Non-Motor Imagery to drive a Brain-Computer Interface

based on: Alvaro Fuentes Cabrera and Kim Dremstrup, "Auditory and spatial navigation imagery in Brain–Computer Interface using optimized wavelets", Journal of Neuroscience Methods, 174 (2008) 135–146

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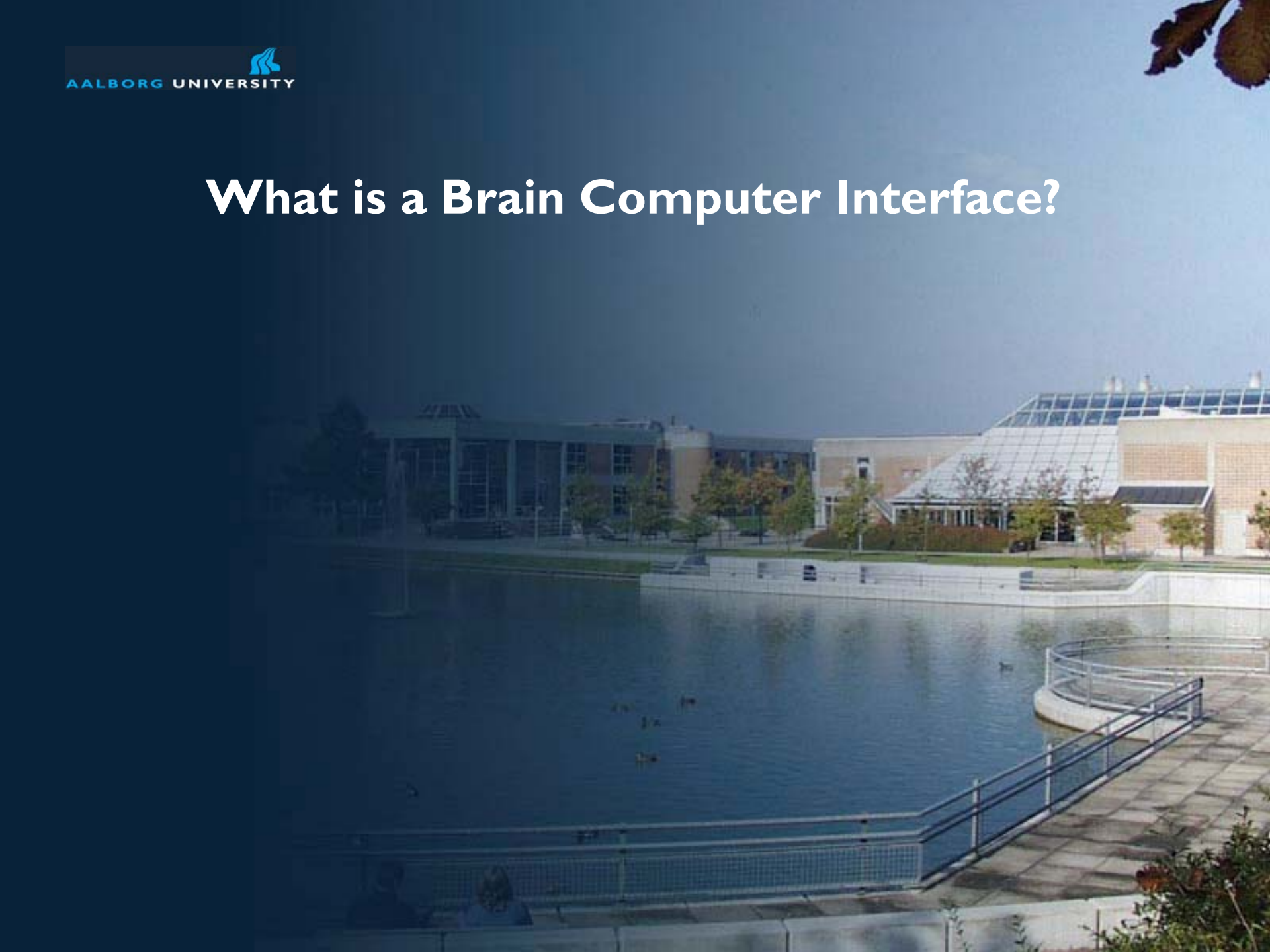
What is a Brain Computer Interface?



