Using data visualization and signal processing to characterize the handwriting process

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Abstract

Introduction: Disturbances in handwriting legibility and speed are found among elementary school-aged children. The aim of this paper is to present a set of sophisticated analytical tools suitable for visualization and evaluation of handwriting disturbances.

Methods: Handwriting samples from 30 children, 15 proficient and 15 non-proficient handwriters, aged 8–9 years were collected with the aid of a digitizing tablet. Temporal and spatial measures of the handwriting process dynamics based on signal processing methods were developed and visually presented.

Results: Significant differences between proficient and non-proficient handwriters were found in handwriting characteristics such as the standard deviations of letter width ($t = 2.96, p = 0.008$), letter height ($t = 3.24, p = 0.005$) and pen elevation ($t = 2.91, p = 0.008$). Significant differences were also found for the number of pen lifts ($t = 2.27, p = 0.03$), for the value of the correlation coefficients between letter length and time ($t = -6.62, p = 0.000$) and between the actual and computed number of words ($t = 2.79, p = 0.01$).

Conclusions: The techniques described in this paper provide objective measures for handwriting performance presented in a way designed to help clinicians and educators visualize handwriting difficulties during clinical evaluation and intervention. Data visualization and analysis appear to enhance information concerning the spatial and temporal dynamics of handwriting.

Keywords: Handwriting, evaluation, digitizer, visualization

Introduction

Handwriting is a complex perceptual-motor task that involves a very rapid sequencing of movements that must be controlled and regulated with considerable precision [1]. Handwriting is generally considered to be an ‘over-learned’ skill, i.e. one that needs to be practiced repeatedly in order to achieve automaticity [2]. During the first 3 years of school, both legibility and fluency of writing improve with continual practice until proficiency is achieved [3,4]. Ideally, the process becomes almost automated such that the generation of text does not interfere with the creative thinking process [5]. Once the skill is learned, handwriting becomes rapid, accurate and mechanical, with little need for active conscious control [6], serving to increase efficiency and reduce redundancy [7].

For many children, the proficiency of their handwriting is reflected by their ability to produce legible text with minimal effort. However, other children fail to reach this level of skill. It has been reported that the act of handwriting presents difficulties for ~10–34% of elementary school-aged children [8–10]. The percentage of children with handwriting difficulties reported depends upon the extent of teacher awareness, as well as the type of evaluation tools that are available [11,12].

Dysgraphia or poor handwriting is a common complaint among children and adults with learning disabilities, appearing with or without other academic difficulties [13–15]. Although poor handwriting may occur for children who have no discernible dysfunction in other areas [16,17], it is often associated with neurological, behavioural or medical conditions including Attention Deficit Hyperactive Disorders (ADHD) [18,19], cerebellar ataxia [20], epilepsy [21] and leukaemia (as a result of cranial radiation) [22].

Currently, the majority of available handwriting evaluations are limited for a variety of reasons including difficulties related to the identification...
Handwriting involves very rapid sequencing of movements and, as such, is of considerable theoretical interest for the study of movement control. Analytic techniques developed in the fields of signal processing and pattern recognition are natural methods for achieving a deeper understanding of both proficient and poor handwriting [39–41]. Regrettably this information has not yet been widely disseminated to the clinical and educational professionals who work directly with people who have handwriting difficulties and remains, in large part, within the sphere of motor control or signal processing laboratories. This problem is reminiscent of the status of human locomotor investigations some 25 years ago when sophisticated motion analysis laboratories first presented the results of detailed gait analysis studies [42]. Typically, clinicians and teachers are not sufficiently adept at the analytic skills required to understand such results in the format in which they are normally presented.

In a recent editorial in *Developmental Medicine & Child Neurology*, O’Hare ([43], p. 651) wrote that there is a ‘need to know more about the longitudinal course, early features, and intervention in dysgraphia’. The work presented in this paper aims to meet this challenge by developing and applying signal processing and data visualization tools for the analysis of the dynamic features relevant to the evaluation and treatment of handwriting difficulties. These tools greatly extend the power of the previously developed digitizer-based program, POET [28] that provided a modular, user-friendly environment for the collection and analysis of handwriting samples. The objectives of this study were (1) to develop tools for computer-aided evaluation and data visualization of handwriting difficulties and (2) to demonstrate the utility of these tools on a data set of proficient and non-proficient handwriters.

