Broadband Frequency-Division Multiplexing in Visually Evoked Potentials Enables Image Transmission and Physical Computing

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Steady-state visual evoked potentials (SSVEPs) are periodic signals in the EEG readout from the visual cortex, generated when the eye perceives a periodically modulated light signal. Until now, SSVEPs have mainly been used in scenarios with a single or double light-modulation frequency. In this study, we extend the concept of SSVEPs to multiple-frequency light modulation and demonstrate that the brain can simultaneously process hundreds of frequencies. At broad bandwidth, the higher harmonics and nonlinear mixing between pairs of signals can overlap with the fundamental harmonics, resulting in a complex EEG signal. We leverage this complexity to reconstruct images based on frequency encoding and create an extreme learning machine capable of performing classification.

The steady-state visual evoked potential (SSVEP) is a phenomenon in which the brain responds to a light signal that is modulated periodically in time, typically within the 3-30 Hz frequency range. This can be detected using implanted electrodes or electroencephalography (EEG). So far, SSVEPs have mostly been studied using single or double light-modulation frequencies [1, 2], neglecting the potential for more complex multiple-frequency excitation. Here, we demonstrate the feasibility of stimulating SSVEPs with hundreds of frequencies using frequency-division multiplexing (FDM), resulting in highly nonlinear mixing. We show that FDM generates sum and difference frequency terms that overlap with the input modulation frequencies (i.e., fundamental harmonics), enabling the brain to function as a nonlinear receiver, processor, or decoder with appropriate light signal design. By analyzing experimental data statistically, we develop a brain model that simulates the input-output response to various light stimuli, which is then used to generate synthetic data for training different machine learning (ML) architectures.

To create a broadband-frequency-encoded brain-computer interface (BCI), we train a deep neural network (DNN) to solve the inverse problem and reconstruct images. We encode each pixel of an image into a different light-modulation frequency between 8 and 24 Hz, and then project the broadband FDM, read as an SSVEP signal. Finally, the EEG signal is decoded back into an image using the DNN decoder.

As a proof of concept for the first extreme learning machine (ELM) utilizing SSVEPs, we use synthetic data to train a feedforward reservoir computing (RC) architecture for classification. We encode a multivariate numerical dataset using a narrowband FDM around 12 Hz and combine it with another narrowband FDM around 15 Hz to optimize linear regression through a genetic algorithm (GA). The overall FDM serves as the ELM input layer, and the optimized linear regression performs the classification task.

Experimental Setup. The EEG device outlayer and a schematic overview of our set-up is shown in Fig. 1. In Fig. 1a, the SSVEP is detected by an EEG with the key electrode, Oz, placed at the central region of the visual cortex at the back of the head. We use a 3-pole EEG device, which has one active electrode located in Oz (medial occipital electrode site) so as to collect SSVEP from the primary visual cortex. The EEG also has one reference electrode above the left ear, M1 position, and one ground electrode above the right ear, M2 position.

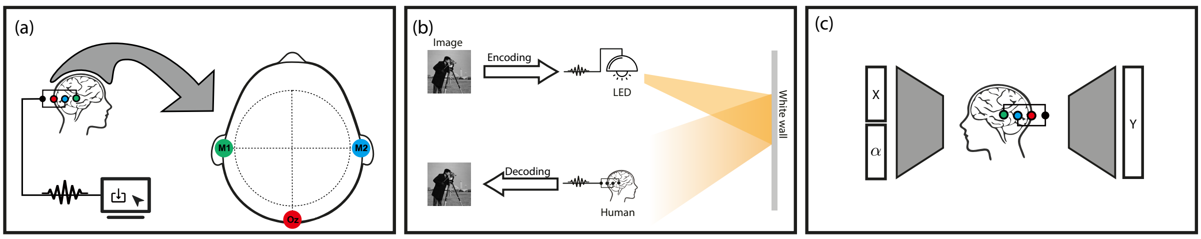

Figure 1: **SSVEP Setup for BCI and RC**. a) EEG device, b) BCI experiment, c) ELM architecture.

