T-SNE visualization of single trial oddball ERP's in controls and patients with schizophrenia

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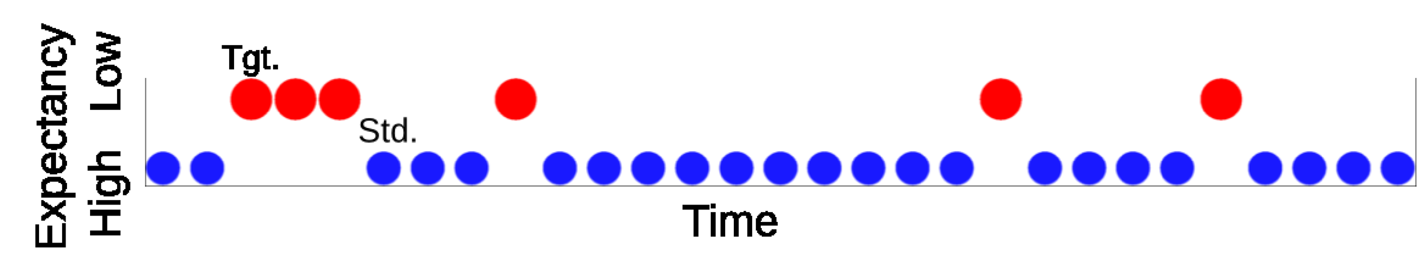
Introduction

Patients with schizophrenia often display deficits in context processing. These processing deficits are often revealed by measuring ERP responses to rare target stimuli embedded within a series of frequently presented non-target stimuli (i.e. the auditory oddball experiment).

However, the conventional analysis of this data often discards considerable information by averaging across trials and focusing on the response within selected channels within a narrow time window. Preserving the information within the single trial multichannel dataset may enhance the ability to identify ERP differences across conditions and individuals, leading to a greater sensitivity to cognitive deficits (Bridwell, et. al., 2018; Kriegeskorte, et. al. 2006).

