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# Advanced Parametrization of Graphomotor Difficulties in School-Aged Children

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**ABSTRACT** School-aged children spend 31–60 % of their time at school performing handwriting, which is a complex perceptual-motor skill composed of a coordinated combination of fine graphomotor movements. As up to 30 % of them experience graphomotor difficulties (GD), timely diagnosis of these difficulties and therapeutic intervention are of great importance. At present, an objective, computerized decision support system for the identification and assessment of GD in school-aged children is still missing. In this study, we propose three novel advanced handwriting parametrization techniques based on modulation spectra, fractional order derivatives, and tunable Q-factor wavelet transform to improve the identification of GD using online handwriting. For this purpose, we analyzed signals acquired from 7 basic graphomotor tasks performed by 53 children attending 3rd and 4th grade at several primary schools around the Czech Republic. Combining the newly proposed features with the conventionally used ones, we were able to identify GD with 84 % accuracy. In this study, we showed that using advanced parametrization of basic graphomotor movements can be potentially used to improve our capabilities of quantifying problems with the development of legible, fast-paced handwriting, and help with the early diagnosis of handwriting difficulties frequently manifested in developmental dysgraphia.

**INDEX TERMS** Advanced parametrization, computerized analysis, graphomotor difficulties, machine learning, online handwriting.

## I. INTRODUCTION

At present, every school-aged child is expected to master legible, well-coordinated and fast-paced handwriting, which is a complex perceptual-motor skill learned by instruction that quantifies a child's timely maturation and integration of psycho-motor, linguistic and mental abilities, and readiness for education [1]. It is known that it takes approximately 10 years to develop handwriting skills [2] on both quantitative (speed) and qualitative (legibility) level [3], [4]. However, before a child starts to write, she/he first needs to learn how to draw [5]. In general, until the age of 6, a child starts to develop a combination of motor and non-motor skills such as motor planning and execution, visual–perceptual abilities, orthographic coding, kinesthetic feedback, and visual–motor coordination, which eventually become automated at the age of 8–9 [6], [7]. These skills are referred to as graphomotor skills (GS) [8], [9], and form the foundation of drawing and consequently, handwriting abilities [2] that accompany every person throughout the life-time.

Even though modern technologies brought new ways of communication, self-expression, and education, handwriting is still an important part of a child's life [9]. In general, it has been estimated that children spend 31–60 % of their school-time performing handwriting [10]. Given that children at school need to write under time constraints, the acquisition of GS is crucial for a child's ability to write legibly, as well as quickly and efficiently. Basically,

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the development of GS affects a child's academic success and professional career [11]. It has also been shown that approximately 10–30 % of children experience graphomotor difficulties (GD) [8], [9] such as motor-memory dysfunction (problems combining memory input with motor output), graphomotor production deficits (poor muscle coordination, unusual pen-grip and less precise graphomotor movements), motor feedback difficulties (over-activation of certain muscles and joints during handwriting as well as problems tracking the location of the pen's tip), etc. Such an impairment of the neuro-muscular system can have serious pedagogical and psychological consequences, and can greatly affect a child's every-day life [12] starting with slow and less-legible handwriting, lack of motivation to write, lower self-esteem combined with poor emotional well-being, bad attitude and behaviour, communication and social interaction problems, and in some cases going as far as being diagnosed with a serious neurodevelopmental disorder such as developmental dysgraphia (DD) [9], [13]–[15]. To provide children with both preventive as well as corrective therapeutic care, GD should be identified and treated as soon as possible [16], [17].

To identify and evaluate GD and handwriting difficulties (HD) in general, occupational therapists and/or special educational counsellors use specialized questionnaires or tests that aim at quantification of the quality of the handwritten product in multiple domains using its visual inspection. Some of the most commonly used questionnaires (rating scales) are the following: Concise Assessment Scale for Children's Handwriting (Brave Handwriting Kinder) (BHK) [18], Handwriting Proficiency Screening Questionnaire (HPSQ) [19] or Handwriting Proficiency Screening Questionnaire for Children (HPSQ–C) [20]. Even though these scales are a well-established way of identification and rating of GD and HD in school-aged children, its administration and coding are time-consuming, which limits the use of this type of evaluation on a regular day-to-day basis. Moreover, it is naturally limited by the perceptual capabilities, subjective judgement and experience of an examiner [21]. Finally, it is also a subject to inter-rater variability [22]. Due to the complexity and limitations associated with GD/HD identification, many children, especially those attending lower grades of a primary school, may remain undiagnosed or may be diagnosed later than appropriate.

To overcome the limitations of the perceptual analysis and search for a more robust view of various hidden complexities of the handwriting process, new methods based on digitization and signal processing techniques have been developed [23]–[28]. More specifically, instead of a conventional data acquisition using a pen and paper, digitizing tablets (digitizers) have been used to record a variety of signals describing the evolution of handwriting in time. Such a collection of data about handwriting (i. e. that one associated with timestamps) is referred to as online handwriting [29]. Using advanced digital signal processing algorithms a variety of handwriting parameters (commonly referred to as handwriting features) quantifying kinematic (velocity, acceleration, jerk) as well as dynamic (pen pressure, tilt and azimuth) components contributing to the execution of the handwriting process have been designed [6], [30]–[32]. Such characteristics are very hard to be perceived and precisely quantified by a human observer and are almost impossible to be extracted using only the final handwritten product.

In recent years, several studies focusing on computerized analysis, identification and assessment of HD, mostly associated with writing in children with developmental dysgraphia, have been conducted. In 2017, Pagliarini *et al.* [27] reported that the governing principles of rhythmic organization, namely homothety and isochrony, describe the handwriting process in school-aged children from the time where the very first handwritten products are made, i. e. before the handwriting is performed automatically. Moreover, they pointed out the potential of quantitative analysis to indicate the development of HD at a very early age. In the same year, Mekyska *et al.* [32] performed a study in a cohort of 27 school-aged children in which they introduced a new intra-writer normalisation method aiming at improving the discrimination capabilities of a large variety of conventional and non-conventional handwriting features. They also built a random forest classifier identifying the presence of DD with 96 % sensitivity and specificity. Next, Rosenblum and Dror [26] employed a study focusing on automatic identification and characterization of DD in a cohort of 99 third-grade children. Using various kinematic and dynamic features, they trained a linear support vector machines classifier achieving 90 % sensitivity and specificity. In 2018, Asselborn *et al.* [28] developed a diagnostic tool for DD evaluated on a cohort of 298 children (56 children with DD) performing the BHK test on a digitizing tablet covered with a sheet of paper. To identify the presence of DD, they computed 53 handwriting features and built a random forest classifier with 96 % sensitivity and 99 % specificity. In 2019, Mekyska *et al.* [33] employed a study that is the closest one to a study proposed in this work. They aimed at exploring the impact of specific elementary graphomotor tasks on the accuracy of computerized diagnosis of GD. For this purpose, they analysed 7 basic graphomotor elements performed by a cohort of 76 school-aged children. Using only conventional handwriting features, they trained an XGBoost [34] classifier and achieved 50 % sensitivity and 90 % specificity. In the same year, Zvoncak *et al.* [35] used features based on fractional order derivatives to enrich a set of conventional features and analysed their correlation with HPSQ–C in 55 children (19 third-grade children, and 36 fourth-grade children) performing an alphabet writing task. With this setup, they reported that features based on fractional order derivatives improved quantification and robustness of the description of in-air movements. And finally, in 2020 Asselborn *et al.* [36] proposed a data driven strategy for estimating handwriting quality in a battery of 448 school-aged children (390 typically developing children and 58 children with HD). They utilized principal component analysis to reduce 53 handwriting features also used in [28] to three dimensions that are independent of the BHK scores.

