Preliminary Validation of a Cursive Handwriting Reconstruction Algorithm from a Sensorized Ink Pen

Simone Toffoli[1], Chiara Gentile[1], Linda Greta Dui[1], Stefania Fontolan[2], Cristiano Termine[2] and Simona Ferrante[1,3]

***Abstract*— Lack of handwriting automatization in childhood can cause difficulties within and outside the school context. Therefore, the objective quantification of the handwriting performance is key. A Smart Ink Pen (SIP) used on paper demonstrated its validity in characterizing primary school children's handwriting process, although missing information on the handwriting product. To overcome this limitation, a trace reconstruction algorithm was developed, based on the force and IMU signals measured by the SIP. A total of 353 words "uno", written in cursive from the BVSCO-3 battery by 50 Italian students of the 5th grade of primary school, was reconstructed. The quality of the reconstructions was validated through an Optical Character Recognition (OCR) algorithm (Google Vision), using the scans of the actual traces as a reference. The character recognition rates were 81.02% and 59.49%, the character error rates 21.48% and 47.65%, for scans and reconstructions, respectively. A deeper analysis revealed that 15% of the reconstructions were read in the opposite direction by the OCR algorithm, likely due to a non sufficient sampling rate for the last portion of the words. A characterization of the differences between the good, bad and opposite reconstructions allowed to identify some directions of improvement. An increase of the SIP sampling rate, a better modeling of the thickness of the trace, a finer estimation of the relative distance between the IMU sensor and the tip and the reconstruction of the tip trajectory during in-air movements could improve the trace reconstruction algorithm. In addition, the possibility to leverage transfer learning approaches on the OCR algorithm using the reconstructed traces for additional training could further improve the performances in terms of character recognition rate. However, the preliminary results obtained are promising and highlight the possibility of reconstructing handwriting traces while maintaining the naturalness of the gesture.**

***Clinical relevance*— This contribution establishes the possibility of reconstructing handwritten traces from the kinematic and force signals recorded by an ecological sensorized ink pen.**

*Finanziato dall'Unione europea- Next Generation EU, Missione 4 Componente 1 CUP D53D23013870006. This work was supported by EU – Next Generation EU, project e-school 2.0, n. 2022XXHKYX, CUP D53D23013870006

[1]Simone Toffoli, Chiara Gentile, Linda Greta Dui and Simona Ferrante are with the Department of Electronics, Information and Bioengineering, Politecnico di Milano, 20133 Milano, Italy {simone.toffoli, lindagreta.dui, simona.ferrante}@polimi.it, chiara1.gentile@mail.polimi.it,

[2]Stefania Fontolan and Cristiano Termine are with the Department of Medicine and Technological Innovation, Università dell'Insubria, 21100 Varese, Italy {stefania.fontolan, cristiano.termine}@uninsubria.it

[3]Simona Ferrante has a double affiliation with the LEARNLab, IRCCS Istituto Neurologico Carlo Besta, 20133 Milan, Italy

I. INTRODUCTION

Handwriting is one of the most complex human neuromotor tasks [1]: it involves several cognitive processes that envisage: (i) a planning phase involved in the semantic construction of the message, (ii) the translation of the message into text, (iii) a motor phase defining the actual writing execution, (iv) and a continuous monitoring phase. These building blocks are based on high-level mechanisms, such as working memory, resource allocation, activity parallelization, planning, and attention [2]. For these reasons handwriting is widely studied in a cross-disciplinary fashion. The handwriting learning path during childhood is one of the most investigated topics [3] since the acquisition of automatization in the gesture is considered as a key point in children's development [1]. Failure in reaching writing efficiency, a condition known as dysgraphia, can lead to detrimental consequences in the long-term, not limited to the school environment [4]. Dysgraphia manifests through difficulties in the mechanics of writing, both from a temporal and spatial standpoint [1], and can result in poor legibility and reduced velocity [5]. Because subjects with dysgraphia use most of their cognitive resources to recall the necessary motor programs, the quality of their handwritten content could also be compromised. In Italy, 4% of the total population is diagnosed with dysgraphia. For this reason, national clinical guidelines claimed the need to assess elementary school children's writing performance, supporting the traditional evaluation with quantitative analyses [6]. Up to now, the clinical assessment of handwriting has been performed through pen and paper tests evaluating both quality and speed [7]. While easy to administer, they suffer from long scoring times and unclear criteria for grading quality. With the rise of technological tools, the possibility to integrate objective information, which does not emerge through visual inspection, became viable. The most widespread solution are digitizing tablets, used for example in the study performed by Asselborn et al. [8]. They allow to record the written trace whilst concurrently extracting spatio-temporal parameters, such as in-air and on-paper time, mean velocity and number of changes in velocity [8]. However, these devices present with a fundamental drawback: they do not offer an ecological writing acquisition. Children in schools are typically taught to write with ink on paper – this is for sure true in Italy – so their performance can coherently be evaluated only in these conditions. Indeed, differences between writing on paper and on the digitizer surface were demonstrated in [9] and in [10].

