

# Bayesian Dictionary Learning for EEG Source Identification

Trine Nyholm Kragh & Laura Nyrup Mogensen  
Mathematical Engineering, MATTEK

Master's Thesis







**Mathematical Engineering**  
Aalborg University  
<http://www.aau.dk>

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### STUDENT REPORT

**Title:**

Bayesian Dictionary Learning for EEG  
Source Identification

**Abstract:**

Here is the abstract
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**Theme:**

**Project Period:**

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Mattek9

**Participant(s):**

Trine Nyholm Kragh  
Laura Nyrup Mogensen

**Supervisor(s):**

Jan Østergaard

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**AALBORG UNIVERSITET**  
STUDENTERRAPPORT

**Matematik-Teknologi**  
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<http://www.aau.dk>

**Titel:**

Bayesian Bibliotek Læring for EEG Kilde  
Identifikation

**Abstract:**

Her er resuméet
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**Tema:**

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**Projektgruppe:**

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**Deltager(e):**

Trine Nyholm Kragh  
Laura Nyrup Mogensen

**Vejleder(e):**

Jan Østergaard

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*Rapportens indhold er frit tilgængeligt, men offentliggørelse (med kildeangivelse) må kun ske efter aftale med forfatterne.*



# Preface

Here is the preface. You should put your signatures at the end of the preface.

Aalborg University, September 17, 2019

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Trine Nyholm Kragh  
<trijen15@student.aau.dk>

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Laura Nyrup Mogensen  
<lmogen15@student.aau.dk>





# Danish Summary

Dansk resume ?



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# Introduction

Introduktion til hele projektet, skal kunne læses som en appetitvækker til resten af rapporten, det vi skriver her skal så uddybes senere. Brug dog stadigvæk kilder.

- kort intro a EEG og den brede anvendelse, anvendelse indenfor høreapparat.
- intro af model, problem med overbestemt system
- Seneste forslag til at løse dette
- vi vil efterviser dette og udvide til realtime tracking
- opbygningen af rapporten



## Chapter 1

# Problem Analysis?

indhold





## Chapter 2

# Theory

### 2.1 Compressive Sensing

Compressive sensing is used to recover high-dimensional signal from incomplete measurements using efficient algorithm. In compressive sensing a linear model is used to describe the relationship:

$$y = Ax,$$

where  $x$  is a  $1 \times N$  vector and  $A$  is a matrix of size  $M \times N$ .

As we want  $M \ll N$  then  $A$  becomes rank-deficient and therefore have a nonempty nullspace.

We want  $x$  to be a sparse representation, meaning that we have a signal of length  $N$  we want to represent it with  $k \ll N$  nonzero coefficient

signal can be well-approximated from a linearly combination of few elements extracted from a known basis or dictionary. If the representation is exact then the signal is sparse. A signal  $x$  said to be  $k$ -sparse when it has at most  $k$  nonzeros in  $x$ :

$$\|x\|_0 \leq k,$$

where

$$\Sigma_k = \{x : \|x\|_0 \leq k\},$$

denote the set of all  $k$ -sparse signals  $\{\bullet\}$ .

$\ell_p$  norm is given as

$$\|x\|_p = \left( \sum_{i=1}^n |x_i|^p \right)^{1/p}, \quad p \in [1, \infty)$$

the norm is used as a measure of the strength of a signal or as an error.

Then  $\ell_0$  norm is np hard to calculate and therefore we seek for an approximation within the  $\ell_1$  norm. Therefore, we instead find the best  $k$ -term approximation of the signal

some conditions must be satisfied to insure that we recover all sparse representation of a signal. Some of the most known conditions explore the null space: Null Space Conditions.

The null space of the matrix  $A$  is defined as

$$\mathcal{N}(A) = \{z : Az = 0\}.$$

NSP do not take account for noise and we must therefore look at some stronger conditions which incorporate noise, the following restricted isometry property (RIP) [1].

**Definition 2.1 (Restricted Isometry Property)**

A matrix  $A$  satisfies the RIP of order  $k$  if there exists a  $\delta_k \in (0, 1)$  such that

$$(1 - \delta_k)\|x\|_2^2 \leq \|Ax\|_2^2 \leq (1 + \delta_k)\|x\|_2^2,$$

holds for all  $x \in \Sigma_k$

If a matrix  $A$  satisfy RIP then it will also satisfy the NSP as RIP is strictly stronger than NSP.

**Theorem 2.1.1**

If  $A$  satisfies the RIP of order  $2k$  with the constant  $\delta_{2k} < \sqrt{2} - 1$ . Then

$$C = \frac{2}{1 - (1 + \sqrt{2})\delta_{2k}}$$

Another measure used for sparsity is coherence [2].

**Definition 2.2 (Coherence)**

Coherence of the matrix  $A$ , denoted as  $\mu(A)$ , is the largest absolute value between two columns  $a_i$  and  $a_j$  from  $A$ :

$$\mu(A) = \max_{1 \leq i < j \leq n} \frac{|\langle a_i, a_j \rangle|}{\|a_i\|_2 \|a_j\|_2}$$

Appendix A

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