



Temporally resolved neural dynamics underlying handwriting

Leisi Pei^a, Marieke Longcamp^b, Frederick Koon-Shing Leung^a, Guang Ouyang^{a,*}

^a Faculty of Education, The University of Hong Kong, Hong Kong, China

^b CNRS, Aix Marseille University LNC, Marseille, France

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ABSTRACT

How do the temporal dynamics of neural activity encode highly coordinated visual-motor behaviour? To capture the millisecond-resolved neural activations associated with fine visual-motor skills, we devised a co-registration system to simultaneously record electroencephalogram and handwriting kinematics while participants were performing four handwriting tasks (writing in Chinese/English scripts with their dominant/non-dominant hand). The neural activation associated with each stroke was clearly identified with a well-structured and reliable pattern. The functional significance of this pattern was validated by its significant associations with language, hand and the cognitive stages and kinematics of handwriting. Furthermore, the handwriting rhythmicity was found to be synchronised to the brain's ongoing theta oscillation, and the synchronisation was associated with the factor of language and hand. These major findings imply an implication between motor skill formation and the interplay between the rhythms in the brain and the peripheral systems.

1. Introduction

Fine motor skills remain amongst the most awe-inspiring abilities of humans, and neuroscientists and robotics engineers strive to understand and replicate these processes (Akkaya et al., 2019; Sejnowski, 2020). Handwriting, shaped by decades of training and exercise, is a representative example of highly efficient fine motor control in humans. Yet this skill is highly complex due to the involvement of visual integration, spatial skills, short- and long-term memory and language processing (Danna and Velay, 2015; Palmis et al., 2017; Rapp and Fischer-Baum, 2015). Therefore, handwriting provides an ideal research venue for the study of neural mechanisms associated with fine motor control through investigation of its interactions with other cognitive processes.

The development of cognitive models and the study of the neuroanatomical substrates of handwriting have a long history (Exner, 1881; van Galen, 1991). In most models, handwriting is seen as a series of hierarchical and modular neural cognitive subprocesses that form a closed loop (Ellis, 1982; Margolin, 1984; Rapp and Fischer-Baum, 2015; van Galen, 1991). First, the grapheme (e.g., which letter to write) is identified. Then, the brain evokes a motor programme from long-term memory that encodes the sequence of strokes forming the character, which then commands the downstream effectors to draw the consecutive strokes (Kadmon harpaz et al., 2014; Palmis et al., 2017; Rapsak and Beeson, 2002). Finally, perception of the writing outcome, including vision and proprioception, serves as an online feedback guidance to maintain the legibility and aesthetics of the written content (Danna and Velay, 2015; Hepp-Reymond et al., 2009). Decades of train-

ing and exercise fully automatise the handwriting process and equip it with specialised and distributed neural networks (Dufor and Rapp, 2013; Longcamp et al., 2014; Planton et al., 2013; Vinci-Booher et al., 2019).

The question of how the various cognitive subprocesses described above are implemented and orchestrated remains unanswered. How these subprocesses are then encapsulated into a precisely controlled series of movements is also unknown. To answer these two questions, we argue that the fast timescale temporal dynamics of the neural activities associated with elementary handwriting processes must first be identified and characterised. However, most handwriting and brain research has been based on functional magnetic resonance imaging, which does not allow the study of rich temporal dynamics. In addition, no studies relying on electrophysiological measurements have yet examined the detailed neural activation patterns associated with elementary processes in handwriting movements, although some studies have looked into the power spectrum of neurophysiological activities aggregated over a long duration of neural signal during handwriting (Kao et al., 2002; Ose Askvik et al., 2020). To study these elementary neural processes, we first need to define and capture the behavioural events associated with them so that the neural activation pattern can be characterised. This characterisation will enable experimental studies of its relationships with other cognitive processes or constructs to answer the first question.

Answering the second question regarding efficiency may involve a theoretical perspective on the coupling of dynamical systems. As studies have shown, precision in the fine motor control of handwriting encompasses both spatial and temporal aspects (Plamondon, 1995b;

* Corresponding author.

E-mail address: ouyangg@hku.hk (G. Ouyang).

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Teulings et al., 1986; Tucha et al., 2008), implying the existence of general laws governing the spatiotemporal coordination of this skill. Several models have proposed computational principles that allow efficient coordination of the effectors to generate complex handwriting patterns (Athènes et al., 2004; Edelman and Flash, 1987; Hollerbach, 1981; Plamondon, 1995a). The general principle is that handwriting patterns, although complex, can be generated by a dynamical system governed by a few parameters, thus substantially reducing the computational load on the neural circuits. Previous work has demonstrated that the coupling of two non-linear oscillators, along with a few modulation parameters, is sufficient to generate a variety of patterns resembling handwriting (André et al., 2014; Athènes et al., 2004; Hollerbach, 1981). The oscillator model is biologically plausible, as it coincides with the biophysical properties of spring muscle (Latash, 2018; Zatsiorsky and Prilutsky, 2012). It is also supported by the intrinsic rhythmicity of handwriting, which starts from an early age (Nutt, 1917; Pagliarini et al., 2017). In support of this, temporal coupling between oscillatory brain activities and the electromyogram during handwriting has been evidenced (Butz et al., 2006; Saarinen et al., 2020). More generally, a behavioural activity displaying a rhythmicity can be coupled with the brain – which also displays prominent oscillations – through neural entrainment (Lakatos et al., 2019). Neural entrainment has been extensively shown to have functional significance, e.g., in modulating attention and speech intelligibility (Ding and Simon, 2014; Ghitzza, 2012; Kerlin et al., 2010; Kösem et al., 2018; Riecke et al., 2018; Zalta et al., 2020; Zion Golombic et al., 2013; Zoefel and VanRullen, 2015). This strongly suggests that the entrainment between the ongoing neural dynamics and handwriting production is thus a plausible mechanism, which may be related to the cost efficiency of a skilled handwriting process. To investigate this question, it is important to first lay out possible scenarios about the relationship between handwriting behavioural events and the brain activity. If an efficient brain-behaviour coupling is achieved, as would be expected in skilled handwriting, the handwriting activity may be able to utilize the ongoing brain resource in a way that little additional energy is incurred. This may be manifested by a synchronisation between the spontaneous brain oscillations and handwriting rhythmicity, which forms the first scenario. The second scenario is that the handwriting behavioural events generate separate neural activity that is additive to the spontaneous activity, thus substantially changing its power, and such additive effect would be associated with cognitive factors such as demand on handwriting.

Based on the two above mentioned rationales, we explored the neural dynamic activation associated with elementary handwriting processes and the association between ongoing oscillatory brain activity and handwriting processes. To capture the relevant neural activation, we developed an electroencephalography (EEG) and handwriting movement co-registration system. We instructed the participants to continuously write scripts on a tablet in a natural manner. From the handwriting stream, we defined and precisely marked the key events of the basic stroke-writing units, which allowed us to examine their neural correlates. We found that the derived neural activations showed a rich and highly reliable dynamic pattern, which was associated with language, hand, cognitive stages and kinematics of handwriting. Our analysis of the oscillatory dynamics of the identified neural activation revealed a synchronisation between the brain activity and handwriting movements mainly located in the brain's 4 Hz theta band. The synchronisation effect was further shown to be associated with factors of language and hand, which implied an interesting link between the brain-behaviour coupling in rhythmicity and complex visual-motor behaviour.

2. Materials and method

2.1. Participants

The participants were 11 healthy right-handed university students (six men, $M_{\text{age}} = 29.9 (\pm 2.9)$ years) recruited in Hong Kong. One partic-

ipant was excluded due to poor signal quality (impedance > 200kOhm). All participants were native Chinese speakers from mainland China and were fluent in English (They started learning English as second language from primary school). Their handwriting activities in schools and life were highly dominated by Chinese and they barely had handwriting experience with left hands. All participants had normal or corrected-to-normal vision and had no history of mental diseases. The research was approved by the Human Research Ethics Committee (HREC) of the University of Hong Kong. Written consent was obtained from each participant.

2.2. Instrumentation and setup

Handwriting movements were recorded using a digitising tablet (HUAWEI MediaPad M5 Pro; screen resolution: 2560×1600 pixels; diagonal size: 10.8 inches; aspect ratio: 16:10) equipped with an active stylus with 4096 levels of pressure sensitivity. The tablet was placed in landscape orientation on an angle-adjustable tablet holder on a desk with the angle set to 40° . Participants were required to write on the tablet while their handwriting trajectories and EEG signals were simultaneously recorded at sampling rates of 60 Hz and 1000 Hz, respectively. EEG signals were collected using a 32-channel amplifier (BrainAmp, Brain Products GmbH, Germany) referenced to the ground electrode. EEG electrodes were placed on the cap according to the 10–20 international system.

