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sed Syntax and

del for ems. Proc.

Robust Speech Repair

After locating and highlighting erroneous sections in the recognizer hypothesis, misrecognitions are corrected.

The *spoken hypothesis correction* method uses N-Best lists for both the initial utterance and the respo-
ken section. The N-Best list for the highlighted section
initial utterance is rescored using scores from
secondary utterance. Depending on the
lists, most misrecognitions can

s correction method requires
ghted erroneous section. A
led sequence of let-
estrict the
N-

2. *The Linguistic Feature Labeler* attaches features and
feature values (if applicable) to these chunks. There
is a classifier for each feature, which finds zero or
e atomic value. Since there are many features,
may get none, one or several pairs of
values. As a feature normally
nk level, the classifier is
ar feature at a par-
prevents the
ing

Concept Based Speech Translation

The basic premise of the concept based approach
is that the structure of the information conveyed is
gely independent of the language used to encode it.
ries to model the information structures
e.g. the scheduling task, and the
resented through words in
extension of the
It

matrix of the speech recognizer used. First, phonetic
transcriptions for all appearances of each word are gen-
erated by the help of a phoneme recognizer. Then, vari-
are infrequent or which would lead to erro-
nfusable phonemes are eliminated.
are retrained allowing for
iants.
for adapt-
y

approach leads to improved performance with appropriate weighting of the output from each strategy.

ognition Performance Analysis

seline JANUS-2 recognizer can be described as

ing: LDA on melscale fourier spectrum
ustic features (power, silence)

g: LVQ-2 or phonetically tied
els

first pass, followed by
dard word bi-

nally, we report on efforts to detect erroneous system output and provide interactive methods to recover
from such errors.

JANUS Overview

Collection

llection to establish a large database of spon-
to-human negotiation dialogs in Eng-
ed about 18 months ago.
ope, the US and
everal

Integrating Different Learning Approaches into a Multilingual Spoken Language Translation System*

P. Geutner[1], **B. Suhm**[2], **F.-D. Buø**[1], **T. Kemp**[1], **L. Mayfield**[2], **A. E. McNair**[1],

I. Rogina[1], **T. Schultz**[1], **T. Sloboda**[1], **W. Ward**[2], **M. Woszczyna**[1] and **A. Waibel**[1,2]

pgeutner@ira.uka.de

Interactive Systems Laboratories

[1] Karlsruhe University (Germany)

[2] Carnegie Mellon University (USA)

Abstract

ual spoken language trans-
knowledge about both
s of each lan-
ansla-