Detecting Changes in the Human Brain caused by Atrial Fibrillation using Ultrasound and Deep Learning

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Introduction

Atrial Fibrillation (AF)
- Causing vascular damage
- Leading to strokes
- Damages can be assessed using MRI

Is ACG able to detect the cerebrovascular changes caused by AF?

Acoustocerebrography (ACG)
- Novel non-invasive method to monitor brain tissue
- Able to detect stroke risk factors [1] and hypertension [2]

Methods

Ultrasound Measurements
- Multispectral ultrasound signal propagating through the human skull
- Ultrasound gel was used for coupling
- Transmitting probe was also used as receiving probe (signal was reflected at the human skull and then sampled)
- One measurement session takes about 3 minutes, with 10 measurements per second
- Measurements were done with ACG device UltraEASY (Sonovum AG)

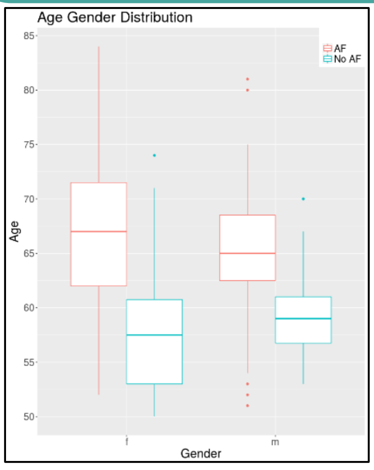
Artificial Neural Networks and Evaluation Procedure
- Already very successful in tasks like image [3] and voice recognition [4]
- Both a vanilla deep neural network (using only fully connected layers) and a deep convolutional network (using fully connected and convolutional layers) are implemented
- ReLU6 and cReLU are used as activation functions
- Training with ADAM optimizer and backpropagation
- Built upon the tensorflow [5] framework in Python 3
- Evaluation with a 4-fold cross-validation

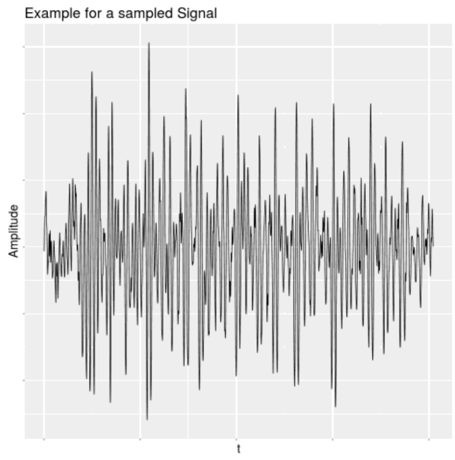
Participants

Participants are from two separate studies, both were recorded in MTZ Warsaw in 2014, approved by the ethics committee of the university of Warsaw.

AF-focused study:
- 102 patients

Cross-sectional study:
- involving 294 probands in total
- 58 were in the same age range and had no pre-existing conditions regarding vascular or heart diseases and therefore only these were included



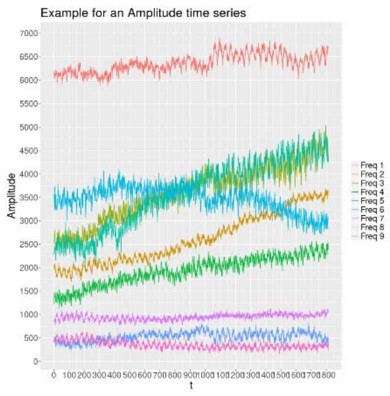


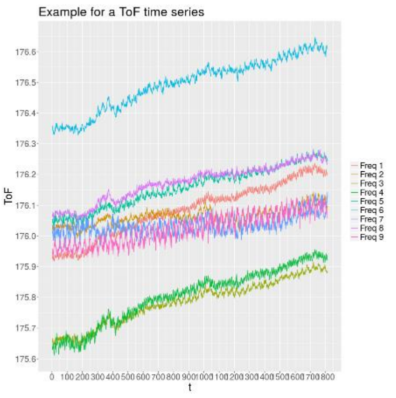
Data Processing

Signal Processing
- Extracting phase and amplitude from raw signal
- Calculating time of flight and attenuation, data are split into 10 second intervals
- Normalization of all variables

