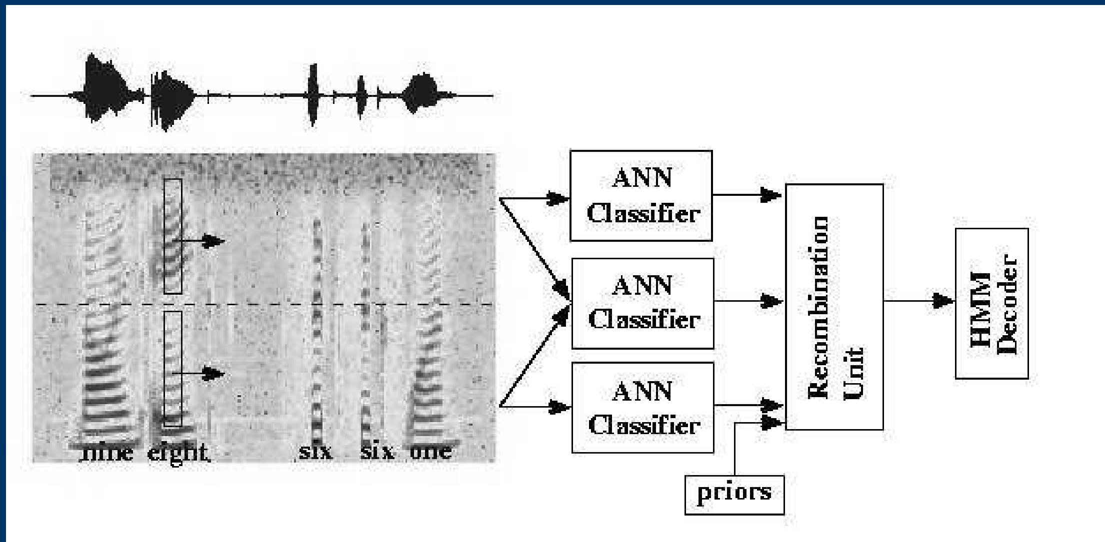
RESPITE – Meeting

Saillon

25.–26.1.1

Introduction



'Full Combination' Subband Approach

Reminder: FC, AFC & PoE

$$\text{FC}: \quad P(q|x) = \sum_{i=1}^{2^n} c_i \, P(q|x_i)$$

➢ no assumptions

$$\text{AFC}: \; P(q|x) = \sum_{i=1}^{2^n} c_i \frac{\prod_{j \in \text{com}} P(q|x_i)}{P(q)^{\text{n}-1}} \Theta$$

➢ assumption of conditional independence

$$\text{PoE}: \; P(q|x) = 1 - \prod_{i=1}^{2^n} (1 - P(q|x_i))$$

➢ assumption of independence

A Model for Context Effects

- [Bronkhorst,Bosman,Smoorenburg,1993] :

2–stage process for the recognition of a stimulus

- use of only **sensory information** to identify a stimulus w

  w consists of n elements i=1..n having the probability q_i for correct recognition

  probability of *complete* stimulus $p(w) = q_1 q_2 \ldots q_n$

  probability of *incomplete* stimulus $p(w_{in}) = (1- q_1) q_2 \ldots q_n$

  probability of *no element correct* $p(w_{in}) = (1- q_1) (1-q_2) \ldots (1-qn)$

- use of **contextual information** to fill in the missing parts of an incomplete stimulus

1. Use of Sensory Information

A stimulus can be perceived with 0 to n errors :

$Q_0 = q_1 q_2 \ldots q_n$

$Q_1 = (1-q_1)q_2 \ldots q_n + q_1(1-q_2) \ldots q_n + \ldots + q_1 \ldots q_{n-1}(1-q_n)$

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$Q_n = (1-q_1)(1-q_2)\ldots(1-q_n)$ $\binom{n}{i}$

- In each Q_i it is summed over possible permutations of i missing elements
- Note: q_i = probability of recognizing element i *without context*

2. Use of Context Information

Use of **contextual information** to fill in the missing parts of an incomplete stimulus

c_i : chance of correctly guessing **one** missing element when i elements were missed

c_1 : chance of correctly guessing 1 missing element when 1 element was missed

$c_1 c_2$: chance of correctly guessing 2 missing element when 2 elements were missed

=> for guessing all missing elements correctly $c_1 c_2 \ldots c_n$

Combine 1. and 2.

The probabilities of occurrence of the elements of all possible percepts:

$Q_0 = q_1 q_2 \ldots q_n$

$Q_1 = (1-q_1)q_2 \ldots q_n + q_1(1-q_2) \ldots q_n + \ldots + q_1 \ldots q_{n-1}(1-q_n)$

.