The synchronisation between EEG amplifier and tablet was implemented via a desktop computer running a customised Python routine. Specifically, the tablet was connected to the desktop computer through a USB port so that the Python routine could monitor events broadcasted by the tablet via Android Logcat command-line tool. Once capturing a key event from the tablet, the Python routine will send this event to the EEG amplifier through a parallel port. During the handwriting process, our self-developed tablet app generated several important event logs for each point in the handwriting trajectory: x, y coordinates; a timestamp; force; and state codes for pen-down (touching the screen), pen-move, and pen-up (leaving the screen). Only the time marker for the first pen-down event of writing each sentence was sent to the online EEG stream for synchronisation (Fig. 1A). The remaining pen-down events (corresponding to the initial points of each single stroke) in the sentence were derived offline according to the event logs generated by the tablet. The integrated experimental setup is illustrated in Fig. 1.

2.3. Stimulus and task design

The data were recorded in a sound-attenuated room. The participants were seated in a comfortable posture squarely facing the tablet on the desk with a sight distance of approximately 35 cm. They were asked to take dictation sentence by sentence, using the stylus to write on a designated area of the tablet screen (Fig. 1B). The experiment was divided into four tasks, each of which contained 30 non-repeated trials of sentence dictation: (1) writing in Chinese with the dominant hand (DC), (2) writing in English with the dominant hand (DE), (3) writing in Chinese with the non-dominant hand (NDC) and (4) writing in English with the non-dominant hand (NDE). The four tasks were pseudo-randomised across participants and ensured hand alternation between adjacent tasks to avoid fatigue. The Chinese characters and English words used in the dictation sentences were simple and common ones. All participants were required to get familiar with the sentences before the experiment.

To ensure homogeneity and fluency in the handwriting processes, the participants were instructed to (1) write stroke by stroke carefully and avoid using a scribbled writing style, (2) write a new character if an error occurred, instead of crossing out the erroneous one, and (3) stop writing when there was no space left. There was no time limit for each trial, and the participants could begin writing whenever they felt ready. An example of a dictation task trial is shown in Fig. 1B.

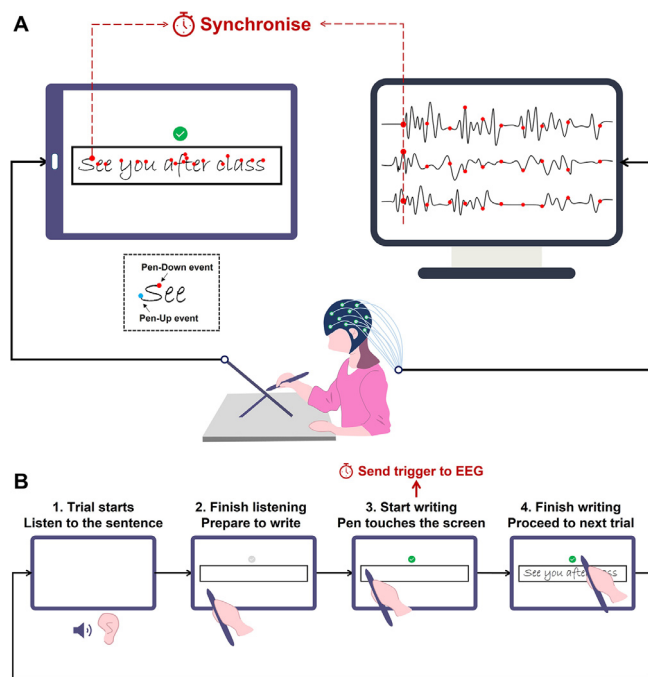


Fig. 1. Illustration of the experimental setup and task. (A) Co-registration and synchronisation of handwriting movements and EEG traces. The two streams were synchronised by sending the time marker of the first pen-down event of each trial (the first large red dot) to the online EEG stream. The remaining pen-down events for all strokes within the same trial (indicated by the remaining small red dots) were derived offline according to event logs generated by the tablet. (B) Dictation task procedure (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

2.4. Neural activation associated with a single stroke

The EEG signals were pre-processed and analysed using a MATLAB and EEGLAB plugin (Delorme and Makeig, 2004). The raw EEG data were first down-sampled to 250 Hz and filtered by an EEGLAB in-built bandpass FIR filter (zero-phase, non-causal, filter order: 827 data points, corresponding to 3.3 s) within 1 and 45 Hz. Independent component analysis was applied and the MARA algorithm (Winkler et al., 2011) was used to automatically identify and remove artifacts using a default cut-off probability of 0.5.

2.4.1. Temporal pattern of writing ERPs

The pen-down time points (see the red dots in Fig. 1A), which represent the initial point of writing each stroke, were used to generate an average ERP for each of the four different tasks separately (i.e., writing in Chinese/English with the dominant/non-dominant hand). The ERP epoch ranged from -500 to 1000 ms after the time point of the pen-down event. As the pen-down event corresponded to the beginning of writing a stroke, it was assumed that there was motor preparation activity before time zero. Therefore, -500 – 200 ms prior to pen-down event was used for baseline correction. This ERP was referred to as the ‘writing ERP’ throughout the article. A hand-related brain asymmetrical pattern was supposed to be observed in the writing ERPs from different hands. After exploring the parameters that best revealed this hand-related asymmetrical pattern, we filtered the ERP at the band of 20 Hz– 30 Hz and obtained the scalp map between -55 ms and -25 ms for the comparison of left and right-hand patterns. The asymmetry pattern can also be revealed in other time windows and larger frequency bands, but not in the original unfiltered ERP as it is overwhelmed by the high-amplitude, low-frequency ERP components.

2.4.2. Time-frequency representation of writing ERPs

In addition to ERPs, a time-frequency analysis was conducted to examine the neural activity pattern in the frequency domain. Wavelet transformation (based on Morse wavelet with the symmetry parameter (gamma) equal to 3 and the time-bandwidth product equal to 60) was applied across the electrodes to every single-trial from -500 to 1000 ms after the pen-down time point. The wavelet coefficients from 1 Hz to 45 Hz were averaged across the single trials in their complex form. The moduli of the averaged complex values were obtained and visualised to reveal the dynamic neural activation across different frequencies, which cannot be visualised by the average ERP.

2.4.3. Reliability of writing ERPs

To examine the reliability of the stroke-associated neural activation characterised by ERPs, we applied the split-half correlation approach. The Pearson’s correlation coefficients of the average ERPs from odd-numbered and even-numbered trials were first computed for each participant and task. The obtained values were then corrected by using the Spearman–Brown formula to adjust for the reduced correlation due to half splitting. The mean split-half reliability for each task conditions was obtained by averaging across all participants (Kaplan et al., 2014).

2.5. Validation of writing ERPs

2.5.1. Modulation of writing ERPs by cognitive factors

To examine whether the amplitude of the writing ERPs depended on language and hand across the four tasks, we applied Linear Mixed Model (LMM) to the average amplitudes of single trials across all tasks and participants. We tested the effects separately on two brain regions (the central region covering the motor cortices and the posterior region covering the visual cortices) in three different time windows (pre-, peri- and post-writing). The central region included the electrodes Fz, Cz, FC1 and FC2 while the posterior region involved Oz, O1 and O2. The three time windows were -200 – 50 ms, 0 – 50 ms and 200 – 300 ms, representing the neural activation before, during and after the event of writing a stroke, respectively. The LMM was conducted using the lme4 (Bates et al., 2015) and lmerTest (Alexandra et al., 2017) packages in R (RCoreTeam, 2020), with language, hand and their interaction specified as fixed effects, and the participants’ intercept as random effects. To rule out the possibility that language and hand effects were caused by stroke length, the stroke length was also specified as an independent variable in the following model.

$$\text{Amplitude} \sim 1 + \text{language} + \text{hand} + \text{language}^* \text{hand} + \text{stroke-} \\ \text{Length} + (1|\text{participant})$$

2.5.2. Cross-validation of the effects of cognitive factors on modulating writing ERPs

To validate the cross-individual robustness of the language and hand effects revealed by the linear mixed model, we further conducted a cross-validation statistical analysis that trains the LMM based on a subset of data to predict the held-out data. Two ways of splitting the data for cross-validation were conducted: one is splitting all participants into two halves and the other is splitting the trials into two halves. The details of applying these two ways of cross-validation are described as follows.