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What is a Brain Computer Interface?

A brain–computer interface is a communication system that does not depend on any kind of muscle activity.

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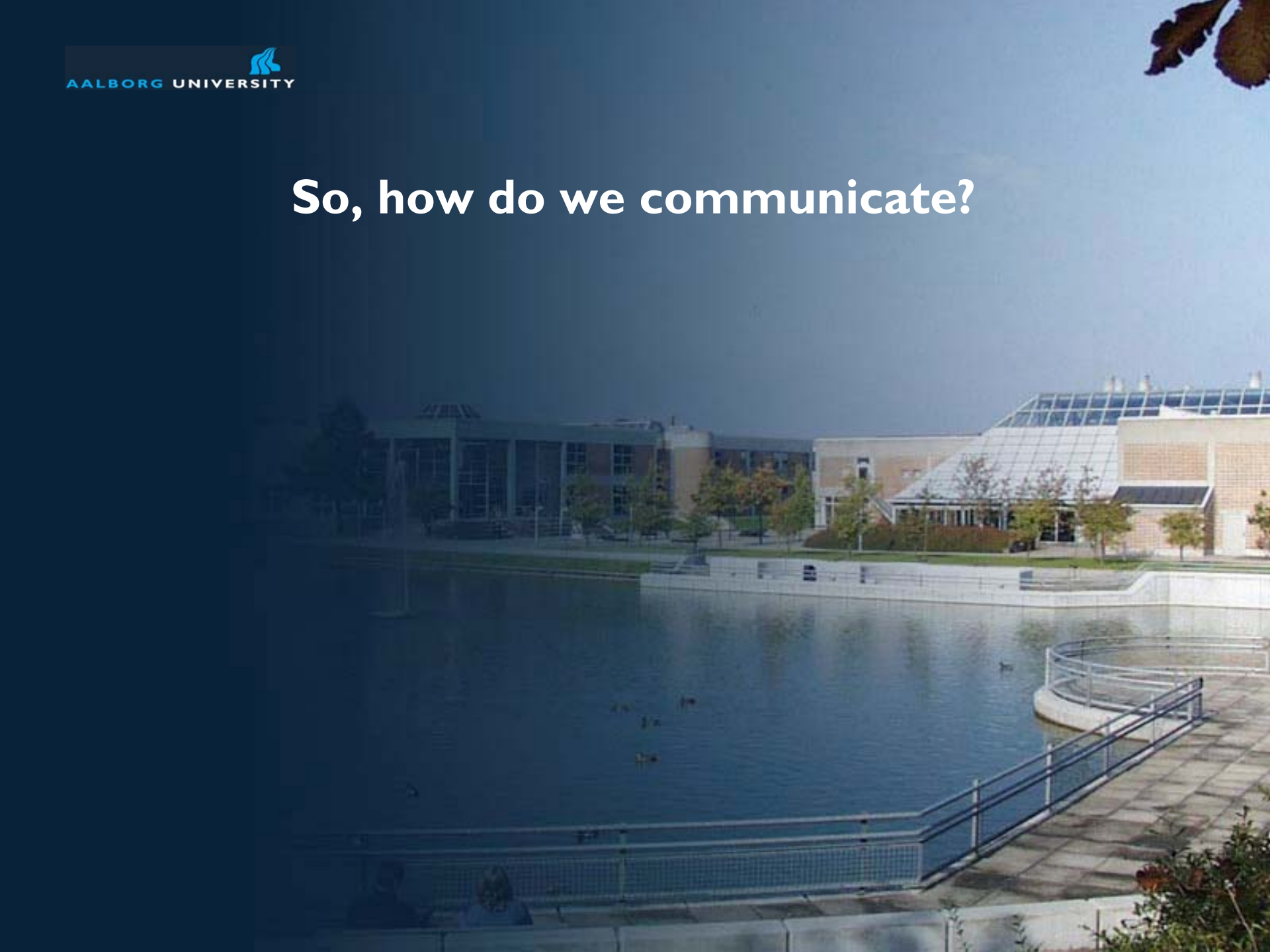
So, how do we communicate?



