Application of Language Models and Natural Language Processing in Brain-Computer Interfaces for Neural Text Translation – a Review

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Introduction

A brain-computer interface (BCI) is a hardware/software system that extracts neural activity as electrical signals and uses them to control computers and other external devices [1]. These devices provide an alternative non-muscular channel of communication for individuals with severe neuromuscular disabilities [2]. An exciting sub-field of BCI research is neural-text translation, whereby neuronal signals are extracted and directly processed via a computer and interpreted into text, bypassing nervous system pathways between the brain and the effector muscles that may be damaged [3]. This technology holds great promise for people with impaired speech capabilities due to high brain stem injuries or neurodegenerative diseases such as amyotrophic lateral sclerosis (ALS) by enabling them to communicate via thought. This review will focus on BCIs for neural-text translation and the application of language models (LMs) and natural language processing (NLP) in this technology. The review will 1) introduce the neural-text translation framework by examining a classic BCI (the P300 Speller), 2) trace efforts to enhance its performance via application of **language models (LMs)**, 3) examine a new BCI paradigm, and finally 4) conclude with a summary and discussion of future work.

The P300 Speller

The P300 Speller is a classic neural-text translation BCI system that uses electroencephalogram (EEG) signals from the scalp to spell letters [3]. The system exploits the phenomenon of the P300 event-related potential produced in the brain when people react to external stimuli [4] to decode intention. In the P300 Speller, the user is presented with a 6×6 grid of characters (including the alphabet, numbers, and the space character) on a screen in front of them to spell words. To spell a letter in some word, the user is instructed to focus on that letter in the character grid for a fixed amount of time. During this period, a sequence of flashes will illuminate single columns or rows of the grid at random, and the corresponding time-synced snapshots of the user's EEG signal are recorded [5]. The flashes that illuminated rows or columns containing the desired letter will elicit the P300 potential in the EEG signal. Relevant features are extracted from the EEG signal and used as inputs to classification algorithms (built from training data) to predict the presence or absence of the P300 potential. Due to the low signal to noise ratio, several trials are needed for each letter to make predictions with adequate levels of accuracy. As a result, the P300 Speller very inefficient, with selection speed ranging from 13 – 42 seconds per letter despite various optimization efforts around experimental parameters to reduce trial time [6], [7], [8], [9], [10].

Application of statistical language models to enhance P300 Speller performance

Earlier attempts to enhance the performance of the P300 Speller were focused on optimizing experimental parameters such as inter-stimulus interval, flash duration and paradigm [11], [12], but did not take advantage of existing knowledge in the **natural language** domain. Classification under this basic form of the P300 Speller is known as the Static Method [5], in which each letter is scored based on its features and the letter with the highest score at the current time is predicted to be the intended letter. Speier et al. [5] pioneered the incorporation of **statistical LMs** to enhance system performance. Specifically, letters from the intended word are modeled as generated from a **statistical distribution** based on a **corpus** of words. Furthermore, **prior** beliefs at the letter/word level based on the **LM** can be added at each time point to improve accuracy. To this end, an improved method known as Dynamic Classification [5] was developed, in which two Gaussian distributions were compiled during training, one for the scores of letters that are illuminated along with the intended letter, the other for scores of letters not illuminated with the intended letter (eqn. 1)

$$f(y_t^i|x_t)=\begin{cases} \frac{1}{\sqrt{2\pi\sigma_a^2}}e^{\frac{1}{2\sigma_a^2}(y_t^i-\mu_a)^2} & \text{if } x_t \in \mathbf{A}_t^i \\ \frac{1}{\sqrt{2\pi\sigma_n^2}}e^{\frac{1}{2\sigma_n^2}(y_t^i-\mu_n)^2} & \text{if } x_t \notin \mathbf{A}_t^i \end{cases} \tag{1}$$

Where y_t^i is the score on the i^{th} flash for t^{th} letter in the sequence, x_t is an illuminated letter on the i^{th} flash, and A_t^i is the group of letters illuminated along with the actual intended letter on the i^{th} flash.

A Naïve Bayes approach is then used to determine for each candidate letter its probability of being the intended letter, based on its score as well as past decisions. The naïve condition assumes that individual flashes are conditionally independent given the current attended letter. The posterior is therefore:

$$\begin{aligned} P(x_t|\mathbf{y}_t, x_{t-1}, \ldots, x_0) &= \frac{P(x_t|x_{t-1},\ldots,x_0)P(\mathbf{y}_t|x_t,\ldots,x_0)}{P(\mathbf{y}_t|x_{t-1},\ldots,x_0)} \\ &= \frac{1}{Z}P(x_t|x_{t-1}, \ldots, x_0)\prod_i f(y_t^i|x_t) \end{aligned} \tag{2}$$

Where Z is a normalizing constant.