For the participant-based data splitting, we split the participants into two halves for training and testing the performance of the model. To separately evaluate the effects of each factor (e.g., language, hand) based on this cross-validation approach, we conducted the cross-validation analysis on the following five models that were organised in a way that one new factor (or interaction) is appended to the previous model:

$$\text{Model 1: Amplitude} \sim 1 + (1|\text{participant})$$

$$\text{Model 2: Amplitude} \sim 1 + \text{language} + (1|\text{participant})$$

$$\text{Model 3: Amplitude} \sim 1 + \text{language} + \text{hand} + (1|\text{participant})$$

$$\text{Model 4: Amplitude} \sim 1 + \text{language} + \text{hand} + \text{language}^* \text{hand} + (1|\text{participant})$$

Model 5: Amplitude $\sim 1 + \text{language} + \text{hand} + \text{language} * \text{hand} + \text{stroke-Length} + (1|\text{participant})$

The cross-validation procedures were conducted as follows. First, we fitted all five models on half of participants and then used the other half to evaluate the performance of these models. As the total number of valid participants is 10 in this study, there are 252 combinations (C_{10}^5) for the selection of training set. Then, we calculated the prediction error from the held-out participants using the fitted models. The prediction error was calculated as the mean squared error (MSE) between the predicted values and real values. It is worth to note that before calculating MSE, the prediction error for each participant was demeaned because the random effect in intercept cannot be predicted by the fitted models. To evaluate the effect of a specific factor (or interaction), we statistically compared the prediction errors from the two adjacent models (e.g., to evaluate language effect, we compared *Model 1* and *Model 2*) following the procedures below: (1) calculating the prediction errors from all 252 combinations for each model; (2) statistically comparing the difference between the two arrays of prediction errors. The underlying hypothesis is that if one model is statistically better than the other, it should generate a statistically lower MSE. As the 252 values obtained from each model are not normally distributed, we conducted non-parametric Wilcoxon test to compare the adjacent models to determine the significance of each factor (or interaction). The results of statistical significance based on Wilcoxon test were reported.

For the second way of splitting training and testing sets, the procedures applied were entirely the same as the first way except for the way of splitting data. In this analysis, we randomly selected half trials from each participant to serve as training set and used the remaining half trials as testing set. Since there are a huge number of combinations to half split the trials, we decided to use 252 randomly drawn combinations to be consistent with the first splitting-participants approach.

In addition, we also investigated whether the order of introducing factors influences the results of factor effects by changing the language factor in *Model 2* into hand. The results showed that the order did not affect the statistical conclusion, so here we reported the results based on the above five models.

2.5.3. Modulation of writing ERPs by cognitive stage

To examine to what degree writing ERPs reflect different stages during the writing of a complex character, we applied LMM to the DC task to test the effect of the stroke order on the amplitude of writing ERPs. This analysis served to demonstrate the existence of the effect of different handwriting stages on the writing ERP, we tested the effect on all electrodes in the time window (200 to 300 ms) in which the effect was predominantly shown. The strokes were labelled based on whether they were the initial stroke of a Chinese character during participants' actual writing. The LMM lmer model was specified as follows.

Amplitude $\sim 1 + \text{strokeType} + (1|\text{participant})$

2.5.4. Cross-validation of the effect of cognitive stage on writing ERPs

In this analysis, we applied the splitting-participants approach to cross validate the effect of cognitive stage (initial versus non-initial strokes). The procedures applied here were the same as the one described for cross-validation of cognitive factors in 2.5.2, except that only two models were involved here because there was only one factor being examined. The two models were specified as below and we conducted this cross-validation analysis on each single electrode.

Model 1: Amplitude $\sim 1 + (1|\text{participant})$

Model 2: Amplitude $\sim 1 + \text{strokeType} + (1|\text{participant})$

Different from the models for examining cognitive factors, there is only one single factor involved in the model for examining the effect of cognitive stage. In this sense, we also investigated to what degree this effect exists at the single participant level. To this end, we applied

independent two sample *t*-test between initial and non-initial strokes within each participant on every electrode. The consistency at single participant level may also reflect the robustness of the effect of cognitive stage across participants.

2.6. Synchronisation between theta oscillation and handwriting

To examine the synchronisation between brain oscillation and handwriting movements, we first bandpass-filtered (zero-phase, non-causal, filter order: 415 points) the EEG data at 3–5 Hz and generated the writing ERPs time-locked to pen-down events as described above to visually observe the difference between conditions. Next, we calculated the phase and amplitude of theta oscillation (4 Hz) surrounding every pen-down event (from –200 to 800 ms) using Fourier transform on Fz electrode (closest to the centre of theta). The phase distribution of theta across the trials and participants was visualised on a polar axis to show the distribution bias. The bias (non-uniformity) of the phase distribution within a single task and between different tasks was tested by the Rayleigh test and Harrison–Kanji tests, respectively, using the CircStat toolbox (Philipp, 2009). Visualisation of the phase distribution was implemented using the CircHist toolbox (Zittrell, 2019). The two-tailed *t*-test was used to test the difference in theta amplitude (averaged from single trials) between tasks.

We estimated the source activations of the theta oscillation based on the grand averaged ERPs (from –500 ms to 1000 ms) that were bandpass-filtered at 3 to 5 Hz across the four tasks, using Brainstorm (Tadel et al., 2011). The default ICBM152 anatomy was used to compute the head model, and the noise variance was regarded as identical. A default EEG electrode position set for 32 channels was used for source estimation. The electrode positions were automatically calibrated to the surface of the head model. The OpenMEEG BEM algorithm (cortex surface) and the Minimum Norm Imaging algorithm (current density) were used to compute the forward modelling and physiologically plausible EEG sources, respectively.

2.7. Encoding of handwriting kinematics in the ongoing neural signal

In addition to analyses at the level of ERP, we further investigated the association between handwriting kinematics and ongoing neural activity by calculating the cross-correlation between the two time series: the kinematic variables associated with each point in the handwriting trajectory and the continuous EEG signal down-sampled to the handwriting sampling rate during writing each sentence. We included three kinematics variables: velocity, pen-touch force and length of unfinished stroke (LUS). At each time point during writing a stroke, there is a remained segment of a stroke to be finished. LUS was defined as the length of the unfinished segment of the current stroke at every time point. LUS was analysed here because it carries information related to the length of a stroke and the cognitive activity at different time points of writing a stroke would be different. On this basis, we expected the neural activation (including planning and online coordination) to be dependant on stroke length. The cross-correlation was calculated for each electrode separately, with a maximum lag of 800 ms. The calculation was conducted on each sentence, and the results were averaged across all sentences. To further evaluate the statistical significance of the cross correlations, we also calculated the cross correlation results from a surrogate data. The surrogate data was generated by temporally reversing the EEG data and thus is not expected to have any association with the kinematic streams.

3. Results

3.1. Basic kinematic characteristics of handwriting

Table 1 summarises the descriptive statistics of the basic kinematic characteristics of stroke writing. Differences related to language and

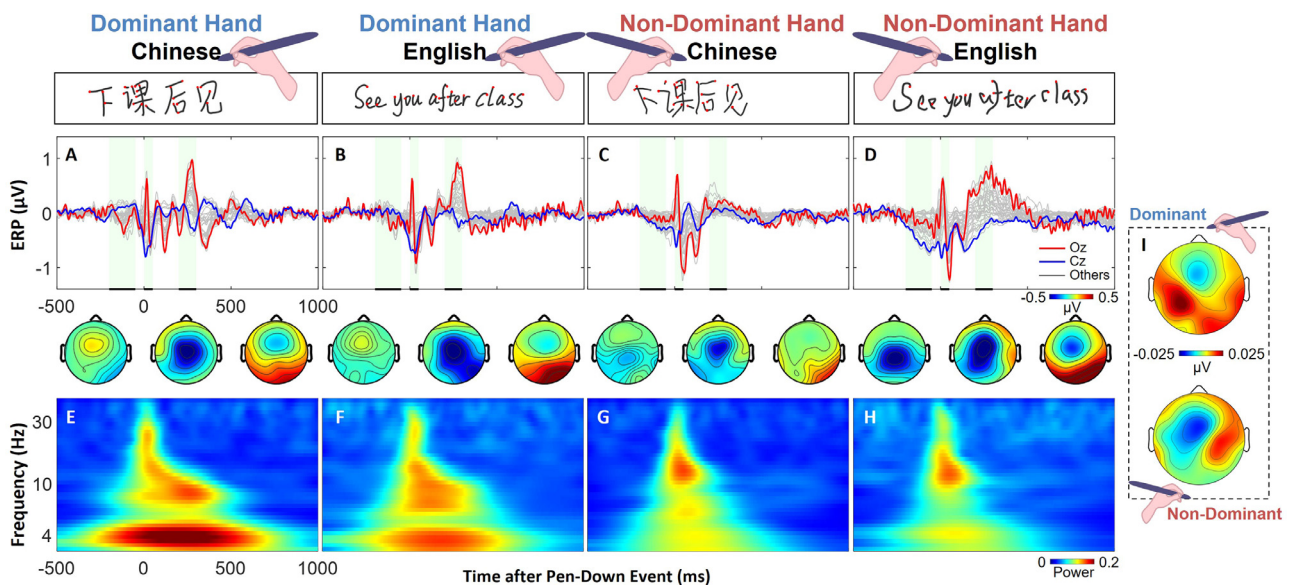


Fig. 2. Writing ERPs and their time-frequency representations time-locked to first points of strokes (red dots as shown on the characters/letters). (A)–(D) Grand averaged ERPs for different electrodes in four different tasks, and scalp topographies averaged from three different time windows: -200 – 50 ms, 0 – 50 ms and 200 – 300 ms. (E)–(H) Time-frequency representations of the writing ERPs averaged across all electrodes. (I) Hand-related asymmetrical pattern of motor activity component (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.).