**Methods**

**Participants**

Participants were 30 third grade children, aged 8 and 9 years old, including 15 proficient handwriters and 15 non-proficient handwriters. The proficient and non-proficient handwriters were recruited from regular public schools, the Hebrew language as their primary means of verbal and written communication and were right-hand dominant. The parents of all the children who participated in the study gave their informed consent.

The 30 participants were identified as having proficient or non-proficient handwriting with the aid of the standardized and validated Teachers’...
Questionnaire for Handwriting Proficiency (TQHP) [44,45], completed by their classroom teachers. The questionnaire was constructed from criteria selected from the literature and handwriting assessments including handwriting legibility, speed, fatigue and complaints of pain or discomfort while writing [8,46,47]. The content validity of the TQHP was established via a table of specifications compiled by 10 occupational therapy clinicians and researchers who were experienced in the assessment and treatment of handwriting difficulties. Inter-rater reliability for the TQHP was shown to be high \( (r = 0.89, p < 0.001) \) [45,48]. The teachers were asked to use the questionnaire to evaluate the handwriting of each student in comparison to what they would expect handwriting legibility and speed for children of that age and background.

Children with documented developmental delay, neurological deficits or physical impairment (e.g. Developmental Coordination disorders, Attention Deficit Hyperactive Disorders, Cerebral Palsy) were excluded from the study. After the children were classified into groups of proficient vs non-proficient handwriters according to the TQHP, one of the authors (SR) administered the Hebrew Handwriting Evaluation (HHE) [47], a standardized, reliable and valid handwriting assessment for the Hebrew language, to all of the children. One hundred per cent agreement between these two measures was found; that is the same 30 children who were categorized as non-proficient or proficient handwriters in accordance with the TQHP were also categorized as poor or proficient with the HHE.

The children with proficient handwriting were matched to the participants in the non-proficient handwriting group, on the basis of gender, age, school and grade. For each child in the non-proficient handwriting group, a matched control participant was chosen from his or her classroom peers and was taught by the same classroom teacher. Thus, there were no differences between the two groups with respect to their age (mean = 8.7 years, SD = 0.27 years for the children with proficient handwriting and mean = 8.6 years, SD = 0.35 years for the children with dysgraphic handwriting) and gender ratio (three girls vs 12 boys in both groups).

**Instruments**

The Hebrew handwriting evaluation (HHE) [49]. The HHE was developed in order to assess the handwriting of children suspected of having difficulty with writing in Hebrew. In the current study, the tool was used to examine a standard paragraph, assessing legibility via both global and analytic measures (e.g. global legibility and number of unrecognizable letters). The inter-rater reliability of the HHE is \( r = 0.75–0.79; p < 0.001 \). Construct validity has been established by demonstrating statistically significant differences between the performance of children with proficient and with poor handwriting \( (t = -2.34; p = 0.027) \) [50].

**POET—penmanship objective evaluation tool** [28,29]. An online computerized handwriting evaluation tool, developed by Rosenblum et al. [28] (http://research.haifa.ac.il/~rosens) with Matlab software toolkits (http://www.mathworks.com/products/matlab) was used to administer the stimuli and to collect and analyse the data. The evaluation was developed in response to the absence of a quantitative objective handwriting tool for the Hebrew language, but is suitable today for use with any other language. The computerized system enables the gathering of spatial, temporal and pressure data while the participant is writing. The software consists of two independent parts, the data collection program and the data analysis program. The data collection program is easy to use by clinicians and educators and is currently in use in different clinical centres in Israel. The data analysis program is under development and new analysis options are still being added. Clinicians collect the digitizer data, transmit it to the tele-evaluation centre via the Internet or on a CD and receive the analysed data back to their clinic within a 1 week period.

Participants were requested to copy a 107 character paragraph onto A4-size lined paper that was affixed to the surface of a WACOM \( (404 \times 306 \times 10 \text{ mm}) \) \( x-y \) digitizing tablet, using a wireless electronic pen with a pressure-sensitive tip (Model GP-110). Displacement, pressure and pen tip angle were sampled at 100 Hz via a 650 MHz Pentium III laptop computer. The task was presented visually on the screen in size 20-point Hebrew font type Gutman Yad-Brush.