The posterior is further simplified by using a uniform prior, and the resulting posterior becomes:

$$P(x_t|\mathbf{y}_t, x_{t-1}, \ldots, x_0)=\frac{1}{Z}\prod_i f(y_t^i|x_t) \tag{3}$$

The classifier ultimately selects the letter that maximizes the posterior probability.

A further enhancement was made in the **Natural Language Processing (NLP)** Method [5], in which the uniform prior probability in eqn. 2 was replaced with frequency statistics of a **trigam model** from the Brown corpus [13].

Results have shown that integration of **LMs** into translation algorithm has significantly improved both accuracy as well bit rate of the P300 Speller [5], with the **NLP** Method outperforming the Dynamic Classification Method, which in turn outperforms the Static Method. These results clearly demonstrate that the addition of extra information from the **natural language** domain can significantly improve signal classification.

A series of studies by the same group built on this new framework of incorporating **LMs** into the P300 Speller and further improved the performance of the system. These include: use of electrocorticography (ECoG) signals and spectral features [14], replacing Naïve Bayes model with a n^{th} order hidden Markov Model (HMM) [15], employing more sophisticated **LMs** and using particle filters to estimate posterior distributions (without sampling the entire state space) [16], and extending **LMs** to generate **priors for complete words** (i.e. predictive spelling) [17]. These new innovations continuously improved the performance of the P300 Speller and cemented **LMs** and **NLP** as key components in the neural-text translation algorithms.

Beyond the P300 Speller - a new direct neural-text decoding paradigm using articulatory phonetics

The P300 Speller, despite going through various iterations of improvements, is a cumbersome system to use due to its data acquisition and decoding paradigm. The system hinges on decoding intention using the P300 potential evoked by external visual stimuli, which is fundamentally an indirect way of identifying intention. Recently, Speier et. al [18] demonstrated a new decoding paradigm for neural-text translation BCIs. Specifically, during the training phase, users are instructed to repeat individual words or singular vowels (with or without preceding consonants) while their ECoG signals were recorded. Spectral features were extracted from the ECoG signals (within a time window encapsulating individual speech utterances) and used to train a long short-term memory (LSTM) neural network classifier. When using the BCI, the user will articulate words as they could, which will produce characteristics ECoG signals which are fed into the LSTM classifier. The classifier at each time point will output a **probability distribution across all phonemes** found in the training dataset. **Laplacian smoothing** is applied to this distribution to ensure that phonemes **not seen during training were assigned non-zero probabilities**. Furthermore, a **n-gram model** was used to derive **prior probabilities** for **observed sequences of phonemes**. A corpus of phonemes was compiled by first finding **word frequencies** from the Brown Corpus [13], then translating the words into their corresponding phonemic sequences using the CMU Pronouncing Dictionary. **Phoneme prior probabilities** were the relative frequencies of each phoneme in the resulting corpus, and phoneme sequence priors were modeled as a n^{th} order Markov process [17]. These prior probabilities together form the **n-gram model.** A particle filter technique employed previously [16] is again used to estimate the posterior probability distributions of the phonemes. The results showed that this new BCI paradigm achieved high levels of accuracy at speeds and bit rates significantly higher than existing BCI communication systems.

Conclusion and future directions

This review provided an overview of BCIs for neural-text translation and the role of **LMs** in decoding algorithms. LM were first incorporated into the classic P300 Speller system to provide additional information in the form of **prior** beliefs on word probability distributions and proved to increase system performance. The P300 Speller continuously evolved in sophistication and performance as more complex **LMs** and methods of estimating **posterior word probabilities** were developed and incorporated. The latest innovations have moved beyond the P300 Speller and are directly using ECoG signals produced during speech articulation to decode intent. The decoder is predicting phonemes at each moment in time and **LMs** are employed to aid in predicting spelling of whole words. **NLP** techniques such as probability **smoothing** and Bayesian inference are employed in this process to great effect. Results have shown that the incorporation of **LMs** and **NLP** methods significantly improved BCI performance and have become an integral part of the decoding paradigm in these systems. Two main directions of future research [18] are: 1) turn the BCI into an online system by incorporation real-time feedback mechanisms and 2) make the system more broadly accessible by leveraging signals that can be acquired non-invasively or less invasively.

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