Figure 1b sketches out our BCI experiment. An image is encoded by FDM to include multiple frequencies simultaneously. These signals are then combined and used to modulate the intensity of LED light. The participant wearing the EEG device observes the light projected onto a white wall, observing a somewhat random flickering light instead of a periodically modulated image as in standard SSVEP experiments. At the same time, the EEG response is collected to retrieve the image.

The input-reservoir-decoding architecture of ELM is shown in Fig. 1c. Here, the input FDM is split in x, encoding the multivariate numerical dataset attributes, and in α, control parameters chosen through a GA that optimize the decoding linear regression.

Broadband-Frequency-Encoded BCI. The experiment uses a reduced MNIST digital dataset of handwriting images of dimensions 16   16. To reduce the encoding complexity, instead of indexing the entire image pixel by pixel, each image is randomly indexed and divided into 16 strips. Each strip is then encoded to modulate LED intensity for 16 trials. After completing all 16 trials, the transmission of one complete image is achieved. At the same time, EEG responses are collected and fed into an EEG-to-Image DNN for retrieving images. Figure 2a reports the ground truth digital handwriting images encoded into the LED light. Reconstructed images obtained via the EEG-to-Image DNN decoder are shown in Fig. 2b.

Figure 2: **BCI image retrieval.** a) Ground truth images; b) Reconstructed images.

Reservoir Computing. Following our work on BCI, we show the first realization of an ELM by SSVEPs, where we exploit the brain nonlinearities to map the input stimuli into a high-dimensional feature domain. Using the same setup shown in Figs. 1a,b, we realize the ML architecture in Fig. 1c. However, for ethical reasons, we chose not to expose the participant to an exhausting data collection for the training of the network, preferring instead to use synthetic data.

In this experiment, the Breast cancer dataset [3] was divided into two parts: training data and testing data. We used the training data along with control parameters optimized by GA. As shown in Fig. 1b by substituting images with multivariate series, we encode the testing data and control parameters as narrowband stimuli in LED modulation around 12 and 15 Hz, respectively. Then, we collect EEG signals to calculate their spectrum in the sum frequency generation interval.

The obtained results are presented in Fig. 3. The first row displays the spectrum, where red lines are obtained employing our phenomenological nonlinear brain model, and black lines represent the true EEG signal. In the second row, the classification probabilities, obtained by optimized linear regression, are reported. We stress that here only the seventh spectrum is not correctly classified.

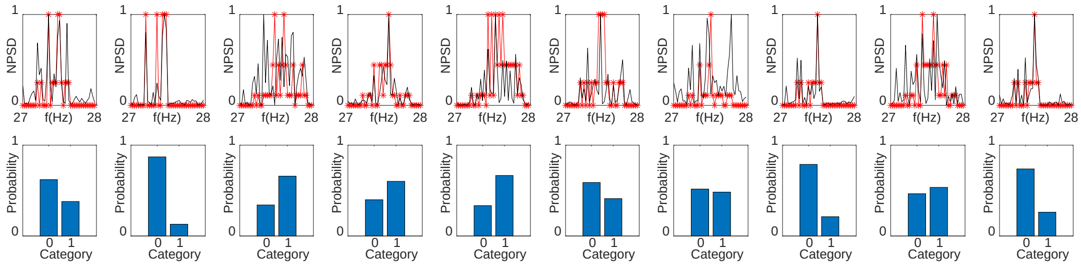

Figure 3: **Classification results.** First row is the spectrum, with red lines theoretically derived, and black lines obtained via EEG. Second row is the classification probability, where 0 stands for *benign* and 1 stands for *malignant*. Only the seventh spectrum is not correctly classified.

References

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[3] P. M. Murphy and D. W. Aha (1994), http://www.ics.uci.edu/ mlearn/MLRepository.html