In order to maintain both the naturalness of the writing act, whilst simultaneously acquiring quantitative information, an innovative sensorized ink pen (SIP) [11], embedding an inertial measurement unit (IMU) and a force sensor, was employed in previous studies. The SIP extracts kinematic and dynamic handwriting process-related parameters, which were able to characterize the handwriting learning curve in primary school children [12]. With respect to the digitizer, the SIP analysis has so far not granted the extraction of space-related quantitative parameters. This work aims at reconstructing the handwriting ink trace from the signals collected by the SIP. Such an information could enrich the SIP quantitative handwriting assessment, paving the way for the characterization of the handwriting product quality and/or correctness. Different handwriting reconstruction algorithms have been proposed in the literature: some exploit artificial intelligence strategies [13], trying to infer the relationships between kinematic data and traces, while others reconstruct the trace through sensor integration [14].

For this work, the latter approach was chosen and adopted on data related to Italian cursive handwriting realized by children attending the fifth grade of primary school. Cursive was selected since it is investigated with reduced frequency in the literature. To evaluate the quality of the reconstructions, both the reconstructed traces and the corresponding scans of the actual handwritten products were fed in input to an optical character recognition (OCR) algorithm. Finally, a series of metrics were derived from the reconstructed traces and statistically compared across different classes of reconstruction quality, to assess whether errors by the OCR where linked to specific characteristics of the reconstructed traces.

II. MATERIALS AND METHODS

A. Protocol

The dataset employed in this work was derived from a previous study [12], which received approval by the ethical committee of Politecnico di Milano (n. 28/2022). Fifty subjects from the fifth grade of Italian primary school took part in the BVSCO-3 battery, the gold standard clinical test for grapho-motor fluency assessment. The task considered in the study involved writing “uno” (“one” in Italian) multiple times in one minute in cursive allograph. According to the manual, the score of the test is computed according to the number of letters written correctly independently of the orthographic accuracy.

B. Sensorized Ink Pen

The SIP represents an innovative tool for recording handwriting data. The ad-hoc designed plastic case is divided into two parts. The upper portion houses a custom printed circuit board which includes all the electronics components, namely the microcontroller, a led communicating the SIP status, the Bluetooth module and three sensors. These are characterized by a sampling rate of 50 Hz and include: a sensor featuring a 3-axes accelerometer and gyroscope, and a sensor featuring a 3-axes magnetometer (magnetic field signals were excluded from the analysis), constituting a 9-dof IMU, and a piezoresistive force sensor. The bottom portion – a cylindrical element linked with a distal, conical one – holds the mechanism connecting the force sensor to the tip and responsible for the pen opening and closing, together with the disposable ink cartridge that allows to write on paper. Data acquisition and communication is handled through Bluetooth Low Energy Protocol, which allows for the interaction between the SIP and a custom android app. The SIP is an ecological acquisition tool, as the user will perceive writing with a normal ink pen on paper surfaces.