Next, they used the reduced feature space to cluster children into two groups (typical handwriting, HD), and evaluated how far a child's score is from the average score of children of the same age and gender. With this approach, they reported four specific handwriting scores for kinematics, pressure, pen tilt and static features to describe the handwriting profile of a child in a finer way that enables measuring the quality of handwriting in multiple domains.

Although there is a body of research dealing with computerized quantitative analysis of HD in school-aged children, several key points have not been fully investigated yet. First of all, most of the studies aimed at identifying HD and/or DD. Studies focusing on quantification and identification of GD are very sparse. This is an important topic as HD can have many forms and can vary even among typically developing children. As mentioned in one of the most recent publications dealing with computerized analysis of handwriting in school-aged children proposed by Asselborn *et al.* [36], dysgraphia is an umbrella term that describes a variety of handwriting difficulties. Therefore, GD play a crucial role in determining the handwriting profile of a child, and should be investigated as well. Moreover, most of the studies focused on writing signals such as writing words, sentences, etc., only. Finally, conventional handwriting features have been used to describe HD almost exclusively. To the best of our knowledge, a comprehensive study aiming at quantifying GD manifested during performing a battery of simple but important graphomotor elements (loops, spirals, etc.) using not only conventional but also more advanced graphomotor features is missing. For this purpose, in this study, we propose the use of seven graphomotor tasks and three novel types of handwriting features based on: a) modulation spectra; b) fractional order derivatives; and c) tunable Q-factor wavelet transform. We hypothesize that these features can bring more information about specific GD accompanying the handwriting process of children with GD in its very basis. In addition, we also hypothesize that a combination of conventional and more advanced parametrization of online handwriting can improve identification of GD and contribute to a development of a decision support system that can be used for diagnosis of HD and eventually DD.

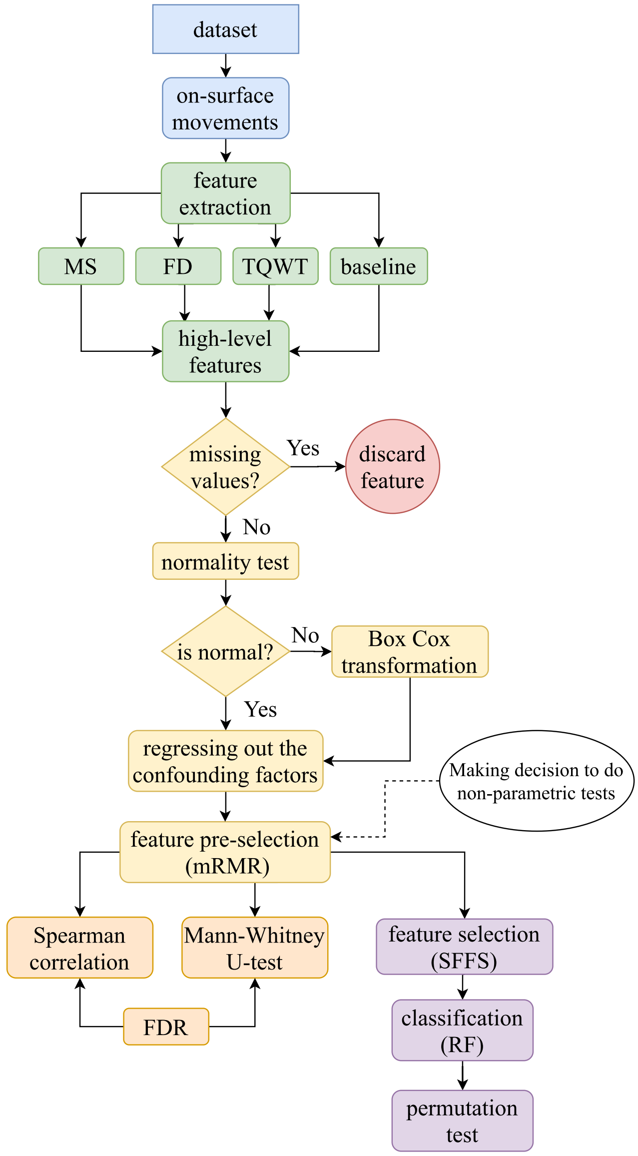


**FIGURE 1.** An overview of the methodology applied in the study.

## II. MATERIALS AND METHODS

The methodology can be briefly summarized as follows: a) dataset description (cohort, acquisition protocol, data acquisition, etc.), b) presentation of the feature extraction methods (conventional, newly-proposed features), and c) statistical analysis and machine learning (normality testing and feature pre-processing, feature selection, correlation analysis, hypothesis testing, and binary classification). Finally, an overview of the methodology can also be seen in Fig. 1.

### A. DATASET

Altogether, we enrolled 53 Czech-speaking children (22 girls and 31 boys) attending 3rd and 4th grade at several primary schools in the Czech Republic: 26 healthy children (HC) (2 3rd-grade girls, 12 4th-grade girls, and 12 4th-grade boys) and 27 children with GD (1 3rd-grade girl, 5 3rd-grade boys, 7 4th-grade girls, and 14 4th-grade boys). Description of the dataset can be seen in Table 1. During the data acquisition, all of the children were asked to perform a specifically designed drawing protocol consisting of 7 elementary graphomotor tasks (TSK) (for more information, see Fig. 2): TSK1 – Archimedean spiral (approximately 15 cm in height); TSK2 – half-sized version of TSK1; TSK3 – connected loops; TSK4 – flipped version of TSK3; TSK5 – sawtooth; TSK6 – rainbow; TSK7 – combination of TSK3 and TSK4. Each of the tasks was first shown to a child and then she/he replicated it on a blank sheet of paper with a comfortable speed. The protocol was designed in cooperation with psychologists and special educational counsellors so that it reflects all coordinated elementary movements that are

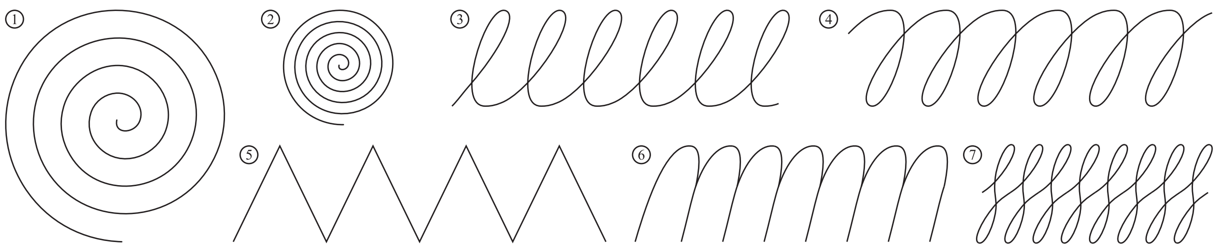


**FIGURE 2.** Drawing acquisition protocol with the selected graphomotor tasks.

**TABLE 1.** Description of the dataset.

| | $\mu$ ($\sigma$) | min. | Q1 | Q2 | Q3 | max. |
|---|---|---|---|---|---|---|
| all children (53 subjects) | | | | | | |
| age [y] | 10.92 (1.65) | 8.46 | 10.73 | 11.33 | 11.67 | 12.32 |
| class | 3.84 (0.36) | 3.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| HPSQ–C | 13.66 (6.31) | 4.00 | 9.00 | 12.00 | 19.00 | 27.00 |
| HC (26 subjects) | | | | | | |
| age [y] | 11.23 (0.62) | 9.77 | 10.99 | 11.43 | 11.66 | 12.32 |
| class | 3.92 (0.27) | 3.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| HPSQ–C | 12.50 (6.21) | 4.00 | 9.00 | 10.50 | 14.00 | 27.00 |
| GD (27 subjects) | | | | | | |
| age [y] | 10.57 (2.19) | 8.46 | 10.52 | 10.95 | 11.66 | 12.27 |
| class | 3.77 (0.42) | 3.00 | 4.00 | 4.00 | 4.00 | 4.00 |
| HPSQ–C | 14.44 (6.30) | 6.00 | 10.00 | 13.00 | 19.50 | 25.00 |

[1] $\mu$ – mean estimate; $\sigma$ – standard deviation estimate; HPSQ–C – Handwriting Proficiency Screening Questionnaire for Children [20] (only total score showing an overall degree of GD is shown); Qx – x-th quartile; y – years.

needed to successfully write cursive letters (i. e. cursive letters are constructed of these basic graphomotor elements, therefore, mastering these elements is a prerequisite for mastering legible handwriting). Examples of the final handwritten product for all graphomotor tasks performed by healthy children and children with GD can be seen in Fig. 3.