The studies described in this paper focused on writing tasks written in the Hebrew language. Hebrew differs in several key ways from Latin-based scripts, as shown in Figure 1. Hebrew writing progresses from right to left, successive letters are usually not connected even during script (cursive) writing and five letters have a different form when they are written at the end of a word. As in other languages, some letters in the Hebrew alphabet are constructed from two separate, unconnected components. This is illustrated in the first line of the square on the left side of Figure 1, which represents a sentence containing six words, each of which is composed of two-to-four letters. The first letter of both the second word (letter ‘Hay’) and the sixth word (letter ‘Aleph’) contain two unconnected components.
VisuDat. This is a suite of visualization tools developed via Mathematica toolboxes (http://www.wolfram.com/products/mathematica/index. html) and based on signal analysis and pattern recognition techniques to support the online presentation of complex handwriting data. These tools facilitate the inspection of complex data by novice users, helping them to discern relationships between variables and to explore specific phenomena in depth.

VisuDat makes it easy to inspect the data qualitatively as well as quantitatively. Initially, the raw data are a structureless stream of six channels including measurements of one channel for temporal measurements (time in seconds), two spatial channels (stroke width and height in mm), one channel of pressure measurements (in non-scaled units ranging from 0–526) and two channels of pen orientation measurements (pen elevation (0–90°) and pen azimuth (0–360°)). The azimuth is a horizontal measure of the angular distance from the direction of writing on the digitizer and the elevation is a vertical measure of the elevation from the surface of the digitizer.

These raw data channels have been manipulated into structured and meaningful entities in order to enable inspection of different handwriting measures via various projections of the data. For instance, one is able to view any measure, raw or calculated, either from an On-Paper viewpoint or an In-air (time while writing that the pen is not in contact with the writing surface) viewpoint. To this end, the data were separated into their On-Paper and In-air components. Each component was then further divided into strokes such that each stroke or group of strokes may be manipulated directly and individually. A stroke is, therefore, the baseline unit that can be described and analysed in terms of its special features, such as its pressure, time and orientation. In order to be able to analyse these data with greater sophistication and automation, VisuDat was designed to have the capability of providing a still higher level of data structuring. Thus, VisuDat can construct words and sentences from the initial structureless lists of strokes. This gives researchers and clinicians greater power and flexibility, enabling them to delve deeper into the process of writing.

Procedure

The study was approved by the institutional review board of the Israeli Ministry of Education. The children's parents signed an informed consent form. All participants were tested individually under similar environmental conditions, a quiet classroom in their school during the morning hours. The participant was seated on a standard school chair and in front of a school desk, appropriate to his or her height. The paragraph copying task was presented visually on the screen. The paragraph was written by the participant on normal writing paper with printed lineature, which was affixed to the digitizing tablet. The same tester carried out all computerized data collection sessions.

Data presentation and analysis

The visualization and processing techniques are illustrated via the presentation of the results of analyses of handwriting texts sampled from two children, a poor handwriter and a proficient handwriter. This series of paired samples illustrates how the two or three dimensional (3-D) monochrome or colour visualization and processing techniques may enhance one's conceptualization of the dynamic handwriting process in the spatial and temporal domains, as well as highlight differences between poor and proficient handwriters. The SPSS statistical package (version 10) was used to compute T-tests to compare group differences across the dependent measures of the handwriting product and process (e.g. letter width, number of times pen lifted from page, number of reversals in direction of writing) for the paragraph writing task.
Results

The visualization and processing techniques are illustrated via the presentation of samples of handwriting texts from two children, a poor handwriter and a proficient handwriter. Figure 1 shows a 30 word, 107 character paragraph copied by a proficient handwriter (left panel) and copied by a poor handwriter (right panel). The novel element is that each text is shown embedded within an $x - y$ grid, which highlights the spatial organization of each written passage. One can readily observe the overall orderliness of the paragraph on the left with even spacing between successive letters and words and the judicious use of available surface space. In contrast, the characters and words in the text on the right are more variable, unevenly spaced and have anomalies in letter height and width. This information is far less apparent when only means and standard deviations are used to summarize the various outcome measures used to analyse the text.

