

Neural Dynamics of a Single Human with Long-Term, High Temporal Density Electroencephalography

John Chuang

Abstract— We undertake a longitudinal study with high temporal recording density, capturing daily electroencephalograms (EEG) of an individual in an in-situ setting for 370 consecutive days. Resting-state EEG retains a high level of stability over the course of the year, and inter-session variability remains unchanged, whether the sessions are one day, one week, or one month apart. On the other hand, EEG for certain cognitive tasks experience a steady decline in similarity over the same time period. Clustering analysis reveals that days with low similarity scores should not be considered as outliers, but instead are part of a cluster of days with a consistent alternate spectral signature. This has methodological and design implications for the selection of baseline references or templates in fields ranging from neurophysiology to brain-computer interfaces (BCI) and neurobiometrics.

I. INTRODUCTION

How do a person's brainwaves change from day to day, week to week, and month to month? How do they change over the course of a year?

Longitudinal electroencephalography (EEG) studies, conducted at timescales ranging from days to weeks, months, and even years, have found strong intra-individual stability of EEG based on pairwise comparisons of recorded signals. However, all of these studies have temporally sparse data – typically 2-3 recording sessions [1], [2], [3], [4], [5], [6], and in one case 9 sessions per subject [7]. Consequently, they are unable to provide a granular view of neural dynamics, robust estimates of inter-session variability, or identification of clusters or trends over time.

In this study, we undertake a long-term, intra-individual, in-situ EEG study with high temporal density. We collected daily EEG recordings for an individual (paper author) for 370 consecutive days. High temporal density is key to this study, allowing us to overcome the limitations of previous studies. First, we can go from point-estimates to actual distributions of inter-session variability, offering a more complete picture of how the signals change from day to day, week to week, etc. Second, we can track changes over the course of a year by comparing daily signals against baseline days from the beginning of the year, allowing us to identify any trends over time. Third, we can identify and analyze clusters of days where the signals exhibit different signatures from one another.

Improving our knowledge on the temporal dynamics of brainwave signals at this timescale is important for many applications. In the field of brain-computer interfaces (BCI),

researchers have long sought the optimal user-training and system-calibration strategies given inter-session variability of the EEG signals [8], [9], [10], [11], [12], [13], [14], [15]. In the field of biometrics, researchers have been investigating the reliability of brainwave-based user-authentication systems over time [16], [17], [18]. For psychiatry, understanding brain changes at the timescale of weeks and months is of great importance to the diagnosis and treatment of major psychiatric disorders [19].

In the spirit of Poldrack's intra-individual longitudinal fMRI study [19], we make the tradeoff between temporal density and subject population size, limiting ourselves to one subject who is also the researcher. The advantages of having the researcher as subject include: consistent execution of tasks, sustained motivation over time, and access to calendar metadata. Researcher bias is avoided by full separation of data collection and data analysis, i.e., the analysis commenced only after the completion of data collection. The high temporal density also necessitates the recording in an in-situ setting, whether in the residence of the subject, or on the road when the subject is traveling. This requirement provides us with an opportunity to measure changes in an everyday, non-laboratory setting. While we carefully control the experimental conditions of the recording sessions, we also take advantage of the fact that the subject may go traveling, fall sick, etc., over the course of the year, and investigate if any of these events may result in observable changes in data.

II. MATERIALS AND METHODS

A. Data Collection

371 daily EEG recordings were collected from a single subject (male, right-handed, age 44 at start of study, no known health issues) who is the study author, using a single-channel wireless EEG device (Mindwave Mobile, Neurosky, San Jose, California). The device consists of a ThinkGear microchip and embedded firmware, along with 10mm dry stainless-steel active, reference, and ground electrodes. The reference and ground electrodes are housed in an ear-clip for the left ear, while the active electrode is connected via a flexible plastic arm from the headset to be positioned at the FP1 site of the International 10-20 System. Electrical potentials at the active and reference electrodes are subtracted through common-mode rejection to derive a single-channel signal which is amplified 8000 times. Sampling and amplification of the raw 512 Hz data are performed on the embedded microchip and transmitted by Bluetooth to a computer for recording and offline analysis.

John Chuang is with the BioSENSE Lab, School of Information, University of California, Berkeley, CA 94720, USA
john.chuang@berkeley.edu

For each daily session, the subject was seated in a stationary position in front of two notebook computers. The first computer ran the Neuroview software for data acquisition, while the second ran a pre-recorded audio-visual stimulus using Quicktime. The stimulus is taken directly from [20] and includes six tasks over 319 seconds. The tasks alternate between eyes-closed and eyes-open, with verbal and on-screen instructions before each task. Each of the tasks lasts 30 seconds. Task 1 (*Rest*) is the eyes-closed resting-state baseline condition. Task 2 (*Math*) is a sequence of twelve on-screen simple arithmetic operations lasting 2.5 seconds each. Task 3 (*Music*) involves eyes-closed listening to a 30-second instrumental piece. Task 4 (*Video*) involves watching a 30-second Superbowl advertisement. Task 5 (*Retrieval*) requires the subject to mentally retrieve as many word items within a given category as possible within 30 seconds. Task 6 (*Color Counting*) is a visual counting task where the subject silently counts the number of rectangles of a chosen color on a sequence of on-screen images. All stimuli are fixed throughout the study, e.g., the arithmetic operations and their sequence, the music piece, are unchanged. However, some tasks require active response to stimuli (*Math*, *Retrieval*, *Color Counting*) whereas others involve only passive consumption of content (*Music* and *Video*).

