on a SPARCstation 10.

| ic-pr | t-pr | ic+pr | t+pr |
|-------|------|-------|------|
| 67.48 | 0.67 | 76.48 | 0.74 |

These figures show a 9% increase of the IC rate when using contextual knowledge in the parser. Most of this improvement was attained in the analysis of very short, elliptical utterances typically provided as answers to yes-no questions. In these cases, exemplified in Figure 2, the linguistic grammar cannot contribute much so that merely contextual expectations allow a well-founded choice among competing alternatives.

5. CONCLUSION AND FURTHER WORK

We have presented a mechanism for integrating contextual knowledge into the linguistic processor of a spoken dialogue system. The reported results show that the use of predictions can improve the IC rate of the parser. Most improvement is gained in the analysis of short utterances. To determine the IC, the parsing results had to be inspected manually. In the near future an annotated test suite of word graphs will be built up in order to automate the evaluation.

Furthermore, we intend to measure the IC given different processing time limits. As mentioned in section 3, the predictions are used as pragmatic seed definitions of the island parser. Thus partial results which are most relevant for understanding are built at an early stage of processing. Due to this strategy we expect acceptable IC rates even with a strong limit on processing time as it may be necessary in a real time system.

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