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So, how do we communicate?

We learn to control brain activity, which is recorded through electro-encephalogram (EEG), Magneto-encephalogram (MEG) or electro-corticogram (ECoG).

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And how do we generate this brain activity?

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And how do we generate this brain activity?

This brain activity is generated by either imagery or external stimuli.

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Non-motor imagery

Imagination of:

- **Familiar tunes**
- **Spatial navigation**

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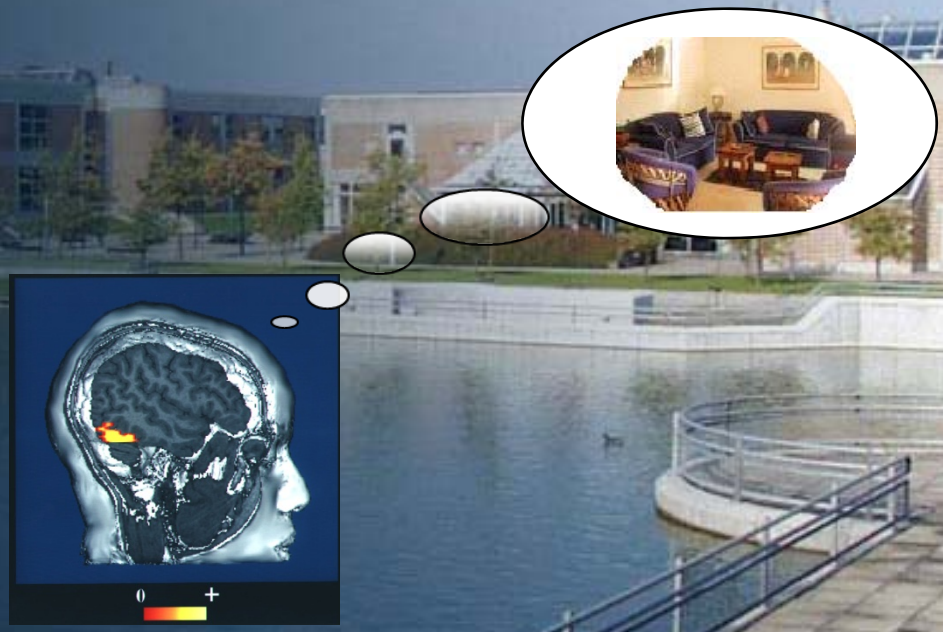
Non-Motor Imagery

Imagination of:

Spatial navigation:

The subject was instructed to imagine being in a familiar environment, scanning the surroundings noticing details while going from room to room and around furniture. The importance that the imagination involved examining the rooms rather than walking around them was stressed, as the latter could cause motor activity.



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Non-motor imagery Experiments

Imagination of:

Auditory Imagery:

The subject was asked to think of a familiar tune. They were instructed to listen to it in their head, without mouthing the words or melody . Well known popular melodies with no association with lyrics were presented to the subjects for them to choose the most familiar one to be used during the auditory imagery.

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Non-motor imagery: Goals

- Find an optimal feature extraction method
- Find electrode location for optimal classification accuracies