We control for circadian rhythms by recording in the same time window (before bedtime) everyday. To avoid any potential bias, we completed the entire year’s data collection before commencing data analysis. The recording from Day 217 is discarded because of technical issues during recording, leaving us with 370 days of EEG data.

B. Data Analysis

We focus on the spectral patterns and properties in this analysis. In particular, we use the periodogram (power spectral density estimate) to quantify the changes of the EEG over time.

To compute the daily periodogram, we start with a simple pre-processing step. From the 30 seconds of raw EEG data for each task, we programmatically extract a 15-second epoch that is absent of any signal spikes above a $\pm 50\mu\text{V}$ amplitude threshold. From this epoch, we use Welch’s method with Hann Window, 2-second window size, 50% window overlap, and median averaging, to compute the periodogram. From the periodogram, we extract the values in the 0.5-40Hz range as a 80-dimensional vector, which spans the delta (δ : 0.5-4Hz), theta (θ : 4-8Hz), alpha (α : 8-12Hz), beta (β : 12-30Hz), and low-gamma (γ : 30-40Hz) bands.

With this set of 370 daily periodograms, we perform a number of analyses. For any given pair of periodograms, we compute the Pearson product-moment correlation coefficient (ρ) to quantify the level of similarity or dissimilarity between the two vectors. We use this correlation metric for temporal analysis at two levels: inter-session variability (changes from session to session), and long-term stability (changes over the course of one year).

For comparison, we apply identical steps to obtain periodograms from the recordings from a single session of 30

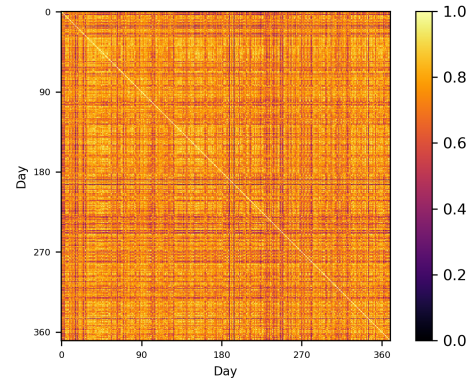


Fig. 1. Matrix of Pearson correlation coefficients between all pairs of daily periodograms for the resting condition.

other subjects from a publicly available reference dataset [20], collected using the same stimulus and hardware as the current study. From these periodograms, we compute inter-individual correlation coefficients against the 30 subjects.

From the same periodograms, we also produce and analyze the following time-series datasets: (i) total power, (ii) absolute and relative power for each frequency band, (iii) peak alpha frequency (PAF) and its corresponding peak alpha amplitude.

We perform hierarchical clustering analysis to determine if there exists clusters of days with similar EEG signals, and if so, identify the characteristics of the clusters. Finally, we access the subject’s calendar to see if particular activities (e.g., travel days, teaching days, sick days) or calendar events (e.g., academic semester in session or semester break, day of the week) may be associated with changes in the signals.

III. RESULTS

We first report results for the eyes-closed resting-state condition, before expanding to the five subsequent cognitive tasks.

A. Long-Term Stability

Pairwise comparisons between daily periodograms produce a correlation coefficient matrix (Fig. 1) that shows a high level of similarity across the entire year. The overall mean correlation of 0.73 is consistent with results from previous longitudinal EEG studies [1], [2], [3], [4], [5], [6], [7]. We can visually observe a small number of days, notably Days 189 and 194, as well as other days spread throughout the year, that are dissimilar from most other days in the year.

Fig. 2A plots, for every day in the year, the mean correlation to all other days of the year ($\mu=0.73$, $\sigma=0.06$). Nineteen days (5%) have their mean correlations more than two standard deviations below the mean. While none of them occur on successive days, they do exhibit some clustering, with 3 days in the first month, and 9 days in the third quarter. In contrast, the second quarter is under-represented with just 1 day. While these low-similarity days lead to a small dip in

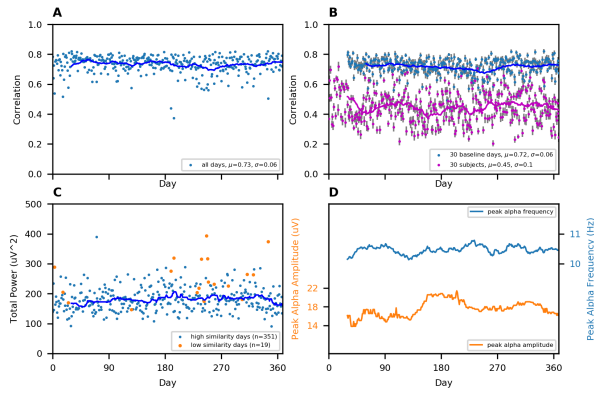


Fig. 2. Daily metrics over the course of one year, with 30-day moving averages. A: Mean correlation to all days. B: Mean correlation to first 30 days of the year, and to 30 other persons in reference dataset. C: Daily total power (0.5-40Hz). The 19 days with correlations two standard deviations below the mean are colored in orange. D: 30-day moving averages of peak alpha frequency (blue) and peak alpha amplitude (orange).

the 30-day moving average (e.g., during the third quarter), there is no trend or seasonality observed overall.