.

$Q_n = (1-q_1)(1-q_2)\ldots(1-q_n)$

are multiplied with the chance c_i of guessing the missed elements.

It is then summed over all possible percepts :

$$p(w) = Q_0 + c_1 Q_1 + c_1 c_2 Q_2 + \ldots + c_1 \ldots c_n Q_n$$

$$= \sum_{i=1}^{2^n} \Big[c_i \prod_{j \in Q_i} q_j \prod_{j \notin Q_i} (1-q_j) \Big]$$

$$= \sum_{i=1}^{2^n} \Big[c_i \prod_{j \in Q_i} P(q|x_j) \prod_{j \notin Q_i} (1-P(q|x_j)) \Big]$$

Comparison to AFC and FC

$$\text{BBS:}\quad P(q|x) = \sum_{i=1}^{2^n} \left[c_i \prod_{j\in \text{com}} P(q|x_j) \prod_{j\notin \text{com}} (1 - P(q|x_j)) \right]$$

$$\text{AFC:}\quad P(q|x) = \sum_{i=1}^{2^n} \left[c_i \prod_{j\in \text{com}} P(q|x_j) \,\Theta\, (1] - \prod_{j\in \text{com}} P(q|x_j)) \right]$$

$$\text{FC:}\quad P(q|x) = \sum_{i=1}^{2^n} c_i \, P(q|x_i) \,\, (1 - P(q|x_{\neg i}))$$

$$\text{PoE:}\quad P(q|x) = 1 - \prod_{i=1}^{2^n} (1 - P(q|x_i))$$

Implementation

Possibilities to choose c_i :

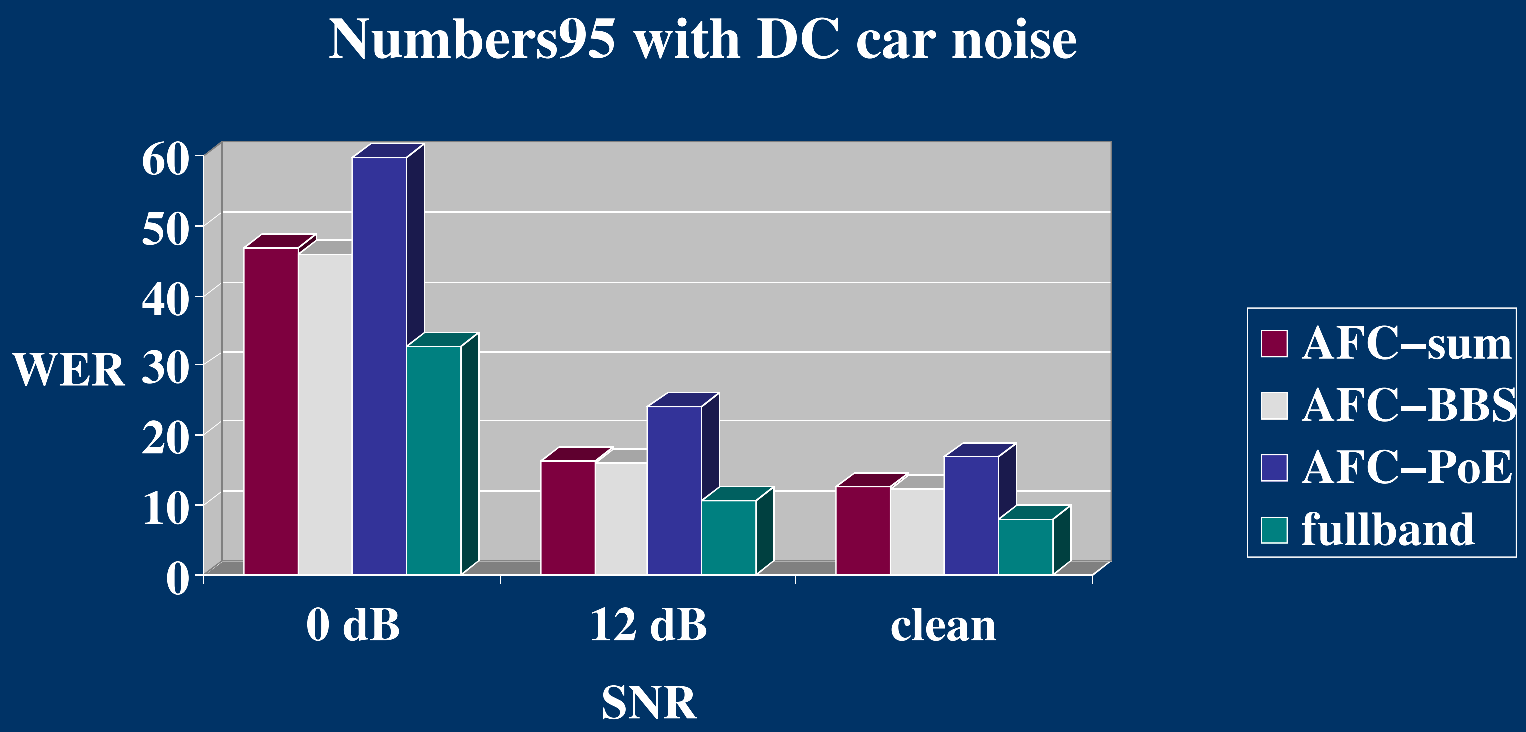
c_i = priors P(q)