Table 1

Descriptive statistics for stroke characteristics in each task (mean (standard deviation)).

Stroke characteristic	DC	DE	NDC	NDE
	$N = 2033$ (± 95.44)	$N = 1261$ (± 46.43)	$N = 2126$ (± 76.38)	$N = 1365$ (± 152.67)
Length (pixel)	73.14 (± 11.33)	110.65 (± 16.23)	77.92 (± 9.54)	114.62 (± 16.24)
Duration (ms)	186.97 (± 25.27)	325.68 (± 76.56)	286.64 (± 70.14)	515.03 (± 93.60)
Mean velocity (pixel/ms)	0.40 (± 0.10)	0.35 (± 0.07)	0.29 (± 0.07)	0.23 (± 0.03)
Max force (n.a.)	0.53 (± 0.12)	0.58 (± 0.09)	0.43 (± 0.09)	0.43 (± 0.07)

Note: DC: dominant hand, Chinese; DE: dominant hand, English; NDC: non-dominant hand, Chinese; NDE: non-dominant hand, English; N is the number of strokes identified; Duration is the time taken to write a stroke. Max force represents the pressure of touch and is normalised between 0 (no touch) and 1 (full touch) used in Android system.

hand are clearly shown: the average stroke length and duration is longer in English than in Chinese, and the velocity and maximum force are strongly dependant on hand due to the difference in dexterity.

3.2. Neural activation associated with single strokes

Based on the assumption that writing a stroke is the basic action unit during handwriting, we expected to find a specific neural activation pattern encompassing the writing process of each stroke. This activation was presumed to include motor preparation, execution and visual processing, and to be consistent from stroke to stroke and subject to variation related to the stroke properties. Fig. 2A–D shows the event-related potentials (ERPs) averaged from the single-trial EEG segments time-locked to pen-down events, i.e., the first points of each stroke, together with the scalp topographies averaged from three time windows marked in green. In line with our assumption, conspicuous ERP waveforms were found for all conditions. The ERP featured a sharp spike at around 12 ms after the pen-down event and pre- and post-event activ-

ities covering the peri-event time from approximately -200 – $+300$ ms. The most positive-directed ERPs were observed over the posterior region (Oz, O1 and O2) and the most negative-directed ERPs were located in the centro-frontal regions (Fz, FC1, FC2, and Cz). This neural activation will be termed as “writing ERP” hereafter.

As temporal ERP provides a limited representation of activation patterns in different frequency bands, we further used wavelet analysis to show the time-frequency representation of the writing ERP. The results were averaged across all electrodes, and the grand average patterns are shown in Fig. 2E–H. Three predominant clusters of transient oscillatory activity in the beta (13–30 Hz), alpha (8–12 Hz), and theta (3–7 Hz) bands can be clearly identified. The beta cluster, localised around the time of the pen-down event, corresponds to the spike activity shown in the temporal ERPs. The activity shown in this spike activity displays a clear hand-related asymmetry (Fig. 2I) consistent with previously reported pattern (Ouyang et al., 2011), which validates the neural origin of the writing ERP. The theta cluster is longer lasting and much stronger for the dominant hand, suggesting a critical role of theta oscillation during dexterous handwriting—a mechanism we will analyse in depth later.

The split-half reliability values of the single-trial writing ERPs for the four task conditions (dominant hand, Chinese [DC]; dominant hand, English [DE]; non-dominant hand, Chinese [NDC]; and non-dominant hand, English [NDE]) were 0.86 (± 0.07), 0.80 (± 0.10), 0.86 (± 0.13) and 0.86 (± 0.10), respectively, showing a very high level of consistency across trials. To visualise the cross-trial consistency, the single trial writing ERPs from one participant in a DC task are shown in Fig. 3.

3.3. Validation of the writing ERPs

If the writing ERPs indeed represent the neural activation of the visual, motor, and cognitive processes underlying handwriting, it should be modulated by factors that affect these processes. To test this, we applied linear mixed model to test the effects of language, hand, their interaction and stroke length on the amplitudes of the writing ERPs at three different time windows. The stroke length was included as an independent variable in the model in order to exclude the confounding effects of low-level physical features on factors of language and hand. The results (Table 2) confirmed that the factors of language and hand had significant modulation effects on the amplitude of the writing ERP even after

Table 2
Fixed effects estimated using linear mixed model (LMM).

	[-200 to -50 ms]						[0 to 50 ms]						[200 to 300 ms]					
	b	SE	CI (95%)		t	CV	b	SE	CI (95%)		t	CV	b	SE	CI (95%)		t	CV
			L	H					L	H					L	H		
Posterior region (Oz, O1 and O2)																		
(Intercept)	-0.17	.22	-0.60	.25	-0.79	×	.18	.33	-0.46	.82	.55	×	.65	.26	.13	1.16	2.46*	×
Language	.06	.14	-0.22	.34	.44		-0.29	.19	-0.66	.07	-1.58		-0.28	.16	-0.59	.03	-1.76	# ^
Hand	.08	.13	-0.18	.33	.58		-0.15	.17	-0.49	.18	-0.91		-0.52	.14	-0.80	-0.24	-3.59***	^
Language * hand	-0.07	.09	-0.24	.10	-0.80		.12	.12	-0.11	.34	1.00		.30	.10	.10	.49	3.00**	^
Stroke length	.00	.00	.00	.00	.97		.00	.00	.00	.00	1.24		.00	.00	.00	.00	6.98***	# ^
Centro-frontal region (Fz, Cz, FC1 and FC2)																		
(Intercept)	.26	.14	-0.01	.53	1.85	×	-0.70	.19	-1.07	-0.32	-3.62***	×	-0.62	.17	-0.97	-0.28	-3.57***	×
Language	.11	.09	-0.07	.29	1.24	# ^	.23	.12	-0.00	.46	1.95	# ^	.43	.10	.23	.63	4.19***	# ^
Hand	-0.05	.08	-0.21	.12	-0.55	# ^	.35	.11	.14	.56	3.22**		.48	.09	.30	.67	5.12***	
Language * hand	-0.14	.06	-0.25	-0.03	-2.49*	^	-0.21	.07	-0.35	-0.07	-2.85**	^	-0.32	.06	-0.45	-0.19	-4.96***	# ^
Stroke length	-0.00	.00	-0.00	.00	-3.74***	# ^	-0.00	.00	-0.00	-0.00	-6.73***	# ^	-0.00	.00	-0.00	-0.00	-6.06***	# ^

Note: b: co-efficient in the linear mixed model; SE: standard error; CI: confidence interval. L: low; H: high; t: t statistics, ***: $p < .001$; **: $p < .01$; *: $p < .05$ (from the original linear mixed model); CV: results of significance from cross-validation analysis; #: significant ($p < .05$) for participant-based splitting approach; ^: significant ($p < .05$) for trial-based splitting approach; ×: not applicable for cross-validation analysis.

