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INTELLIGENT HANDWRITING ASSESSMENT ALGORITHM USING THE CATMULL-ROM SPLINE

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Abstract

The article is devoted to the development and application of an algorithm for analyzing graphomotor writing trajectories in digital educational systems using the Catmull-Rom spline. The problem of improving the accuracy and stability of processing user input received from touch devices (stylus or finger) in the context of digital writing learning is considered. The proposed method includes the stages of coordinate data collection, normalization, noise filtering, and trajectory smoothing. The Catmull-Roma spline is used to ensure the continuity of curves and preserve key motion features, which increases the accuracy of comparison with reference patterns.

The paper presents a computational algorithm that implements an automatic assessment of the quality of letter writing based on a number of parameters: curvature, angular deviations, speed stability and the number of strokes. The algorithm is integrated into a digital diagnostic system capable of generating detailed reports, identifying common errors, and offering personalized tasks. The developed solution can be used in intelligent learning platforms, biometric authentication systems, neuropsychological diagnostics and computer forensics.

The proposed approach demonstrates high adaptability to various input scenarios and provides the basis for building more complex machine learning systems focused on recognizing, analyzing, and generating handwritten text.

Keywords: Catmull–Rom spline, algorithmic analysis, digital diagnostics, processing of writing trajectories, intelligent systems, mathematical modeling, educational technologies.

КЭТМУЛЛ-РОМ СПЛАЙН КӨМЕГІМЕН ҚОЛЖАЗБАНЫ БАҒАЛАУДЫҢ ИНТЕЛЛЕКТУАЛДЫ АЛГОРИТМІ

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Аңдатпа

Мақала Катмулл-Ром сплайнын қолдана отырып, цифрлық білім беру жүйелерінде графомоторлы жазу траекториясын талдау алгоритмін әзірлеуге және қолдануға арналған. Сандық жазуды оқыту контекстінде сенсорлық құрылғылардан (қалам немесе саусақ) алынған пайдаланушы енгізуін өңдеудің дәлдігі мен тұрақтылығын арттыру мәселесі қарастырылуда. Ұсынылған әдіс координаталық деректерді жинау, қалыпқа келтіру, шуды сүзу және траекторияларды тегістеу қадамдарын қамтиды. Катмулл-Ром Сплайн қисықтардың үздіксіздігін қамтамасыз ету және қозғалыстың негізгі ерекшеліктерін сақтау үшін қолданылады, бұл анықтамалық үлгілермен салыстыру дәлдігін арттырады.

Жұмыста әріптер сызбасының сапасын бірқатар параметрлер бойынша автоматты бағалауды жүзеге асыратын есептеу алгоритмі берілген: қисықтық, бұрыштық ауытқулар, жылдамдық тұрақтылығы және соққылар саны. Алгоритм егжей-тегжейлі есептерді қалыптастыруға, типтік қателерді анықтауға және жеке тапсырмаларды ұсынуға қабілетті сандық диагностикалық жүйеге біріктірілген. Әзірленген шешім интеллектуалды оқыту платформаларында, биометриялық аутентификация жүйелерінде, нейропсихологиялық диагностикада және компьютерлік криминалистикада қолданылуы мүмкін.

Ұсынылған тәсіл әртүрлі енгізу сценарийлеріне жоғары бейімделуді көрсетеді және қолжазба мәтінін тануға, талдауға және генерациялауға бағытталған күрделі Машиналық оқыту жүйелерін құруға негіз береді.

Кілт сөздер: Catmull–Rom spline, алгоритмдік талдау, сандық диагностика, жазу траекториясын өңдеу, интеллектуалды жүйелер, математикалық модельдеу, білім беру технологиялары.