C. Trace Reconstruction

The trace reconstruction procedure was performed in Matlab R2023b (© 2023 The MathWorks, Inc.) and was applied only to the words which were written as a single tract on paper, with no liftoff during execution. Firstly the SIP raw data (acceleration, angular velocity and force) were split into different rows, in order to avoid kinematic drift build up. Then, the kinematic signals of each row were low pass filtered at 7 Hz to remove high frequency noise. The filtered acceleration and angular velocity were fed into MATLAB’s *imufilter* (https://ch.mathworks.com/help/nav/ref/imufilter-system-object.html) function. This function employs Kalman filtering to fuse data from the accelerometer and gyroscope, returning a series of quaternions representing the IMU 3D orientation with respect to the global reference system NED (North, East, Down) at each time instant. However, being the writing surface orientation with respect to NED unknown, the orientation representation was transferred to the SIP initial reference frame (i. e., the SIP orientation at the first time instant) [15], now acting as the global reference frame. According to the force signal, the whole row was segmented into single words and for each word the relative quaternions were extracted, used to project gravity into the global reference frame and remove it from each axis, thus retaining the linear acceleration of the sensor. The discrete double integration of the linear acceleration yielded the linear displacement of the IMU. To reconstruct the actual written trace, a similar strategy to the one used in [15] was adopted. Since the IMU lies in the upper part of the SIP case, the extracted orientation and translation information was transferred to the tip. This was achieved through a rigid body coordinates transformation, exploiting the known distance between the IMU and the SIP tip. The final output consisted in the 3D coordinates of the tip in the global reference frame. Principal component analysis (PCA) was then applied to the 3D spatial information of each word to find the writing plane, which was identified by the first two principal components. Finally, in order to find the common writing plane, the normals to each identified plane (i. e., the third principal component) were extracted from each word and averaged. An alignment procedure was implemented to align all words in the common writing plane. The output of the trace reconstruction procedure consisted of a series of jpg files, each representing the reconstructed words in each row. These images were then automatically combined to form a new jpg file representing the whole considered row.

D. Optical Character Recognition

An OCR algorithm was employed to validate the obtained trace reconstructions. OCR algorithms are designed to extract text from images or documents which can contain either handwritten or printed text. Through a series of internal processing steps, such as segmentation, transformations, zoning and projections, they provide the text contained in the input as output [16]. Two kinds of input were considered: i) the jpg reconstruction files; ii) the corresponding paper scans (a scan for each reconstructed row), acting as a reference. The scans were obtained using a commercial scanner and then manually segmented to obtain the rows of interest. The ground truth was manually assigned according to the actual words written by the subjects. In this work, Google Vision, an OCR algorithm developed by Google Cloud Services, was used in python version 3.11.11 through proprietaries API (https://cloud.google.com/vision/docs), specifying Italian as text language to be recognized. This algorithm recognizes text in a hierarchical way: the output is organized, in decreasing order of hierarchy, in *pages*, *blocks*, *paragraphs*, *words* and *symbols* (i. e., the single letters). The algorithm provides the coordinates of the bounding box for each hierarchical element recognized in the image. These allowed identifying elements that were recognized in the opposite direction (i. e., from right to left and from bottom to top) by the OCR, as well as elements that were superimposed to each other. For each word recognized by the OCR, the Character Recognition Rate (CRR), measuring the percentage of correctly classified characters, and the Character Error Rate (CER), that is the percentage of deletions, additions and substitutions needed to convert the recognized word into the ground truth, were computed. Both measures are expressed as a percentage of the total characters present in the ground truth. Measures at the character level were chosen since the BVSCO-3 test considers graphemic accuracy for score assignment. The error rate percentage for each character in the word "uno" was computed to assess whether some letters were more difficult to recognize than others. The percentage of excess and missed characters, words reconstructed in opposite direction and superimposed words were extracted too. Notably, CRR, CER, percentage of excess and missed characters were computed only for non-superimposed words recognized in the correct direction. Based on the metrics obtained by the OCR, an a posteriori analysis only on the SIP trace reconstructions was performed as follows. Words were divided into three classes: good (G), bad (B) and opposite (O). Good and bad words were the ones characterized by a correct reconstruction direction: if the CRR was higher or equal to 66% a word was assigned to the good group, otherwise it was assigned to the bad one. The opposite group included the words recognized in the wrong writing direction by the OCR. Several parameters, both dynamic and kinematic, were extracted from each reconstructed trace: maximal velocity in horizontal (x) and vertical (y) direction (see Fig. 1, panel b) for x and y axes direction), maximum value of the velocity norm, percentage of the word duration in which the maximal velocity was encountered (in x and y direction and for velocity norm), number of changes in velocity norm, median value of the force derivative, number of samples during the force signal's ascending front, number of samples during the force signal's descending front. The focus on ascending and descending fronts of the force signal was motivated by the assumption that these traits would be the most relevant in trace reconstruction errors. The parameters underwent a statistical test to assess the eventual presence of differences across classes. Since all the data were not normally distributed, the Kruskal-Wallis test was performed at the 5% significance level, followed by post-hoc comparison with the Bonferroni's method when the null hypothesis was rejected.