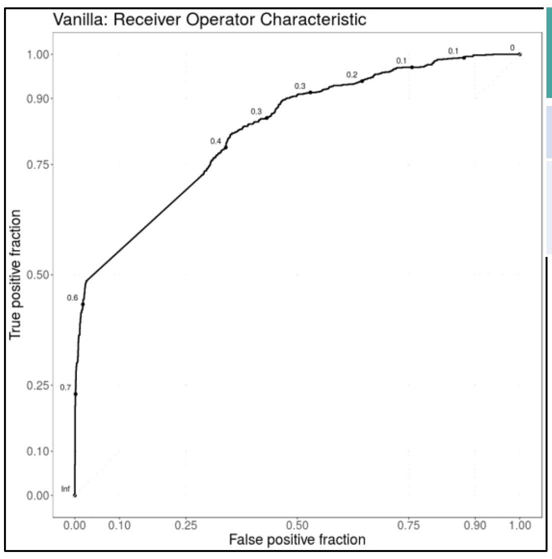
Artificial Neural Networks
- Training, then evaluating with a holdout dataset

Postprocessing
- Plots were done in R using ggplot2



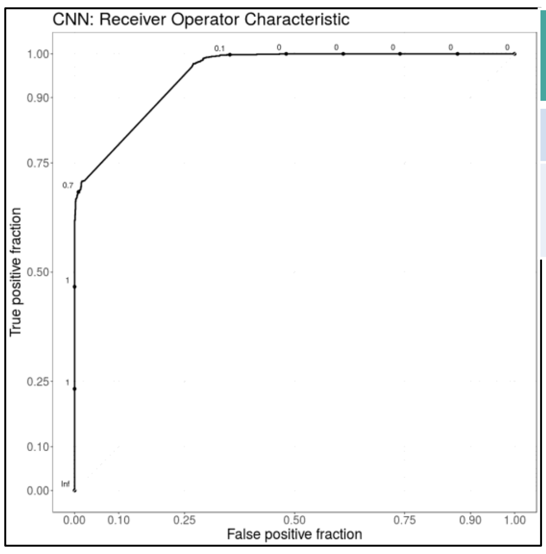


Results



Ref/ Pred	AF	No AF
AF	1786	522
No AF	50	496

Sensitivity: 0.4872
Specificity: 0.9728



Ref/ Pred	AF	No AF
AF	1795	296
No AF	41	722

Sensitivity: 0.7092
Specificity: 0.9777

Conclusions

- Although not perfect, a separation between participants with AF and without AF seems possible using ultrasound data
- Further data and other ANN (f.e. RNN, ResNet) could improve the result
- CNN outperforms the vanilla network

Conflict of Interest

The author has a financial interest in the company manufacturing the software used for the device

Sources

[1] Wrobel et al. On ultrasound classification of stroke risk factors from randomly chosen respondents using non-invasive multispectral ultrasonic measurements and adaptive profiles. Biocybernetics and Biomedical Engineering 2015, Vol. 35(4), pp. 19-28.
[2] Olszewski et al. The novel non-invasive ultrasound device for detecting an early change in the brain in patients with heart failure. European Journal of Heart Failure 2016, Vol. 18 (Suppl. 1), pp. 307-308.
[3] He K. et al. Deep Residual Learning for Image Recognition. http://arxiv.org/abs/1512.03385 2015.
[4] Sak et al. Fast and Accurate Recurrent Neural Network Acoustic Models for Speech Recognition. http://arxiv.org/abs/1507.06947 2015.
[5] Abadi et al. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. Whitepaper (2015) and Software available at http://tensorflow.org/ (March 30th 2017).