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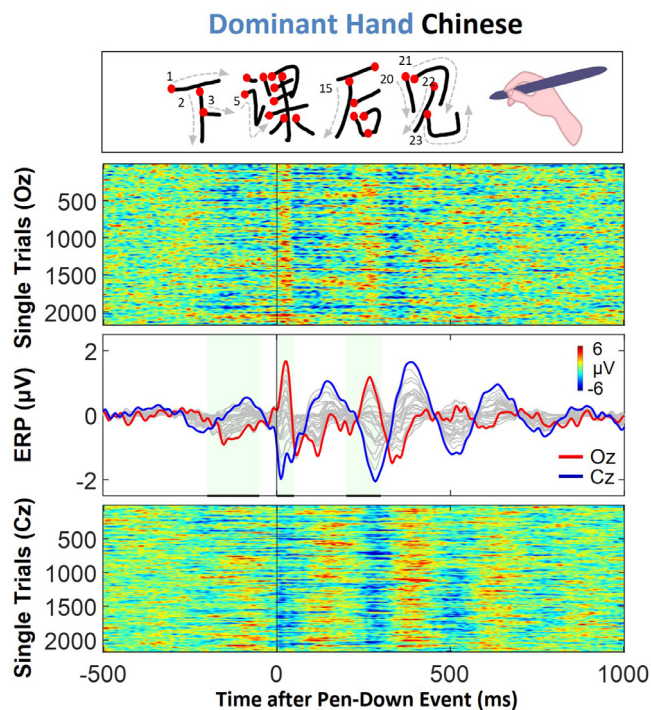


Fig. 3. Single-trial writing ERPs from one participant in a dominant hand, Chinese task (middle). The single trials are from two representative electrodes (Oz and Cz), located in the posterior (top) and centro-frontal regions (bottom). The single trials were sorted by the force of pen-down action and were smoothed by averaging every 20 successive trials.

the stroke length effect had been regressed out. Hand showed significant effects in the peri- and post-event (pen-down) time windows in the centro-frontal region, and in the post-event window in the posterior region. Language showed a significant effect in the post-event window in the centro-frontal region. Besides, we also observed the interaction effects between language and hand across the entire course in the centro-frontal region and in the post-event window in the posterior region. The difference in spatial distribution and time course between language and hand effects suggests the differential cognitive engagement between the factors of language and hand.

Due to the small number of participants, we conducted additional cross-validation analyses (see Method) to examine if the factor effects are significant when the model is trained on half of the dataset and is used to predict the held-out data. We conducted two ways of splitting the data (see Method). The statistical significance of the effects based on the cross-validation tests are reported in the column ‘CV’ in Table 2.

To examine the degree to which writing ERPs reflect different cognitive stages, we compared the neural activations generated by the initial and non-initial strokes of Chinese characters containing multiple strokes (Fig. 4). Initial strokes should entail more cognitive preparation (e.g., grapheme retrieval and motor planning), compared with subsequent strokes for the same character. As shown in Fig. 4, the ERP amplitudes were larger for initial strokes over a large portion in the time course and spatial locations. The results showed that the difference in average amplitudes in the time window of 200–300 ms between two stages was significant over the majority of the electrodes (see Supplementary Information, SI) and it displayed the strongest effect over posterior region (Oz: $t = -10.60$, $p < .001$; O1: $t = -10.69$, $p < .001$; O2: $t = -10.15$, $p < .001$). The cross-validation test also confirmed the significant effect of cognitive stage on modulating writing ERPs (see SI), and this effect was robust at single participant level (see SI). These results suggest that writing ERPs are indicative of different cognitive stages in handwriting.

3.4. Entrainment of theta oscillation to handwriting

The descriptive differences in theta power between conditions as shown in the grand average (Fig. 2E–H) may originate from three different data scenarios at single-trial level: (1) the power of the single-trial theta oscillation was larger or (2) the single-trial theta oscillation was more phase-synchronised to the pen-down event or (3) a combination of both. As different scenarios may be supported by fundamentally different neural mechanisms, we sought to further unveil the data characteristics with greater details. To this end, we first examined the writing ERPs in the theta band (3–5 Hz). As shown in Fig. 5A–D, the theta scalp topographies have a typical frontal location (Cavanagh and Frank, 2014; Kropotov, 2009), and the theta oscillation appears longer lasting for the dominant hand, echoing with the results in Fig. 2E–H.

To examine the phase synchronisation of the single-trial theta oscillation to the process of writing single strokes, we calculated the phase at 4 Hz from Fz from the single trials surrounding the pen-down events (–200 ms–800 ms). The phase distribution of theta (4 Hz) is shown in Fig. 5E–H. Statistical testing (Rayleigh’s test) showed that the distribution bias was significant for all task conditions (DC: $Z = 262.40$, $p < .001$; DE: $Z = 64.36$, $p < .001$; NDC: $Z = 14.42$, $p < .001$; NDE: $Z = 15.59$, $p < .001$). The bias of phase distribution is stronger in dominant hand conditions with a higher probability in the range of 180° to 270° (Kuiper’s test showed a significant difference between the dominant and non-dominant hands. DC vs NDC: Kuiper statistics = 6.37, $p < .001$; DE vs NDE: Kuiper statistics = 2.90, $p < .001$). Interestingly, significant difference between Chinese and English only exist in dominant hand (DC vs. DE: Kuiper statistics = 2.91, $p < .001$; NDC vs NDE: Kuiper statistics = 0.98, $p > .05$). The individual results of the statistical tests (Rayleigh’s and Kuiper’s tests) are shown in Supplementary Information.

Then, we examined the difference in the amplitude of single-trial theta oscillation across the four conditions. The average theta amplitude of each task as well as the mean and SEM across participants are shown in Fig. 5I. The t -test found no significant difference in the average amplitude between the dominant and non-dominant hands (DC vs NDC: $t(9) = 0.47$, $p = .647$; DE vs NDE: $t(9) = 1.07$, $p = .313$) or between Chinese and English (DC vs DE: $t(9) = -0.68$, $p = .512$; NDC vs NDE: $t(9) = -1.30$, $p = .226$).

We further conducted source localisation of the theta oscillation. The result shows that the neural sources of theta oscillation were distributed predominantly within BA6 (the premotor cortex and supplementary motor area), an area engaged in the planning and control of complex and coordinated movements (Nachev et al., 2008, 2007).

3.5. Encoding of handwriting kinematics in the ongoing neural signal

Finally, we characterised the cross-correlations between continuous neural activity and three handwriting kinematics streams during writing each sentence. The results illustrated in Fig. 6 reveal clear structures in the cross-correlograms, and the magnitude is substantially higher than the results from surrogate data (light green areas behind the curves). The clear temporal structures in cross-correlogram support the close association between the neural and behavioural streams. The association appears to be centred in the centro-frontal regions, just as the 4 Hz theta oscillation identified above.

4. Discussion

The aim of this work was to investigate and present the basic characteristics of dynamic neural activity associated with stroke production during handwriting as a manifestation of complex fine motor control in everyday life, and to examine their cognitive associations. Based on the EEG-handwriting co-registration system, we identified a highly reliable and structured neural activation pattern with centro-frontal distribution time-locked to single stroke production during handwriting. We termed this activation “writing ERP”. This study is the first to identify such

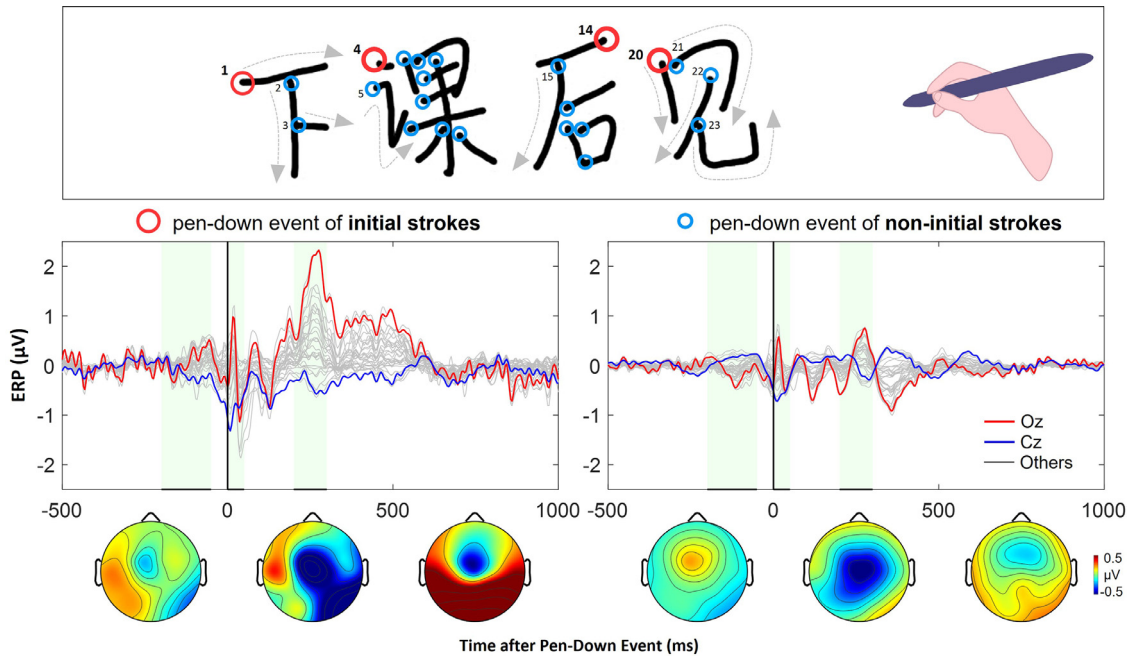


Fig. 4. Grand averaged writing event-related potentials (ERPs) generated from the pen-down events of initial and non-initial strokes of Chinese characters in a dominant hand, Chinese task, together with scalp topographies for three different time windows: -200 – -50 ms, 0 – 50 ms and 200 – 300 ms.