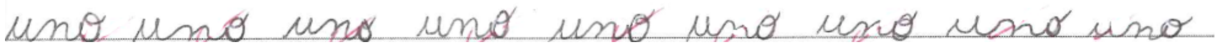
III. RESULTS

A total of 1059 characters (353 words, 83 rows) were available for OCR analysis, which results are reported in Table I, separately for the paper scans ("Scan" column) and the SIP trace reconstructions ("Reconstruction" column). Specifically, CRR and CER are reported as mean $\pm$ standard deviation, while the single character error rates are expressed as a ratio with respect to their total number of occurences in the ground truth. Excess and missed characters are presented as a percentages of the overall number of characters of the ground truth. Opposite and superimposed words are expressed as percentages on the number of ground truth words. Overall, the results were better when the scans were provided as input to the OCR. Some examples are reported in Figures from 1 to 3.

TABLE I: Measures obtained from OCR analysis

Parameters	Scan	Reconstruction
CRR [%]	81.02 ± 29.56	59.49 ± 33.55
CER [%]	21.48 ± 32.08	47.65 ± 39.95
"u" error rate [%]	15.86	54.96
"n" error rate [%]	11.61	40.79
"o" error rate [%]	28.33	50.71
Additional characters [%]	10.76	24.08
Missed characters [%]	18.98	60.91
Opposite words [%]	0.85	15.01
Superimposed words [%]	0.57	8.22

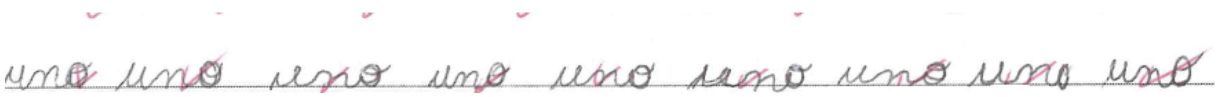
Kinematic and dynamic characteristics of three different classes of reconstructed words (good, bad and opposite) were statistically investigated in the a posteriori analysis (N_{good} = 205, N_{bad} = 103, $N_{opposite}$ = 45). The results are reported in Table II for each parameter and class as median (25th percentile; 75th percentile), since all parameters were not normally distributed. The "p-value" column contains the p-value of the Kruskal-Wallis statistical test. The last three columns (G/B, B/O, G/O) report the results of the post-hoc comparison with Bonferroni's method, showing which pairs of classes exhibit significant differences for each parameter.



(a)

(b)

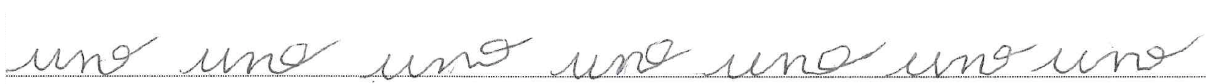
Fig. 1: Example reconstructed in the correct direction. a) Paper scan. CRR = 100% and CER = 0%. b) SIP reconstructed traces. CRR = 70.36% and CER = 18.52%. The first three words were correctly recognized as “uno”, the following five words were recognized as “und”. The last word was not recognized at all.



(a)

(b)

Fig. 2: Example of scan recognized in the correct direction and trace reconstruction in the opposite one. a) Paper scan. OCR performance was high despite the presence of red ticks that were written during the test scoring. The fifth word was misclassified as “uso”, while the sixth one as “samo”. b) SIP reconstructed traces. Here, the OCR firstly recognized the entire row in the opposite direction. Then, the fifth word alone was recognized again in the correct direction as “uno”.



(a)

(b)

Fig. 3: Example of excess characters in the SIP reconstructions. a) Paper scan. The only wrongly recognized character was the letter “o” in the fourth word, which was interpreted as an “e”. b) SIP reconstructed traces. In the third and sixth words, the loops present in letter “u” made the OCR recognized two separate characters: “re” in the former word, “ce” in the latter.

