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## **Towards high performance and efficient brain computer interface character speller : convolutional neural network based methods**

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### **Citation**

Shan, H. (2020, February 25). *Towards high performance and efficient brain computer interface character speller : convolutional neural network based methods*. Retrieved from <https://hdl.handle.net/1887/85675>

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**Author:** Shan, H.

**Title:** Towards high performance and efficient brain computer interface character speller : convolutional neural network based methods

**Issue Date:** 2020-02-25

**Towards High Performance and Efficient  
Brain Computer Interface Character Speller:  
Convolutional Neural Network based Methods**

Hongchang Shan



**Towards High Performance and Efficient  
Brain Computer Interface Character Speller:  
Convolutional Neural Network based Methods**

**PROEFSCHRIFT**

ter verkrijging van  
de graad van Doctor aan de Universiteit Leiden,  
op gezag van Rector Magnificus Prof.mr. C.J.J.M. Stolker,  
volgens besluit van het College voor Promoties  
te verdedigen op woensdag 25 februari 2020  
klokke 16:15 uur

door

Hongchang Shan  
geboren te Heilongjiang, China  
in 1989

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Towards High Performance and Efficient  
Brain Computer Interface Character Speller:  
Convolutional Neural Network based Methods  
Hongchang Shan. -  
Dissertation Universiteit Leiden. - With ref. - With summary in Dutch.

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This dissertation was typeset using  $\text{\LaTeX}$  in Linux and version controlled using Git.

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# List of Abbreviations

<b>ALS</b>	Amyotrophic Lateral Sclerosis
<b>AP</b>	Action Potential
<b>AUC</b>	Area Under the Receiver Operating Characteristic
<b>BCI</b>	Brain Computer Interface
<b>CNN</b>	Convolutional Neural Network
<b>CWT</b>	Continuous Wavelet Transform
<b>DWT</b>	Discrete Wavelet Transform
<b>ECoG</b>	Electrocorticography
<b>EEG</b>	Electroencephalography
<b>EoCNN</b>	Ensemble of Convolutional Neural Networks
<b>ERD</b>	Event Related Desynchronization
<b>ERP</b>	Event-Related Potential
<b>FLD</b>	Fisher's Linear Discriminants
<b>ITR</b>	Information Transfer Rate
<b>LDA</b>	Linear Discriminant Analysis
<b>LFP</b>	Local Field Potential
<b>max-ITR</b>	maximum ITR
<b>MSE</b>	Mean Squared Error
<b>NN</b>	Neural Network
<b>OCLNN</b>	One Convolution Layer Neural Network
<b>OSLN</b>	One Spatial Layer Network
<b>OTLN</b>	One Temporal Layer Network
<b>PEoCNN</b>	EoCNN with parameterized ensemble processing
<b>ReLU</b>	Rectified Linear Unit

<b>SAE</b>	Stacked Autoencoder
<b>SGD</b>	Stochastic Gradient Descent
<b>SLES</b>	Spatial Learning based Elimination Selection
<b>SMAC</b>	Sequential Model-based Algorithm Configuration
<b>SNR</b>	Signal to Noise Ratio
<b>SSNR</b>	Signal to Signal and Noise Ratio
<b>SSVEP</b>	Steady State Visual Evoked Potential
<b>SVM</b>	Support Vector Machine
<b>SWLDA</b>	Stepwise Linear Discriminant Analysis
<b>II</b>	BCI Competition II - Data set IIb
<b>III-A</b>	BCI Competition III - Data set II Subject A
<b>III-B</b>	BCI Competition III - Data set II Subject B