Poster #3270

Improving BCI-based Color Vision Assessment Using Gaussian Process Regression

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Introduction

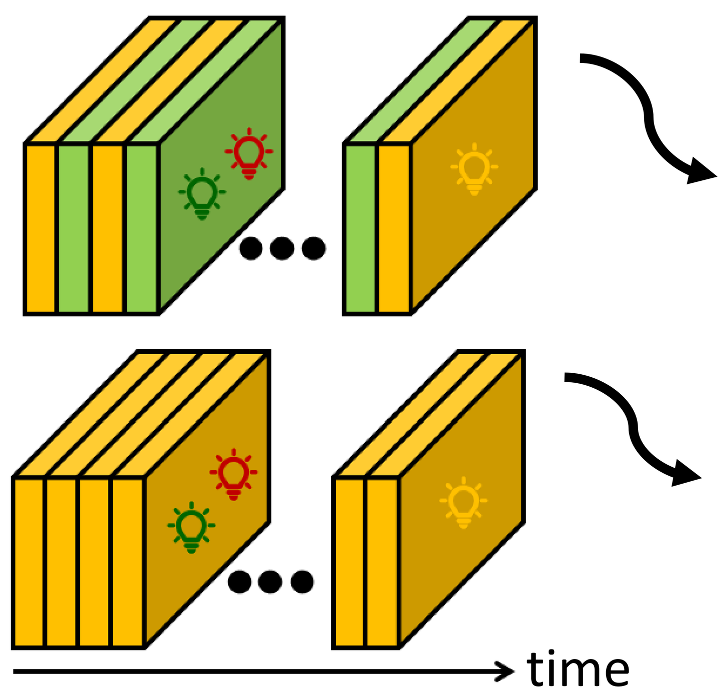
- Color vision deficits (CVDs) affect ~20% of the population.
- ***Metamers:*** light sources with different spectral distributions that are the same color

Fig. 1. Example of a metamer – (left) Monochromatic (590 nm) and (right) dichromatic (525 (green) and 625 (red) nm) light sources that are both yellow.

- BCI-based Color Vision Assessment:

  Alternating between two light sources at fixed intervals

  (1) monochromatic amber LED & (2) dichromatic red/green LED



Color mismatch (non-metamers) eliciting steady-state visual evoked potentials (SSVEPs)

Color match (metamers) eliciting no SSVEP

Fig. 2. Visual stimulation in BCI-based color vision assessment

- Measuring SSVEPs using electroencephalography (EEG)

Existing color vision assessment methods	BCI-based color vision assessment
✗ Behavioral response	Brain response ✓
✗ Subjective	Quantitative ✓
✗ Extensive Training	Easy to use ✓
✓ Accurate	Slow and noisy ✗

- metaID+ → Making BCI-based color vision assessment **61.3% faster** while **reducing noise**

metaID+

- **Measurement**: Output of the inference module to quantify the color difference

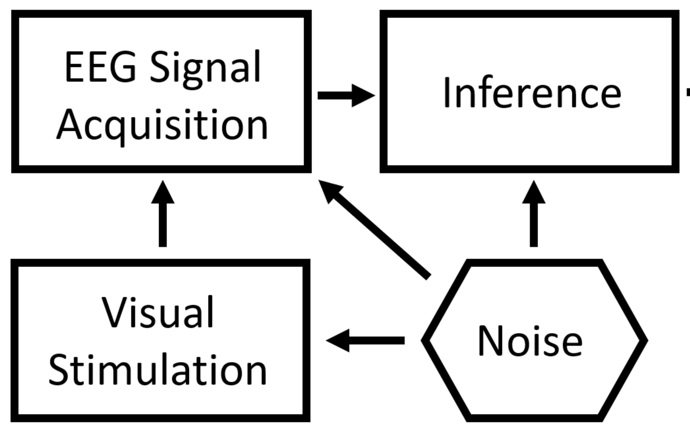


Fig.3. The architecture of metaID+ includes a denoising filter that uses the spatial correlation of measurements to reduce the effect of noise

