

# Influence of Sampling Rate on Handwriting in Children with Developmental Dysgraphia

Jan Mucha<sup>\*‡</sup>, Jiri Mekyska<sup>\*†</sup>, Katarina Zvoncakova<sup>†</sup>, Adam Klocek<sup>†</sup>

<sup>\*</sup>Department of Telecommunications, Brno University of Technology, Brno, Czech Republic

Email: mucha@vut.cz

<sup>†</sup>Department of Research Methodology, Institute of Psychology, Czech Academy of Sciences, Brno, Czech Republic

<sup>‡</sup>Tecnocampus Universitat Pompeu Fabra, Mataró, Spain

**Abstract**— Digital handwriting analysis provides objective, quantitative measures of fine motor skills with growing application in the assessment of neurodevelopmental disorders. However, standardized data acquisition protocols remain underdeveloped. This study investigates the impact of sampling frequency on kinematic features of handwriting in children with Developmental Dysgraphia (DD;  $n = 155$ ) and Intact Controls (IC;  $n = 114$ ). Participants completed three graphomotor tasks and a paragraph copy task on a Wacom Cintiq 16 tablet. Original signals ( $f_s = 187$  Hz) were systematically downsampled from 170 Hz to 10 Hz. Ninety-four kinematic, dynamic, spatial, and temporal features were extracted. Mixed-design ANOVAs (sampling frequency  $\times$  diagnosis) were performed on the Normalized Root Mean Squared Error (NRMSE) between original and downsampled signals for each feature. Significant interactions between sampling frequency and diagnosis were observed for several kinematic features: overall and horizontal on-surface velocity and overall and vertical in-air velocity. These findings indicate that downsampling disproportionately affected the DD group.

**Keywords**— *developmental dysgraphia, graphomotor disabilities, sampling rate, sampling frequency, online handwriting, down-sampling*

## I. INTRODUCTION

Digital tools and technologies are increasingly transforming the assessment and analysis of psychological and neurological states. This trend is particularly evident in studies of neurodevelopmental and neurodegenerative disorders, where objective, quantifiable measures are essential for early diagnosis, monitoring disease progression, and evaluating treatment efficacy [1], [2]. Online and remote assessment methods are growing, offering the potential for broader access to care and facilitating longitudinal studies [3]. Reflecting this broader trend, our research has focused on applying digital handwriting analysis to characterize and differentiate neurological conditions, including Parkinson's disease, Dementia with Lewy Bodies, and developmental disorders such as Developmental Dysgraphia (DD) in children [4], [5].

Handwriting, a complex fine motor skill involving the coordination of cognitive, perceptual, and motor processes, is often impaired in children with neurodevelopmental conditions such as Developmental Dysgraphia (DD). This disability is a specific learning disorder characterized by impaired handwriting fluency and legibility despite adequate cognitive abilities [6]. Affected children struggle with letter formation and broader graphomotor tasks [4]. These difficulties stem from impairments in motor control, visual-motor integration, and/or orthographic coding—the ability to represent the visual form of letters and words. Children with DD exhibit less automated writing and drawing movements, requiring greater effort and control than their typically developing peers [7], [8]. The kinematic handwriting characteristics, readily captured using digital devices, can offer insights into these underlying motor inefficiencies.

Traditionally, handwriting assessment relied on qualitative observations by clinicians. However, the emergence of digital tablets and specialized software has enabled precise measurement of handwriting characteristics, including kinematic, dynamic, spatial, or in-air movement features [9]. These parameters offer objective and quantifiable indicators of handwriting performance, facilitating a more nuanced and sensitive analysis of motor control deficits. Recent advancements, such as the DiaGraMo system [10], have focused on developing online tools for objective assessment of graphomotor difficulties. This trend towards remote, digital assessment holds significant promise for improving access to care, especially for individuals in underserved areas or with limited mobility.