Methods: ERP's and T-SNE

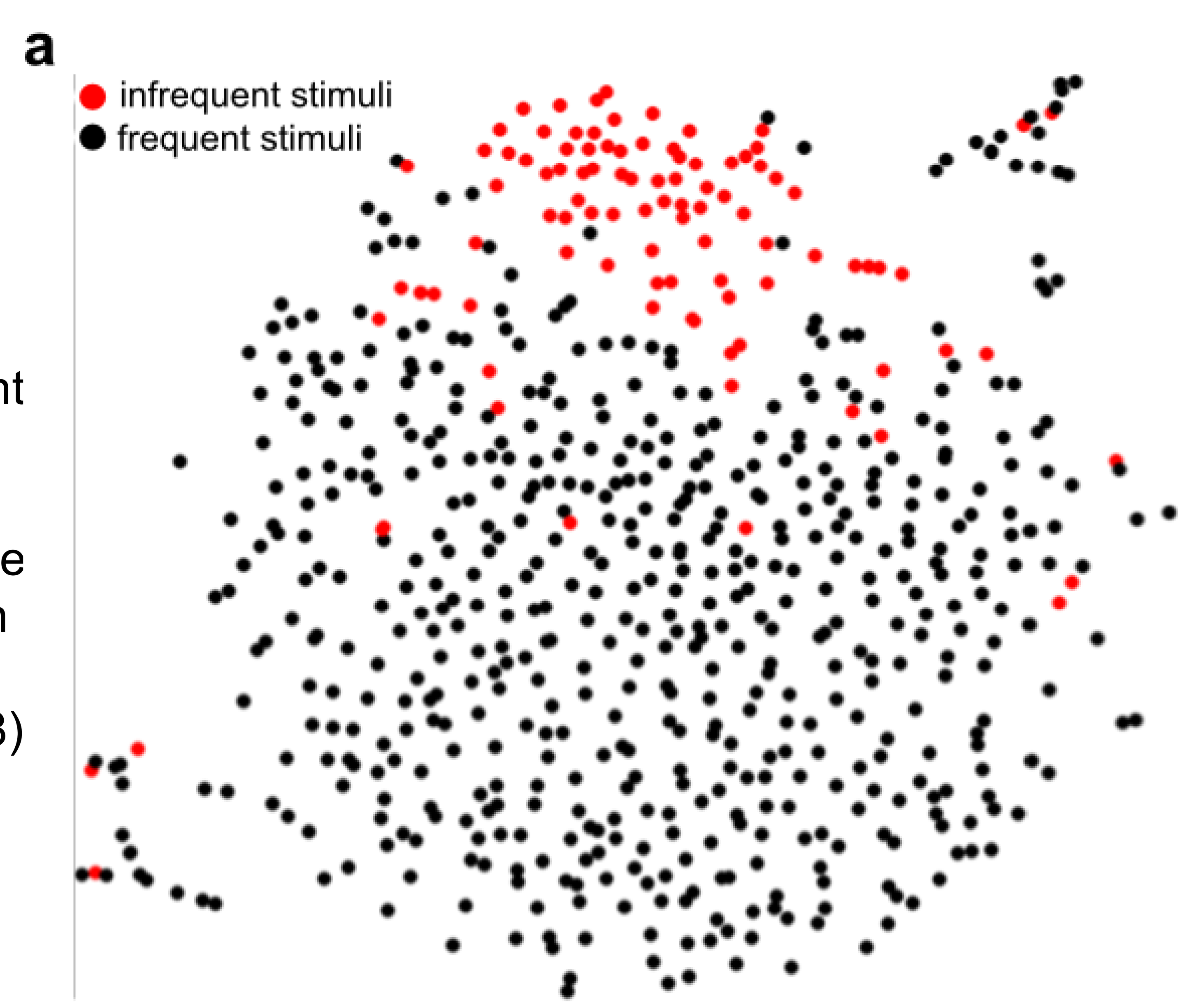
64 channel EEG was recorded to frequent targets (1500 Hz) and infrequent non-target (1000 Hz) auditory stimuli. The tones were presented every 1.3 s over the course of the 14 min 50 s experimental session (15% probability).