The protocol was printed on an A4 paper that was laid down and fixed to a digitising tablet. To acquire the handwriting data, we used Wacom Intuos Pro L (PHT-80) with the sampling frequency of 150 Hz, and the Wacom Inking pen. This set-up enabled us to take advantage of two facts: a) it provided the children as well as an examiner with immediate visual feedback and made it possible to simulate the feeling of using a conventional inking pen; and b) it allowed for recording of a variety of signals describing the drawing process: x and y position ($x[n]$ and $y[n]$); timestamp ($t[n]$); a binary variable ($b[n]$; 0 – in-air movement, i. e. movement of pen tip up to 1.5 cm above the tablet's surface, and 1 – on-surface movement, i. e. movement of pen tip on the paper), pressure exert on the tablet's surface during drawing/writing ($p[n]$); pen tilt ($a[n]$); and azimuth ($az[n]$). For more information, we refer to our previous works [32], [37].

Moreover, to assess legibility and performance time during handwriting as well as physical and emotional well-being, the children were asked to evaluate themselves using HPSQ–C (rating scale) [20], which is composed of 10 questions scored on a 5-point Likert scale (0 – never, i. e. no GD, 4 – always, i. e severe GD; total score, i. e. sum over all questions: 0 – min. value, 40 – max. value; legibility – items 1, 2, and 10, performance time – items 3, 4 and 9, and physical and emotional well-being – items 5–8). Using HPSQ–C brings two important advantages: a) the scale is language independent and therefore well-comparable across studies employed on cohorts coming from different language groups; b) it has already been validated in a couple of previous studies such as [8], [32], [38], [39]. The overall HPSQ–C scores, as well as the final handwritten product, were both examined by experienced psychologists and special educational counsellors. The decision about a child's assignment into HC or GD group was performed on a PC after the examination of a child's handwritten product, where an expert (remedial teacher) had no information about her/his sociodemographic information (e. g. sex, class, HPSQ–C, etc.). The description of HC/GD groups mentioned at the beginning of Section II presents the numbers after the final examination and assignment.

Parents of all children participating in this study signed an informed consent form approved by the Ethical Committee of the Masaryk University. Throughout the entire duration of this study, we strictly followed the Ethical Principles of Psychologists and Code of Conduct released by the American Psychological Association (https://www.apa.org/ethics/code/).

### B. FEATURE EXTRACTION

To quantify GD, we extracted the following conventionally used graphomotor features (CONV) [25], [30], [40]: a) spatial features – width (WIDTH), height (HEIGHT), and length (LEN) of the signals (also referred to as writing). Even though the in-air movements can be used to capture a certain aspect of GD [25], [40], all graphomotor tasks proposed in this work should be performed using a single stroke. Since the number of multi-stroke signals analyzed in this study was only marginal, we did not distinguish between signals and strokes and used the stroke notation, i. e. stroke width (SWIDTH), height (SHEIGHT), and length (SLEN), as it is used in general; b) kinematic features (horizontal and vertical projection) – velocity (VEL), acceleration (ACC), and jerk (JERK); and c) dynamic features – pressure (PRESS), tilt (TILT), and azimuth (AZIM). These features were used as a baseline feature set. To build on top of these conventional features and to enhance their capability of describing GD in a more robust and complex way, we present three new feature-types aiming at improving the quantification and description of GD in school-aged children, namely:

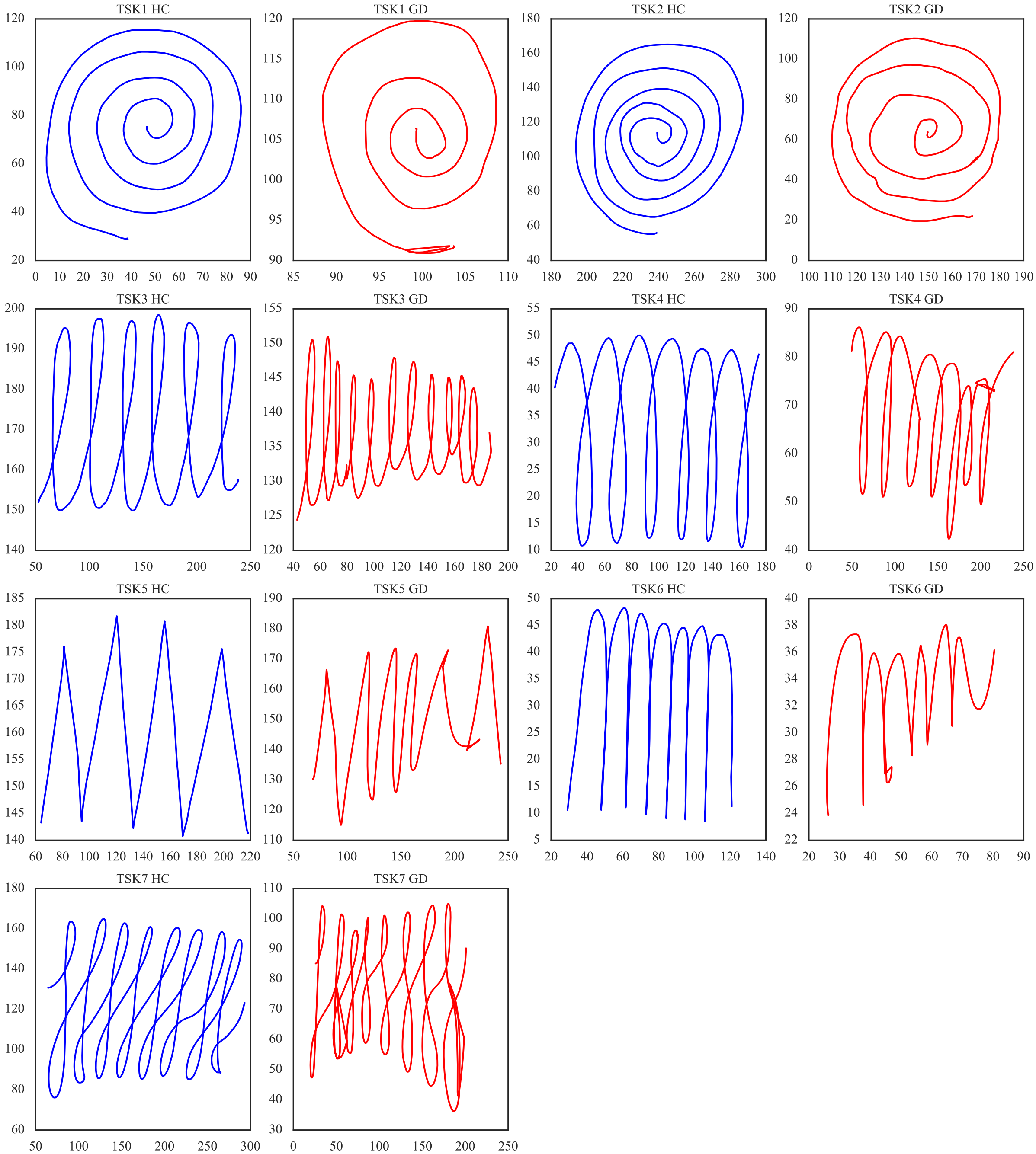


**FIGURE 3. Example of the final handwritten product for all graphomotor tasks performed by randomly selected healthy children (blue) and children with GD (red) (units are in millimeters).**

a) features based on modulation spectra (MS); b) features based on fractional order derivatives (FD); and c) features based on tunable Q-factor wavelet transform (TQWT). All vector-valued features were transformed to scalar values using mean and coefficient of variation (cv) estimates (some of the novel features used additional statistical functions that are described along with the features themselves).

