(2-F-56) Histogram of Gradient Orientations of Signal Plots applied to Brain Computer Interfaces

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Introduction

- **Where are the Waveforms?**
  - Around **71.2%** of BCI Research is based on Noninvasive EEG [1]
- EEG has traditionally focused on temporal waveforms. Few methods exploited automatically signal waveforms:
  - Matching Pursuit (Mallat 1993)
  - Permutation Entropy (Bandt-Pompe 2002)
  - Slope Horizontal Chain Code[2].
  - Merging of Increasing and Descending Sequences[3].
- Clinical atlases and guidelines were developed based on waveforms.
  - More interaction between BCI stakeholders should be fostered[7].

Materials

- Research Oriented Digital EEG Device
  - g.Nautilus, 8-channel, wet electrodes, g.Tec.
- Open Source Platform and Software
  - OpenVibe
  - Matlab
  - C++ VLFeat Computer Vision Library.
- Offline datasets
  - Physiobank Alpha Wave
  - Motor Imagery BNCI-Horizon 002-2014
  - ALS P300 BNCI-Horizon 008-2014

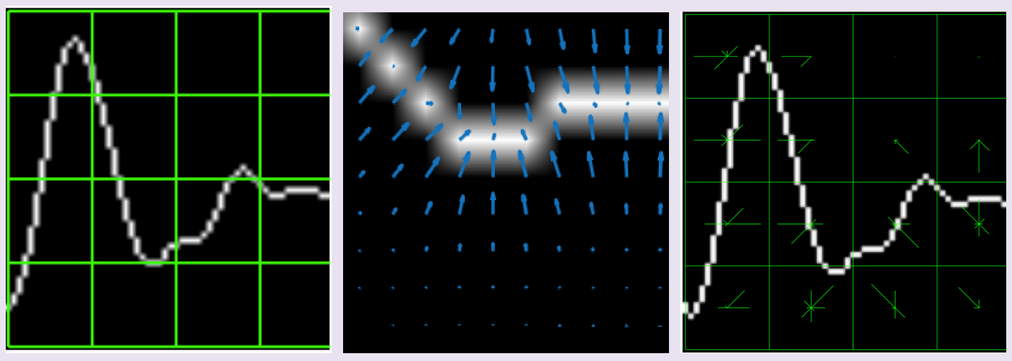
Figure 1: Subject performing a P300 Speller experiment

Methods: Processing Pipeline and Feature Extraction

1. Signal Preprocessing and Segmentation
2. Signal Plotting: single channel binary image

$$I(z_1, z_2) = \begin{cases} \mathbf{255} \text{ if } z_1 = \gamma \cdot n;\ z_2 = EEG(n, c) + z(c) \\ \mathbf{0} \text{ otherwise} \end{cases}$$

   - **Bresenham** algorithm interpolates straight lines between consecutive sample points.



(a) Patch over a Signal Complex (b) Gradient vector field around the signal (c) Oriented histogram on each block

Figure 2: Sample patch around a signal complex. The patch is divided in $\mathbf{4} \times \mathbf{4}$ blocks and **8** orientations (bins) are calculated on each block, forming a **128** normalized feature called *descriptor*.

3. The Histogram of Gradient Orientations
   - Popular and powerful tool from Computer Vision and basis of SIFT[5] feature extraction method.
   - Inspired on how the visual cortex identify shapes.
   - For every pixel **p** on the image plot:

$$h(\theta, i, j) = 3s \sum_{\mathbf{p}} w_{\text{ang}}(\angle J(\mathbf{p}) - \theta)\, w_{ij}\left(\frac{\mathbf{p} - \mathbf{kp}}{3s}\right) |J(\mathbf{p})|$$

with s as the scale of the patch, $J(\mathbf{p})$ is the finite differences gradient vector, $\theta \in \{0, 45, 90, 135, 180, 225, 270, 315\}$, $i, j = \{0, 1, 2, 3\}$, using the following trilinear interpolation functions [6]

$$w_{ij}(\mathbf{v}) = w(v_x - x_i)w(v_y - y_i),\ w_{\text{ang}}(\alpha) = \sum_k w(\frac{8\alpha}{2\pi} + 8r)$$

$$w(z) = \max(0, |z| - 1)$$

Methods: Classification

- Straightforward supervised classification model based on **Naive Bayes Near Neighbor**.
  - Binary (oscillatory) or unary (transient) classification
- For *descriptors* d_i obtained from test signals, the class where the image (and the signal) belongs can be inferred by resolving

$$\hat{C} = \arg\min_C \left\{ \sum \|d_i - NN_C(d_i)\|^2 \right\}$$

- where $NN_C(d_i)$ are the set of prototype descriptors.

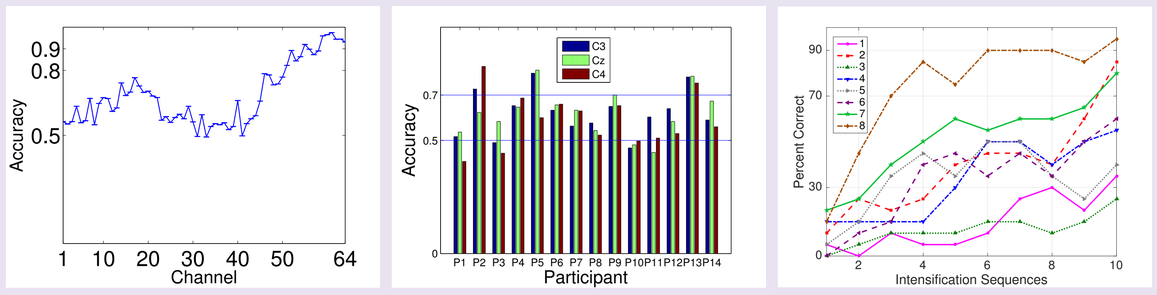
Results

- Transient and oscillatory phenomena have been studied.

Waveform	Best ACC	Intra-Subject Avg
μ	**75%**	**65%**
P300	**95%**	**45%**
α	**95%**	**80%**

Table 1: Classification Accuracy percentage

Results



(a) α Wave (b) μ Wave (c) P300

Figure 3: Classification accuracy percentages.

Significance

- A method which is biomimetically based on how the visual cortex works by detecting orientations, ironically, is used preciely to detect information from the brain.
- It has universal applicability because the same basic methodology can be applied to detect different patterns in EEG for BCI
- It has the potential to foster close collaboration with physicians and electroencephalograph technicians.
- Follows the established procedure of the clinical EEG of analyzing waveforms by their shapes.
- Eases the clinical acceptance and use of qEEG technologies.

References

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