For comparison, we compute daily inter-individual correlations using a reference dataset of 30 subjects, who participated in a single session using the same hardware and audio-visual stimulus as the current study [20]. We also compute daily intra-individual correlations using the first 30 days of the year as baseline. Fig. 2B shows the inter-individual correlations ($\mu=0.45$, $\sigma=0.10$) to be significantly below the intra-individual ones throughout the year. This gap is consistent with the within-subjects and between-subjects similarity scores in [16], and is the basis underlying many brainwave-based authentication systems [21], [22], [23], [24], [25], [26], [27].

Total signal power exhibits no trend or seasonality, hovering in the 100-300 μV^2 range, with a 30-day moving average under 200 μV^2 (Fig. 2C). Absolute and relative powers of individual frequency bands show no trend or seasonality either. Of the 19 low-similarity days, not all have above-average power levels. Conversely, not all days with elevated power levels have low similarity. This suggests that signal power alone is insufficient in explaining differences between signals from different days.

Previous work found the peak alpha frequency as a stable neurophysiological trait marker [28]. Here, we see that it stays within the 10-11Hz range, and the corresponding peak alpha amplitude within the 14-21 μV range, for the entire year (Fig. 2D).

B. Inter-Session Variability

We can take the correlation coefficient of the pair of periodograms from adjacent-day sessions as a random variable, and obtain 369 data points from the 370 daily sessions.

Individual inter-session correlation values can be as low as 0.25 and as high as 0.96. The resulting distribution ($\mu=0.75$, $\sigma=0.11$) has a strong left skew (skew=-0.99), due to the

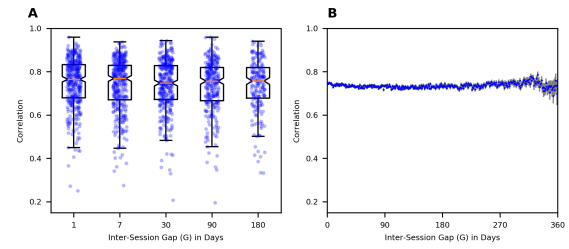


Fig. 3. Inter-session variability unchanged, whether the sessions are one day, one week, one month, or longer apart. A: Boxplots of correlations for different inter-session gaps. B: Mean correlations for all pairs of periodograms separated by a gap of G days.

closeness to the upper bound for correlation coefficients. We can see the long tail in the boxplot (Fig. 3A, first column). Applying Fisher's transformation results in a normal distribution ($\mu=1.01$, $\sigma=0.26$) in the z' coordinate, consistent with the distribution for Pearson correlations for bivariate normal observations.

Changing the gap between session pairs from one day to other durations (e.g., 7 days, 30 days, 90 days, 180 days) produces very similar distributions (Fig. 3A). This suggests that inter-session variability is not affected by the temporal distance between sessions.

More generally, if we pick a pair of periodograms from G days apart, how similar are they? Fig. 3B shows, for each value of the inter-session gap G , the mean correlation of all day-pairs with gap G . Remarkably, we find that the correlation coefficient to be consistently at the 0.73 level, regardless of whether the sessions are a day, a week, a month, or even a year apart.

Different frequency components exhibit very different patterns of inter-session variability (Fig. 4). Individual bands like delta and theta can produce inter-session correlations that span almost the entirety of the -1 to +1 range, whereas gamma remains highly similar across sessions. The combination of alpha and beta bands (8-30Hz), as well as the combination of alpha through gamma bands (8-40Hz), retain distributions most similar to that of the overall signal.

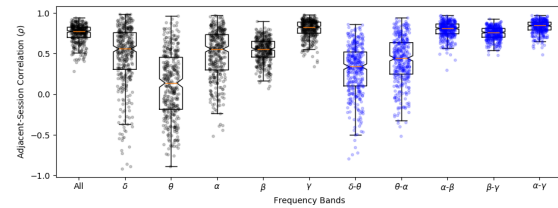


Fig. 4. Inter-session variability by frequency bands. Different frequency bands exhibit very different patterns of inter-session variability.

C. Cluster Analysis

We perform hierarchical clustering to investigate if the low-similarity days are truly outlier days, or are similar among themselves. Employing agglomerative clustering with Ward's linkage criterion [29], we identify a primary cluster

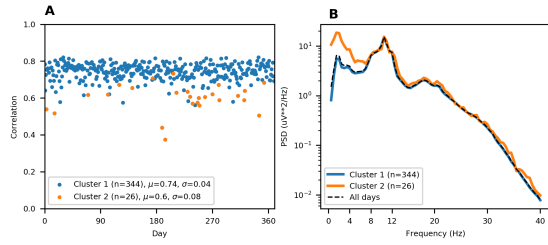


Fig. 5. **Daily EEG signals can be grouped into clusters.** A: The 26 days in small cluster (in orange) have low similarity scores compared to the rest of the year, but they are highly similar to other days within the same cluster. B: The median periodogram of this cluster (in orange) has higher magnitudes in the delta (0.5-4Hz) and theta (4-7Hz) bands.