Despite growing interest in digital handwriting analysis and the proliferation of online assessment tools, limited research has addressed data quality in acquired handwriting signals. Specifically, the impact of a digitizing tablet's sampling frequency on the fidelity of the captured signal and the subsequent effects on derived kinematic features remain underexplored. While higher sampling frequencies capture more detailed information, they also increase data storage and computational demands. Conversely, low sampling frequencies may lead to information loss, potentially obscuring the handwriting signal's subtle but clinically relevant features. We hypothesize that inadequate sampling frequencies can introduce variability and noise into handwriting data, thus impacting the validity and reliability of diagnostic and research findings. This inconsistency hinders the ability to detect meaningful differences between groups (e.g., children with DD versus intact children (IC)) and to track changes over time. The lack of standardized guidelines for handwriting data acquisition represents a significant gap in the field, potentially limiting the comparability and reproducibility of research findings [4].

Therefore, our primary motivation in this study is to advance the discussion within the scientific community regarding establishing digital handwriting signal acquisition standards. To address this, the primary aim of this paper is to preliminarily determine the impact of sampling frequency on the quality of handwriting features and to investigate potential differences between children with DD and IC. The findings will contribute to identifying a "cut-off" sampling frequency that balances data fidelity with practical constraints, thereby promoting more robust and comparable research in digital handwriting analysis.

## II. MATERIALS AND METHODS

### A. Database

In this study, we used a dataset comprising handwriting samples from children in Czech primary schools. A total of 269 children participated, stratified into two groups: IC and children diagnosed with DD by a special education needs teacher. The IC group included 50 third-grade students (age  $9.1 \pm 0.5$  years; 34 boys, 16 girls) and 64 fourth-grade students (age  $10.2 \pm 0.5$  years; 50 boys, 14 girls). The DD group consisted of 59 third-grade students (age  $9.1 \pm 0.5$  years; 38 boys, 21 girls) and 96 fourth-grade students (age  $10.2 \pm 0.5$  years; 75 boys, 21 girls).

Data was acquired using a Wacom Cintiq 16 (DTK1660K0B) display tablet. Participants were instructed to complete four graphomotor tasks (upper loops fast, combined loops precise, lower loops precise) and one writing task (a paragraph copy task, with different versions for third and fourth graders). These tasks were chosen to elicit handwriting movements that allow for the detailed analysis of kinematic parameters, such as velocity, acceleration, and fluency, across varying levels of task complexity.

The parents of all participating children provided informed consent, and the Ethics Committee of the Institute of Psychology at the Czech Academy of Sciences approved the study. All procedures adhered to the Ethical Principles of Psychologists and Code of Conduct outlined by the American Psychological Association.

### B. Feature Extraction

The handwriting data were processed to extract a comprehensive set of kinematic, dynamic, spatial, and temporal features. Where applicable, these features were computed separately for both on-surface (pen-down) and in-air (pen-up) movements. All features were calculated using custom Python scripts, leveraging the *handwriting-sample* and *handwriting-features* packages.

The original sampling frequencies of the handwriting samples varied across participants, with a mean of 187 Hz. To investigate the impact of sampling frequency on feature quality, we systematically downsampled the original signals to target frequencies of 170, 150, 130, 110, 90, 70, 50, 30, and 10 Hz. Downsampling was performed using linear interpolation to preserve the overall shape of the signals.

We computed a range of features for each handwriting sample (both original and downsampled). Kinematic features included velocity (overall, horizontal, and vertical components), acceleration (overall, horizontal, and vertical), jerk (overall, horizontal, and vertical), and the relative number of changes in the velocity profile as a measure of movement smoothness. Dynamic features comprised pen pressure, azimuth, and tilt angles. Spatial features included stroke length, height, and width, calculated for both on-surface and in-air strokes where applicable. Temporal features encompassed stroke duration (on-surface and in-air) and the relative number of interruptions. The mean, standard deviation, and median were computed for all vector-based features, yielding scalar values for each participant, task, and sampling frequency. The relative number of changes in the velocity profile and the relative number of interruptions were calculated as single scalar values. This process resulted in 94 handwriting features for each sampling frequency.