ИНТЕЛЛЕКТУАЛЬНЫЙ АЛГОРИТМ ОЦЕНКИ ПОЧЕРКА С ИСПОЛЬЗОВАНИЕМ СПЛАЙНА КЭТМУЛЛ-РОМА

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Аннотация

Статья посвящена разработке и применению алгоритма анализа графомоторных траекторий письма в цифровых образовательных системах с использованием сплайна Кэтмулл-Рома. Рассматривается задача повышения точности и устойчивости обработки пользовательского ввода, полученного с сенсорных устройств (стилус или палец), в контексте цифрового обучения письму. Предложенный метод включает этапы сбора координатных данных, нормализации, фильтрации шумов и сглаживания траекторий. Сплайн Кэтмулл-Рома используется для обеспечения непрерывности кривых и сохранения ключевых особенностей движения, что повышает точность сравнения с эталонными шаблонами.

В работе представлен вычислительный алгоритм, реализующий автоматическую оценку качества начертания букв по ряду параметров: кривизна, угловые отклонения, стабильность скорости и количество штрихов. Алгоритм интегрирован в систему цифровой диагностики, способную формировать детализированные отчёты, выявлять типовые ошибки и предлагать персонализированные задания. Разработанное решение может применяться в интеллектуальных обучающих платформах, системах биометрической аутентификации, нейропсихологической диагностике и компьютерной криминалистике.

Предложенный подход демонстрирует высокую адаптивность к различным сценариям ввода и обеспечивает основу для построения более сложных систем машинного обучения, ориентированных на распознавание, анализ и генерацию рукописного текста.

Ключевые слова: Catmull–Rom spline, алгоритмический анализ, цифровая диагностика, обработка траекторий письма, интеллектуальные системы, математическое моделирование, образовательные технологии.

Introduction

Writing analysis on a device is a promising field combining pedagogy, neurotechnology, artificial intelligence and digital interfaces. Digitization of handwriting, digital handwriting diagnostics and the creation of digital standards of letters is one of the urgent interdisciplinary problems of modern education, medicine and criminology. Analyzing handwriting and writing letters and symbols using digital tools, methods, models, and algorithms can be used to solve a variety of tasks. For example:

– Diagnosis and development of graphomotor skills in children;

– Automatic verification of written papers;

– Neuropsychological diagnostics (early diagnosis of neurological diseases such as Parkinson's disease, dementia, stroke; to monitor patients' condition by changing their handwriting);

– Assessment of cognitive functions (analysis of motor coordination, reaction speed and cognitive deviations);

– Identity authentication (biometric identification by handwriting, signatures, security signatures on documents);

– Forensic examination (comparison of handwriting to establish forgeries or authorship of manuscripts).

– Digitization and translation of historical and archival documents, simplification of archive search;

– Automation of office processes (recognition and translation of handwritten notes, forms and questionnaires into electronic documents).

– Helping people with disabilities. Converting handwriting into text for the visually impaired or people with motor impairments and generating "handwriting" based on text to simulate writing.

– The use of human-machine interfaces, for example, the creation of intelligent recognition systems (based on machine learning).

The relevance of this study is due to the fact that the development of models, methods and algorithms for early diagnosis of graphomotor skills of preschoolers when learning to write using digital devices will help to timely select corrective tasks, which will have a positive impact on school preparation.

The purpose of the study is to substantiate and test the use of the Catmull-Rom spline for letter spelling analysis in the framework of digital writing training. The article presents algorithms for writing analysis and error analysis when learning to write, as well as demonstrates the possibilities of their use to assess the accuracy and quality of writing letters, identify deviations from the standard and personalize training tasks when using a digital learning platform.

Let's consider research in the field of digitization of handwritten text and recognition of handwritten images. In the study [1], the authors presented advances in handwriting recognition (HTR), focusing on the digitization of historical documents such as civil registry records in Belfort. The article [2] presents an improved handwriting recognition system that digitizes handwritten texts using CNNS and RNNS with LSTM cells, providing an error rate of 8% in characters and 12% in words after integrating the autocorrect function. The article [3] discusses handwritten digit recognition using deep learning, in particular convolutional neural networks (CNNS), with an accuracy of 99.87%. It highlights the potential of future research in the field of handwriting recognition and symbolism, as well as the application of these systems in various real-world scenarios. The article [4] presents an author-independent handwriting recognition system using a pen equipped with a sensor, which allows achieving promising results in recognizing characters on plain paper without special user training.

