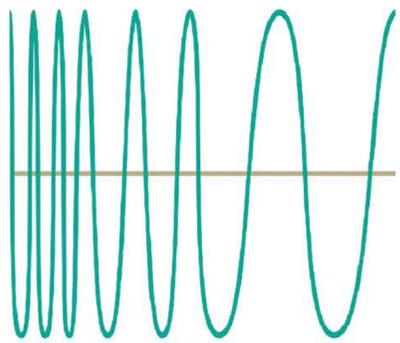


Approximating the Number of White Matter Lesions for Patients with Atrial Fibrillation using Acoustocerebrography and Deep Learning

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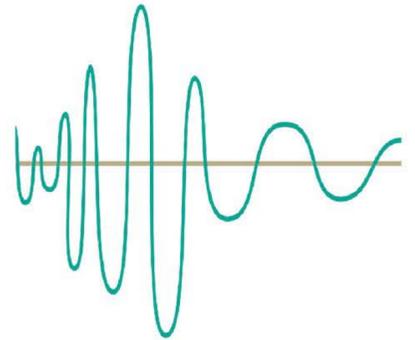
TRANSMITTER



Multispectral Signal Packages
Frequency $f_1 \dots f_{10}$



RECEIVER



Attenuation ATT (dB)
Time of Flight ToA (μ s)

Figure 1: ACG measurement procedure

MOTIVATION

White matter lesions (WML) are a common finding in patients with atrial fibrillation (AF) [1]. The exact number of WML can be obtained from MRI scans, which are costly in both time and money. Acoustocerebrography (ACG) [2] [3] can be used as a non-invasive method to pre-categorize and classify patients before MRI scans.

METHODS

Participants were measured with ACG (Sonovum AG, Germany) three times for one minute with a pause of 10 minutes between measurements. A schematic of the measurement procedure can be seen in Figure 1. This procedure was followed by a MRI scan with focus on WML. The scans were analyzed by radiologists in order to find out the approximate number of WML. The distribution of the WML is shown in Figure 2.

The received multispectral ACG signal was processed by eliminating amplification factors and using the fast Fourier transform. These acoustic spectral data were used as the input data for the following classification.

In order to find out if ACG is able to pre-classify the patients going to MRI, the patients were split into 2, 3, 4 and 5 groups, based on the quantiles of their WML, the exact splitting points and group sizes can be found in Table 1. These groups are used as a classification target for a deep convolutional neural network with 2 convolutional layers, 1 dense layer and max pooling between the convolutional layers. Tanh was used as activation function, the network was trained using backpropagation and ADAM-optimization with cross entropy as loss function. The implementation was done using TensorFlow [4].

PARTICIPANTS

58 patients with asymptomatic AF were measured at the MTZ in Warsaw, Poland. The study was approved by the ethics commission of the University of Warsaw. Patients were Caucasian, age 64.81 ± 6.08 years, 25 females and 33 males.

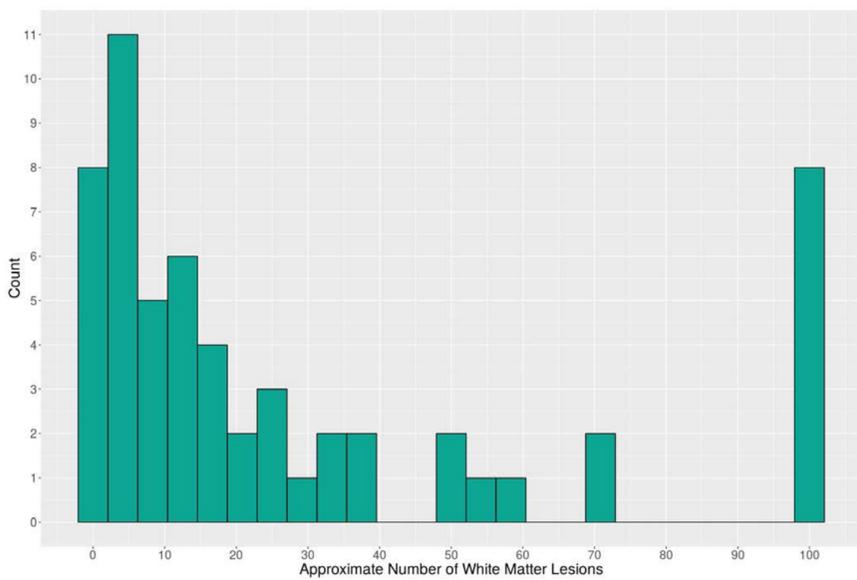


Figure 2: Distribution of white matter lesions amongst 58 patients with asymptomatic atrial fibrillation. Patients were 64.81 ± 6.08 years old, including 25 females and 33 males. Patients with more than 100 WML were cut at 100.