$$c_i\, c_{i-1} \ldots c_1 = \frac{\text{recognition correct} \wedge \text{expert } i \text{ correct}}{\text{expert } i \text{ correct}}$$

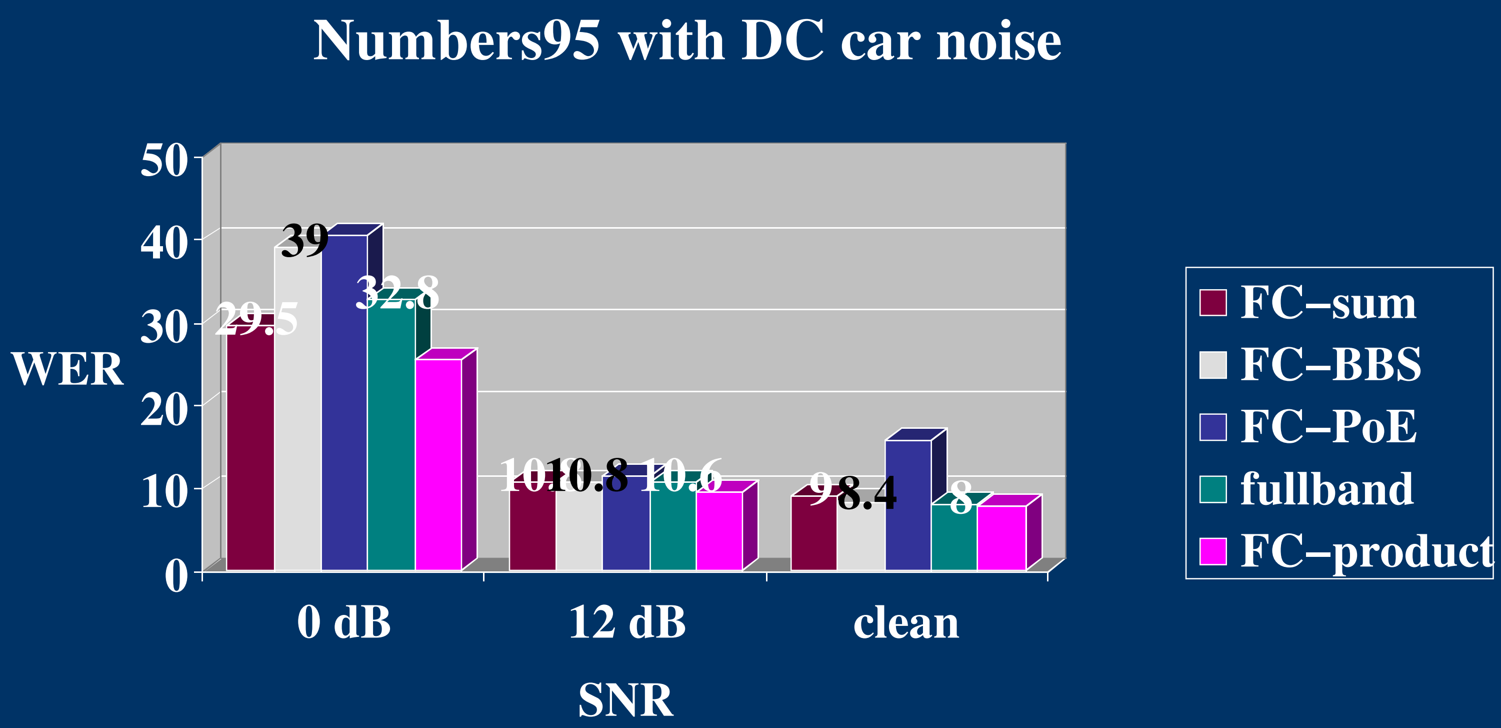
$$\text{AFC-BBS}: \; P(q|x) = \sum_{i=1}^{2^n} \Big[c_i \frac{\prod_{j \in \text{com}} P(q|x_j)}{P(q)^{n-1}} \prod_{j \notin \text{com}} (1 - P(q|x_j)) \Big]$$

$$\text{FC-BBS}: \; P(q|x) = \sum_{i=1}^{2^n} c_i\, P(q|x_i)\,(1 - P(q|x_{\neg i}))$$

