

APPLICABILITY OF AUTOMATIC CLASSIFICATION OF mfVEP SIGNALS in MS ASSESSMENT

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INTRODUCTION. Motivation and Goal

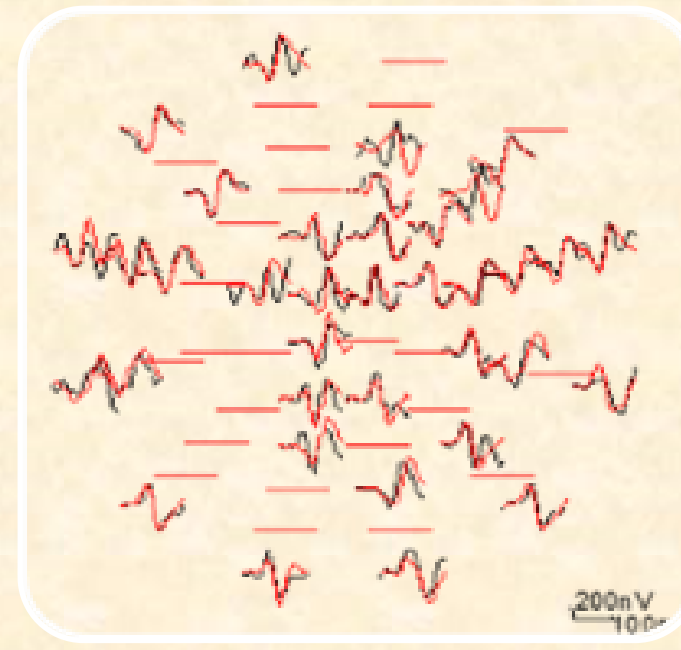
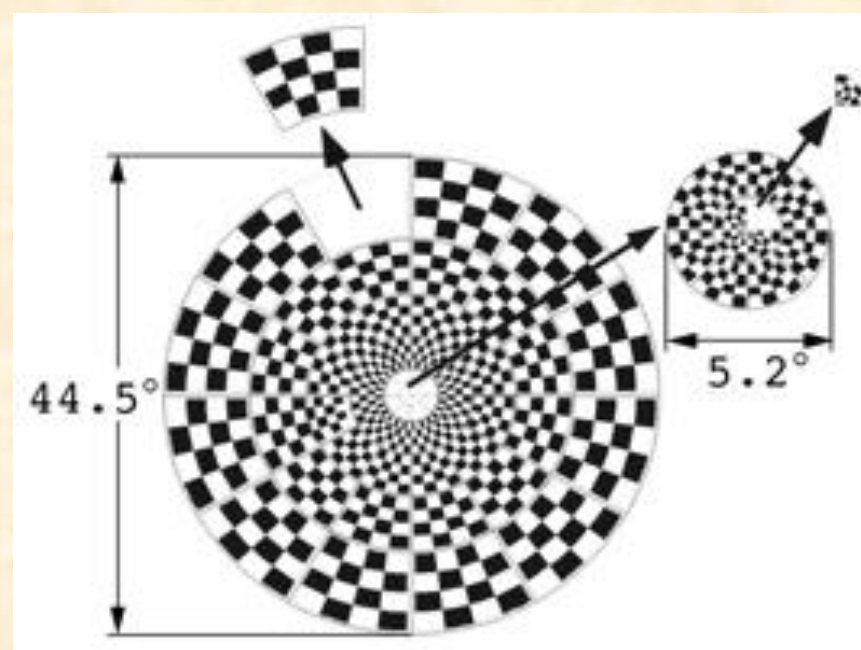
- Previous works found significance difference between controls and Multiple Sclerosis (MS) definitive subjects using amplitude and latencies from mfVEP (1,4).
- Appropriate preprocessing of biomedical signals improves the patient diagnosis based on the results of signal classification.
- The goal of automatic classification is to predict labels for new test examples based on previous relations label-example.
- This work studies the performance of automatic classification applied to mfVEP signals using a k-nearest neighbor's algorithm.