Groups	Splitting Points (number of patients in group)
2	$WML \leq 14$ (30), $WML > 14$ (28)
3	$WML \leq 6$ (19), $6 < WML \leq 24$ (20), $WML > 24$ (19)
4	$WML \leq 6$ (19), $6 < WML \leq 14$ (11), $14 < WML \leq 38$ (14), $WML > 38$ (14)
5	$WML \leq 4$ (14), $4 < WML \leq 10$ (10), $10 < WML \leq 19$ (11), $19 < WML \leq 55$ (12), $WML > 55$ (11)

Table 1: Distribution of patients amongst groups. The 58 patients were grouped by the quantiles of the WML distribution, which means for 2 groups, the split was made at the 50% quantile, for 3 groups at the 33.33% and the 66.67% quantiles and so on.

RESULTS

On average, a patient had 29.08 ± 33.51 WML, 8 patients had more than 100 WML. The classification accuracy is decreasing, as the number of groups is increasing, the accuracies of the classifications are shown in Table 2. The convergence of the algorithm is displayed in Figure 3.

Groups	Accuracy in %
2	95,88
3	88,52
4	76,96
5	56,34

Table 2: Accuracies of the WML group classification using a five-fold-cross-validation.

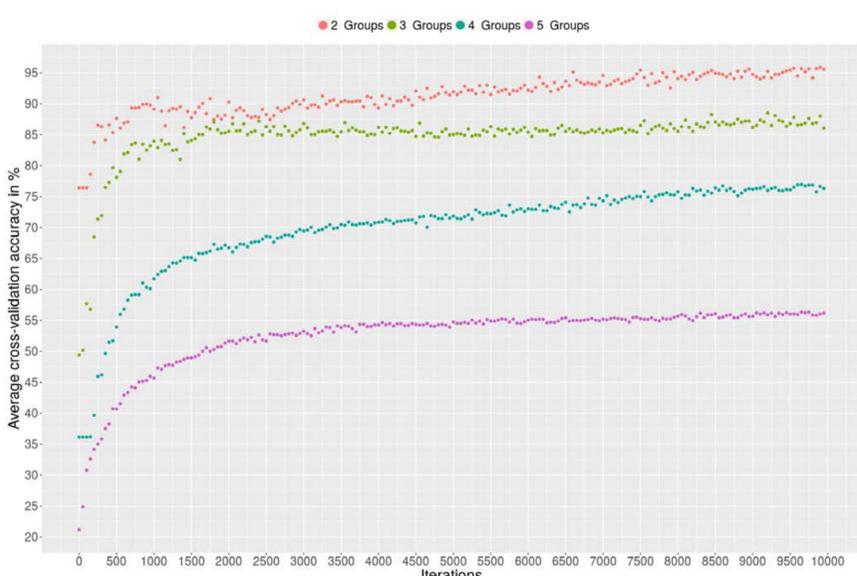


Figure 3: Average accuracy across all five folds with dependency on the number of iterations made by the neural network. The colors indicate how many different WML groups were regarded. The maximum number of iterations was set to 10,000.

CONCLUSIONS

Although ACG is not as sensitive as the gold standard MRI, it can be used for a preclassification of patients into groups which might be beneficial for cardiologists with no direct access to MRI. The results should be improvable by adding more patients from new studies, also the only data used were the values from the fast Fourier transform. An addition of different measurement values like time of flight could also further improve the classification.

References:

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- [4] Abadi et al.: *TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems*. Whitepaper (2015) and Software available at <http://tensorflow.org/> (March 9th 2018).