Noise in measurements

$$\boldsymbol{y}(X) = \boldsymbol{f}(X) + \boldsymbol{\epsilon}$$

Spatial correlation in measurements

$$\boldsymbol{f}(X) \sim \mathcal{GP}(\boldsymbol{0}, K(X, X'))$$

$$\boxed{\begin{aligned} \hat{f}|X,y &= \mathcal{N}\left(E\left[\hat{f}|X,y\right], \Sigma_{\hat{f}}\right) \\ E\left[\hat{f}|X,y\right] &= K[K + \sigma_n^2 I]^{-1} y \\ \Sigma_{\hat{f}} &= K - K[K + \sigma_n^2 I]^{-1} K \end{aligned}}$$

X: colors of dichromatic light source

$\boldsymbol{y}(X)$: measurements

$\boldsymbol{f}(X)$: noise-free measurements

$\boldsymbol{\epsilon}$: IID Gaussian noise with zero mean variance σ_n^2

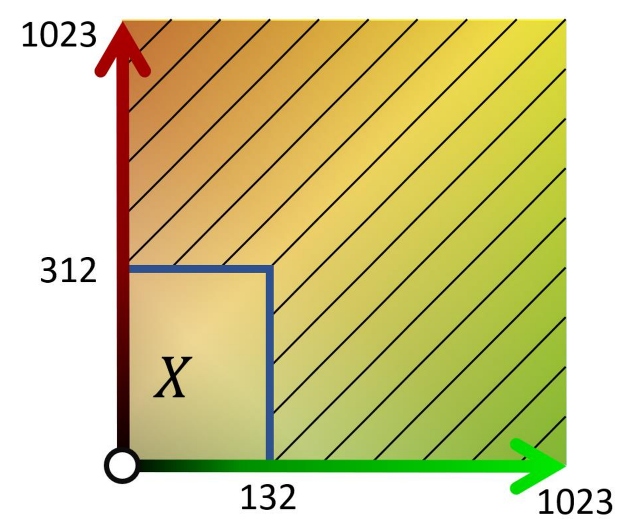
$K(X, X')$: covariance function

$\hat{\boldsymbol{f}}$: Estimates of noise-free measurements

Methods

- Ten participants with no neurological impairments
- Five runs of data collection, each containing 168 trials
- Noisy measurements obtained using metaID (an existing algorithm) for each trial
- 10-fold cross validation was used to train metaID and metaID+

Fig.4. Two 10-bit PWMs controlled the dichromatic light source, resulting in a 1024×1024 search space. We sampled subspace X, where the luminance values of the dichromatic and monochromatic light sources were expected to match. 168 uniformly distanced locations were sampled in X.



Results

- Performance metric: **SSE** defined as the ℓ_2 norm distance between all measurements and their corresponding ground truth