TABLE II: OCR statistical analysis

Parameters	**G**	**B**	**O**	**p-value**	**G/B**	**B/O**	**G/O**
Max vel x [m/s]	0.01 (0.06; 0.14)	0.09 (0.06; 0.11)	0.13 (0.09; 0.18)	< 0.001	0.19	< 0.001	0.0017
Max vel y [m/s]	0.08 (0.06; 0.11)	0.09 (0.06; 0.12)	0.10 (0.08; 0.13)	0.0037	1.00	0.008	0.0035
Max vel norm [m/s]	0,12 (0.09; 0.16)	0.12 (0.08; 0.16)	0.15 (0.13; 0.23)	< 0.001	0.75	< 0.001	< 0.001
NC norm [#]	24 (22.00; 27.00)	23 (20.25; 25.00)	27 (23.00; 30.25)	< 0.001	0.25	< 0.001	0.0054
Max vel pos x [%]	0.96 (0.84; 0.98)	0.89 (0.32; 0.98)	0.97 (0.93; 0.98)	0.0039	0.032	0.0068	0.45
Max vel pos y [%]	0.75 (0.35; 0.97)	0.59 (0.20; 0.96)	0.98 (0.71; 0.99)	< 0.001	0.42	< 0.001	< 0.001
Max vel pos norm [%]	0.97 (0.65; 0.99)	0,86 (0.29; 0.98)	0.98 (0.96; 0.99)	< 0.001	0.029	< 0.001	0.066
Median force der [A.U]	775.3 (148.6; 1803.4)	922.5 (201.21; 1757.79)	332,4 (0.03; 1117.5)	0.015	1	0.022	0.018
Force desc samples [-]	3 (2; 4)	3 (3; 4)	3 (2; 4)	0.099			
Force asc samples [-]	3 (2; 4)	3 (3; 4)	3 (2; 4)	0.75			

IV. DISCUSSION

This work investigated the validity of a trace reconstruction algorithm adopted on time series acquired by a novel sensorized ink pen. As for the handwriting data, the Italian word "uno" written in cursive (a standardized and validated task from the BVSCO-3 battery) by pupils attending the fifth grade of primary school was considered.

After the estimation of the tip trajectories, the reconstructed traces and the paper scans of the actual written words were given as input to the Google Vision OCR algorithm to validate the proposed reconstruction method. As expected, the OCR algorithm achieved the best performances on the paper scans. However, it is worth noting that the CRR and CER metrics highlighted the nonneglibile presence of recognition errors. This is likely due to the OCR model itself. In fact, these algorithms, by design, perform better on printed text than on handwritten one. When dealing with the latter, the cursive allograph poses an additional challenge due to its interconnected joints and inter-subject variability in the handwriting style [17]. Moreover, the effect of text language cannot be neglected, as the algorithms are typically better trained on English. Lastly, when documents are provided as input, the algorithm is able to exploit the hierarchical structure of the document in the recognition problem. In the current work, scans presented with the paper sheets horizontal lines, on top of which words were written. The absence of such a structure could lie among the reasons of the poorer results revealed for the SIP trace reconstructions. Indeed, considering that single reconstructions were combined to form the jpg input files, slight misalignments could occur despite the estimation of the common writing plane, also caused by differences in the computed size of words. For example, in Figure 1 the last word written by the subject was slightly smaller than the others, as evident in the paper scan. This translated coherently into a smaller reconstruction, which in turn caused the word to be slightly above the other ones. This word was indeed not recognized by the OCR algorithm, underlining the importance of word alignment and size consistency, regardless of the accuracy of the reconstruction itself. Thus, dealing with the OCR problem on its own to improve the results, transfer learning approaches could be beneficial. Already implemented machine or deep-learning algorithms could be finely tuned on reconstructed handwriting traces, which do not come within a structured context. To do so, a different dataset, including heterogeneous content, should be used.

The 59.49% CRR obtained in the current work is far from the 92.2% reported in the study taken as reference for the projection of the IMU roto-translation to the writing plane [15], although relevant differences can be pointed out. In the cited work, character recognition was evaluated on single, lowercase, latin letters. This scenario is certainly favorable for an OCR algorithm, particularly if one considers that the 92.2% CRR outperforms even the metric obtained in the current study for the paper scans (81.02%). Nevertheless, additional factors that could explain the current findings are discussed here after.