Much attention in the scientific literature is paid to assessing the development of graphormotor skills of preschoolers using digital devices. The article [5] discusses a tablet-based platform designed to quantify graphomotor skills, focused on both the speed of pen movement and the quality of graphics output. In the article [6], the author studied the development of handwriting and fine motor skills in preschoolers using digital devices and analyzed the influence of handwriting on academic success.

The article [7] analyzes the graphomotor skills of young children (aged 6 years) when writing and drawing on a tablet screen. It highlights such characteristics as writing speed and pressure during these actions. The study involved 108 children, and it was found that those who created both text and drawings were more common than those who only wrote. It was also noted that the children showed lower speed and greater stress when drawing compared to writing, which allowed them to gain an idea of their movement control skills.

The article [8] discusses an experimental study that tests an innovative tactile device designed to analyze graphomotor performance and coordination of movements in real time. The article [9] discusses an original approach to the diagnosis of graphomotor disorders using an objective analysis of handwritten text on the Internet. It presents the "Graphomotor and

Handwriting Disorders Assessment Scale" (GHDRS), which allows a detailed assessment of children's difficulties with writing. The article [10] discusses the assessment of graphomotor skills in preschoolers and elementary school students using graphic tablets. The article [11] presents an analysis of graphomotor skills using graphic tablets, which focuses on a tool for the preliminary diagnosis of dysgraphy.

Materials and methods

It was revealed that when doing tasks on the tablet, preschoolers make the same mistakes as when doing tasks in the registration form. The most commonly used tools for solving problems of the accuracy of writing letters and lines of various trajectories on digital devices are:

– Polygonal approximation – dividing the trajectory into segments;

– Piecewise linear model - analysis of shapes and angles in letter elements;

– Splines (for example, Catmull-Rom) – smoothing of trajectories for shape analysis;

– Speed filtering – removing noise, identifying significant phases of movement;

In our case, the mathematical apparatus underlying the analysis of the results of drawing a curve on a tablet screen is a polygonal chain (Piecewise linear function). The input data for constructing the trajectory is formed from a sequence of user touch points $S = \{P_0, P_1, \ldots, P_m\}$, where each point $P_j = (x_j, y_j)$ represents coordinates on the touch screen. This sequence of points is used to form a polygonal chain (polyline) [12].

A polygonal chain L is defined as the union of straight line segments connecting consecutive points of tangency (1):

$$L = U_{j=0}^{m-1}\overline{P_jP_{j+1}}. \tag{1}$$

Each segment $\overline{P_jP_{j+1}}$ is a linear function. Thus, the entire trajectory at this stage is a piecewise linear function.

To improve the visual quality and eliminate the sharp angles characteristic of a polygonal chain, smoothing based on the Catmull-Rum spline is used. The Catmull-Roma spline is a type of cubic Hermitian spline that has the property of interpolation, that is, the constructed curve passes through all specified control points.

To construct a segment of the Ck(t) curve of the Catmull-Roma spline between two control points P_k and P_{k+1} (where P_k are the points of the original polygonal chain), four consecutive control points are used: $P_k -1$, P_k, $P_k +1$, $P_k +2$. The parameter t varies from 0 to 1.

The segment of the curve $C_k(t)$ for $t \in [0,1]$ can be represented in the following matrix form (2):

$$C_k(t) = [t^3\ t^2\ t\ 1]M_{CR}\begin{bmatrix}P_{k-1}\\P_k\\P_{k+1}\\P_{k+2}\end{bmatrix} \tag{2}$$

where M_{CR} is the Catmull-Rum basis matrix:

$$M_{CR} = \frac{1}{2}\begin{bmatrix}-1 & 3 & -3 & 1\\2 & -5 & 4 & -1\\-1 & 0 & 1 & 0\\0 & 2 & 0 & 0\end{bmatrix}. \tag{3}$$

This shape corresponds to the standard Catmull-Roma spline with a tension parameter τ=0.5, which provides a so-called "centripetal" spline that copes well with possible self-intersections and sharp angles with uneven point distribution.