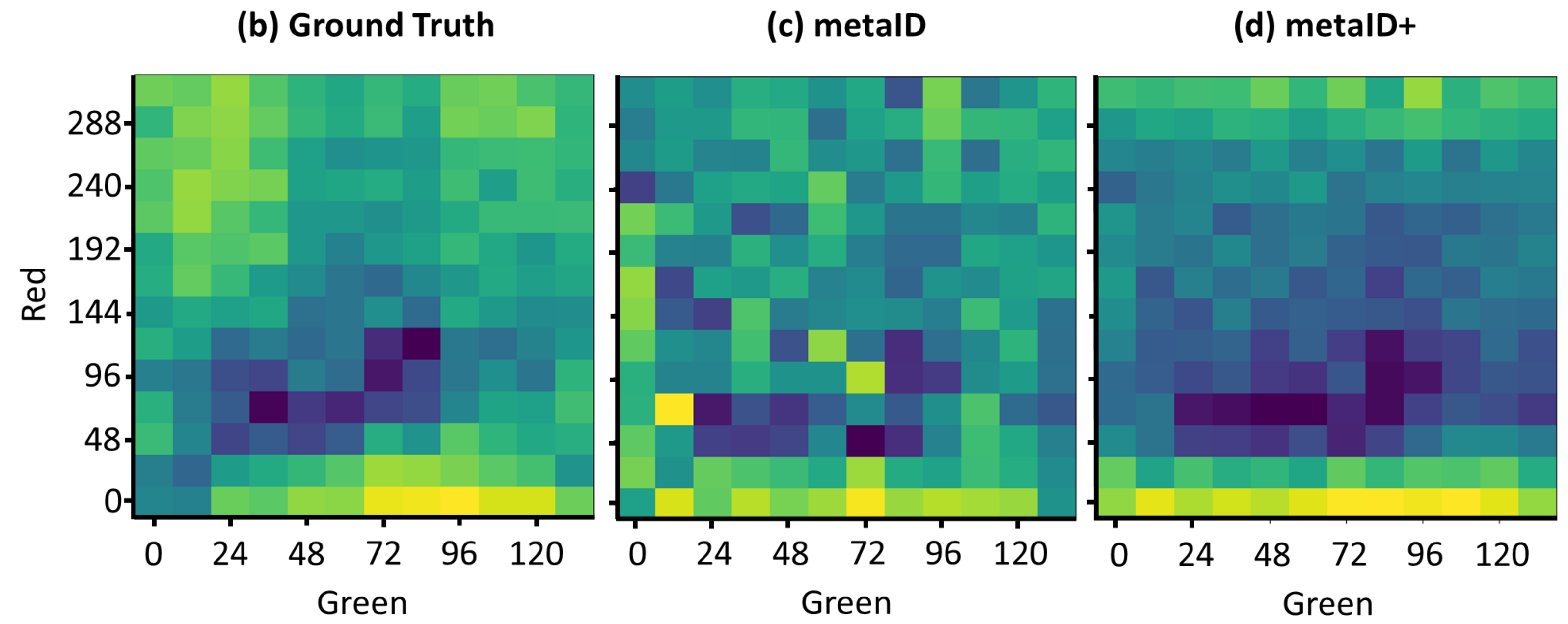


Fig. 6. Example grids for ground truth (obtained by averaging all data for the user), metaID, and metaID+. The colors of each cell represent the amplitude of the measurement. The ground truth is based on 84 minutes of data. The measurements of metaID+ are based on 2.8 minutes of data.

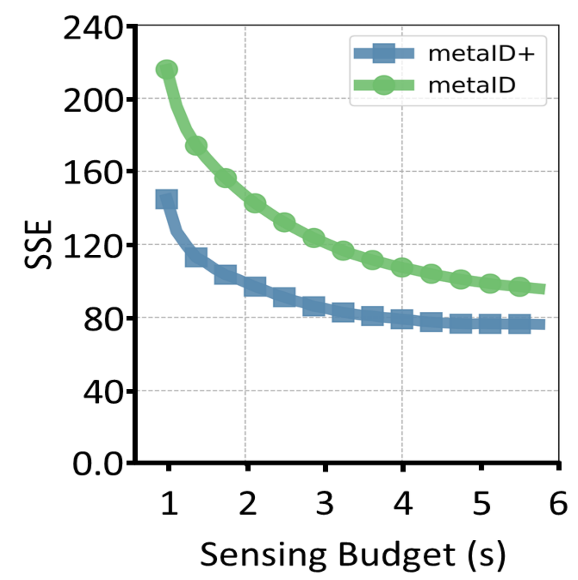


Fig. 7. Average SSE of all participants for metaID compared to metaID+.

- metaID+ needs only 2.1 seconds of data to achieve lower error than metaID that 5.5 seconds of data, **resulting in 61.3% reduction in the amount of data required while providing lower error.**

Conclusion

- metaID+ leverages the spatial correlation among measurements to reduce noise
- metaID+ could lower the SSE error by requiring 61.3% less data, making BCI-based color vision assessment faster and more accurate at the same time.

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