Despite the differences in CRR and CER, a striking gap was identified in the percentage of words reconstructed in the opposite direction: less than 1% in scans, 15% in reconstructions. Given that the visual inspections of the reconstructed traces did not highlight peculiar characteristics in opposite words (see the example in Fig. 2, where the entire row was processed in the opposite direction by the OCR algorithm, despite being fairly comparable to the reconstruction in Fig. 1), the a posteriori analysis on the words' kinematic and dynamic parameters was run. The results showed a consistent pattern in the velocity profile. Opposite words were characterized by significantly greater maximum values of velocity, both in the x and y direction as well as when the norm was considered. This was coupled with the significant trend of the location of the peak in vertical velocity. In opposite words, the peak was found at the 98% of the word length (median value), but the biggest discrepancies emerged in the variability of such a measure. While good and bad words exhibited interquartile ranges crossing the middle point of the word ($<$ 50%), the 75% of opposite words had the maximum value after the 70% of the word length. A similar behavior, not reaching significance in the post-hoc comparison with good words, was revealed also for the horizontal and the absolute velocity, where the 25th percentile of opposite words was always above the 90%. On the other hand, the only significant results for dynamic parameters regarded the force signal's derivative median value which was significantly lower in opposite words, possibly highlighting a higher impact of descending fronts in such words. Given these findings, it appears that opposite words are consistently characterized by highest velocities at the end of the letter "o" in "uno", likely due to the execution of the letter horizontal join. For this reason, such a join is typically of great length, developing both horizontally and vertically from the body of letter "o". The absence of other characters after such evident tract could cause the trace reconstruction in the opposite direction, with the join identified as the beginning of the word. The problems with the letter "o" translated into half (50.71%) of the characters wrongly recognized. Therefore, the final portion of the letter "o" drives the text reconstruction, despite representing a limited portion of the original kinematic data. A possible improvement in this sense could involve increasing the sampling frequency of the IMU. This would reduce the effect of the velocity peaks on the reconstruction rendering, while providing more details in the previous parts of the words.

A further element worsening the OCR was related to the presence of loops in word reconstructions, particularly in the letter "u". This caused the OCR algorithm to reconstruct extra letters such as the character "l" or "e". Loops were unavoidably reconstructed since they were actually present in the written words, although with reduced evidence because of the thickness of the ink trace on paper. This could explain why the worst error rate at the single character level was revealed for the letter "u". The loops are due to wider movements at the IMU level, which are transposed by the trace reconstruction algorithm at the level of the pen tip. It is worth pointing out that the acquisitions were carried out using different SIPs, but the IMU-tip distance was considered constant across different devices. Thus, future work should include a device-specific calibration of the relative distance between IMU and tip, together with the modelling of the thickness of the ink trace.

The constrained scenario explored in the presented work was already sufficient to highlight the challenge posed by the IMU-based handwriting trajectory estimation. On top of the refinements previously discussed, the next steps will need to intervene at different levels to improve and extend the approach. First of all, the integration of in-air movements is of critical importance for two reasons: i) the adaptation of the algorithm to words and personal handwriting styles, as pen lifts are part of the writing act; ii) the improvement of the overall row reconstruction. By including in-air trajectories, the relative position among words will closely resemble the one of the ground truth, thus improving words relative alignment. The trace reconstruction procedure should also be refined, to better correct sensors drifts and artifacts. Lastly, the proposed strategy should be applied to a more heterogeneous dataset, including samples coming from younger and older subjects, different words and allographs.

This work represents a first step towards Italian, cursive handwriting reconstruction from IMU data embedded in an ink pen. Although additional work is needed, the presented findings could open up the possibility of accessing quantitative information on handwritten traces while preserving the natural experience of writing on paper in the end user.

REFERENCES

[1] M. Faundez-Zanuy, J. Fierrez, M. A. Ferrer, M. Diaz, R. Tolosana, and R. Plamondon, “Handwriting Biometrics: Applications and Future Trends in e-Security and e-Health”, Cognit Comput, vol. 12, no. 5, pp. 940–953, Sep. 2020, doi: 10.1007/s12559-020-09755-z.