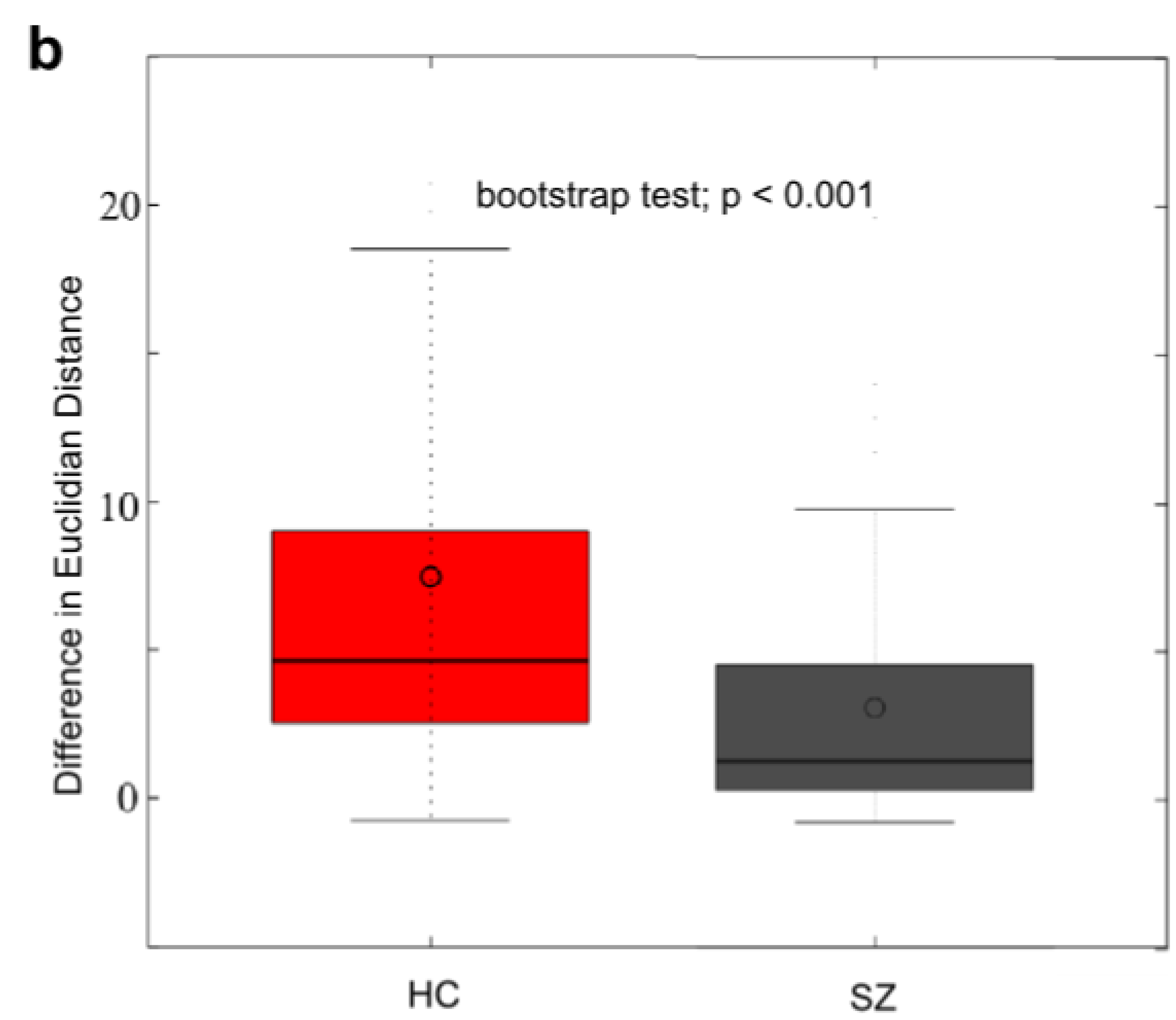


In order to preserve the rich information of single-trial multichannel ERP's, we used t-Distributed Stochastic Neighbor Embedding (t-SNE) (van der Maaten & Hinton, 2008) (perplexity = 25; PCA dimensions = 50; tolerance = 0.0001) to project the individual subject 64 channel single-trial dataset onto two dimensions. T-SNE perserves the high-dimensional structure of the data in the distances of the points in the two dimensional plot.

Results

The trials containing frequent stimuli (in black) reasonably separate from the trials containing infrequent stimuli (in red). This separation was quantified by computing the average Euclidian distance among infrequent and frequent stimuli minus the average distance among infrequent stimuli. Using this measure, we observed a greater separation between the two trial types among healthy controls (N=58) than among individuals diagnosed with schizophrenia (N = 58) (Fig. 1b) (bootstrap test; $p < 0.001$) (for additional details about participant and experiment information, see Bridwell et al., 2014).





What We Found

While t-SNE has been a useful visualization tool for fMRI and MRI datasets (Du et al., 2015; Mahfouz et al., 2015; Mwangi, et. al., 2014; Panta et al., 2016), it has been underutilized within EEG. **The present results demonstrate that the information within single-trial EEG's may be meaningfully projected to a two-dimensional representation with t-SNE.** Preserving the information within the single trial multi-channel dataset (as opposed to focusing only on the latency or amplitude of ERP components) may enhance the ability to identify differences in evoked responses across conditions and individuals, leading to a greater sensitivity to cognitive deficits (Bridwell, et al., 2018). Future studies may compare results from t-SNE with multidimensional scaling (MSD) (Edelman, et al., 1998), since they preserve different aspects of the data (i.e. local vs. global structure, respectively) in the two dimensional projection.

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