An important fact to point out is that these features were designed not only to improve the robustness of the conventional features but also to maintain as much interpretability as possible. This is crucial especially for their real use in clinical practice because the complexity and great discrimination power without understanding the meaning of the features are not likely to bring trust and convenience. If psychologists and special educational counsellors are able to link the features with the specific physiological phenomena, the computerized quantitative analysis of GD can be finally deployed.

To present the features in a compact and easy to read way, we used the following naming convention: *TSK INF: DIR-FN (HL)*, where *TSK* denotes the specific graphomotor task, *INF* represent information about the movement (ON – on-surface, AIR – in-air), PRESS – pressure, TILT – tilt, and AZIM – azimuth), *DIR* stands for direction (H – horizontal and V – vertical), *FN* shows the feature name, and *HL* holds an applied statistic (if any). Moreover, each specific novel feature-type also sets *FN* accordingly (described in the section devoted to the proposed features). As all features presented in this work are computed from on-surface movements, the on-surface/in-air information is considered redundant and is not shown in the feature names.

#### 1) MODULATION SPECTRA FEATURES

The first type of the novel features proposed in this work is based on modulation spectra as a non-parametric method for representing modulations in an analyzed biomedical signal. MS has already been used for parametrization of dysarthric speech in patients with Parkinson's disease (PD) [41]. These features however aimed at describing instability of vocal folds vibrations. The features proposed in this work aim at quantifying the ratio between the low and high-frequency movements present in a given handwriting signal of children attending a primary school.

To compute the modulation spectra features, Short-Time Fourier Transform (STFT) of the input handwriting signal $s[n]$ of length $N$ is computed as

$$S[k,m] = \sum_{n=0}^{N-1} s[n]w[n-mL]\mathrm{e}^{-\mathrm{j}k\frac{2\pi}{N}n}, \quad k = 0,1,\ldots,N-1, \quad m = 0,1,\ldots,M-1, \tag{1}$$

where $M$ denotes the number of segments obtained using a segmentation window $w[n]$ composed of $L$ samples. In the frame of this work, we used Hamming segmentation windows with $L = 75$ samples ($f_s = 150$ Hz, windows of 0.5 s with the overlap of 50 %).

Next, power spectrum $|S[k,m]|^2$ of each segment is computed and filtered by a filer-bank $P$ consisted of $P_n$ filters. For this purpose, we used a filter bank of 50 linearly distributed triangular filters. After the filtration, the matrix $X[p,m]$ contains $P_n$ sub-bands $p = 1,2,\ldots,P_n$. Subsequently, each sub-band is normalized [42] as follows

$$\hat{X}[p,m] = \ln\left(X[p,m]\right) - \overline{\ln\left(X[p,m]\right)}, \tag{2}$$

where $\overline{*}$ refers to the averaging operator applied over $m$.

To obtain a modulation spectra matrix, Discrete Fourier Transform (DFT) is applied on $\hat{X}[p,m]$.

$$\Psi[p,l] = \sum_{m=0}^{M-1} \hat{X}[p,m]\mathrm{e}^{-\mathrm{j}l\frac{2\pi}{M}m}, \quad l = 0,1,\ldots,M-1, \tag{3}$$

where $p$ and $l$ denote the handwriting and modulation frequency, respectively. Finally, $\Psi[p,l]$ is normalized by the mean of each sub-band.

After obtaining the modulation spectra matrix, a vector of handwriting cut-off frequencies $f_c = 1,2,\ldots,C$ [Hz] is defined. The values of $f_c$ are subsequently converted to the filter indices $c$ using their center frequencies. In this work, we used $f_c \in F_c$, where $F_c = 1,2,\ldots,10,15,20,25$ Hz. Next, for each value of $f_c$, low ($E_l$) and high frequency ($E_h$) summation components of $\Psi[p,l]$ are computed as

$$E_{l(f_c)}[l] = \sum_{p=0}^{c} \Psi[p,l],$$

$$E_{h(f_c)}[l] = \sum_{p=c}^{P_n} \Psi[p,l], \quad l = 0,1,\ldots,M-1, \tag{4}$$

$$fc = F_c. \tag{5}$$

Finally, $E_{l(f_c)}$ and $E_{h(f_c)}$ are used to compute the final energy ratio $R_{f_c}$ between the low and high frequency movements in the analyzed handwriting signal. It is defined as

$$R_{f_c} = \frac{\sum_{l=0}^{M-1} E_l[l]^2}{\sum_{l=0}^{M-1} E_h[l]^2}. \tag{6}$$

We used the following naming convention for the MS features: $F\mathrm{R}f_c$, where $F$ represents the name of the handwriting feature, R stands for ratio, and $f_c$ holds the value of the specific handwriting cut-off frequency used to compute the energy ratio.

#### 2) FRACTIONAL ORDER DERIVATIVE FEATURES

The second type of the novel features is based on the theory of fractional order derivatives. Handwriting features based on FD have already been explored in our previous studies focusing on the quantitative analysis of parkinsonian dysgraphia [43]–[46], where they brought a promising improvement in the power of the FD-based features to objectively discriminate between healthy and dysgraphic handwriting using machine learning. In this work, we aim at exploring the possibilities of utilizing FD to describe GD in school-aged children.

The most common approaches to compute FD are Riemann–Liouville, Caputo, and Grünwald–Letnikov formulations [47]–[49]. Parameterization of online handwriting using FD is performed by substituting the conventional differential derivative during the calculation of the basic kinematic features (velocity, acceleration, and jerk). The advantage of FDs lies in their wide range of settings (order $\alpha$, kernel function, etc.). In this study, we followed the Grünwald–Letnikov approximation [48], [50] and used the implementation of FD by Jonathan Hadida. To decrease the computational requirements, we used a segmentation-based computation.

A direct definition of the $D^\alpha y(t)$ is based on the finite differences of an equidistant grid in $[0,\tau]$, assuming that the function $y(\tau)$ satisfies certain smoothness conditions in every finite interval $(0, t)$, $t \leq T$. Choosing the grid [48]

$$0 = \tau_0 < \tau_1 < \ldots < \tau_{n+1} = t = (n+1)h \tag{7}$$

with

$$\tau_{k+1} - \tau_k = h \tag{8}$$

and using the notation of finite differences

$$\frac{1}{h^\alpha}\Delta_h^\alpha y(t) = \frac{1}{h^\alpha}\left(y(\tau_{n+1}) - \sum_{v=1}^{n+1} c_v^\alpha y(\tau_{n+1-v})\right), \tag{9}$$

where

$$c_v^\alpha = (-1)^{v-1}\binom{\alpha}{v}. \tag{10}$$

The Grünwald–Letnikov definition from 1867 is defined as

$$D^\alpha y(t) = \lim_{h\to 0}\frac{1}{h^\alpha}\Delta_h^\alpha y(t), \tag{11}$$

where $D^\alpha y(t)$ denotes a derivative with order $\alpha$ of a function $y(t)$, and $h$ represents a sampling lattice. Following our previous works focused on optimization of $\alpha$ [43], [46], we used the ranges: from 0.1 to 0.4, and from 0.65 to 0.9, with iteration step of 0.05.