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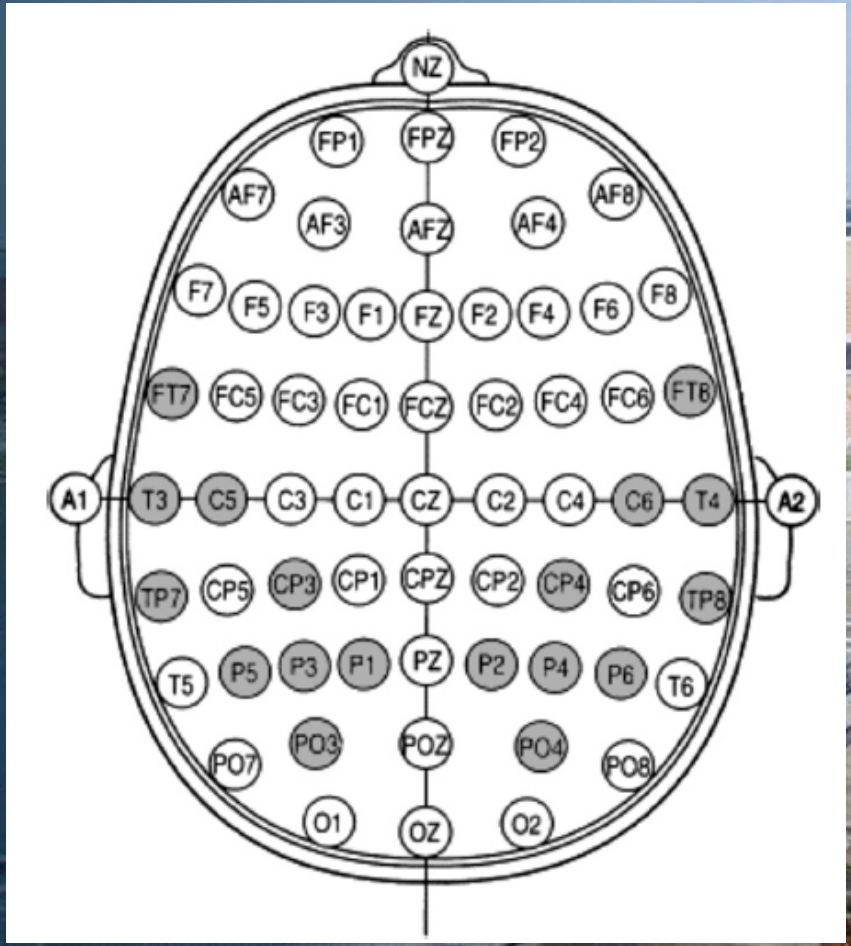
Non-motor imagery: experiment

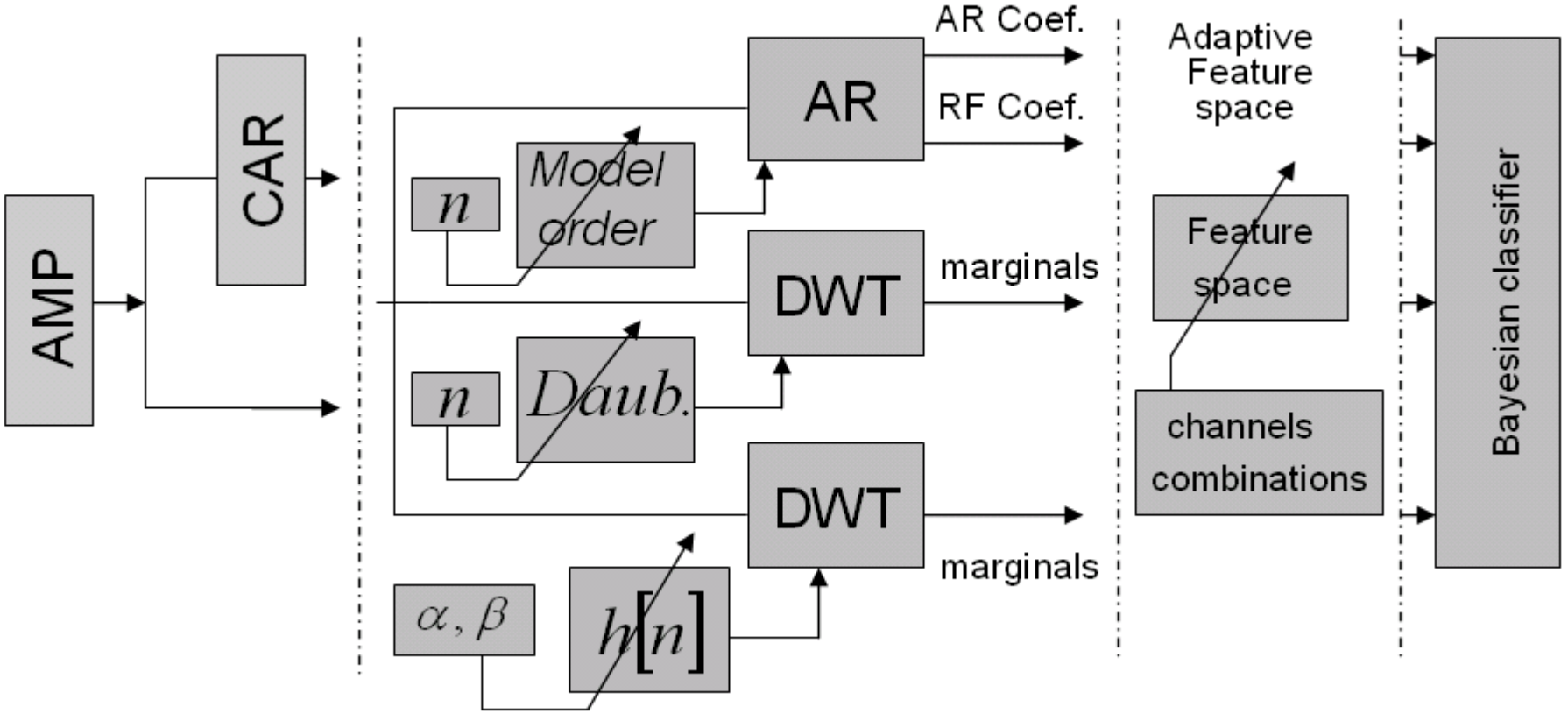
19 healthy subjects (no previous experience in BCI).