(Cluster 1) with 344 days and a secondary cluster (Cluster 2) with 26 days spread throughout the year. Cluster 2 days (Fig. 5A) have a lower mean correlation of 0.60, compared against 0.74 for Cluster 1, and 0.73 for the entire year. 14 of the 19 low-similarity days belong to this cluster.

More importantly, we can quantify the within-cluster and between-cluster similarities. Within Cluster 1, the mean correlation is 0.76. Within Cluster 2, the mean correlation is 0.74, approaching that of Cluster 1. Both of these are higher than the overall mean of 0.73. Conversely, between the two clusters, the mean correlation is significantly lower at 0.59 (first three rows of Table I).

Cluster	Days	Power	MF	PAF	PAA	ρ_{ii}	ρ_{ij}
All Days	370	160.8	10.0	10.0	14.5	0.73	–
1	344	158.7	10.5	10.0	14.4	0.76	0.59
2	26	241.5	8.0	10.0	15.5	0.74	0.59
1A	113	177.9	10.0	10.0	20.5	0.81	0.77, 0.71
1B	138	138.4	10.5	10.0	11.3	0.78	0.77, 0.73
1C	93	181.9	9.5	10.0	13.6	0.76	0.71, 0.73

TABLE I

Characteristics of clusters. DAYS: NUMBER OF DAYS. POWER: TOTAL POWER OF MEDIAN PERIODOGRAM (μV^2). MF: MEDIAN FREQUENCY OF MEDIAN PERIODOGRAM (Hz). PAF: PEAK ALPHA FREQUENCY OF MEDIAN PERIODOGRAM (Hz). PAA: PEAK ALPHA AMPLITUDE OF MEDIAN PERIODOGRAM (μV). ρ_{ii} : MEAN CORRELATION WITHIN CLUSTER. ρ_{ij} : MEAN CORRELATION BETWEEN CLUSTERS.

Fig. 5B shows the median periodograms of the two clusters. We see that Cluster 2 days have higher delta and theta band powers than Cluster 1 days. The median periodogram for Cluster 2 also has a significantly lower median frequency (8.0Hz) than that of Cluster 1 (10.5Hz).

Within Cluster 1, we can identify three sub-clusters with distinct metrics (last three rows of Table I). Cluster 1A has high peak alpha amplitude (20.5 μV), Cluster 1B has low signal power (138.4 μV^2) and low peak alpha amplitude (11.3 μV), while Cluster 1C has low median frequency (9.5Hz), indicating relative strength in the delta and theta bands. The sub-clusters see elevated within-cluster similarities (0.81, 0.78, 0.76) even as they retain high between-cluster similarities with one another (0.77, 0.73, 0.71).

We can examine inter-session variability on a per-cluster

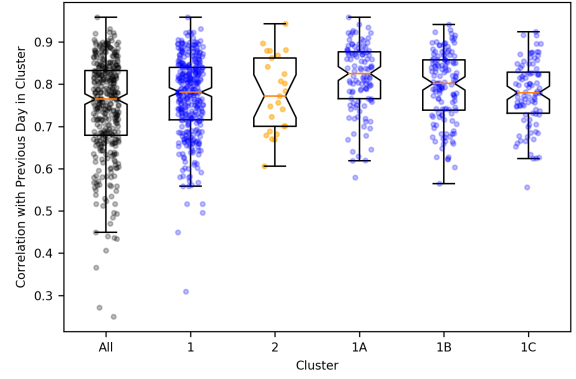


Fig. 6. **Inter-session variability for different clusters.** Cluster 2 has a significantly higher floor, and Clusters 1A, 1B, and 1C have significantly higher means and/or smaller inter-quartile ranges, than the overall dataset.

basis. Taking the correlation coefficient of the pair of periodograms from adjacent sessions from the same cluster, we see significantly higher means and/or smaller inter-quartile ranges for Clusters 1A, 1B, and 1C (Fig. 6), and significantly higher floors for 1A, 1B, 1C, and 2.

These results suggest that the low-similarity days are actually not outliers, but rather belong to an alternate cluster of days with an alternate brainwave signature. Even within the “high similarity” main cluster, it is possible to further differentiate the days into more homogeneous sub-clusters with various signal feature distinctions.

D. Calendar Analysis

We use the subject’s calendar metadata to investigate if the results of our analysis might be explained by the calendar activities of the subject (Fig. 7). We identify teaching days ($n=83$), faculty meeting days ($n=12$), travel days ($n=22$, over 4 trips), and sick days ($n=5$, with headaches and other symptoms of the flu or cold). We also assign the days into four groups according to the institution’s academic calendar: spring semester ($n=123$), summer break ($n=94$), autumn semester ($n=122$), and winter break ($n=31$).