The naming convention for FD-based features can be described as: $F\alpha$, where $F$ represents the name of the handwriting feature and $\alpha$ stands for the order of FD.

#### 3) TUNABLE Q-FACTOR WAVELET TRANSFORM FEATURES

The last type of the novel features is based on tunable Q-factor wavelet transform [51]–[53]. Recently, we have shown that HD manifest themselves in higher energies of the residual component of the decomposed signal computed by TQWT [39]. Following our previous research, we aim at investigating the potential of TQWT to describe limited motor skills, poor dexterity and muscle tone or unspecified motor clumsiness in school-aged children suffering from GD.

TQWT is a non-linear discrete-time resonance-based signal decomposition technique that separates an input signal into high-resonance (sustained rhythmic oscillations), low-resonance (non-rhythmic and transient behaviour) and residual components (stochastic nature of the decomposed signal) [51]. It is parameterized by a tunable Q-factor and an oversampling rate (redundancy). In this study, we utilized the implementation of TQWT based on morphological component analysis (MCA) [54] and split augmented Lagrangian shrinkage algorithm (SALSA) [55] described in [52].

To decompose an input signal into high and low resonance components, an iterative $J$-level decomposition of its low-pass channel by a two-channel filter-bank composed of low- and high-pass filters is used [52]. The frequency responses of the low-pass $H_l(\omega)$ and the high-pass $H_h(\omega)$ filters are defined as

$$H_l(\omega) = \theta\frac{\omega + (\beta - 1)\pi}{\alpha + \beta - 1}, \tag{12}$$

$$H_h(\omega) = \theta\frac{\alpha\pi - \omega}{\alpha + \beta - 1}, \tag{13}$$

for $(1-\beta)\pi < \omega < \alpha\pi$, where $\alpha$ and $\beta$ are the low- and high-pass scaling parameters, and $\theta$ is the Daubechies frequency response [52] given as

$$\theta(\omega) = 0.5(1 + \cos\omega)\sqrt{2 - \cos\omega}, \tag{14}$$

for $|\,\omega\,| \leq \alpha$. More details can be found in [51], [52].

To describe the proposed features, we define the clean graphomotor signal $x_c[n]$ as

$$x_c[n] = x[n] - x_r[n], \tag{15}$$

where $x[n]$ is a handwriting signal, and $x_r[n]$ is a residual signal given as $x_r[n] = x[n] - x_h[n] - x_l[n]$ ($x_h[n]$ and $x_l[n]$ are the high- and low-resonance components).

With $x_c[n]$ and $x_r[n]$ being defined, the signal-to-noise ratio is computed as

$$SNR = 10\log_{10}\left(\frac{E(x_c[n])}{E(x_r[n])}\right)[\text{dB}], \tag{16}$$

where $E$ denotes energy computed as

$$E(s[n]) = \sum_{n=0}^{N-1} s[n]^2, \tag{17}$$

for $s$ being a substitution for $x_c[n]$ and $x_r[n]$.

Next, absolute value of the first order derivative of $E(x_r[n])$ is computed as $E_d(x_r[n]) = |E'(x_r[n])|$. To quantify the variability of $E_d(x_r[n])$, a slope of its cumulative sum is computed as

$$E_\Delta = \Delta C(E_d), \tag{18}$$

where $C(E_d)[n]$ for $n = 0, 1, \ldots, N-1$ refers to the cumulative sum applied on $E_d$, and $\Delta$ denotes the slope of a function. Finally, to compute the number of significant changes in $E_d(x_r[n])$, the number of its peaks $E_p$ above the median value is computed.

Naming convention for TQWT-based features can be described as: $FN$, where $F$ represents the name of the handwriting feature and $N$ stands for the specific TQWT feature: signal-to-noise ratio (SNR), $E_\Delta$ as RES (csum), and $E_p$ as RES (npeaks).

### C. STATISTICAL ANALYSIS

At first, the features with any missing values were discarded from the analysis. Consequently, normality of the features was tested using Shapiro-Wilk test [56]. All non-normally distributed features were adjusted using Box-Cox [57] transformation. After the normalization, the features were re-inspected. As not all of the features were fully-normalized, an entire feature set was considered as being non-normally distributed. As a result, only non-parametric statistical methods were employed during the subsequent statistical analysis. Next, to control for the effect of confounding factors (also known as covariates), we computed the Spearman's correlation between the values of the features and the following characteristics: age, gender, grade (these characteristics were chosen after the consultation with psychologists and special educational counsellors). With this approach, age and grade were identified as having a statistically significant effect on the feature values. The effect of children's gender on the features was only marginal. Therefore, during the statistical analysis, we controlled for the effect of age and grade only. After the feature-transformation, we reduced the size of the feature set using a feature pre-selection process independently for each analyzed feature-type. More specifically, we used a filter method named minimum Redundancy Maximum Relevance (mRMR) to select a relevant sub-set of the features with minimum redundancy and cross-correlation among the features. After the feature pre-selection, we obtained 15 features per feature-type. Having the same number of the features for each features-type is important especially for the classification analysis, where each classifier is built starting with the same feature-space complexity.

Next, to compare the distribution of the graphomotor features for healthy children and children with GD, we used Mann-Whitney U-test with the significance level of 0.05. Moreover, to assess the strength of a relationship between the features and the children's clinical status (HC/GD), we computed Spearman's correlation coefficient with the significance level of 0.05. To control for the issue of multiple comparisons, p-values were adjusted using the False Discovery Rate (FDR) method.

Subsequently, to identify the presence of GD, we built binary classification models using an ensemble learning algorithm named Random Forests (RF) [58]. This particular algorithm was chosen due to its robustness to outliers, ability to find complex interactions among features as well as the possibility of ranking their importance. Using a randomized search strategy, we selected the following model settings: number of estimators (500), maximum tree depth (10), minimum number of samples required for splitting (2), minimum number of samples at a leaf node (1). Additionally, to train the models using only a parsimonious, information-rich subset of the features, to considerably decrease the risk of overfitting, and to reduce the computational performance requirements, we employed a feature selection process using a wrapper method named Sequential Floating Forward Selection (SFFS). As shown previously, reduction of the feature space complexity can significantly improve the model's prediction power [59].

i To quantify the classification performance of the trained models as well as to control the addition and removal of the features during the feature selection, we used Matthew's correlation coefficient (MCC) [60]. This particular metric was chosen due to its ability to summarize the confusion matrix with the focus on obtaining a balance between the model's sensitivity and specificity [61]. The training and testing features were standardized before classification on a per-feature basis to have 0 mean and a standard deviation of 1. The trained models were evaluated conducting a stratified 5-fold cross-validation (we chose the 5-fold cross-validation scheme as a reasonable compromise between the number of samples in the training and validation folds) with 20 repetitions, and the classification test performance was determined using the following classification metrics: MCC, accuracy (ACC), sensitivity (SEN), and specificity (SPE).

Finally, to evaluate the statistical significance of the prediction performance obtained by the trained classification models, a non-parametric statistical method named permutation test was employed (exact p-values were computed to mitigate the type I error rate and the multiple testing issues) [62], [63]. In this work, we used 1 000 permutations and the significance level of 0.01 (to estimate the performance of the models on the permuted data, we used the same classification setup as in the training phase [64]).