INTRODUCTION. The mfVEP

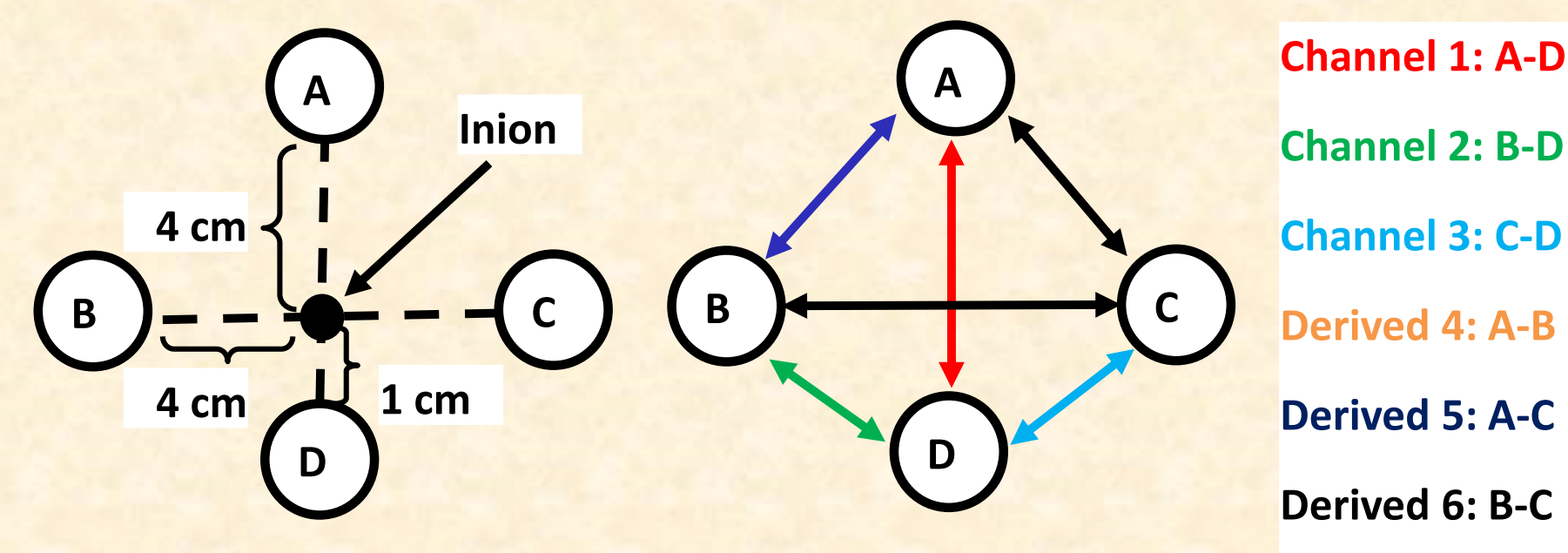
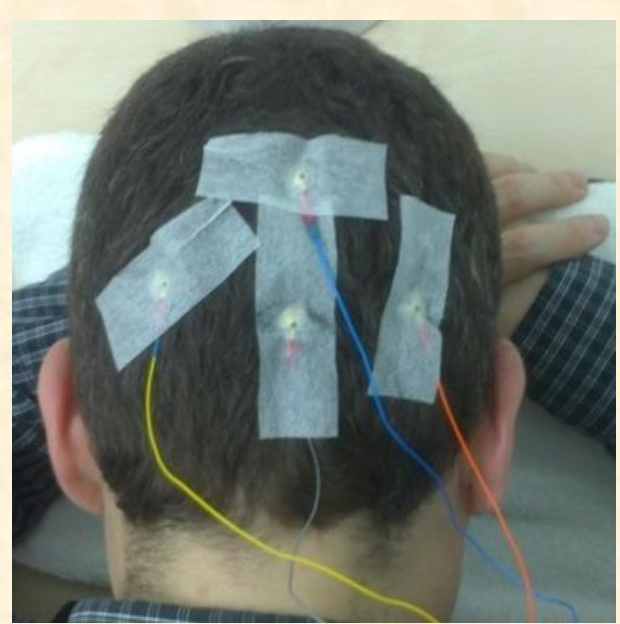
- The mfVEP test, measures the potentials obtained by stimulating the visual field divided in sectors using a flash or checkerboard visual stimuli.
- The mfVEP allows practitioners to analyze the topographical features of different segments of the visual field represented in the primary visual cortex. It is a valid tool for assessment of visual function in patients with pathologies that affect the visual pathway.