We find no instance where patterns in the resting-state brainwave signals can be explained by the calendar activities. Running a battery of two-sample Komolgorov-Smirnov tests for the various groupings of days, we find no support for differences in mean similarities between (i) teaching days vs. non-teaching days, (ii) days before teaching days vs. other days, (iii) faculty meeting days vs. other days, (iv) travel days vs. non-travel days, (v) sick days vs. non-sick days, (vi) semester in-session vs. semester break days, and (vii) weekdays vs. weekend days.

Projecting the periodogram vectors onto a 2-dimensional feature space using the t-distributed stochastic neighbor embedding algorithm [30], we also find no clustering of days based on these calendar groupings (Fig. 8).

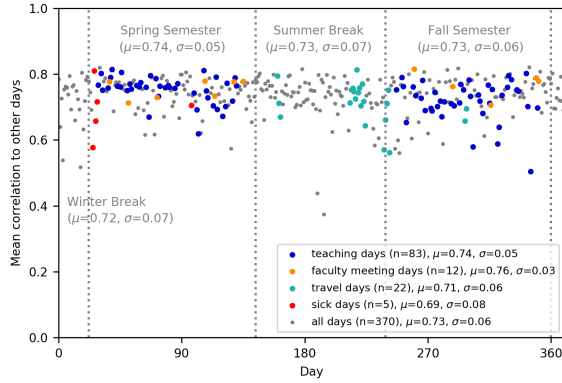


Fig. 7. **Calendar analysis.** None of the calendar groupings of days reveal differences from other days.

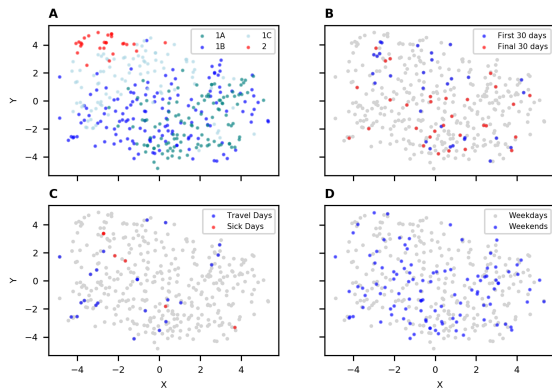


Fig. 8. **Stochastic neighbor embedding of periodograms in 2D feature space.** We can observe agglomeration of days according to the four clusters (Panel A), but not for other groupings on the calendar, such as the first and final 30 days in the year (Panel B), travel days and sick days (Panel C), and weekdays and weekends (Panel D).

E. Non-Resting Cognitive Tasks

The subject performed six tasks (*Rest, Math, Music, Video, Retrieval, Color Counting*) per session, starting with the eyes-closed resting-state task, then alternating between eyes-open and eyes-closed for the subsequent tasks. Each task has its own distinct spectral signature that persists throughout the year, seen in the quarterly median periodograms in Fig. 9. The eyes-open tasks (bottom row) have lower alpha peaks, both in amplitude and frequency, than the eyes-closed tasks (top row) due to alpha attenuation. It is noteworthy that the split alpha peak [31] is clearly visible for the *Music* task, the beta rhythm peak at 18-20Hz is absent for the *Video* task, and the *Retrieval* task produces narrower/sharper peaks for the alpha, delta, and theta bands.

The median periodogram for the first 90 days of the year (Q1, or first quarter) differs from those of the other three quarters for several tasks. Most prominently, we see a strengthening of the alpha and beta peaks for the *Math* task after Q1. Conversely, we see a weakening of the delta band

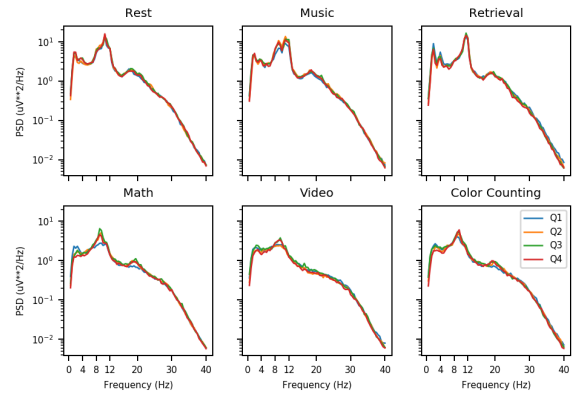


Fig. 9. **Median periodogram for each quarter (90 days) of the year.** Each task has its own distinct spectral signature that persists throughout the year, with the strengthening and/or weakening of various peaks at different times.

for the *Math, Retrieval, and Color Counting* tasks after Q1. For the *Video* task, we see a strengthening of the alpha band, but only after Q2. While the sources of these shifts are not clear, it is possible that they reflect the effects of habituation, sensitization, or implicit subject learning, occurring over different periods in the year.

Using the first 30 days as baseline, we compute the correlation between each day’s periodogram and each of the 30 baseline periodograms, and plot the mean correlation over time (Fig. 10). Different temporal dynamics emerge for the eyes-open versus eyes-closed tasks.