[2] N. L. . Mertens, Writing: processes, tools and techniques. Nova Science Publishers, Inc., 2010.

[3] Y. Fogel, N. Josman, and S. Rosenblum, “Functional abilities as reflected through temporal handwriting measures among adolescents with neuro-developmental disabilities”, Pattern Recognit Lett, vol. 121, pp. 13–18, Apr. 2019, doi: 10.1016/j.patrec.2018.07.006

[4] S. A. Cermak and J. Bissell, “Content and construct validity of here’s how i write (hhiw): A child’s self-assessment and goal setting tool”, American Journal of Occupational Therapy, vol. 68, no. 3, pp. 296–306, May 2014, doi: 10.5014/ajot.2014.010637.

[5] P. J. Chung, D. R. Patel, and I. Nizami, “Disorder of written expression and dysgraphia: definition, diagnosis, and management”, Transl Pediatr, vol. 9, no. S1, pp. S46–S54, Feb. 2020, doi: 10.21037/tp.2019.11.01.

[6] Sistema Nazionale Linee Guida dell’Istituto Superiore di Sanità, “Linee guida: Gestione dei Disturbi Specifici dell’Apprendimento (DSA),” 2021.

[7] C. Cornoldi, R. Ferrara, and A. M. Re, BVSCO-3-Batteria per la Valutazione clinica della Scrittura e della Competenza Ortografica. Firenze, Giunti - Psychometrics, 2022

[8] T. Asselborn et al., “Automated human-level diagnosis of dysgraphia using a consumer tablet”, NPJ Digit Med, vol. 1, no. 1, Dec. 2018, doi: 10.1038/s41746-018-0049-x.

[9] S. Gerth et al., “Is handwriting performance affected by the writing surface? Comparing preschoolers’, second graders’, and adults’ writing performance on a tablet vs. paper”, Front Psychol, vol. 7, no. SEP, Sep. 2016, doi: 10.3389/fpsyg.2016.01308.

[10] L. G. Dui et al., “Digital Tools for Handwriting Proficiency Evaluation in Children”, in 2021 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI), IEEE, 2021, pp. 1-4. doi: 10.1109/BHI50953.2021.9508539

[11] F. Lunardini et al., “A Smart Ink Pen for the Ecological Assessment of Age-Related Changes in Writing and Tremor Features”, IEEE Trans Instrum Meas, vol. 70, pp. 1–13, 2020, doi: 10.1109/TIM.2020.3045838.

[12] S. Toffoli et al., “Digital Characterization of Primary School Pupils’ Handwriting with a Sensorized Ink Pen”, in 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, Jul. 2024, pp. 1–4. doi: 10.1109/EMBC53108.2024.10782390.

[13] M. Wehbi et al., “Surface-Free Multi-Stroke Trajectory Reconstruction and Word Recognition Using an IMU-Enhanced Digital Pen”, Sensors, vol. 22, no. 14, p. 5347, Jul. 2022, doi: 10.3390/s22145347.

[14] Guanglie Zhang et al., “Towards an ubiquitous wireless digital writing instrument using MEMS motion sensing technology”, in Proceedings, 2005 IEEE/ASME International Conference on Advanced Intelligent Mechatronics., IEEE, pp. 795–800. doi: 10.1109/AIM.2005.1511080.

[15] Y. Bu et al., “Handwriting-assistant: Reconstructing continuous strokes with millimeter-level accuracy via attachable inertial sensors”, Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 5(4), pp. 1-25, Dec. 2021, doi: 10.1145/3494956.

[16] N. Arica and F. T. Yarman-Vural, “An overview of character recognition focused on off-line handwriting”, IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews), vol. 31, no. 2, pp. 216–233, May 2001, doi: 10.1109/5326.941845.

[17] R. Ahmad, M. Z. Afzal, S. F. Rashid, M. Liwicki, and T. Breuel, “Scale and rotation invariant OCR for Pashto cursive script using MDLSTM network”, in 2015 13th International Conference on Document Analysis and Recognition (ICDAR), IEEE, Aug. 2015, pp. 1101–1105. doi: 10.1109/ICDAR.2015.7333931.