For the extreme segments of the polygonal chain (initial and final), special processing is required, for example, by duplicating the extreme points ($P_{-1} = P_0$ и $P_{m+1} = P_m$) in order to provide a sufficient number of control points for the formula [13].

Using the Catmull-Rom spline allows you to achieve C^1 – curve continuity at the junction points of the segments (with the possible exception of the start and end points of the entire curve), which ensures a smooth transition between segments and eliminates visual kinks. This approach effectively combines the accuracy of the basic polygonal chain approximation with the aesthetics of a smooth curve without the need for additional manual correction [14].

Effective line drawing analysis in teaching writing to children requires consideration of individual motor skills, sensory input parameters, and the ability to track the dynamics of changes. This system implements an adaptive algorithm for processing trajectories, including the steps of determining the method of data entry, filtering and smoothing, comparing them with reference samples, as well as saving results and building progress reports. The developed algorithm for analyzing emails with the stages of saving and tracking progress is shown in Fig. 1.

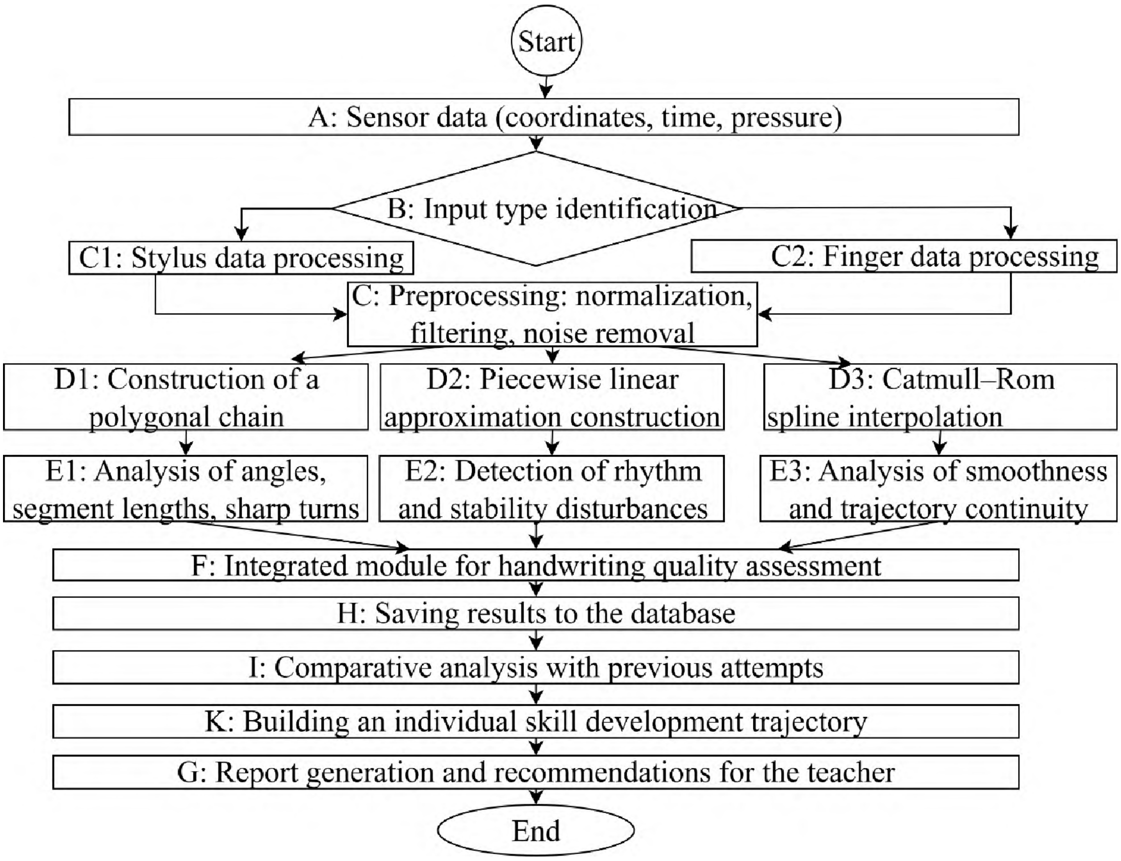

Figure 1. Writing analysis algorithm

Changing the input method – with a stylus or a finger – significantly affects the algorithm for analyzing the outline of lines, especially in tasks to assess the quality of writing in children.