The recordings and analysis

- Monocular mfVEP recordings are obtained using VERIS software 5.9 (Electro-Diagnostic Imaging, San Mateo, USA). The stimulus was a scaled dartboard with a diameter of 44.5, containing 60 sectors, each with 16 checks, (8 white / 8 black).



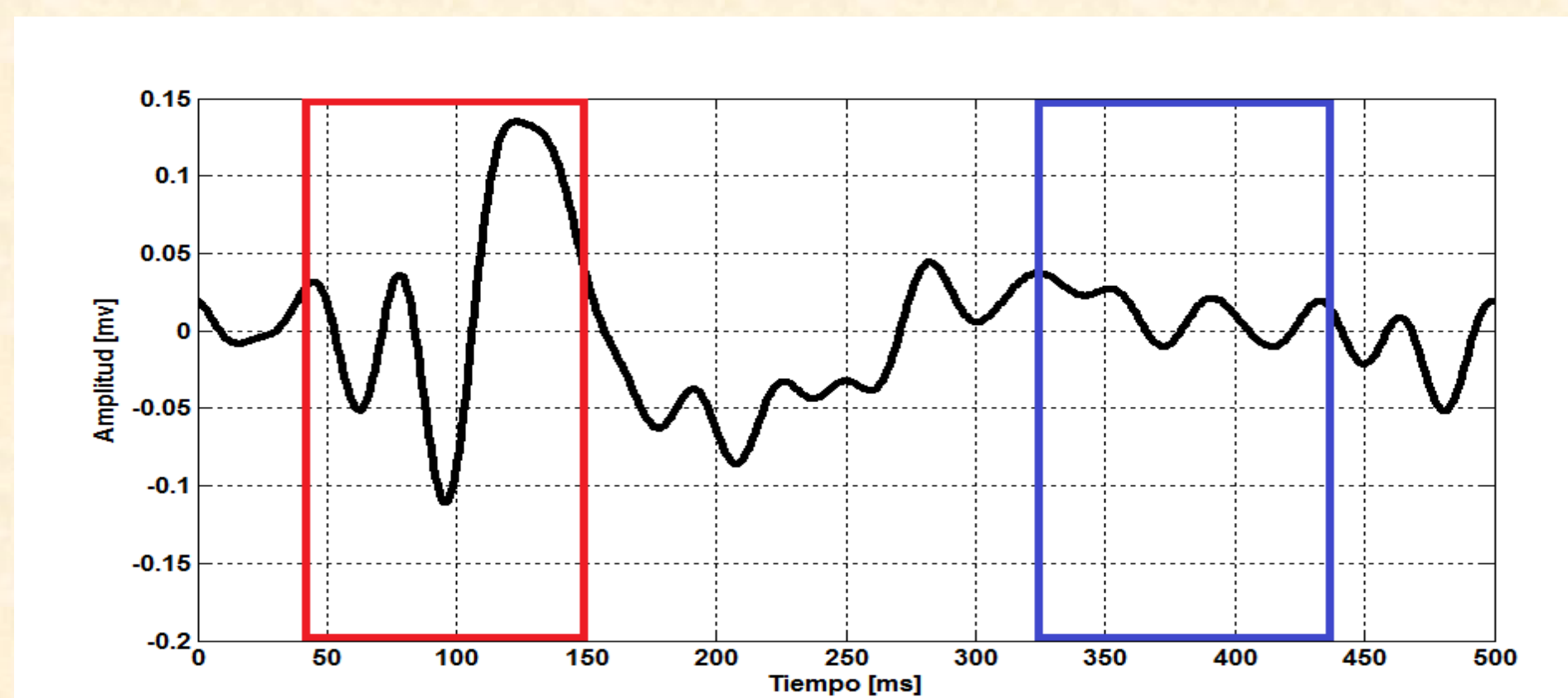
- Three channels of continuous mfVEP recordings are obtained using gold cup electrodes. Three others channels derived are obtained by subtracting.