The presentation of the text within a grid, as shown in Figure 1, enhances one’s ability to discern the spacing between successive letters and words and to identify anomalies in letter height and width and the line slope. Moreover, it enables the ready selection of segments of text that warrant further study. For example, it is easier to notice words with insufficient spacing between successive letters such as the last word in the third line.

It is especially important to note that the handwriting anomalies of the poor handwriter (right panel) become more apparent as the child progresses in the writing of the paragraph. It is only towards the end of the first sentence that corrections appear and the writing veers increasingly upward and downward from the line as the text progresses. Increasing the resolution of the grid would further enhance the visibility of handwriting anomalies.

A replay of the recorded traces of such texts (which cannot be shown in the hard copy medium of this report) was also developed and implemented via Mathematica. This animated process enhances the visualization of disruptions in the flow of writing and provides important information about writing inconsistencies and dysfluencies in the non-proficient handwriting.

Figure 2 shows the In-air trajectories (i.e. excursion of the pen when it was above the writing surface) for the same text shown in Figure 1, again for a proficient writer (left) and for a poor writer (right). Strokes that occurred when the pen was positioned above the tablet are marked in grey or bold black strokes, where grey strokes are the ‘obligatory’ lifts (i.e. those the writer creates when going from one word to the next or from one line of writing to the next) and bold black strokes are the ‘unnecessary’ lifts (i.e. those the writer creates when the pen is lifted for no purpose related to the flow of writing). Closer examination of these data revealed that the number of times that the child raised his pen to a height greater than 6 mm while writing is a meaningful measure as will be described below in greater detail. For example, the proficient writer raised his pen 28 times while writing this text, whereas the poor writer raised his pen 37 times. This example illustrates the unnecessary effort expended by some children while writing.

An analysis of pen lifts showed that proficient writers raised the pen primarily when obligatory, that is at essential places such as the end of lines and the end of words. In contrast, non-proficient writers frequently lifted the pen at non-essential locations which may have been due to poor planning and the need to correct errors. It is important to note that the identification of the occurrence and type of pen lifts was entirely automatic.

Figure 2. The In-air trajectories during the writing of a 30 word text by a proficient 8-year-old writer (left) and a poor writer of the same age (right).
Previous studies [28,29] have shown the importance of the In-air measure for differentiating between poor and proficient writers; analyses of the ‘temporal dynamics’ were performed with particular emphasis on when the pen moved while In-air. In Figure 3, the results of a newly developed analysis technique shows the distribution of these In-air segments for a proficient (black) and poor (grey) writer when they copied a 107 character paragraph.

The $x$-axis represents the length of In-air segments in milliseconds and the $y$-axis represents relative frequency as a function of segment length. The distribution for the proficient writer is skewed to the left of the graph, with the majority of segment lengths being less than 100 ms and extending to no more than 250 ms. In contrast, the poor writer has a wider distribution of segment lengths extending to almost 600 ms.

In order to further develop ways to document variability in the temporal domain of non-proficient handwriters, as well as the spatial features of the handwriting product, an analytic procedure was developed to identify words via the automatic grouping of successive characters into logical units. The algorithm takes into account the relative spacing between the start and finish of each character and each word. Too much space between character strokes will cause it to remain isolated from adjacent strokes. Too little space between character strokes will lead to the formation of pseudo-words, usually created from the conjunction of two successive words. This procedure enables a connecting line to be drawn from the location of the first stroke until the completion of the last stroke of each unit of writing. As shown in the left panel of Figure 4, one is able, at a glance, to perceive the division of the text into logical units which, for a proficient writer, are words. Indeed, for this writer, there are neither isolated segments nor letters associated incorrectly into pseudo-words. In contrast, as shown in the right panel of Figure 4, the logical units do not always correspond to words for the non-proficient writer.

Figure 3. The distribution of In-air segments for a proficient 8-year-old writer (black) and poor (grey) writer of the same age when they copied a 107 character paragraph.

Figure 4. An automatic computerized division of the text (as above) written by a proficient 8-year-old handwriter (left) and a non-proficient handwriter of the same age (right).
In this case, 16 letters have been misconnected into pseudo-words (usually made up of two successive words) and there are four isolated segments.