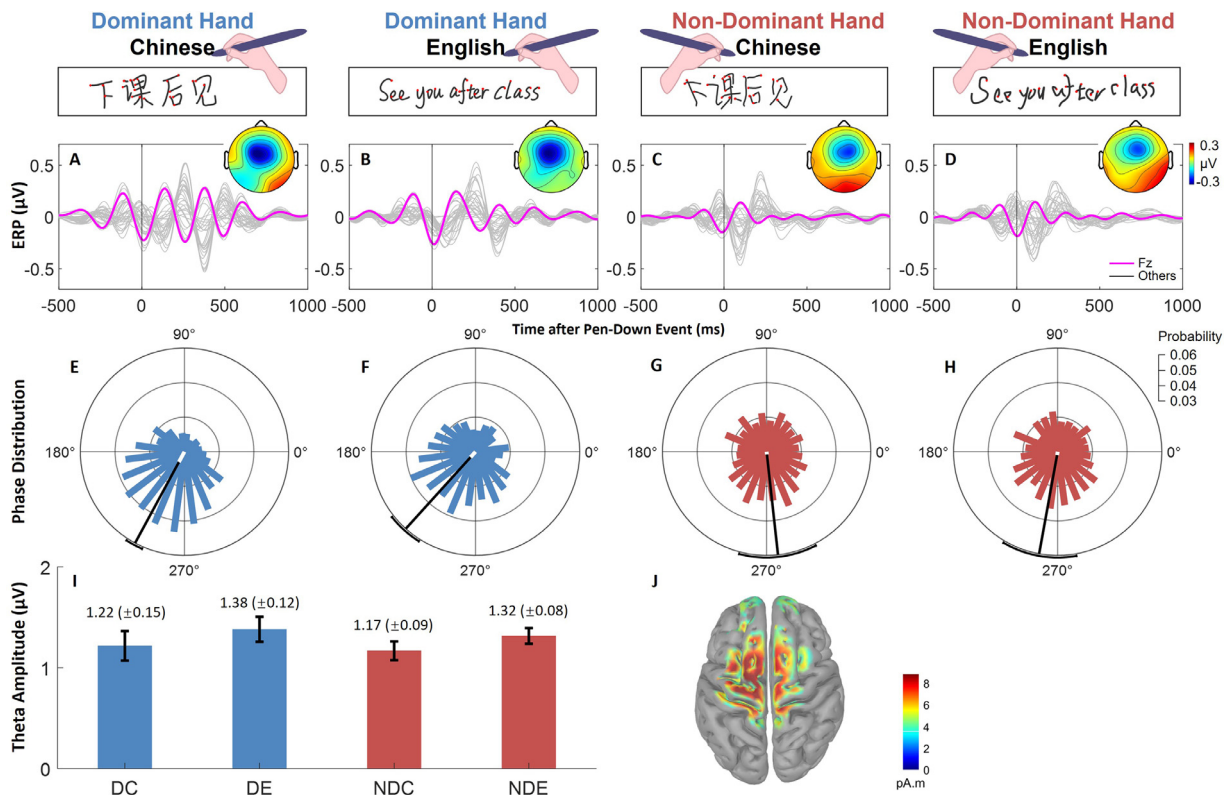


Fig. 5. Theta oscillation during the fine motor control of stroke writing. (A)–(D) Writing ERPs bandpass-filtered in the theta band during the four tasks. (E)–(H) Phase distribution of theta oscillation measured in probability. The black line denotes the average phase angle, and the black arc denotes the 95% confidence interval of average phase angle. (I) Mean and standard error of the mean for theta oscillation amplitude across the four tasks. (J) Neural source estimation of theta oscillation in writing ERPs at the pen-down time point (time zero). Note: DC, dominant hand, Chinese; DE, dominant hand, English; NDC, non-dominant hand, Chinese; NDE, non-dominant hand, English.

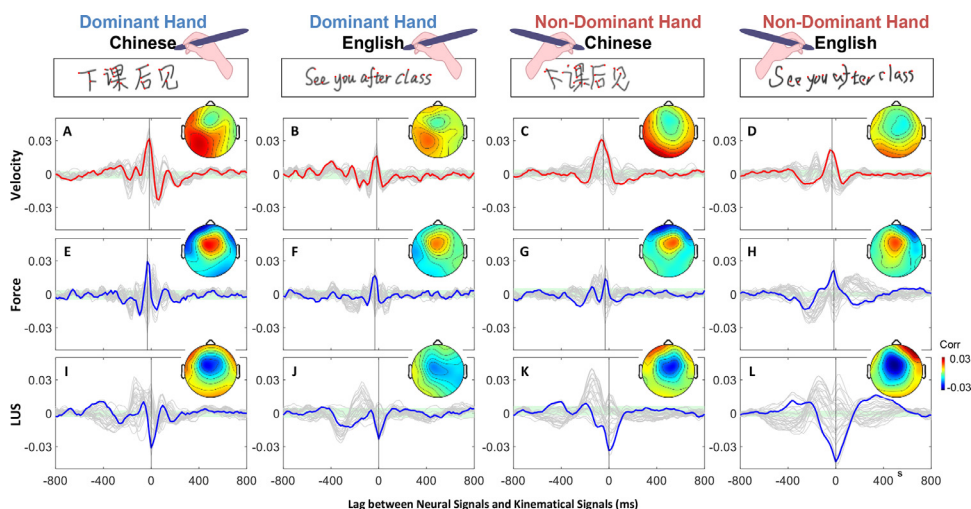


Fig. 6. Cross-correlations between continuous neural signals and three types of kinematic signal (velocity, force and length of the unfinished stroke [LUS]) during writing each sentence. Different traces represent different electrodes. Oz and Cz are shown in red and blue, respectively. The topographical patterns are spatial distribution of cross-correlation coefficients from all electrodes at the peaks or troughs closest to the zero lags. The upper and lower limits of the cross-correlation calculated from the surrogate EEG data were marked by the light green shadow behind the curves (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

a clear neural activation associated with elementary handwriting processes. The activation was shown to be associated with major cognitive factors of language and hand. In addition, we found a rhythmicity synchronisation between EEG and handwriting activity predominantly at 4 Hz. Statistically, this synchronisation effect mainly accounts for the difference in the writing ERPs generated by the four different tasks manipulated in language and hand, which implied an important role of the rhythmicity features of both brain and handwriting activity that may be linked to complex visual-motor functions and skills. Finally, a cross-correlation analysis demonstrated a close association between neural activity and handwriting kinematics, which further supported the value of this new paradigm in cognitive research studying visual-motor processes.

4.1. Basic motor action unit during handwriting and its associated neural activation

Our exploration of handwriting-associated neural activation was driven by the assumption that the handwriting process is composed of elementary, dissociable action events. The stroke has been proposed as the basic action unit during handwriting (Plamondon, 1995a, 1995b, 1998) based on behavioural modelling. However, a stroke is not always easy to define, especially in cursive handwriting (Kandel et al., 2006; Maarse and Thomassen, 1983; Teulings et al., 1983; Wing, 1978). A generalised and well-accepted definition of a stroke is 'the trajectory between successive minima of the absolute velocity' (Brooks et al., 1973; Teulings, 1996, p. 578). This kinematics-based definition allows the capture of similar neural processes across a variety of individualised handwriting styles or skills. In this study, we incorporated convenient tablet technology and defined a stroke as the trajectory between a pair of adjacent pen-down and pen-up events as recorded by the tablet (Xiaolin and Dit-Yan, 1997), namely, a planned and produced unbroken movement. Although this working definition does not strictly correspond to the kinematic definition of a stroke, it guarantees that the initial point (pen-down) is the start of a kinematic stroke and captures the relevant neural activation of planning and execution, despite that additional strokes might occur at a later stage.

As our results showed, using the initial point of a stroke to derive the neural activation associated with the basic action unit in handwriting led to our discovery of the reliable writing ERPs. This well-structured ERP may serve as the foundation for future research on handwriting-related neural dynamics. Although the writing ERP is clearly structured, its amplitude is much smaller than a typical visual or auditory ERP in which the peak amplitude can reach $10 \mu\text{V}$ (Calculus et al., 2019; Cohen et al., 2020). The reason for this may be that handwriting is a natural task

paradigm in which the discrete cognitive events are too densely distributed and overlapping with each other which may cause inter-event interfering and suppression, unlike traditional task paradigms with well-separated serial stimulus presentation. Our current paradigm provides a novel and reliable solution for identifying meaningful events by generating a large number of trials from natural behaviour, thus compensating for the low signal-to-noise ratio and providing reliable neural signals for the study of subtle neural processes such as fine motor control.