- The records are amplified with the low and high frequency cut-offs set at 3 and 100 Hz, and sampled at 1200 Hz. Impedance was <2 KΩ for all electrodes. The length of each record is 500 ms.

METHOD. Amplitude measurements

- The signal to noise ratio (SNR) is the parameter used to quantify the quality of the mfVEP recordings (2,3).
- The recordings are divided in: signal window (45-150 ms) and noise window (325-450 ms). The SNR is computed as the Root Mean Square (RMS) of the signal windows divided by the RMS of the noise window mean of the 60 sectors.



$$SNR_S = \frac{RMS_S}{RMS_N}$$

$$SNR_N = \frac{RMS_N}{RMS_S}$$

METHOD. Latency measurements

- Latency was measured as the temporal shift producing the best cross-correlation value between:
 - Each individual and a template constructed by averaging responses from a control database (Monocular Latency = Mo_La)
 - The corresponding responses of each eye (Interocular Latency = In_La)

METHOD. Features vector

- For each subject, a features vector is constructed with the information of SNR, Mo_La and In_La of each sector:

Sector 1	Sector 1	Sector 1	Sector 2	Sector 2	Sector 2	...	Sector 60	Sector 60	Sector 60
SNR	Mo_La	In_La	SNR	Mo_La	In_La	...	SNR	Mo_La	In_La

METHOD. Subjects Database

- 22 right eyes from control subjects (Control label)
- 33 right eyes from patients with MS (MS label)
- The eyes of MS subjects were also divided in Optic Neuritis affected (ON label) and no affected (noON label).

METHOD. K-nearest neighbor's algorithm

The nearest-neighbor method is a simple algorithms for predicting the class of a test example.

The training step: store every eye features vector with its label.

Subject	Features vector	Label 1	Label 2
Control 1_OD	FV(Control 1_OD)	CON	--
Control 2_OD	FV(Control 2_OD)	CON	--
...
MS_01_OD	FV(MS_01_OD)	MS	ON
MS_02_OD	FV(MS_02_OD)	MS	noON
...

To make a prediction for a test eye:

- Compute its Euclidean distance to every eye features vector.

$$d(F_1, F_2) = \|F_1 - F_2\| = \sqrt{(F_1 - F_2) \cdot (F_1 - F_2)} = \left(\sum_{se=1}^{se=60 \times 3} (F_{1_{se}} - F_{2_{se}})^2 \right)^{1/2}$$

- Keep the k closest features vectors, where k ≥ 1 is a fixed integer.
- Look for the label that is most common among these eyes. This label is the prediction for this test example.

RESULTS

Confusion matrix for each classification:

	Control	MS	%
Control	32	2	94.11 5.88
MS	1	20	91.00 9.00
%	96.97 3.03	95.24 4.76	95.8 4.2

	MS	ON	noON	%
MS	12	7	63.16 36.84	
ON	3	11	61.12 38.88	
%	80.00 20.00	21.40 78.60	71.1 29.9	

- The global accuracy obtained for Control-MS classification is 95.8%.
- The global accuracy obtained for MS eyes: ON-noON is 71.1%.
- The best values were obtained for K=1
- Pool computation was used to reduced computing time to 1.87 and 1.18 seconds in each case.

DISCUSSION

- Good classification accuracy results were obtained between control and patients.
- Moderate classification accuracy for ON-noON due to subclinical affection.
- Our results suggest that automatic classifier as k-NN used in combination with the actual techniques (MRI, OCT) could improve multiple sclerosis diagnosis.
- Proposed future works:
 - use more sophisticated automatic classifier: neural networks.
 - comparison between different comercial register equipment (example: VERIS vs. ROLAND).
 - Study MS-risk patients.

LITERATURE

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