The outcome of this procedure provides a measure of the difference between the actual number of words in the paragraph (30) and the number of words computed by the algorithm. For example, in Figure 4, there is no difference in the number of actual words and the number of computed words for the proficient handwriter whereas, for the non-proficient writer, only 17 out of the 30 words are identified correctly as words.

Based on the evidence revealed in Figures 1–4 regarding the inconsistency and variability of the writing product and process, an algorithm was developed to quantify the relationship between temporal and spatial variables for each written character. In Figure 5, the rectangles represent the actual width and height of each stroke while the circles represent the time spent in drawing the stroke. The presentation of the data in this way highlights incongruencies between the size of the rectangles (representing the character’s spatial dimensions) and the circles (representing the character’s temporal history). These incongruencies indicate that the writer is inefficient, spending too much time in the formation of certain characters.

For clarity’s sake, Figure 6 shows the same results for a sub-set of the data presented in Figure 5. Again, the key feature of this figure is the incongruent relationship between character size (as depicted by the rectangles) and time spent forming the character (as depicted by the circles). For example, the poor handwriter (lower panel) spends an inordinate amount of time when writing final letters such as the final zadi (ת"א) (indicated in Figures 5 and 6 by the black arrows) relative to the size of this letter. These final letters are known to be difficult characters in Hebrew writing due to their complex shape [51,52].

These results are summarized in Figure 7, which depicts individual strokes as points in the space-time co-ordinate system. Each stroke is represented by its length in millimetres and by the time needed to produce it in milliseconds. Observing this cloud of points provides a visual overview of the correlation between the spatial and temporal behaviour of proficient and non-proficient writers and to what extent the data represented by the cloud of points are close to a straight line fit. Of course, a correlation coefficient for the whole paragraph containing 107 characters is also calculated. However, Figure 7 reflects visually. It is evident from this figure that the distribution of characters for the poor handwriter (right) is much more dispersed than that of the proficient handwriter (left), as reflected by the respective correlation coefficient values ($r = 0.93$ for the proficient and $r = 0.65$ for the poor writer).

This graph also highlights the temporal and spatial values while writing different characters. For example, most letters written by the proficient writer (left), with the exception of six characters, are no larger than 15 mm and require 1.00 s to write. In contrast, the non-proficient handwriter (right) has
written more characters that are far from the ‘best least squares fit’ line, i.e. five characters which are around the 10 mm but required between 3.0–10.0 s to write.

The computerized system not only records the temporal and spatial measures of the handwriting process, it also records changes with which the angle of the pen is held while writing. The goal is to depict the way a person holds his/her pen. The 3-D plot shown in Figure 8 represents the location of the pen tip at the centre of a cube. The lower plane of the cube represents the writing surface. The length of the pen is represented by two lines; the smooth line indicates its position and orientation at the start of the word, whereas the striped line represents its position and orientation at the end of the word. The blue arcs located between these two lines represent the angular trajectory of the upper end of the pen resulting from changes in its azimuth and tilt in the \( x \), \( y \) and \( z \) axes. The left panel of Figure 8, representing a sample from a proficient writer, demonstrates that this writer held the pen tilted forward towards the paper and made only small changes in angle while writing the word. In contrast, the sample shown in the right panel, which was taken from a poor writer, shows an angle of 90\(^\circ\) between the initial position of the pen and paper as well as a greater range of pen angles. This graphic visualization highlights the pen’s angular trajectory by eliminating translational movement of the pen from character to character within the word.

These dynamic visualization techniques are capable of revealing additional information on handwriting difficulties when they are applied to an entire text. For example, the differences in pen angular trajectory between the poor and proficient handwriters are even more apparent when the graphical analysis described above is applied to the complete text of the 107 character paragraph used in this study. Figure 9 illustrates the curves of the pen’s trajectory used in writing samples from the same proficient writer (left) and poor writer (right) whose data were presented above. Note how much variability is apparent in the poor writers’ sample in comparison to the highly consistent trajectory used.
by the proficient writer when the entire text is represented.