18 electrodes over the temporal and parietal lobes

Task were performed without feedback



Flow Diagram of off-line Signal Processing for BCI using a Bayesian Classifier



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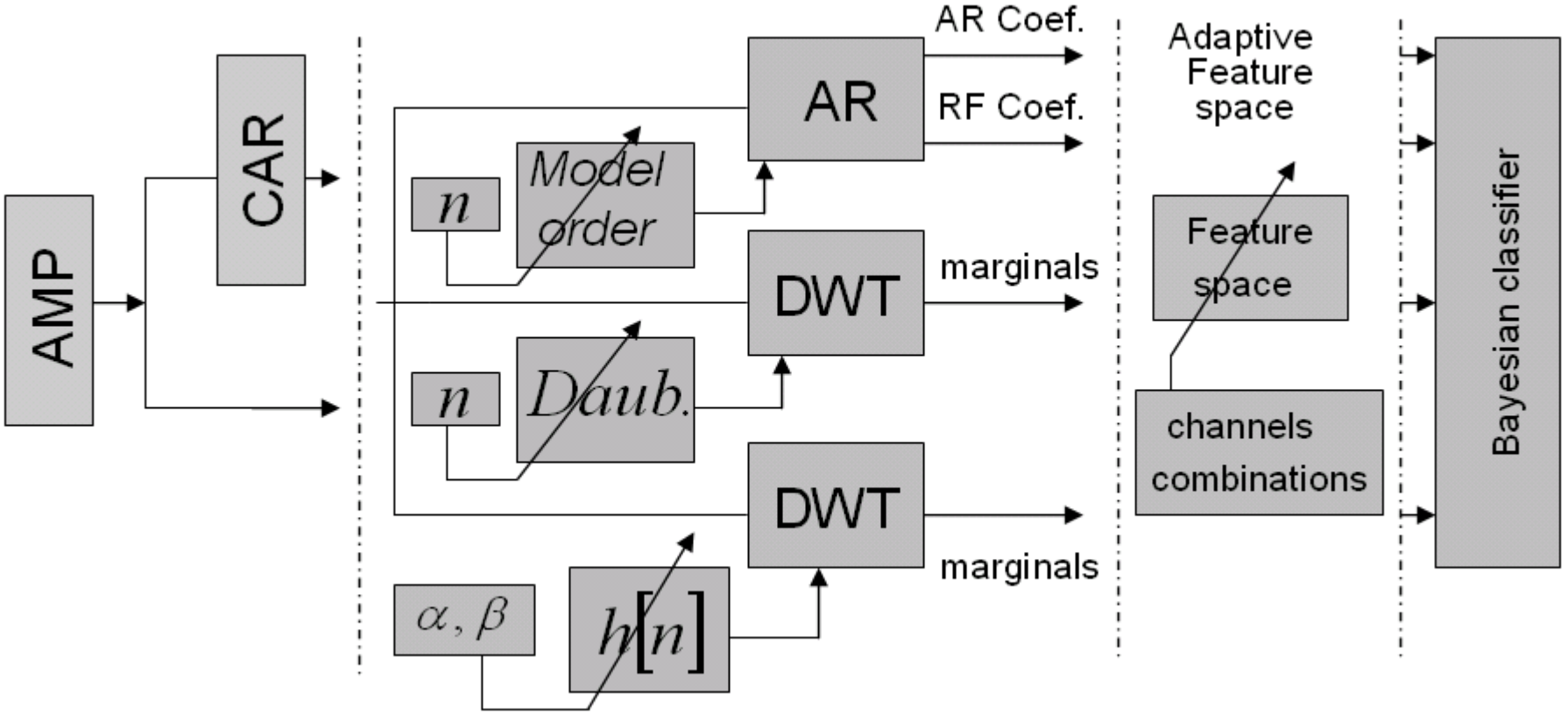
Feature Spaces