Following an initial correlation analysis (described in the next section), we focused on quantifying the impact of downsampling on these features. To this end, we computed several metrics comparing the original features to the corresponding features at each downsampled frequency: root mean squared error (RMSE), normalized RMSE (NRMSE), and the mean and standard deviation of the absolute difference. These metrics were calculated for each feature, participant, and downsampled frequency. RMSE and absolute differences provide measures of the overall magnitude of the discrepancy between the original and downsampled signals. The NRMSE was calculated as follows:

$$\text{NRMSE} = \frac{\text{RMSE}}{\max(X_{\text{original}}) - \min(X_{\text{original}})} \quad (1)$$

where  $X_{\text{original}}$  represents the time series of the original feature, normalizes the RMSE by the range of the original signal. This normalization provides a scale-invariant measure of the error, allowing for comparisons across features with different units and magnitudes.

### C. Statistical Analysis and Machine Learning

Prior to statistical analysis, we considered grade and gender as confounding factors and removed their effects using linear regression [11]. Subsequently, we calculated Spearman's correlation (with False Discovery Rate (FDR) correction for multiple

comparisons) to explore the relationships between handwriting features, clinical group (IC/DD), and, for the paragraph copy task, handwriting quality as measured by a Handwriting Legibility Scale (HLS) [12].

To evaluate the impact of sampling frequency on handwriting features and to compare performance between the DD and IC groups, we employed a mixed-design Analysis of Variance (ANOVA). This approach was chosen because it allows for the simultaneous analysis of both within-subjects factors (sampling frequency) and between-subjects factors (diagnosis group). The dependent variable in all ANOVA models was the NRMSE.

Prior to conducting the ANOVA, the normality of the data was assessed using the Shapiro-Wilk test ( $p < 0.05$ ). Mauchly's test of sphericity was performed for each ANOVA to assess the assumption of sphericity for the within-subjects factor. For the interaction effect, the uncorrected p-value ( $p$ -unc) was used. For any feature exhibiting a significant interaction effect ( $p < 0.05$ ), post-hoc pairwise comparisons were performed with Bonferroni correction for multiple comparisons.

### III. RESULTS

Table I presents Spearman's correlation ( $\rho$ ) and FDR-corrected p-values for selected handwriting features across all sampling frequencies, correlated with either the clinical group (DD/IC) or the HLS score (for copy tasks only). For the upper loops fast task, mean pressure showed significant correlations with the clinical group at all frequencies. For the combined loops precise task, the standard deviation of on-surface tilt showed significant correlations with the clinical group at most frequencies, except 170 Hz. The mean on-surface stroke duration for the lower loops precise task showed significant negative correlations with the clinical group at all frequencies. For the third-grade copy task, mean in-air velocity correlated with the HLS close to the significant level at the original frequency, with significance maintained down to 130 Hz. For the fourth-grade copy task, the relative number of velocity changes showed a significant negative correlation with the HLS score at the original frequency, with significance maintained down to 110 Hz.

Table II presents the significant interaction effects (sampling frequency  $\times$  diagnosis IC/DD) found in the mixed-design ANOVAs. The table includes the F-statistic ( $F$ ), numerator (df1) and denominator (df2) degrees of freedom, uncorrected p-value ( $p$ -unc), partial eta-squared ( $\eta_p^2$ ), and the sampling frequencies showing significant group differences in post-hoc tests.