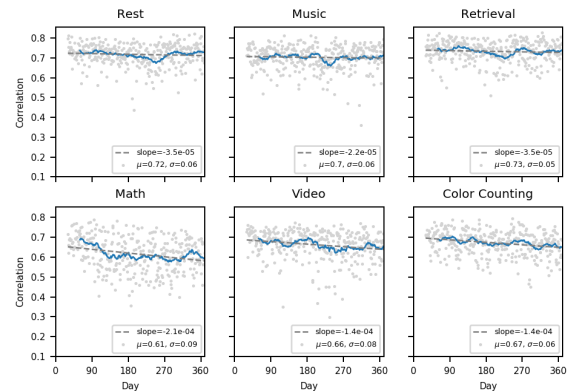


Fig. 10. **Daily mean correlation to 30 baseline days from the beginning of the year.** 30-day moving average in blue. Linear regression fit line in grey. The three eyes-open tasks (bottom row) show steadily declining similarity over time, while the three eyes-closed tasks (top row) show temporary dips in the third quarter.

The three eyes-closed tasks (*Rest, Music, Retrieval*) show a slight dip in Q3 in an otherwise stable similarity level of 0.70-0.73. A possible reason is the time-of-year and its effects on the EEG. In this case, Q3 corresponds to the summer season, and previous studies have found evidence that EEG may be modulated by variations in temperature, humidity, and daylight hours [32], [33].

For the *Math* task, we see a steady decline from 0.7 to 0.6 over the course of the year. We see similar but less steep declines for the *Video* and *Color Counting* tasks. These patterns suggest that the effects of any possible learning and/or sensitization to the task stimuli emerge in a steady and gradual manner over time.

An analysis of inter-session variability provides additional support for the temporal similarity decline. For example, for the *Math* task, we see that the general shape of the distribution is retained, with a strong left skew and a long tail in the boxplot (Fig. 11A). As we increase the inter-session gap from one day to one week, one month, three months, and six months, we see a rightward (downward) shift in the distribution. Correspondingly, we see a steady decline in the mean correlation with increasing inter-session gap (Fig. 11B).

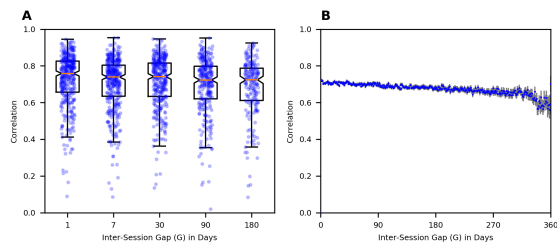


Fig. 11. **Inter-session variability for Math Task.** A: Increase in inter-session gap causes a rightward (downward) shift in the distribution of inter-session correlation. B: Mean correlations for all pairs of periodograms separated by a gap of G days also declines with increasing G .

Clustering analysis indicates that these temporal shifts are driven by the days in the main cluster, not the secondary cluster that has fewer days. For example, for the *Rest* task, the 3rd quarter dip is seen only for Cluster 1 days. For the *Math* task, only Cluster 1 days exhibit significant decline in similarity against their corresponding baseline days (Fig. 12). The 39 days in the secondary cluster, which have elevated delta and theta powers, actually maintain a higher similarity level to their baseline days within their cluster.

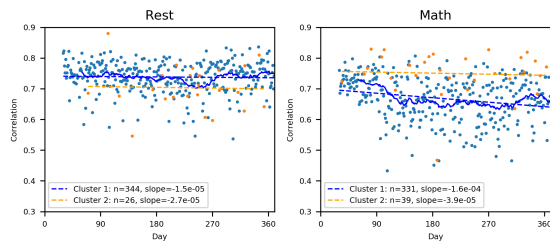


Fig. 12. **Daily mean correlation to baseline days for two clusters for the Rest and Math tasks.** For the *Rest* task, only the main cluster (blue) shows a dip in the third quarter. For the *Math* task, the main cluster (blue) shows much more significant decline in similarity to the baseline days in its cluster over time. The secondary cluster days (orange) actually maintain high similarity to the baseline days within its cluster.

Collectively, these results suggest that temporal shifts may occur, either temporarily or more permanently, depending on the specific cognitive task. Further research is needed

to uncover the relationship between task characteristics and temporal dynamics, and establish the presence or absence of seasonality effects at the periodicity of 12 months.

IV. DISCUSSION

By increasing temporal recording density by two orders-of-magnitude over the state-of-the-art, we obtain a highly granular view of neural dynamics over time. For our subject, his resting-state signals retained a high similarity level over one year. At the same time, the signals from any given day may deviate significantly from the others. This has important methodological implications – we should avoid using a single day as baseline/reference, and the choice of baseline/reference days is very important for any EEG analysis.

Furthermore, we find that “outlier” days are actually not outliers, but rather belong to an alternate cluster of days with an alternate brainwave signature. Further sub-clustering with additional fine-grained features is also possible. This has implications not just for experimental design but also for the design and calibration of BCI and EEG-based authentication systems. For example, a biometric system that supports multiple brainwave templates, corresponding to the clusters, may yield improvements in reducing false-rejection rates.

Beyond the resting-state, the eyes-open cognitive tasks show steady declines in similarity over the entire year. We do not know if these declines would have continued at the same rate beyond the study’s duration, and if there is some level at which the declines will end. We also asked earlier if the third quarter dips for the eyes-closed tasks would recur seasonally. These open questions point to future studies with even longer durations.