The visualization approach introduced in this study has the potential to lead to a deeper understanding of the handwriting process and appears to identify many salient features for individual handwriters. However, although this approach is instructive in and of itself, further measures need to be identified to enable a quantitative analyses of the handwriting product and process. To accomplish this, the paragraph copying tasks of the 15 proficient and 15 poor handwriters in the study sample were analysed with the algorithms used to produce Figures 1–9. T-tests were then used to determine which spatial and temporal measures differentiated between poor and proficient handwriters. As presented in Table I, significant differences were found between proficient and non-proficient handwriters for some of the developed measures including the standard deviation of letter width \( (t=2.45, p=0.02) \) and letter height \( (t=2.25, p=0.03) \), the standard deviation of pen elevation \( (t=2.91, p=0.001) \), the number of pen lifts \( (t=2.27, p=0.03) \), the difference between actual and computed number of words \( (t=2.79, p=0.001) \) and the correlation coefficient between letters size and performance time \( (t=-5.18, p=0.001) \).

**Discussion**

Some 45 years ago, Herrick [53] remarked on the benefits of having evaluation tools sophisticated enough to document an individual’s handwriting, in a way that would be responsive to the variability of different handwriting features among typical
children and adults. Much more recently, O’Hare [43] has called for further research to be able to better respond to the challenge of dysgraphia evaluation and intervention. Throughout the intervening years there have been regular appeals to develop objective tools feasible for use by educators and clinicians [54].

The objective of this paper was to respond to these needs by presenting an overview of how visualization tools based on signal processing methods may be used to support the online presentation of complex handwriting data. These innovative techniques, providing new options for the analysis and presentation of the spatial and temporal dimensions of handwriting, greatly extend the power of the recently developed POET digitizer-based handwriting analysis program [28].

First, they help to achieve a bridge between information obtained via traditional evaluation and the more recent objective, digitizer-based data. The figures in this paper illustrate some of the spatial features that have been previously considered in handwriting product evaluation scales, most of which include criteria such as letter size and slant, spacing between letters and words, the straightness of lines, letter forms and shapes and the general merit of the writing [8,26,49,55–57]. Despite the years of study, many questions remain regarding which of these criteria constitute the critical components of handwriting readability and how these criteria can be measured [8,58–62]. The contribution of the current study is in its presentation of a variety of novel techniques in which these criteria may be visually represented and easily measured and in the demonstration of how they may be used to gain a more comprehensive appreciation of the distinctive characteristics of the poor handwriting process.

Consider, for example, the criteria of letter size and the spacing between letters and words which are typically included in analytic handwriting scale evaluations. Display of the written product on a scaled grid, as shown in Figure 1, enhances inspection of the phenomena and facilitates objective measurement of the spaces between letters and words in millimetres (rather than by making subjective estimations as usually performed (e.g. CHES evaluation, [61] or BHK [33]). Since this technique is computerized, it enables an automated tabulation of objective measures for letter width, height and the distance between letters and words (cf. Table I and Figure 4).

Secondly, the analytical and visualization techniques presented in this paper provide the possibility of presenting a readily understood display of objective measures of handwriting to a child with handwriting difficulties as well as to the parents. This visual presentation of the data may contribute to the client’s participation in the evaluation process. The graphic representations provided by the VisuDat system illustrate phenomena that would have been otherwise obscure to non-expert viewers. Thus, the implications of the variability of the child’s spatial and temporal handwriting may be demonstrated via visual images that may contribute to the evaluation and treatment of handwriting difficulties. For example, the intricate trajectories of the pen and movement reversals shown in Figures 5 and 6 highlight the letters most problematic for the child and for which an inordinate amount of effort is expended. Close examination of the individual letters that entail large variability and extraneous pen movements provide clues to therapists and educators regarding the source of the child’s handwriting difficulties (e.g. whether letter formation has been sufficiently internalized or whether strokes have been correctly produced in the correct sequence).

Much literature exists to support the effectiveness of visual and/or auditory feedback for evaluation and treatment goals. Commonly referred to as biofeedback, a person receives visual or auditory feedback regarding internal processes that are normally unconscious [61]. The benefits of the visual images for evaluation and treatment among children with different pathologies such as ADHD [63], migraine [64] or childhood seizure disorders [65] have been widely discussed. Furthermore, such visualization tools facilitate the inspection of complex data by novice users so that they may discern relationships between variables and explore specific phenomena in depth [66].