## III. RESULTS

At first, the cross-correlation matrices (using Pearson's correlation) of the 15 features per feature-type selected using feature pre-selection performed by the mRMR algorithm are visualized in Fig. 4. As can be seen, there are some features that can be considered redundant, i. e. having a strong correlation with one/more features, however, as we did not want to reduce the feature-space complexity too much (the redundancy is not the same in every feature-type, so by reducing the feature space complexity any further, some relevant features could be removed as well. This would most likely result in having sub-optimal feature space for some of the feature-types.), we decided to use all of the 15 features, and analyze them accordingly (having the possibility of cross-correlated features appearing in the results of the statistical analysis together in mind).

Results of the statistical analysis can be seen in Table 2. The table shows the top 5 features for each of the feature-types according to the p-value computed by the Mann-Whitney U-test (if some of the cross-correlated features appeared together, we selected only one of them and replace the other with the feature/s bellow the top 5). Regarding the p-values of the Mann-Whitney U-test, the following number of features can be considered as coming from a distribution that is significantly different for the two subject groups (threshold of 0.05): a) CONV features – 5/5 (prior adjustment), 1/5 (after adjustment); b) MS features – 5/5 (prior adjustment), 4/5 (after adjustment); c) FD features – 5/5 (prior adjustment), 1/5 (after adjustment); and d) TQWT features – 3/5 (prior adjustment), 1/5 (after adjustment). With respect to the Spearman's correlation, the following features were found to have the strongest correlation with the presence of GD (where $**$ denotes p-value $<$ 0.01, and $*$ denotes p-value $< 0.05$): a) CONV features – TSK1 TILT (mean) $\rho = -0.42^{**}$; b) MS features – TSK2 V-JERKR25 $\rho = 0.41^{**}$; c) FD features – TSK1 TILTVEL0.3 (mean) $\rho = -0.41^{**}$; and d) TQWT features – TSK6 V-VELSNR $\rho = -0.39^{**}$. All of these features were found to have a statistically significant relationship with the presence of GD (both prior and after p-value adjustment). For better visualization, violin plots showing the distribution estimates of the best-discriminating

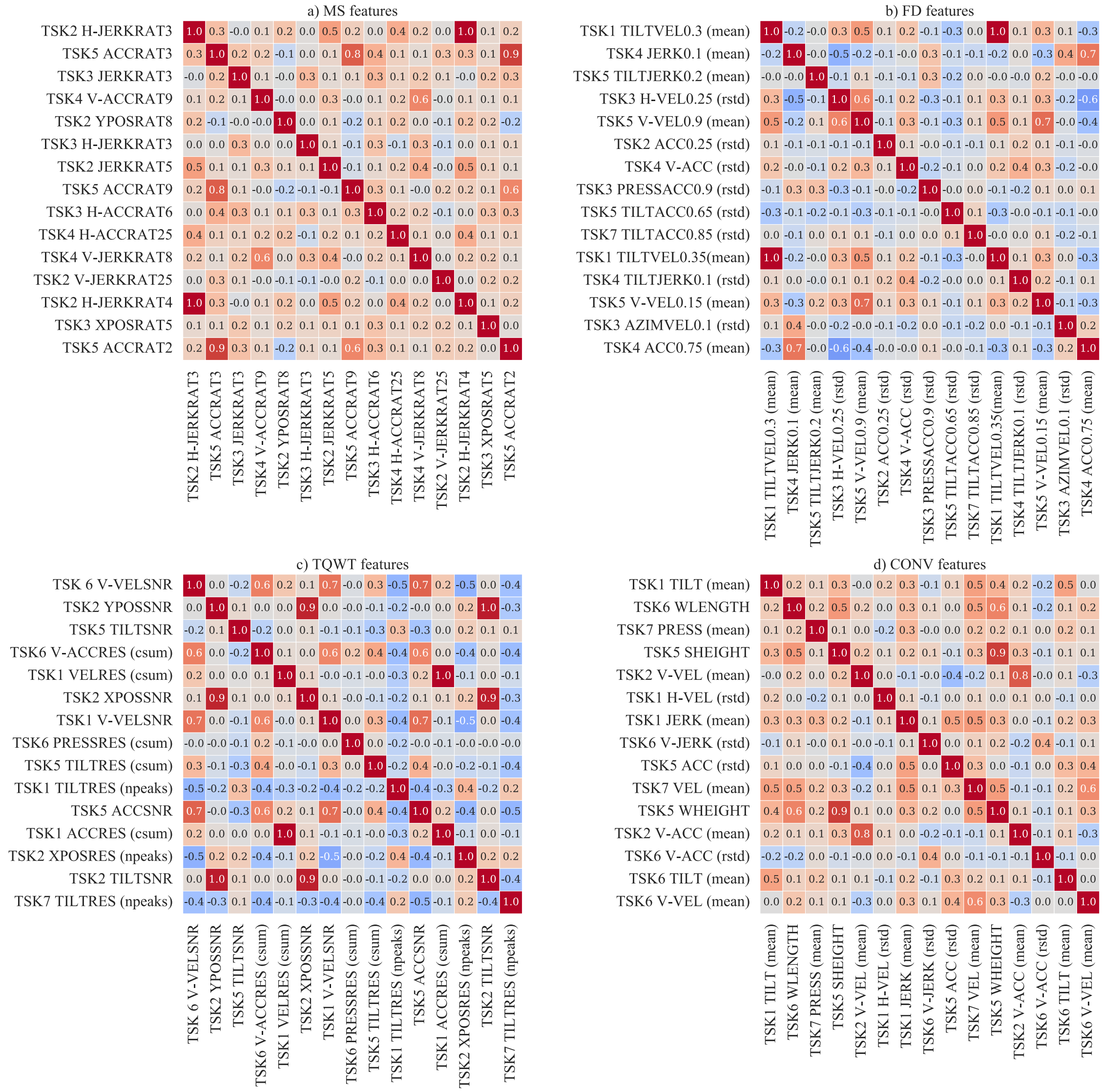


**FIGURE 4. Cross-correlation matrices of the feature sets (Pearson's correlation coefficient (r); 15 features per feature-type) after the pre-selection. Color notation: linear scale in the range of < −1, 1 >, where the maximum positive correlation is denoted by the red color, and the maximum negative correlation is denoted by the blue color. More information about the features can be seen in Section II-B.**

features of every feature-type for both healthy children and children with GD are presented in Fig. 5.

And finally, results of the classification analysis can be seen in Table 3. Regarding the individual feature-types, the following results were achieved (where ∗∗ denotes p-value $<$ 0.01, and ∗ denotes p-value $<$ 0.05): a) CONV features (7 features selected) – ACC = 0.74**; b) MS features (8 features selected) – ACC = 0.73**; c) FD features (3 features selected) – ACC = 0.76**; and d) TQWT features (2 features selected) – ACC = 0.71**. Features used to train these classification models for each feature-type are summarized in Table 4. With respect to an overall feature set (all 60 features combined), the classification performance was: ACC = 0.84** using 10 features. All classification results were evaluated by the permutation test as being statistically significant.