In this study, each task is performed once daily. For BCI and neurobiometric applications, it may be worthwhile to investigate if repetition spacing [34] or task execution frequency (e.g., more than once daily, weekly, monthly) has an impact. Similarly, future work can investigate additional types of cognitive tasks, e.g., motor-imagery tasks for sensorimotor rhythms.

Previous studies have investigated and validated the performance of mobile/portable, single-channel EEG systems [35], [36], [37], and measured test-retest reliability using the same EEG system as the current study [5]. Our study was able to collect data with clean and rich signal features that allow for robust analysis in the spectral dimension. Future work can investigate coherence dynamics using multi-electrode systems, or combine EEG with fNIRS, fMRI modalities to interrogate structural and functional changes over different timescales.

V. CONCLUSION

This study demonstrates that long-term, temporally dense, in-situ EEG studies can reveal important insights on the temporal dynamics of neural signals. Over the course of one year, the signals either retain high similarity, or undergo a gradual and steady similarity decline, while exhibiting significant inter-session variability. Thanks to the high recording density,

we establish the existence of primary and secondary clusters of days where the EEG recordings consistently exhibit alternate spectral signatures. Days within each cluster show high within-cluster similarity, suggesting that they should not be treated as outlier days in analysis. A calendar analysis finds no evidence that the subject's calendar activities, such as teaching or traveling, or day of the week, have effects on the similarity of the signals.