Bruinsma and Nieuwenhuis [55] have suggested that self-assessment may encourage students to improve their handwriting and to become aware of changes. The extent to which the provision of visual images highlighting handwriting difficulties is able to contribute to a child’s participation in the evaluation and intervention process should be investigated as this is an element of handwriting assessment that has not been sufficiently feasible to date [23].

The contribution of visualization in other disciplines has been recognized to nurture a meaningful dialogue between researchers and practitioners. For example, visualization techniques have led to advances in medical informatics research as well as in medical education and have also had significant clinical implications for application in both diagnosis and intervention [66,67]. Moreover, such visualization systems likely represent the initial stages towards the development of more reliable and valid evaluation tools, a need well recognized by researchers familiar with the currently available handwriting assessments [59].
The visualization options presented in this paper will likely stimulate the development of new measures to assist in the identification of additional important features of handwriting. For example, the data as presented in Figure 1 have already led researchers to attempt to find a measure that can be used to reveal the consistency in the size of letters and in the spacing of letters and words as they are produced within a given text. The results shown in Figure 4 underscore the difficulty that some handwriters have in spacing successive letters and words, and the results shown in Figures 5 and 6 highlight discrepancies between stroke length and time to write.

Some of the routines developed for this paper result in the presentation of results on the handwriting process that the human eye alone is incapable of discerning. For example, in a previous study, In-air time was found to be an important variable capable of significantly distinguishing between proficient and non-proficient handwriters [29]. In the current study, the In air phenomena was further investigated through the use of the newly developed analytic techniques. The spatial inconsistencies and dysfluencies that typify the On paper pen movements of poor handwriters are particularly apparent when the In-air pen trajectories are illustrated as shown in Figure 2. The difficulties that plague non-proficient writers during their ‘non-writing’ periods seem to be similar to those that limit their performance during their ‘writing’ periods with respect to writing dysfluencies and the increased energy requirements that characterize their writing. This feature of non-proficient handwriting is also emphasized by the graph in Figure 3, which illustrates the increased distribution of the lengths and frequencies of In-air segments produced by a poor writer vs the proficient writer. Furthermore, the computerized calculation of the number of non-obligatory pen lifts that characterize the writing sample produced by a non-proficient handwriter as compared to that of a proficient handwriter (cf. Figure 2) further highlights the atypical writing dynamics and dysfluencies that characterize non-proficient handwriting production. Indeed, the number of pen lifts was found to significantly distinguish between poor and proficient handwriters.

The angular trajectory of the pen is a feature of the handwriting process that has not previously been examined in detail. The dynamic visualization techniques illustrated in Figures 8 and 9 revealed a remarkable difference in the consistency of the pen’s elevation and azimuth when manipulated by a proficient vs a non-proficient handwriter. The present results demonstrated that the non-proficient handwriters utilized a significantly more variable range of pen elevations due to an increased number of translational movements made by the pen as they progressed from character to character while writing a word. Indeed, the range of pen angular trajectories seemed to be the major differentiating aspect of the poor handwriting process, as no significant differences were found between the study groups for the mean elevation and azimuth of the pen when in contact with the writing surface.

Conclusions

The graphical and analytical techniques illustrated in this paper highlight the major features that characterize poor handwriting including a lack of movement precision, dysfluency and inconsistency in spatial and temporal measures. They support the findings of previous studies [9,19,21,26,27,31,32]. These automated, language-independent visualization and analysis procedures have highlighted many salient features of the differences between poor and proficient writing which have the potential to be very useful for clinicians, educators, parents and children in the evaluation and remediation of handwriting deficiencies. One of the main purposes of this work was to develop a tool that would become a useful clinical tool. Hence, the data collection part of the software has been designed to be easy to use. It has already been implemented in several clinical and educational centres around the world and used in different languages. The clinician and teacher only requires a laptop computer and x–y digitizer. The portability of these instruments means that the evaluation can take place in the child’s natural environment. Data analysis is carried out centrally from data transmitted by clinicians. They, in turn, receive a full report of the child’s handwriting difficulties.

The authors are continuing to develop additional analytical routines that will provide greater capabilities for identifying handwriting difficulties. Results of the type presented in this paper point to the benefit of flexible visualization and analysis techniques. A future study will directly examine the responses of clinicians and educators to these results and modify the data presentation in accordance with this feedback.

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