1) Single channel (SCH): each of the eighteen recorded EEG channels was classified independently (18 classification procedures).

2) *Exhaustive search of a two-channel combination (ES): all possible* combinations of two channels were classified using all features from both channels (153 classification procedures).

Flow Diagram of off-line Signal Processing for BCI using a Bayesian Classifier



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Classification

Bayesian Classifier

5 folders Cross-Validation

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Results: Spatial Filtering

The Common Average Referenced signal gave slightly worse results than the non-spatially filtered signal

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Results: Classification Acuracies

TABLE II
CLASSIFICATION ACCURACY

	Classification Accuracy [%] SCH					Classification Accuracy [%] ES				
subject	ARC	RFC	OW 4 taps	OW 6 taps	Daub.	ARC	RFC	OW 4 taps	OW 6 taps	Daub.
1	59.00	60.25	61.00	61.50	60.00	62.25	61.00	62.75	66.00	61.75
2	59.25	59.50	64.75	66.00	60.75	61.75	63.50	65.25	67.75	63.25
3	64.40	66.00	58.20	61.20	56.80	69.40	70.20	62.20	69.40	61.40
4	63.00	63.00	61.00	65.00	59.75	65.75	68.00	63.50	65.75	62.25
5	60.50	62.50	60.00	63.50	60.25	63.75	64.50	64.75	67.50	64.75
6	60.50	58.00	59.25	61.75	60.00	60.25	63.25	62.00	65.50	61.00
7	66.33	62.67	70.33	71.00	65.33	71.67	69.33	71.33	75.67	68.00
8	59.00	60.75	59.75	63.00	57.75	63.00	64.50	62.75	67.00	63.00
9	61.00	60.67	65.33	65.00	60.00	65.00	64.33	65.00	69.67	64.33
10	76.00	76.00	79.00	80.67	75.33	81.33	81.67	81.33	83.33	79.67
11	62.33	61.00	65.33	66.33	59.33	65.00	67.00	70.33	71.33	64.67
12	62.00	62.67	67.33	69.67	66.00	67.33	67.33	68.67	71.00	68.33
13	57.67	59.33	59.33	62.67	56.00	60.33	61.33	61.00	66.67	58.67
14	61.67	62.00	66.00	69.33	63.67	69.33	68.67	70.00	74.33	69.67
15	58.50	56.00	59.00	61.75	56.00	60.00	60.75	62.75	63.25	60.25
16	70.33	70.67	70.67	74.00	68.00	74.00	73.67	74.67	75.67	75.00
17	58.50	58.50	61.50	62.50	59.00	60.25	60.50	65.25	65.75	62.25
18	67.00	65.67	67.67	70.33	64.00	68.00	68.00	69.33	71.00	66.33
19	72.33	73.33	70.33	73.67	72.33	74.67	75.67	72.33	74.33	74.33
Average	**63.12**	**63.08**	**64.51**	**66.78**	**63.23**	**66.48**	**67.01**	**67.12**	**70.05**	**65.73**
SD	**σ=5.13**	**σ=5.24**	**σ=5.47**	**σ=5.35**	**σ=5.48**	**σ=5.84**	**σ=5.53**	**σ=5.30**	**σ=4.91**	**σ=5.58**

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Results: Statistical Analysis

Two-way ANOVA (null hypothesis rejected for p-values)>0.05

Two Factors: Feature Vector (2 levels) and Feature extraction methods (5 levels).