Five features showed significant interactions. For the lower loops precise task, a significant interaction was found for horizontal on-surface velocity ( $F_{(8,1744)} = 4.86$ ,  $p < 0.001$ ,  $\eta_p^2 = 0.022$ ). Post-hoc comparisons revealed significant differences between the DD and IC groups at 10 Hz, 30 Hz, 50 Hz, and 70 Hz. For the fourth-grade copy task, significant interactions were found for both overall on-surface velocity ( $F_{(8,112)} = 3.21$ ,  $p = 0.003$ ,  $\eta_p^2 = 0.187$ ) and horizontal on-surface velocity ( $F_{(8,112)} = 3.21$ ,  $p = 0.003$ ,  $\eta_p^2 = 0.187$ ). Post-hoc tests for on-surface velocity revealed significant group differences at 30, 50, 90, and 150 Hz, while for horizontal on-surface velocity, significant differences were found at 30, 50, 90, 110, and 150 Hz. For the upper loops fast task, significant interactions were found for both overall in-air velocity ( $F_{(8,136)} = 2.18$ ,  $p = 0.033$ ,  $\eta_p^2 = 0.114$ ) and vertical in-air velocity ( $F_{(8,136)} = 2.26$ ,  $p = 0.027$ ,  $\eta_p^2 = 0.117$ ); for both features post-hoc test showed significant group difference at 10 Hz.

TABLE I. SELECTED RESULTS PER TASK OF THE SPEARMAN'S CORRELATION ANALYSIS

| Task              | Feature                 | Scale | original |         | 170 Hz |         | 150 Hz |         | 130 Hz |         | 110 Hz |         | 90 Hz  |         | 70 Hz  |         | 50 Hz  |         | 30 Hz  |         | 10 Hz  |         |
|-------------------|-------------------------|-------|----------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|--------|---------|
|                   |                         |       | $\rho$   | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ | $\rho$ | adj $p$ |
| lp <sub>up</sub>  | press (m)               | IC/DD | 0.22     | 0.008   | 0.21   | 0.027   | 0.21   | 0.027   | 0.23   | 0.007   | 0.23   | 0.003   | 0.22   | 0.007   | 0.22   | 0.007   | 0.22   | 0.010   | 0.22   | 0.007   | 0.22   | 0.007   |
| lp <sub>com</sub> | tilt <sub>s</sub> (s)   | IC/DD | 0.23     | 0.010   | 0.19   | 0.100   | 0.22   | 0.025   | 0.22   | 0.017   | 0.22   | 0.010   | 0.23   | 0.010   | 0.23   | 0.010   | 0.23   | 0.010   | 0.23   | 0.010   | 0.23   | 0.010   |
| lp <sub>low</sub> | strk_d <sub>s</sub> (m) | IC/DD | -0.19    | 0.013   | -0.18  | 0.062   | -0.16  | 0.076   | -0.18  | 0.030   | -0.19  | 0.016   | -0.19  | 0.014   | -0.19  | 0.012   | -0.19  | 0.008   | -0.19  | 0.009   | -0.19  | 0.010   |
| cp <sub>3</sub>   | vel <sub>a</sub> (m)    | HLS   | 0.23     | 0.042   | 0.00   | 1.000   | 0.14   | 0.777   | 0.25   | 0.099   | 0.29   | 0.007   | 0.26   | 0.013   | 0.25   | 0.019   | 0.23   | 0.038   | 0.22   | 0.043   | 0.21   | 0.052   |
| cp <sub>4</sub>   | rel_num_vel             | HLS   | -0.31    | 0.001   | -0.14  | 0.988   | -0.24  | 0.533   | -0.28  | 0.009   | -0.22  | 0.019   | -0.18  | 0.073   | -0.14  | 0.186   | -0.08  | 0.509   | –      | –       | –      | –       |

\*  $\rho$  – Spearman's correlation coefficient; adj  $p$  – adjusted p-value of Spearman's correlation; IC/DD – diagnosis state; lp<sub>up</sub> – upper loops fast; lp<sub>com</sub> – combined loops fast; lp<sub>low</sub> – lower loops precise; cp<sub>3</sub> – copy task for third grade; cp<sub>4</sub> – copy task for fourth grade; press – pressure; tilt<sub>s</sub> – tilt on surface; strk\_d<sub>s</sub> – stroke duration on surface; vel<sub>a</sub> – velocity in air; rel\_num\_vel – relative numbers of changes in velocity profile; (m) – mean; (s) – std.