## IV. DISCUSSION

In the search for novel and more robust graphomotor features that can be used to improve the quantification and identification of GD in school-aged children, we introduced three non-conventional advanced types of features, specifically, features based on modulation spectra, features based on fractional order derivatives, and features based on tunable Q-factor wavelet transform. As each feature-type produced a different number of features, we employed feature pre-selection to reduce the feature-space complexity and minimize the effect of the curse of dimensionality occurring when the number of analyzed features greatly outnumbers the number of observations present in the dataset, as well as to unify the number of features among the feature sub-sets. With this approach, we reduced each feature-type to 15 features with minimal cross-correlation. An important

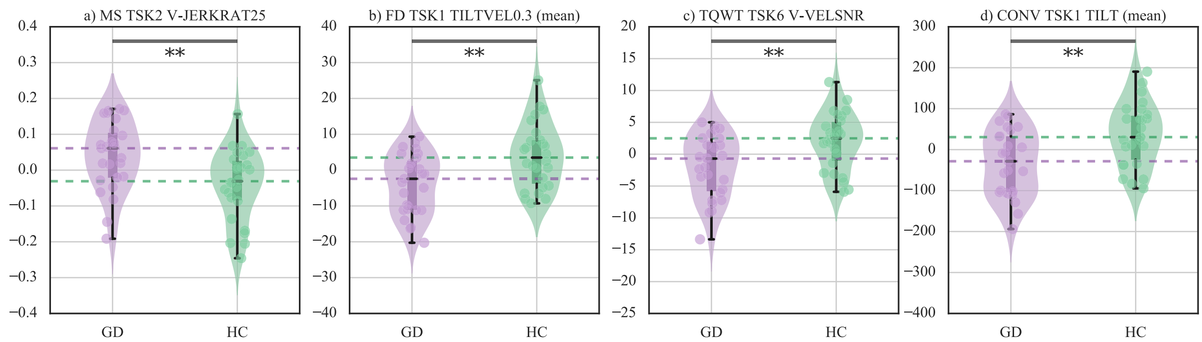


**FIGURE 5.** **Violin plots of graphomotor features in both GD and HC groups (after removing the covariates). Figure notation: background of the box plots represents vertically mirrored kernel density estimations; horizontal dashed lines represent medians; and a star(s) between two violins mean(s) the p-value of Mann-Whitney U-test (∗∗ denotes p-value < 0.01, and ∗ denotes p-value < 0.05).**

**TABLE 2.** **Results of the statistical analysis.**

| feat. | TSK | $\rho$ | p($\rho$) | p($\rho$)* | p(U) | p(U)* |
|---|---|---|---|---|---|---|
| | | | CONV features | | | |
| TILT (mean) | TSK1 | -0.42 | 0.001 | 0.027 | 0.001 | 0.019 |
| TILT (mean) | TSK6 | -0.32 | 0.017 | 0.129 | 0.009 | 0.072 |
| SHEIGHT (mean) | TSK5 | -0.31 | 0.028 | 0.142 | 0.015 | 0.076 |
| WLENGTH | TSK6 | -0.25 | 0.074 | 0.190 | 0.038 | 0.096 |
| WHEIGHT | TSK5 | -0.25 | 0.074 | 0.190 | 0.038 | 0.096 |
| | | | MS features | | | |
| V-JERKR25 | TSK2 | 0.41 | 0.002 | 0.024 | 0.001 | 0.016 |
| XPOSR5 | TSK3 | 0.40 | 0.003 | 0.024 | 0.002 | 0.016 |
| ACCR3 | TSK5 | 0.36 | 0.009 | 0.033 | 0.005 | 0.020 |
| JERKR3 | TSK3 | 0.36 | 0.009 | 0.033 | 0.005 | 0.020 |
| H-ACCR25 | TSK4 | 0.27 | 0.058 | 0.146 | 0.030 | 0.075 |
| | | | FD features | | | |
| TILTVEL0.3 (mean) | TSK1 | -0.41 | 0.002 | 0.031 | 0.001 | 0.020 |
| H-VEL0.25 (cv) | TSK3 | -0.32 | 0.021 | 0.094 | 0.011 | 0.050 |
| V-VEL0.9 (mean) | TSK5 | -0.31 | 0.028 | 0.094 | 0.015 | 0.050 |
| ACC0.75 (mean) | TSK4 | 0.30 | 0.031 | 0.094 | 0.016 | 0.050 |
| ACC0.25 (cv) | TSK2 | -0.25 | 0.074 | 0.152 | 0.038 | 0.077 |
| | | | TQWT features | | | |
| V-VELSNR | TSK6 | -0.39 | 0.004 | 0.070 | 0.003 | 0.044 |
| V-ACCRES (csum) | TSK6 | -0.26 | 0.061 | 0.345 | 0.031 | 0.177 |
| ACCSNR | TSK5 | -0.26 | 0.069 | 0.345 | 0.035 | 0.177 |
| TILTSNR | TSK2 | -0.23 | 0.110 | 0.409 | 0.055 | 0.206 |
| V-VELSNR | TSK1 | -0.21 | 0.136 | 0.409 | 0.068 | 0.206 |

[1] feat – feature; TSK – graphomotor task; $\rho$ – Spearman's correlation coefficient; p($\rho$) – p-value of $\rho$; p($\rho$)* – adjusted p($\rho$); p(U) – p-value of Mann-Whitney U-test; p(U)* – adjusted p(U); for the feature naming convention, see Section II-B.

**TABLE 3.** **Results of the classification analysis.**

| type | MCC | ACC | SEN | SPE | N | p |
|---|---|---|---|---|---|---|
| CONV | 0.50 (0.26) | 0.74 (0.12) | 0.80 (0.19) | 0.71 (0.21) | 7 | ∗∗ |
| MS | 0.48 (0.27) | 0.73 (0.14) | 0.75 (0.19) | 0.73 (0.21) | 8 | ∗∗ |
| FD | 0.51 (0.30) | 0.76 (0.13) | 0.75 (0.20) | 0.77 (0.20) | 3 | ∗∗ |
| TQWT | 0.42 (0.29) | 0.71 (0.14) | 0.74 (0.19) | 0.68 (0.23) | 2 | ∗∗ |
| ALL | 0.65 (0.25) | 0.84 (0.13) | 0.83 (0.17) | 0.81 (0.18) | 10 | ∗∗ |

[1] the results are shown as mean (standard deviation); type – specific type of graphomotor feature; MCC – Matthew's correlation coefficient; ACC – accuracy; SEN – sensitivity; SPE – specificity; N – Number of selected features; p – p-values computed by the permutation test (1 000 permutations); ALL (combination of all feature-types, i. e. 60 features); for the feature naming convention, see Section II-B.

**TABLE 4.** **Features selected for the trained classification models.**

| CONV | MS | FD |
|---|---|---|
| TS6 V-ACC (cv) | TS5 ACCR2 | TS3 H-VEL0.25 (cv) |
| TS1 H-VEL (cv) | TS3 H-ACCR6 | TS7 TILTACC0.85 (cv) |
| TS7 VEL (mean) | TS2 YPOSR8 | TS5 V-VEL0.9 (mean) |
| TS2 V-ACC (mean) | TS4 V-JERKR8 | |
| TS1 TILT (mean) | TS2 JERKR5 | |
| TS5 WHEIGHT | TS3 JERKR3 | |
| TS2 JERK (mean) | TS2 V-JERKR25 | |
| | TS5 ACCR3 | |
| **TQWT** | **ALL** | |
| TS2 YPOSSNR | TSK1 H-VEL (cv) | |
| TS1 VELRES (csum) | TSK1 TILTVEL0.35 (mean) | |
| | TSK2 JERKR5 | |
| | TSK3 JERKR3 | |
| | TSK2 V-VEL (mean) | |
| | TSK6 V-ACC (cv) | |
| | TSK1 V-VELSNR | |
| | TSK3 PRESSACC0.1 (cv) | |
| | TSK7 TILTACC0.85 (cv) | |
| | TSK5 TILTRES (csum) | |

[1] TSK – graphomotor task. For the feature naming convention, see Section II-B.

observation to note here is that in all cases, the selected features do not cover an entire spectrum of the graphomotor tasks (TSK1–TSK7) under investigation. Moreover, the distributions of the tasks per feature-type vary as well. This indicates that each individual type of the features can potentially be used to describe slightly different task-specific aspects of GD experienced by school-aged children supporting the use of a variety of specialized feature-types to provide a more robust and wide-scale description of the hidden complexities underlying GD in general.