Null hypotheses: classification results are not affected by:

1. *Features extraction method*
2. *Feature space*
3. *Combination of both*

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Results: Statistical Analysis

The null hypothesis, "classification results are not affected by the feature space" was rejected with a p-value<<0.01

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Results: Statistical Analysis

Feature Space:

Exhaustive Search is significantly better than Single Channel

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Results: Statistical Analysis

The null hypothesis, "classification results are not affected by feature extraction method" was rejected with a p-value=0.01

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Results: Statistical Analysis

Feature Extraction Method:

	ARC	RFC	OW4	OW6	Daub.
ARC	1	0.99	0.93	0.04	0.99
RFC		1	0.97	0.06	0.99
OW4			1	0.25	0.83
OW6				1	0.01
Daub.					1

***p-Values obtained with the TUKEY HSD post hoc test applied on the classification accuracy* percentages. Shaded values are statistically significant.**

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Results: Statistical Analysis

The combination of Feature Extraction Method and Features space did not show significant differences (p-value=0.9)

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Results: Time Consumption

TABLE 1
PROCESSING TIME FOR EACH FEATURE EXTRACTION METHOD.
h stands for hours and *m* for minutes

	Processing time			
	AR	**OW 4**	**OW 6**	**Daub.**
SCH	~7 *m*	~1 *m*	~1 h 20 *m*	<1 *m*
ES	~60 *m*	~11 *m*	~12 *h*	~5 *m*

h stands for hours and m for minutes.

The entire process takes approximately 14 hours per subject using 12 processors

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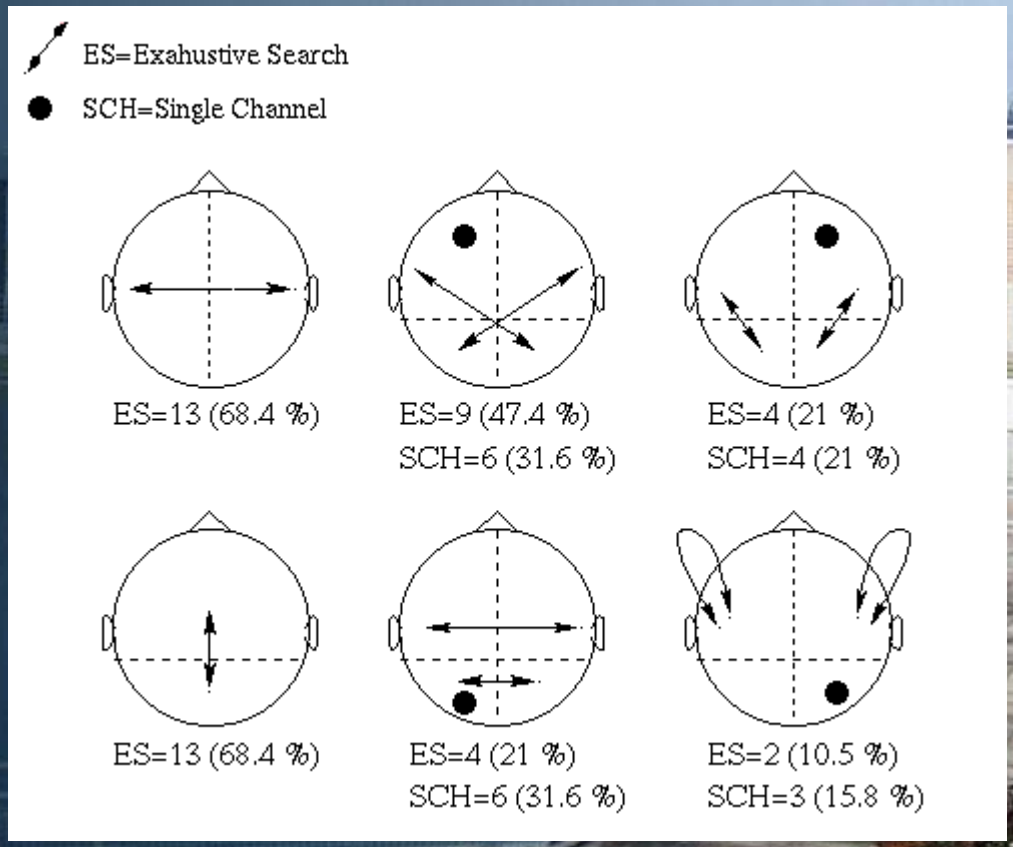
Results: Location of best performing channels