### IV. DISCUSSION AND CONCLUSION

Initial correlation analyses revealed generally weak, though sometimes statistically significant, associations between handwriting features and clinical group or handwriting quality. While average Spearman's  $\rho$  values were below 0.3, spatial, dynamic, and temporal features exhibited relatively high resistance to downsampling. This is attributed to their representation of more global aspects of handwriting production, which are less sensitive to the fine-grained temporal variations captured by higher frequencies.

Given the more significant impact of downsampling on kinematic features observed in the correlation analysis, subsequent ANOVA analyses focused on velocity, acceleration, and jerk. Significant interactions ( $p < 0.05$ ) between sampling frequency

TABLE II.

SUMMARY OF SIGNIFICANT INTERACTION EFFECTS FROM MIXED-DESIGN ANOVA

| Feature                        | Task                       | Source      | $F$  | df1 | df2  | $p$ -unc | $\eta_p^2$ | Significant Frequencies |
|--------------------------------|----------------------------|-------------|------|-----|------|----------|------------|-------------------------|
| velocity horizontal on surface | lower loops precise        | Interaction | 4.86 | 8   | 1744 | 0.001    | 0.022      | 10, 30, 50, 70          |
| velocity on surface            | copy task for fourth grade | Interaction | 3.21 | 8   | 112  | 0.003    | 0.187      | 30, 50, 90, 150         |
| velocity horizontal on surface | copy task for fourth grade | Interaction | 3.21 | 8   | 112  | 0.003    | 0.187      | 30, 50, 90, 110, 150    |
| velocity vertical in air       | upper loops fast           | Interaction | 2.26 | 8   | 136  | 0.027    | 0.117      | 10                      |
| velocity in air                | upper loops fast           | Interaction | 2.18 | 8   | 136  | 0.033    | 0.114      | 10                      |

\* Only features with a significant interaction effect (sampling frequency  $\times$  diagnosis,  $p \leq 0.05$ ) are included. df1 and df2 represent the numerator and denominator degrees of freedom, respectively.  $\eta_p^2$  represents partial eta-squared. Significant Frequencies shows the list of frequencies after post-hoc analysis with significant differences.

and diagnosis were found for several kinematic features: horizontal on-surface velocity ( $F_{(8,1744)} = 4.86$ ); overall and horizontal on-surface velocity ( $F_{(8,112)} = 3.21$ ); and overall and vertical in-air velocity ( $F_{(8,136)} = 2.18$  and  $F_{(8,136)} = 2.26$ , respectively). These interactions indicate a differential effect of reduced sampling frequency on these measures between children with DD and IC. The DD group exhibited significantly more significant performance degradation (measured by NRMSE) at lower sampling frequencies. For example, the mean NRMSE for horizontal on-surface velocity in the lower loops precise task increased by 10% for the DD group between 180 Hz and 30 Hz, compared to a 7% increase for the IC group. This suggests that higher-frequency information is critical for characterizing the handwriting of children with DD, likely because DD involves less automated and more variable movements [4], [13], which are obscured at lower sampling rates.

This study's limitations include its preliminary nature, the use of linear interpolation for downsampling (which differs from straightforward data point dropping), and the limited set of tasks ( $n=4$ ) and features ( $n=94$ ) examined. Future research should include classification analysis and investigate the impact of sampling frequencies in a broader range of handwriting tasks and features. Nevertheless, this work represents a step toward establishing digital handwriting data acquisition standards. The findings highlight the sensitivity of kinematic features to sampling frequency, particularly when assessing children with DD. Further research should confirm and refine these preliminary results.

#### ACKNOWLEDGMENT

This work was supported by the Czech Science Foundation, project no. GN23-06074O (Research of advanced methods of graphomotor disabilities analysis based on fractional calculus), by the project Mediated Society (MEDIS:ON) CZ.02.01.01/00/23\_025/0008713 co-financed/supported by the European Union and Czech Republic, and projects no. 25-15668S supported by the Czech Science Foundation.