Regarding the results of the statistical analysis, it can be seen that basic parameters such as mean tilt, height, and length of writing were found as the most statistically significant features in the case of the conventional (baseline) feature set. More specifically, mean tilt during the drawing of Archimedean spiral (TSK1) and rainbow (TSK6) showed the strongest relationship with the presence of GD. As can be seen, children with GD held the pen less steeply when performing such spiral- and rainbow shape-based movements. In addition, when compared with the cohort of healthy children, sawtooth (TSK5) and rainbow (TSK6) drawn by children with GD were found to be smaller in both height as well as length further underlining the difficulties associated with these tasks.

Another fact that can be observed in the results of the statistical analysis is that as opposed to the conventional features which consisted solely of the spatial (stroke length and height) and dynamic (tilt) parameters, the top-ranking non-conventional features mostly consisted of kinematic features (velocity, acceleration, and jerk) computed in both horizontal as well as vertical projections, and dynamic features (tilt). This observation is in line with the analysis performed by a variety of previous studies [6], [65]–[67] using kinematic features to quantify GD, and confirms the fact that kinematic features are an important measure of the quality of handwriting as well as drawing. Furthermore, such features are specific to computerized analysis as they are almost impossible to be quantified precisely using the human perception of the final handwritten product.

With respect to the features based on modulation spectra, all of the top-ranking features showed a positive correlation with the presence of GD indicating the existence of an increased low-frequency noise in the analyzed handwriting signals. This noise seems to be relatively task-independent as it appeared in all spiral-, loop- as well as sawtooth-based movements. Moreover, in four out of five cases, the features were based on acceleration or jerk, which points out to inability of children with GD to perform a given graphomotor task with steady and controlled velocity that is eventually reflected in an increased noise in the acquired kinematic signals (mathematical point of view) as well as in the lack of fluency and efficiency during handwriting (clinical point of view). Such observation is in line with the previous research reporting non-fluent handwriting as being present in children with HD (diagnosed with DD) [32], [68].

Regarding the top-ranking FD-based features, it may be noticed that all of them were extracted from different graphomotor tasks (TSK1–TSK5) further underlying the need for a variety of specifically-designed features to quantify GD. The most significant FD-based feature, the mean velocity of tilt extracted from TSK1, probably refers to the difficulties in changing the direction of the Archimedean spiral caused by hesitancy, distress, etc. This is an interesting finding as it is in line with the most significant conventional feature being the mean tilt, which highlights the importance of different tilt parametrizations. The rest of the most correlated FD-based features are derived from velocity and acceleration. This shows that FDs can be advantageously applied to both kinematic as well as dynamic features. Additionally, the values of $\alpha$ suggest that regular derivation is not optimal for kinematic handwriting features, which is in line with our previous research [43], [45].

Regarding the top-ranking TQWT features, the only statistically significant correlation was found for the signal-to-noise ratio of the vertical velocity extracted from the rainbow task (TSK6). This probably shows that maintaining steady velocity while performing this particular task is not causing problems to healthy children, but is challenging for children with GD, which is in line with the previous publication reporting problems in vertical movements in children with DD [6] caused by the psychological and muscular fatigue in the finger system. The vertical movement requires coordinated movement and finer flexions/extensions of more joints (interphalangeal and metacarpophalangeal) and therefore it is more complex than ulnar abductions of the wrist [69], [70], which plays a key role in the horizontal one, i. e. GD are more pronounced in the vertical projection of handwriting/drawing. Next, we assume, that children with GD are unable to quickly change the acceleration of their handwriting. On the other hand, healthy children have fewer problems with handwriting automation and therefore can change the acceleration more fluently. This can indirectly cause higher noise-level in the residual component of vertical acceleration in the handwritten product of healthy children, as can be seen in the second most significant TQWT feature.

Finally, concerning the results of the classification analysis, it can be seen that all of the three novel feature-types achieved similar classification performance in comparison to the conventional handwriting features. This shows that a single type of feature, even if more complex, is not likely to improve the identification of GD provided by the conventional features significantly. However, as the results suggest, when these features are combined, the classification performance can be increased by approximately 10 % in terms of accuracy, 3 % in terms of sensitivity and 10 % in terms of specificity. An important fact to note is that when compared with the previous research, the results proposed in this work might at first seem unsatisfactory as some of the recent publications reported over 90 % sensitivity [26], [28], [32]. However, those studies aimed at identifying HD in children with DD using a complex acquisition protocol comprising writing. The results proposed in this work are based solely on graphomotorics and aim at predicting the presence of GD that can lead to HD and possibly to DD. It is of great importance to also focus on simple graphomotor movements as they form the basis of handwriting, hence, a robust parametrization of GD has a potential to be used as an early marker of DD in children in pre-school age or first grades of a primary school. Another important fact to note is that all of the feature-types, as well as the conventional features, were selected when training the combined model. In addition, except TSK4 (flipped version of the connected loops in TSK3), all of the graphomotor tasks are present as well, This shows that all of the selected features extracted from almost all of the graphomotor tasks contributed to an improvement in the identification of GD confirming the hypothesis of enhancing the model's capability to model the relationship between the properties of the handwriting signals and the presence of GD in school-aged children.

## V. LIMITATIONS OF THE STUDY

This work has several limitations. First, we need to be aware of the restricted statistical strength of the inference about the population of school-aged children given a relatively small sample size of 53 children. Next, only children attending 3rd and 4th grade of the primary school were enrolled in this study. To obtain a more complex spectrum of handwriting signals, i. e. to have additional information about the performance of the proposed graphomotor features and their relationship with children's age, grade, etc., handwriting signals of children attending 1st and 2nd grade of the primary school (possibly even pre-school children) as well as children attending the higher grades should also be analyzed. On the other hand, our cohort includes children from the 3rd and 4th grade of primary schools, where the handwriting should become automatic. Therefore a possibility to identify GD in this stage is critical for the consequent diagnosis and therapeutic care of DD. The results proposed in this work therefore laid the foundations (baseline) for future studies that should bring even more information about GD in various age profiles and their evolution in time. Next, deeper investigation and design of the features can be performed, e. g. additional tuning of the filter-banks to compute modulation spectra, other formulations of fractional order derivatives or sub-bands of the tunable Q-factor wavelet transform could be analyzed. Next, various machine learning models should be trained and compared in the future studies to get more information about the classification performance of the proposed features and to obtain the most robust models for GD identification. Finally, the relationship between the classification performance of the trained models with the feature space complexity as well as the cross-validation setup should be investigated to evaluate and confirm the robustness of the proposed methodology. To sum up, concerning the limitations mentioned above, this study should be considered as being rather exploratory and pilot in nature, and its results should be confirmed by the subsequent scientific research.

## VI. CONCLUSION

In this study, we presented three novel types of graphomotor features providing more robust and complex quantification of GD in school-aged children. In each feature-type, we identified several features that significantly differentiate healthy children and children with GD. Of note is the fact that the novel features mostly quantified kinematic aspects of the handwriting process that are very hard to be perceived by a human examiner using only a final handwritten product. In addition, we also showed that combining the proposed graphomotor features with the set of conventionally used ones can increase the prediction capability of the trained binary classifier significantly. With respect to the acquisition protocol, all of the chosen graphomotor tasks but one appeared in the final selection of the features used to train the combined classification model. This confirms that using a variety of basic graphomotor tasks requires coordinated movement of fingers, wrist, elbow, shoulder as well as visuospatial cognitive functions that allow the more advanced features to quantify subtle and rather imperceptible manifestations of GD using online handwriting.

To the best of our knowledge, it is the first work exploring the possibilities of using modulation spectra, fractional order derivatives and tunable Q-factor wavelet transform to extract advanced graphomotor features for the purpose of quantification and identification of GD in school-aged children. Based on the reported results, we conclude that the proposed features have a great potential to improve the computerized identification and assessment of GD. However, to generalize the results, our findings should be confirmed by further scientific research.

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