Multi-channels EEG recording are necessary to find features that best separate both classes



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Conclusions

- CAR did not improve the classification accuracy
- Highest classification rates are found on different electrode locations for different subjects
- Exhaustive search (2 channels) gives better results than Single channel (would ES on a 3 basis channels improve classification?)
- Wavelet Optimization (6 taps filter) gives better results than all the other 4 feat. extraction methods
- Parallel processing plays an important part due to the high time consumption of the processes

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Conclusions

- This BCI paradigm is feasible to be implemented
- A possibility to use BCI systems for stroke patients and persons who have never had motor control, people for which is not possible to elicit movement related potentials
- Provide BCI systems with more degrees of freedom

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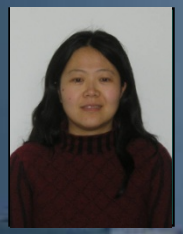
CENTER FOR SENSORY-MOTOR INTERACTION SMI

Laboratory for Brain-Computer Interfaces

Kim Dremstrup, Ph.D., Associate Professor: Head of Laboratory



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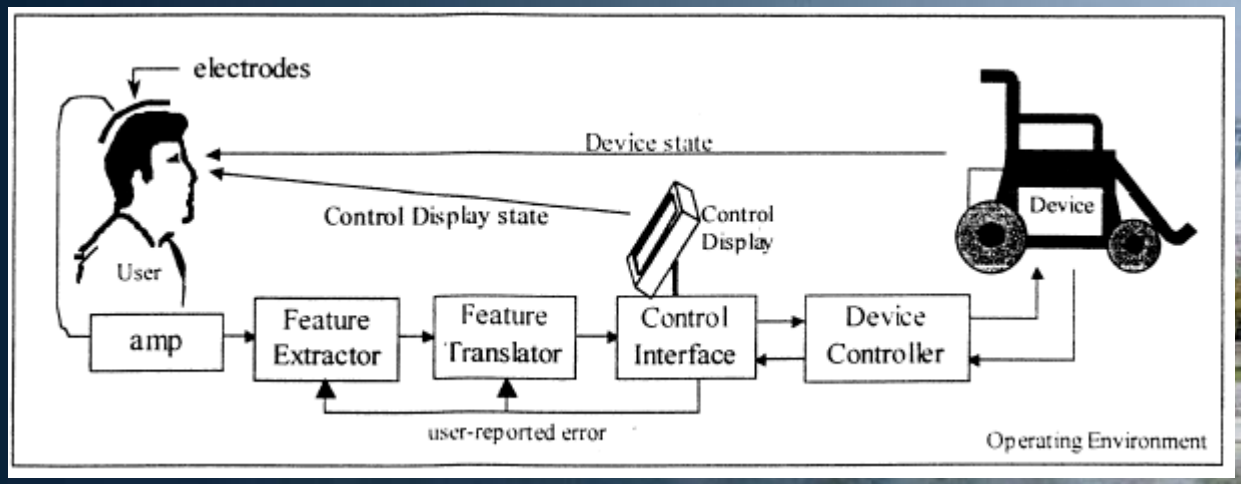
Functional model of a BCI system



Functional model of a BCI System proposed by Mason, 2003.