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REFERENCES

- [1] T. Gasser, P. Bächer, and H. Steinberg, "Test-retest reliability of spectral parameters of the EEG," *Electroencephalography and Clinical Neurophysiology*, vol. 60, no. 4, pp. 312–319, 1985.
- [2] M. Salinsky, B. Oken, and L. Morehead, "Test-retest reliability in EEG frequency analysis," *Electroencephalography and Clinical Neurophysiology*, vol. 79, no. 5, pp. 382–392, 1991.
- [3] A. Kondacs and M. Szabó, "Long-term intra-individual variability of the background EEG in normals," *Clinical Neurophysiology*, vol. 110, no. 10, pp. 1708–1716, 1999.
- [4] M. Näpflin, M. Wildi, and J. Sarnthein, "Test-retest reliability of resting EEG spectra validates a statistical signature of persons," *Clinical Neurophysiology*, vol. 118, no. 11, pp. 2519–2524, 2007.
- [5] J. M. Rogers, S. J. Johnstone, A. Aminov, J. Donnelly, and P. H. Wilson, "Test-retest reliability of a single-channel, wireless EEG system," *International Journal of Psychophysiology*, vol. 106, pp. 87–96, 2016.
- [6] C. E. Tenke, J. Kayser, J. E. Alvarenga, K. S. Abraham, V. Warner, A. Talati, M. M. Weissman, and G. E. Bruder, "Temporal stability of posterior EEG alpha over twelve years," *Clinical Neurophysiology*, vol. 129, no. 7, pp. 1410–1417, 2018.
- [7] M. Corsi-Cabrera, L. Galindo-Vilchis, Y. Del-Río-Portilla, C. Arce, and J. Ramos-Loyo, "Within-subject reliability and inter-session stability of EEG power and coherent activity in women evaluated monthly over nine months," *Clinical Neurophysiology*, vol. 118, no. 1, pp. 9–21, 2007.
- [8] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," *Electroencephalography and Clinical Neurophysiology*, vol. 78, no. 3, pp. 252–259, 1991.
- [9] M. Krauledat, M. Tangermann, B. Blankertz, and K.-R. Müller, "Towards zero training for brain-computer interfacing," *PLoS One*, vol. 3, no. 8, p. e2967, 2008.
- [10] J. C. Christensen, J. R. Estep, G. F. Wilson, and C. A. Russell, "The effects of day-to-day variability of physiological data on operator functional state classification," *NeuroImage*, vol. 59, no. 1, pp. 57–63, 2012.
- [11] Y.-P. Lin, S.-H. Hsu, and T.-P. Jung, "Exploring day-to-day variability in the relations between emotion and EEG signals," in *International Conference on Augmented Cognition*. Springer, 2015, pp. 461–469.
- [12] S. Fazli, S. Dähne, W. Samek, F. Bießmann, and K.-R. Müller, "Learning from more than one data source: data fusion techniques for sensorimotor rhythm-based brain-computer interfaces," *Proceedings of the IEEE*, vol. 103, no. 6, pp. 891–906, 2015.
- [13] V. Jayaram, M. Alamgir, Y. Altun, B. Scholkopf, and M. Grosse-Wentrop, "Transfer learning in brain-computer interfaces," *IEEE Computational Intelligence Magazine*, vol. 11, no. 1, pp. 20–31, 2016.
- [14] Z. Yin and J. Zhang, "Cross-session classification of mental workload levels using EEG and an adaptive deep learning model," *Biomedical Signal Processing and Control*, vol. 33, pp. 30–47, 2017.
- [15] S. Perdakis and J. d. R. Millan, "Brain-machine interfaces: A tale of two learners," *IEEE Systems, Man, and Cybernetics Magazine*, vol. 6, no. 3, pp. 12–19, 2020.
- [16] J. Chuang, H. Nguyen, C. Wang, and B. Johnson, "I think, therefore I am: usability and security of authentication using brainwaves," in *International Conference on Financial Cryptography and Data Security*. Springer, 2013, pp. 1–16.
- [17] E. Maiorana, D. La Rocca, and P. Campisi, "On the permanence of EEG signals for biometric recognition," *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 1, pp. 163–175, 2015.
- [18] E. Maiorana and P. Campisi, "Longitudinal evaluation of EEG-based biometric recognition," *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 5, pp. 1123–1138, 2017.
- [19] R. A. Poldrack, T. O. Laumann, O. Koyejo, B. Gregory, A. Hover, M.-Y. Chen, K. J. Gorgolewski, J. Luci, S. J. Joo, R. L. Boyd, *et al.*, "Long-term neural and physiological phenotyping of a single human," *Nature Communications*, vol. 6, no. 1, pp. 1–15, 2015.
- [20] J. Chuang, N. Merrill, T. Maillart, and Students of the UC Berkeley Spring 2015 MIDS Immersion Class, "Synchronized brainwave recordings from a group presented with a common audio-visual stimulus," 2015, data retrieved from <https://www.kaggle.com/berkeley-biosense/synchronized-brainwave-dataset>.
- [21] M. Poulos, M. Rangoussi, N. Alexandris, and A. Evangelou, "Person identification from the EEG using nonlinear signal classification," *Methods of information in medicine*, vol. 41, no. 1, pp. 64–75, 2002.
- [22] S. Marcel and J. d. R. Millan, "Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 29, no. 4, pp. 743–748, 2007.
- [23] R. Palaniappan, "Two-stage biometric authentication method using thought activity brain waves," *International journal of neural systems*, vol. 18, no. 1, pp. 59–66, 2008.
- [24] C. Ashby, A. Bhatia, F. Tenore, and J. Vogelstein, "Low-cost electroencephalogram (EEG) based authentication," in *2011 5th International IEEE/EMBS Conference on Neural Engineering, NER 2011*, 2011, pp. 442–445.
- [25] P. Campisi and D. La Rocca, "Brain waves for automatic biometric-based user recognition," *IEEE transactions on information forensics and security*, vol. 9, no. 5, pp. 782–800, 2014.
- [26] M. T. Curran, J.-k. Yang, N. Merrill, and J. Chuang, "Passthoughts authentication with low cost EarEEG," in *IEEE 38th Annual International Conference of the Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2016, pp. 1979–1982.
- [27] N. Merrill, M. T. Curran, S. Gandhi, and J. Chuang, "One-step, three-factor passthought authentication with custom-fit, in-ear EEG," *Frontiers in Neuroscience*, vol. 13, p. 354, 2019.
- [28] T. H. Grandy, M. Werkle-Bergner, C. Chicherio, F. Schmiedek, M. Lövdén, and U. Lindenberger, "Peak individual alpha frequency qualifies as a stable neurophysiological trait marker in healthy younger and older adults," *Psychophysiology*, vol. 50, no. 6, pp. 570–582, 2013.
- [29] J. H. Ward Jr, "Hierarchical grouping to optimize an objective function," *Journal of the American statistical association*, vol. 58, no. 301, pp. 236–244, 1963.
- [30] L. v. d. Maaten and G. Hinton, "Visualizing data using t-SNE," *Journal of Machine Learning Research*, vol. 9, no. Nov, pp. 2579–2605, 2008.
- [31] E. Olejarczyk, P. Bogucki, and A. Sobieszek, "The EEG split alpha peak: phenomenological origins and methodological aspects of detection and evaluation," *Frontiers in Neuroscience*, vol. 11, p. 506, 2017.
- [32] C. K. Peterson and E. Harmon-Jones, "Circadian and seasonal variability of resting frontal EEG asymmetry," *Biological Psychology*, vol. 80, no. 3, pp. 315–320, 2009.
- [33] M. Zhu, W. Liu, and P. Wargocki, "Changes in EEG signals during the cognitive activity at varying air temperature and relative humidity," *Journal of Exposure Science & Environmental Epidemiology*, vol. 30, no. 2, pp. 285–298, 2020.
- [34] B. Tabibian, U. Upadhyay, A. De, A. Zarezade, B. Schölkopf, and M. Gomez-Rodriguez, "Enhancing human learning via spaced repetition optimization," *Proceedings of the National Academy of Sciences*, vol. 116, no. 10, pp. 3988–3993, 2019.
- [35] O. E. Krigolson, C. C. Williams, A. Norton, C. D. Hassall, and F. L. Colino, "Choosing MUSE: Validation of a low-cost, portable EEG system for ERP research," *Frontiers in Neuroscience*, vol. 11, p. 109, 2017.
- [36] S. Debener, F. Minow, R. Emkes, K. Gandras, and M. De Vos, "How about taking a low-cost, small, and wireless EEG for a walk?" *Psychophysiology*, vol. 49, no. 11, pp. 1617–1621, 2012.
- [37] S. J. Johnstone, R. Blackman, and J. M. Bruggemann, "EEG from a single-channel dry-sensor recording device," *Clinical EEG and Neuroscience*, vol. 43, no. 2, pp. 112–120, 2012.