#### REFERENCES

- [1] M. Choo, D. Park, M. Cho, S. Bae, J. Kim, and D. H. Han, "Exploring a multimodal approach for utilizing digital biomarkers for childhood mental health screening," *Frontiers in psychiatry*, vol. 15, p. 1348319, 2024.
- [2] H. Motahari-Nezhad, M. Fgaier, M. Mahdi Abid, M. Péntek, L. Gulácsi, and Z. Zrubka, "Digital biomarker-based studies: scoping review of systematic reviews," *JMIR mHealth and uHealth*, vol. 10, no. 10, p. e35722, 2022.
- [3] J. M. Hatcher-Martin, N. A. Busis, B. H. Cohen, R. A. Wolf, E. C. Jones, E. R. Anderson, J. V. Fritz, S. J. Shook, and R. M. Bove, "American academy of neurology telehealth position statement," *Neurology*, vol. 97, no. 7, pp. 334–339, 2021.
- [4] J. Mekyska, K. Safarova, T. Urbanek, J. Bednarova, V. Zvoncak, J. M. Havigerova *et al.*, "Graphomotor and handwriting disabilities rating scale (GHDRS): Towards complex and objective assessment," *Australian Journal of Learning Difficulties*, vol. 29, no. 1, pp. 1–34, 2024.
- [5] J. Mucha, M. Gavenciak, J. Mekyska, M. Faundez-Zanuy, L. Brabenec, and I. Rektorova, "Evaluation of fractional calculus and delta parameters in prodromal diagnosis of dementia with Lewy bodies utilizing online handwriting," in *2024 32nd European Signal Processing Conference (EUSIPCO)*, 2024, pp. 1731–1735.
- [6] P. J. Chung, D. R. Patel, and I. Nizami, "Disorder of written expression and dysgraphia: definition, diagnosis, and management," *Translational pediatrics*, vol. 9, no. Suppl 1, p. S46, 2020.
- [7] T. Gargot, T. Asselborn, H. Pellerin, I. Zammouri, S. M. Anzalone, L. Casteran, W. Johal, P. Dillenbourg, D. Cohen, and C. Jolly, "Acquisition of handwriting in children with and without dysgraphia: A computational approach," *PloS one*, vol. 15, no. 9, p. e0237575, 2020.
- [8] S.-H. Chang and N.-Y. Yu, "Handwriting movement analyses comparing first and second graders with normal or dysgraphic characteristics," *Research in developmental disabilities*, vol. 34, no. 9, pp. 2433–2441, 2013.
- [9] J. Mekyska, Z. Galaz, K. Safarova, V. Zvoncak, J. Mucha, Z. Smekal, A. Ondrackova, T. Urbanek, J. M. Havigerová, J. Bednarova *et al.*, "Computerised assessment of graphomotor difficulties in a cohort of school-aged children," in *2019 11th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*. IEEE, 2019, pp. 1–6.
- [10] "DiaGraMo: Diagnostic System for Graphomotor Difficulties," <https://shop.propsyco.cz/diagramo>, accessed: [Insert Date You Accessed the Website].
- [11] M. T. Todd, L. E. Nystrom, and J. D. Cohen, "Confounds in multivariate pattern analysis: theory and rule representation case study," *Neuroimage*, vol. 77, pp. 157–165, 2013.
- [12] E. Hamstra-Bletz, J. de Bie, and B. den Brinker, *Beknopte beoordelingsmethode voor kinderhandschriften*. Lisse: Swets & Zeitlinger, 1987, [Concise assessment method for children's handwriting].
- [13] L. Deschamps, L. Devillaine, C. Gaffet, R. Lambert, S. Aloui, J. Boutet, V. Brault, E. Labyt, and C. Jolly, "Development of a pre-diagnosis tool based on machine learning algorithms on the BHK test to improve the diagnosis of dysgraphia," *Advances in Artificial Intelligence and Machine Learning*, vol. 1, no. 2, pp. 114–135, 2021.