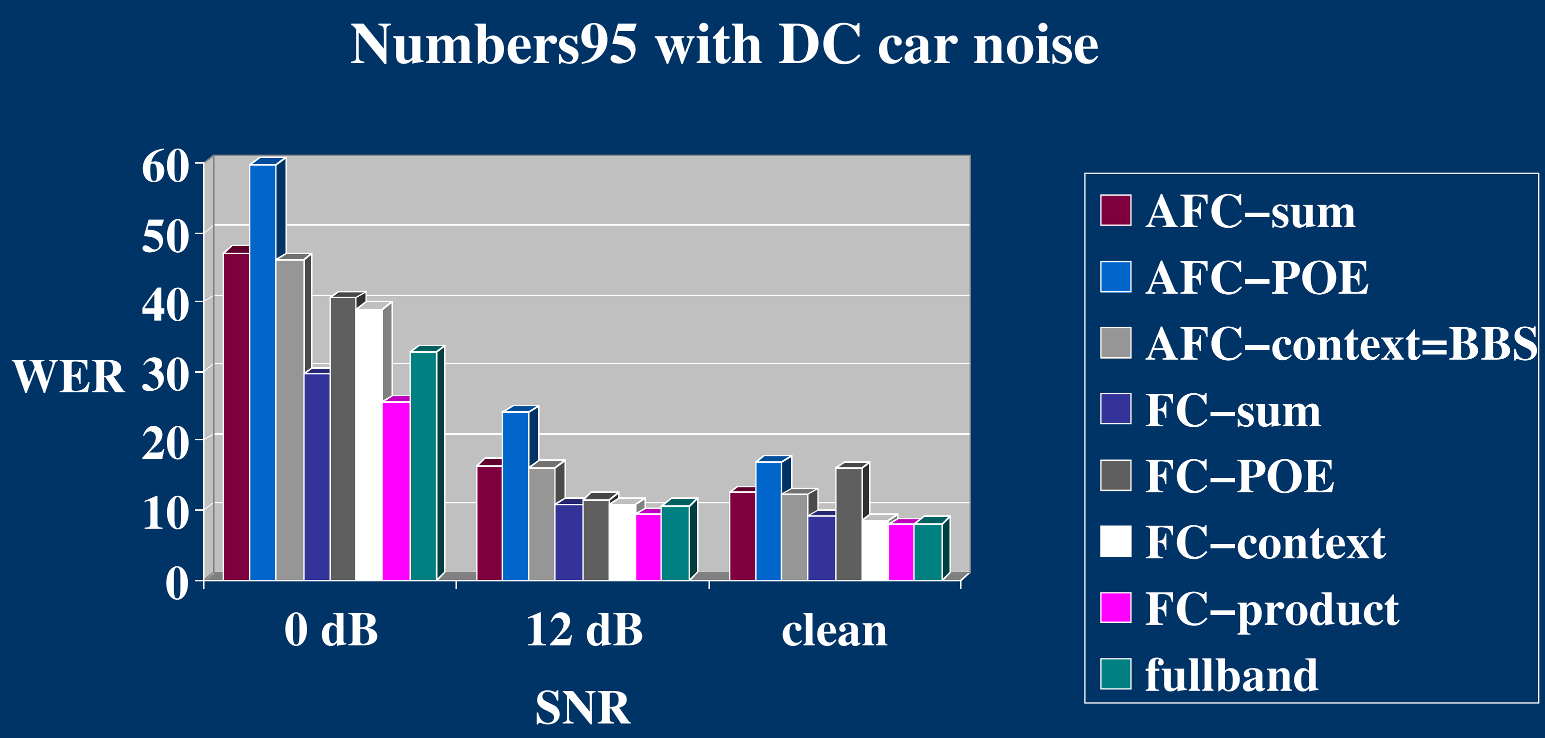
Experiments



Experiments



Experiments



Conclusion

- AFC: no significant improvement with BBS' context model
- FC:
  - using BBS' context model gave a small improvement in clean (from 9 to 8.4 %)
  - but degradation in high noise
- PoE :
  - cannot compete on its own (except for some noise cases)
  - does not seem to harm in BBS