These two input methods differ in sensor specifications, accuracy, pressure level, and trajectory characteristics, which requires algorithm adaptation.

Description of the stages:

Block B determines the type of input (with a finger or a stylus) using the touch API. Divides the data into two streams: TOOL_TYPE_STYLUS and TOOL_TYPE_FINGER.

Changing the smoothing and filtering parameters. For example, you can use more aggressive filtering for finger input (for example, median filters or a spline with a large smoothing parameter). To enter with a stylus, apply smoothing with a lower level that preserves details.

A system of parameters reflecting the key characteristics of the writing process has been developed for the quantitative and qualitative assessment of a child's graphomotor skills. These parameters allow you to capture and interpret the features of the outline of the lines, providing an objective diagnosis of deviations and developmental dynamics. The analysis methods are based on mathematical representations of trajectories and consideration of time characteristics. Table 1 shows the key parameters for analyzing a letter based on sources [15-19].

Table 1. Key parameters for letter analysis

Parameter	Analysis method	Characteristic of the measured parameter
Curvature and angles of rotation	Polygonal chain	Frequency and sharpness of direction changes
Length and regularity of segments	Piecewise linear function	The stability of the writing pace
Smoothness and continuity	Catmull Spline-Roma	Assessment of motor coordination, detection of tremors
Writing speed	All methods (by point time)	Associated with confidence and experience
Fluctuations and jerks	Spline + velocity filtering	Indicators of motor disorders or overwork

A comparative analysis of the characteristics of various input methods makes it possible to increase the accuracy of interpretation of graphomotor data and adapt processing algorithms taking into account the specifics of the device. Special attention is paid to the differences between the stylus and the finger as the main tools for user interaction with the screen. These differences affect both the physical and technical parameters (accuracy, sensitivity, pressure support) and the shape features, which affects the choice of filtering, smoothing, and interpretation methods. Table 2 shows the key differences between a stylus and a finger, which are taken into account in the analysis process based on sources [20-23].

Table 2. Key differences between a stylus and a finger

Parameter	Stylus	Finger
Positioning accuracy	High (up to ~0.1mm)	Medium/Low (~2-4 mm)
Sensor frequency	Higher (60-240 Hz)	No Lower (30-60 Hz)
Pressure support	Yes (for many models)	No
The presence of tilt (tilt)	Yes (for some models)	No
Line thickness	Variable (depending on pressure)	Static or severely limited
The naturalness of writing	Closer to the paper	Less controlled, more rounded

When analyzing a curve drawn with a finger, the permissible deviations increase when compared with the reference. For a stylus, a lower error is allowed, and the accuracy requirements are higher.

Blocks C1 and C2 contain different filtering parameters (softer for the stylus, harder for the finger); different tolerance standards and sampling rates.

Block F aggregates the results from all three approaches, forming a comprehensive characterization of the child's handwriting, taking into account both the structure of the line and its dynamic features.

Block H stores numeric metrics, type of analysis, timestamps, device type, and preschooler ID.

Block I performs a comparative analysis and compares current data with previous ones (child's profile, date, age).

Block J evaluates the level of assimilation by calculating dynamics based on key metrics (improvement of smoothness, reduction of fluctuations, etc.).

Metrics used in J:

– average angular deformation (along a polygonal chain);

– the variance of the length of the segments (piecewise linear function);

– the average curvature and its continuity (spline);

– the smoothing coefficient of the trajectory;

– motor stability index (for fluctuations in pressure and speed).

Block K is the formation of an individual trajectory. Output of writing skill level (low, medium, high), tasks are offered.

Block G. Generates a report on the formation of graphomotor skills in preschool children.

Results and discussion

Creating a digital reference for a letter or font is an important task in the context of learning to write using digital devices. The importance of creating a digital benchmark is due to the following factors:

– The lack of uniform standards in digital writing education. Most applications use arbitrary or stylized letter shapes, which can lead to incorrect learning of the shapes and negatively affect the child's handwriting.

