EBCI

The EPFL Brain-Computer Interface

Classification of EEG Signals Using Dempster Shafer Theory and a K-Nearest Neighbor Classifier

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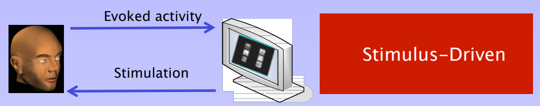
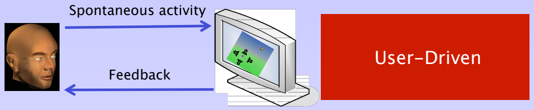
Introduction

– A BCI is a communication system, which allows a subject to act on his environment only by means of his brainwaves, without using the brain's normal output pathways of peripheral nerves and muscles.

Different types of BCI





-One of the most important parts in BCI systems is the classification method and employing different classifiers may lead to considerably different system performances, depending on the structure and distribution of the data to be classified.

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K Nearest Neighbor classifier

Advantage

- Nonparametric architecture
- Simple
- Powerful
- Requires no training time

Disadvantage

- Memory intensive
- Classification is slow
- equal priority and weight for all the neighbors

– Distance weighted KNN classifier will assign different weights to the neighbors of a test sample with respect to their distances from it as follows

$$w^{(i)} = \frac{d^{(k)} - d^{(i)}}{d^{(k)} - d^{(1)}}$$

Proposed Method

Dempster Shafer Theory of Evidence

- Framework of discernment Θ
- mass function:
  mass: $P(\Theta) \rightarrow [0,1]$, s.t.
  (1). mass(∅)=0
  (2).∑mass(X)=1, for X ⊆Θ

$$Bel(A) = \sum_{B|B\subseteq A} m(B)$$

$$Pl(A) = \sum_{B|B\cap A \neq \emptyset} m(B)$$

-The Dempster's rule of Combination for combining two sets of masses, and is defined as follows.

$$m_{1,2}(\phi) = 0 \quad , \quad m_{1,2}(A) = (m_1 \oplus m_2)(A) = \frac{1}{1-k} \sum_{B\cap C = A \neq \phi} m_1(B) m_2(C)$$

$$k = \sum_{B\cap C = \phi} m_1(B) m_2(C)$$

-Using the theory of evidence formalism we can assign part of the belief to each neighbor of a test sample and since this evidence does not support any other hypothesis, the rest of the belief will be assigned to the whole frame of discernment

$$m^{s,i}(\{C_q\}) = \alpha\, e^{-\gamma_q d^B} \quad , \quad m^{s,i}(C) = 1 - m^{s,i}(\{C_q\})$$

$$m^{s,i}(A) = 0 \quad \forall A \in 2^{\Theta} \setminus \{C, \{C_q\}\}$$

-In the next step, we can combine the belief functions of the evidences showing that the sample belongs to class q as follows:

$$m_q^s(\{C_q\}) = 1 - \prod_{x^i \in \Phi_q^s} \left(1 - m^{s,i}(\{C_q\})\right) \quad , \quad m_q^s(\{C\}) = \prod_{x^i \in \Phi_q^s} \left(m^{s,i}(C)\right)$$

-Now that the BPAs are at hand, a global BPA for all the M classes can be obtained through dempster rule of combination as follows:

$$m^s(\{C_q\}) = \frac{m_q^s(\{C_q\}) \prod_{r\neq q} m_r^s(C)}{K} \quad , \quad m^s(C) = \frac{\prod_{q=1}^{M} m_q^s(C)}{K}$$

$$K = \sum_{q=1}^{M} m_q^s(\{C_q\}) \prod_{r\neq q} m_r^s(C) + \prod_{q=1}^{M} m_q^s(C)$$

Results

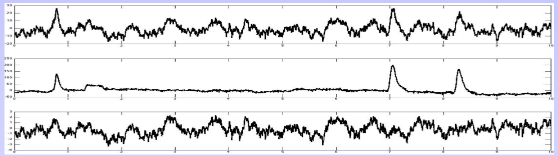
Experimental data

– The EEG data used in this study was recorded from 6 channels (C3, C4, P3, P4, O1, and O2) according to the 10-20 system of electrode placement.

– The subjects were asked to perform five different mental tasks during different trials. These mental tasks are: baseline or total relaxation, multiplication (non-trivial),, and finally letter composition.

Results

– Independent component analysis (ICA) was used to remove the EOG artifacts from the acquired signals.



-For feature extraction, AR modeling was performed for each segment containing 250 samples, and Burg algorithm was employed to estimate the AR coefficients .

-Furthermore, to extract more information from the signal, Discrete Wavelet Transform (DWT) was employed to decompose the signal into five levels using dabechies-4 wavelet.

CORRECT CLASSIFICATION RATES OF THE THREE USED CLASSIFIERS FOR SUBJECTS 1,2,3, AND 4

	KNN	DWKNN	DSTKNN
Subject 1	89.58± 2.8	91.85±3.3	93.04±3.7
Subject 2	88.77±2.5	90.99±3.1	92.62±2.6
Subject 3	81.48±2.8	84.36±2.9	85.74±3.4
Subject 4	85.27±3.2	86.20± 2.7	88.90±3.2

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