# RECENT ADVANCES IN JANUS: A SPEECH TRANSLATI ON SYSTEM

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### **ABSTRACT**

robustness, generality and speed of JANUS, CMUs to-speech translation system JANUS is a speakernt system which translates spoken utterances in also in German into one of German, English or system has been designed around the task stration (CR). It has initially been built h database of 12 read dialogs, encompassaround 500 words. Whave since been ong several dimensions to improve tage and to move toward sponta-

### UCTI ON

ibe recent improvements of o speech translation system Imve been made mainly along the following ons: 1.) better context-dependent modeling importance in the speech recognition module,

2.) improved language models, smoothing, and word
equivalence classes improve coverage and robustness of
the sentences that the systemaccepts, 3.) an improved
N-best search reduces run-time from several minutes to
nowreal time, 4.) trigramand parser rescoring improves
selection of suitable hypotheses from the N-best list for

subsequent translation. On the machine translation side,
5.) a cleaner interlingua was designed and sy

and domain-specific analysis were separateusability of components and lation, 6.) a semantic anal

Th

pendent segment weights.

Error rates using context dependent phonemes are lower by a factor 2 to 3 for English (1.5 to 2 for German) than using context independent phonemes. Results are shown in table 1.

l anguage no	odel	Engl PP	ish VXX	Gen PP	rmaun VXX
none	400	0.0 58.	2	425.0 6	3.0
word-pairs	28	8.9 83.	1	20.8 8	9.1
bigrans	16	. 2 92. 6	[	18.3 93	. 7
smoothed bigrams	18.1	91.5	28	. 90 84. 7	[ ]
after resorting		98.8			

Table 1: Word Accuracy for First Hypothesis

The performance on the RM task at comparable perplexities is significantly better than for the CR-task, suggesting that the CR-task is somewhat more difficult.

### 2.2. Se arc h

The search module of the recognizer builds a sorted l of sentence hypotheses. Speed and memory required have been dramatically improved: Tho of hypotheses computed for each up from 6 to 100 hypotheses computation was a seconds.

This was a N-be

When the standard GLR parser fails on all sentence candidates, this robust GLR parser is applied to the best sentence candidate.

## 3.2. The Interlingua

The output of the parser, known as "syntactic f-structure", is then fed into a mapper to produce an Interlingua representation. For the mapper, we use a software tool known as Transformation Kit [10]. An ping grammar with about 300 rules is writt Conference Registration domain of En

((PREV-UTTERANCES ((SPECH-ACT\*ACK NOWL) (WALE
(PARTY
((DEFINTE+) (NABER\*SG)
(ANM-)
(THE \*CONFIENE)
(CONEPT \*CFI CE)))
(SPECH-ACT\*I DENII FY-OHER)

Figure 2: Example: Interlingua Output

Figure 2 is an example of Interlingua representation produced from the sentence "Hello is this the conference of fice". In the example, "Hello" is represented act \*ACKNOWLEDGEMENT, and the rest act \*I DENIFY-OTHER.

#### 3.3. The Generator

The generation of target 1:
representation invo

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side there is a "built-in" robustness against these phenomena in a connectionist system

The connectionist parsing process is able to combine

symbolic information (e.g. syntactic features of words)
with non-symbolic information (e.g. statistical likelihood of sentence types). Moreover, the system can easily
integrate different knowledge sources. For example
stead of just training on the symbolic ir
trained PARSEC on both the symbolic
the pitch contour. After trai
temwas able to use t

as able to use t mine the se were