4.2. Modulation of writing ERPs by cognitive factors

If writing ERPs represent the neural processes of fine motor control activity during handwriting, it should be modulated by cognitive factors that directly affect the relevant neural processes. We identified three main factors that are highly likely to have a modulation role: language, hand and the cognitive stages of handwriting.

Chinese and English, representing logographic and alphabetic language systems, respectively, were used as two forms of written language to examine the language effect. Chinese is a meaning-based writing system constructed from complex morphemes that lack phoneme mapping, whereas English is a sound-based writing system built on graphemes with systematic grapheme-phoneme mapping rules (Cook, 2004; DeFrancis, 1989; Mattingly, 1992; Wang et al., 2005). This may affect the memory retrieval stage that interferes with the motor process. In addition, Chinese and English scripts have very different morphologies (Fig. 2). Chinese scripts comprise complex character blocks, each composed of interlaced and mostly straight strokes, whereas English scripts have lower spatial complexity and mostly cursive strokes (Kao et al., 2002). Culturally, the writing of Chinese characters requires each character block to be well-shaped and harmonious, which may impose an extra coordination process. These differences in script characteristics may lead to substantially different interference with the action unit of stroke production. In addition to the difference between writing systems, another possible factor that may contribute to the language effect in this study is the difference in cognitive demand of handwriting between using primary and secondary language as all participants included in this study were native Chinese who learned English as their second language.

The hand effect is more straightforward because it is directly associated with dexterity (Bernard et al., 2011; Hammond, 2002). Ample evidence has shown that manual dexterity depends on hand (Mathew et al., 2019). At neural levels, handwriting with non-dominant hand has been shown to trigger a larger and more bilateral neural recruitment than handwriting with dominant hand (Potgieser et al., 2015). Interestingly, handedness has also been reported to influence the language ability

construct, possibly due to brain lateralisation of language processing (Gao et al., 2015; McManus, 1999). Therefore, we think that the dexterity factor should be the major cause of the hand effect we found on the writing ERP, given that the participants barely had handwriting experience with their non-dominant hands. The substantial difference in dexterity was also clearly reflected in the handwriting outcome (see examples in Figs. 2, 5).

Finally, the cognitive stage of writing a complex character is also expected to modulate the writing ERP because more strokes have to be held in the motor buffer before writing initial strokes as compared to non-initial ones (van Galen, 1991), which has been proposed as a mechanism of parallel processing of serial movements in the brain (Averbeck et al., 2002). Based on this view, we would expect significant difference in writing ERPs between initial and non-initial strokes in a Chinese character as it usually comprises many strokes. In addition, initial and non-initial strokes have different baseline activities: one is preceded by inter-character activity and the other by inter-stroke activity. This difference in baseline neural states may also contribute to the ERP differences.

We tested the language and hand effects using a LMM that also included the low-level confounding factor of stroke length. The original LMM revealed significant effects of these two cognitive factors in the amplitude of writing ERP in the post-event time window (200–300 ms). In the time window near the pen-down event (0–50 ms), hand displayed a main effect over the centro-frontal region, suggesting a link to the motor control processes. As compared to the main effects, the interaction effects between language and hand appeared to be more widespread across space and time. However, it has to be noted that the cross-validation analysis (especially the one based on splitting participants) did not yield full consistency with the significance results generated by the original LMM analysis applied on the full dataset (Table 2). This implies a high level of cross-individual variability which rendered a low fit of the models trained from a subset of the data in explaining the held-out data. It is also a limitation of the present study that only involved ten participants. However, the interaction effect (between language and hand) robustly existed across all analyses in the post-stimulus time window (200–300 ms) in centro-frontal area. Assuming that the hand factor mainly captures dexterity in handwriting, one possible interpretation of the interaction effects is that the spatial complexity of language scripts has differential effects on neural cognitive process of handwriting between the two hands. The spatial complexity here refers to the organisation styles of Chinese and English scripts, which we assumed that the former is much complex, and such complexity may be the major factor accounting for language effect. However, there are certainly many other cognitive processes related to the two languages that may also contribute to the language effect, which requires more specific experimental design to investigate in the future.

In terms of cognitive stages, we examined Chinese characters because in Chinese handwriting, the stroke and character represent distinct hierarchical levels, given that a character comprises many strokes. As such, the neurocognitive processes associated with the initial and non-initial strokes of a character should be quite different because the initial strokes are accompanied by memory retrieval and motor planning for the entire character, whereas the non-initial strokes may be more associated with executive activities. In line with this assumption, the results showed that the initial strokes generated stronger and better-shaped ERP activation, whereas non-initial strokes generated weaker and more oscillatory activity (Fig. 4). The effect of cognitive stages on ERP was robust as revealed by the cross-validation analysis and by individual-based *t* tests.

4.3. Theta entrainment as a neural indicator of dexterity in fine motor control during handwriting?

Fine motor skills are highly complex human abilities requiring extremely precise control of effectors in coordination with sensory feed-

back. Many such skills require years of training to achieve dexterity (Gardner and Broman, 1979; Mathiowetz et al., 1986; Poole et al., 2005; Waldron and Anton, 1995). Handwriting, especially in Chinese, takes decades to develop from basic legibility to decent dexterity and finally calligraphy. The difference in dexterity between the two hands is an embodiment of this decades-long training (Andersen and Siebner, 2018; Walker and Henneberg, 2007). Undoubtedly, complex neural architecture, including neuroanatomical circuits and pathways, must be formed through prolonged training to support dexterous handwriting. Skilled behaviour usually leads to a reduced amplitude in neural activity. However, this does not appear to be true for writing ERPs, as those generated by dominant hands were greater in amplitude. This result appears to contradict the low-cost theory but echoes with an earlier work that also revealed enhanced theta power in brain activity after training in Chinese brush writing (Kao et al., 2002). This seemingly contradictory result may be explained by the theta entrainment phenomenon as we elaborate below.

Theoretically, event-locked average ERPs can be generated by two mechanisms: being evoked or being induced by the event (Woodman, 2010). In the former case, the ERP is an additional activation elicited by an event. In the latter case, the ERP is formed by the re-organisation of ongoing activity (e.g., phase resetting). The latter case appears to be a more cost-efficient mechanism because it utilises existing resources and activities. Neural entrainment is a form of reorganising ongoing neural activity by coupling it with external behaviour or stimuli (Obleser and Kayser, 2019; Will and Berg, 2007). Many neural entrainment phenomena are associated with selective attention (Clayton et al., 2015; Obleser and Kayser, 2019). Neural entrainment entails an oscillatory activity with a distinctive frequency (Obleser and Kayser, 2019). We propose that neural entrainment may occur during dexterous handwriting, based on the following rationales: (1) When high handwriting dexterity has been achieved, the handwriting process appears rhythmic, peaking at 5 Hz, with individual differences (Palmis et al., 2017; Teulings and Maarse, 1984). This type of rhythmicity may partly explain the pleasant feeling of flow during many types of fine motor control activities (e.g., typing, video game playing, music instrument playing). (2) Dexterity should lead to a more cost-efficient neural process, and the utilisation of ongoing activity is a form of cost efficiency.

From the time-frequency representation of the writing ERP (Fig. 2E–H), we did observe strongly enhanced oscillation power in the theta band in the dominant hand conditions, compared with the non-dominant hand conditions. Our statistical analysis results showed that the increased theta power in the dominant hand was mainly accounted for by phase synchronisation, which is in line with the hypothesis that theta entrainment indexes dexterity. Moreover, the phase distribution in the dominant-hand Chinese writing was significantly more biased than in the dominant-hand English writing, which is also compatible with the hypothesis, as all participants were native Chinese speakers whose handwriting experiences were intensively dominated by Chinese handwriting.

The motor association of theta in the present work coincides with one of the functional roles of hippocampal theta that has been associated with voluntary motor behaviour in animal models (Bland, 1986) and in humans (Tomassini et al., 2017). The coordination function can be seen as active top-down control. A large body of research has shown that the theta wave, measured by scalp EEG displaying a central frequency of 4 to 8 Hz with a mid-frontal scalp map, plays a crucial role in top-down cognitive control and sustaining attention and memory (Cavanagh and Frank, 2014; Clayton et al., 2015; Fiebelkorn et al., 2018; Kamiński et al., 2020; Knudsen and Wallis, 2020; Ullsperger et al., 2014). Similar to the entrainment to handwriting rhythmicity, the theta wave has been extensively shown to be entrained to human speech rhythmicity, a process that modulates attention to and increases the intelligibility of speech (Ding and Simon, 2014; Ghitzia, 2012; Kerlin et al., 2010; Riecke et al., 2018; Zion Golumbic et al., 2013; Zoefel and VanRullen, 2015). Interestingly, the writing rhythmicity in our data dis-

plays a characteristic frequency of 4 to 5 Hz, matching the typical frequency of speech across different languages (Chandrasekaran et al., 2009; Ding et al., 2017; Tilsen and Johnson, 2008). Such writing rhythmicity occurs only in highly skilled handwriting with dominant hands. Similarly, speech is undoubtedly a highly skilled motor ability that is (implicitly) subject to lifelong training and involves a complex set of articulators and laryngeal structures. Indeed, the entrainment between brain and speech is not only confined to speech perception, but also to speech production (Ruspantini et al., 2012). Ruspantini et al. showed a clear oscillatory coupling between the sensorimotor cortex and mouth muscle activity. Along the same line, many studies have reported oscillatory coherence between brain activity and continuously recorded body movements, including self-paced finger movements, handwriting, hand movements and keyboard typing at various frequencies, mostly below 10 Hz (Butz et al., 2006; Duprez et al., 2021; Gross et al., 2002; Jerbi et al., 2007; Saarinen et al., 2020). Strikingly, a study showed that the intermittent correction-related sub-movements during free motor control in monkeys was driven by intrinsic brain rhythms (Hall et al., 2014). These pieces of evidence collectively support a framework of brain and body interplay with a rhythmic core, which may be governed by the universal dynamics theory (Klimesch, 2018).

Integrating all the findings listed above, we propose a theory that rhythmicity is a manifestation of high skilfulness in fine motor control. This skilfulness exploits the intrinsic brain oscillation such that skilful behavioural rhythmicity is eventually coupled with intrinsic brain oscillatory activity. In this vein, the degree of dexterity in handwriting (or any other fine motor skill) can be indexed by the degree of phase entrainment. Our statistical results are largely in favour of this theory. The theta phase was more synchronised to stroke onset in dominant-hand writing – more so in Chinese than in English. The sustained theta could be a result of synchronised theta playing a top-down coordination and monitoring role. That said, the writing ERP is a combination of both evoked and induced (phase-reset) neural activity. This finding provides a finer-grained explanation of a previously observed theta wave enhancement during handwriting (Ose Askvik et al., 2020) and decrease of low frequency band power due to increase of motor task demand (Van Galen et al., 1990). However, finer-grained experimentation that targets at more specific processes and variables would need to be designed to firmly support the role of entrainment in motor dexterity, which we will discuss in the limitation section below.

Our finding that the entrained theta covered the centro-frontal region and was localised in the SMA and pre-SMA areas is in contrast to the abovementioned brain-body coherence studies, which observed the effects mostly in the primary motor areas. However, it coincides with the fact that the SMA and pre-SMA are constantly activated during speech production (Alario et al., 2006; Lima et al., 2016). Furthermore, based on the functional roles of the SMA and pre-SMA in the control of voluntary and complex movements (Nachev et al., 2008, 2007), we propose that theta entrainment may also be a manifestation of active motor control under its general role of top-down control, which needs to be tested in the future.

4.4. Direct association between neural signal streams and writing kinematic signals

The cross-correlation analysis is complementary to the event-based approach because certain neural activities may not be associated with discrete events but rather with an ongoing dynamic state that co-varies with external continuous variables – in the present case, the kinematic variables of handwriting. The neural association and encoding of basic kinematic features in visual information and motor processes has already been confirmed, both macroscopically and microscopically (Jerbi et al., 2007; Lauren et al., 2005). We have confirmed the moment-to-moment association between neural activity and writing kinematics with a novel finding that the association appears to occur in centro-frontal region (Fig. 6). Further investigation is needed to determine

whether this association stems from active control or simply from the neural coding of movement kinematics. This association may shed light on the development of brain-computer interfaces that aim to decode motor-related information from non-invasive measurements of brain signals.

4.5. Artefact issue

Artefact issue remains for data interpretation. As the handwriting paradigm contains a major motor component, it may be speculated that the neural activity is a manifestation of muscle artifacts (Muthukumaraswamy, 2013) generated by hand and finger movements. However, the following evidence contradicts this assumption: (1) The writing ERPs exhibited a structured pattern located in centro-frontal region, suggesting their neural origin. An artefact due to external physical sources (e.g., speech, muscle vibrations) is unlikely to exhibit a structured scalp map localised in a specific functional area. (2) Cognitive factors (e.g., language, hand, cognitive stages) significantly affected the writing ERPs even after the low-level effect (stroke length) was regressed out. If the neural activity was an artefact, we would expect only low-level features (not cognitive factors) to affect the activation pattern. (3) We conducted a specific experiment to test the pattern of the handwriting-generated artefact. In this experiment, we asked a participant to either write a sentence or remain still during 30 time slots. We then analysed the difference in the scalp maps of spectral activity between these two conditions. The results showed that the handwriting session clearly generated an artefact pattern across different frequency bands (Fig. S1, SI). This scalp pattern resembled a typical artefact feature radiating from one side of the scalp to the other, potentially due to the stretching of the cap by the muscle vibration. Most importantly, this artefact showed no resemblance to the pattern of the writing ERPs.

4.6. Limitations

The present study was mainly dedicated to presenting the temporally-resolved neural dynamics underlying the handwriting processes and its cognitive associations. Aside from this main goal, there are several issues and limitations remained to be separately addressed in future work, which we summarised here. First, the factors of language and hand are very coarse factors. Although they served to demonstrate the cognitive association of the writing ERPs, this design is not able to probe the functional signature of the handwriting-related neural activation at a finer-grained level of cognitive processes such as visual, motor, central cognition, memory, and so on. Studying of them requires more specific designs with clearly targeted and isolated cognitive factors, and with stricter control of low-level variables.

The sample size of this study is another issue that constrains the interpretability of subtle effects, one example being the amplitude difference in single-trial theta between conditions. A larger scale study would be needed to more strongly support the claim of pure phase synchronisation. Related to the small sample size issue, we conducted several additional analyses to assess the robustness of the results related to the cognitive factors (language and hand) and cognitive stage (initial versus non-initial strokes) effect. The cross-validation results confirmed a consistent interaction effect between language and hand in post-stimulus time window in centro-frontal region and a consistent effect of cognitive stage. The main effects of language and hand were significant in the original LMM analysis but were not robustly shown in cross-validation analysis. Study with larger sample size will be needed in this regard. Nevertheless, the association of handwriting ERPs with cognitive factors were confirmed, which serves as a validation of them for studying visual-motor processes and neural mechanisms therein. In addition to the cross-validation analysis, we also separately reported the results of main figures and table in this paper derived from odd and even trials of the original data in SI.

Another issue worth to note is the eye movements activities during the naturalistic handwriting process. Their engendered artifacts seemed to have been cleaned in our data as no ocular pattern can be seen from the scalp maps of writing ERPs. However, the eye movements associated with strokes will inevitably generate visual processes associated with the motor processes for writing each single stroke, which complicates the interpretation of the writing ERPs. High spatial resolution technologies such as fMRI may be resorted to for tackling this limitation.

4.7. Implications for future research

The development of a new paradigm, discovery of elementary neural activation and elaboration of the neural dynamics underlying handwriting in this work may provide a new venue for the study of fine motor control processes in the brain. We have demonstrated that through a deliberate design, subtle yet reliable neural activation can be tracked, and its functional signature can be analysed to study complex behaviours in naturalistic settings. The ability to reliably characterise the neural characteristics underlying visual-motor abilities may also benefit intervention research. Lastly, the close association between a non-invasively recorded neural stream and a handwriting movement stream suggests the potential to retrieve the handwriting content by decoding the neural signals using advanced machine learning approaches, similar to the decoding of human speech directly from neural activity (Anumanchipalli et al., 2019).

Declaration of Competing Interest

The authors declare no competing interests.

Credit authorship contribution statement

Leisi Pei: Conceptualization, Methodology, Formal analysis, Data curation, Software, Writing – original draft, Writing – review & editing, Visualization. **Marieke Longcamp:** Methodology, Writing – review & editing. **Frederick Koon-Shing Leung:** Writing – review & editing, Supervision. **Guang Ouyang:** Methodology, Formal analysis, Software, Writing – review & editing, Resources, Supervision, Funding acquisition.

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Data code statement

All the data and scripts that support the findings of this study are available from the corresponding author, G.O., upon request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.neuroimage.2021.118578](https://doi.org/10.1016/j.neuroimage.2021.118578).

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