– Early correction of violations. The standard allows you to record deviations from the norm (for example, in children with impaired development of fine motor skills), which makes it possible to connect corrective techniques in time.

– Integration with artificial intelligence. Digital benchmarks are used as a base for training machine learning models that can recognize, interpret, and correct writing errors, as well as generate adaptive feedback.

– Consideration of age and physiological characteristics. With digital standards adapted to age categories, it is possible to more accurately select the level of difficulty of tasks and letter shapes, taking into account the child's motor and cognitive abilities.

The standard letter should be not just a static image, but a sequence of reference points and, possibly, additional information about the order and direction of the stroke.

Let's present the main steps for the formation of reference letters and their storage.

1. Graphical representation. A sequence of anchor points (x, y): This is the basic way. Each letter (or its individual element/stroke) is set as an array of coordinates through which the line should pass. In fact, this is a piecewise linear function, similar to the one that a child draws.

For example, for the letter "A" it can be three dots: upper, lower center, upper right. For more complex curves, more points will be needed to adequately describe the shape.

2. Bezier curves or splines. For smoother and more complex reference curves, mathematical descriptions such as Bezier curves or splines can be used, for example, the same Catmull-Rom. The control points of these curves will determine the reference.

3. Metadata of the reference. Number of strokes (elements): How many individual lines form a letter.

– The order of strokes. In what order should the letter elements be drawn (critical for learning the correct writing technique).

– The direction of each stroke. The start and end points of each element, indicating the correct direction of movement.

– Key points. Particularly important points on the trajectory through which the line must pass (for example, the points of the beginning, end, bend).

– Acceptable deviations (tolerance): You can set a "corridor" around the reference line, within which writing is considered acceptable.

4. Ways to create benchmarks. Manual rendering by an expert, i.e. the teacher or designer draws the perfect letter in a graphic editor, then the coordinates of the key points are exported.

Software definition: based on standard fonts and inscriptions, followed by vectorization and selection of reference points.

An example of storing standards. Letter standards, including their coordinate representation and metadata, must be stored in the application as JSON or XML files.

The algorithm for error analysis in writing training shown in Figure 2 provides a comprehensive error analysis when performing graphomotor tasks by the user. The process begins with receiving input data and ends with the formation of an assessment and feedback.

A: The beginning. This block represents the entry point to the error analysis algorithm.

B: Data from the user (points, events). At this stage, the system receives primary data about user actions. This data includes a sequence of coordinate points (x, y) recorded when touching the touchscreen, timestamps for each point, and the type of accompanying event (for example, the beginning of the touch is ACTION_DOWN, movement is ACTION_MOVE, and the end of the touch is ACTION_UP). This information forms the "raw" trail left by the user.

C: A reference for standard assignments/letters. In parallel with user input, the system accesses its database to download a reference representation of the current task. The standard is a digital model of perfect execution. It can be a trajectory for a simple graphic element ("Track"), the shape of an unbroken letter, or a set of strokes indicating their characteristics (shape, order, direction) for discontinuous letters. Benchmarks are usually stored in a structured format (for example, JSON) and contain all the necessary information for comparison.

D: Preprocessing user input.

Before the main analysis, the user's "raw" data goes through a preprocessing stage. This may include:

– determining the type of input tool (stylus or finger, which may affect the thresholds for analysis),

– filtering noise (for example, removing points that are too close due to shaking),

- preparing data for further segmentation and analysis.

E: The type of task. This is a key decision-making node, where the algorithm determines the nature of the current task in order to choose the appropriate analysis path. There are three main types of tasks:

F: A simple line/Track (for example, tracing straight, wavy lines).

G: An unbroken letter (1 stroke) (letters that are written in one continuous movement).

H: A discontinuous letter (several strokes) (letters consisting of two or more separate elements/strokes).

Processing for paths F (Simple Line/Track) and G (Continuous Letter):

Since both of these types of tasks usually involve a single continuous stroke on the user's part, their initial processing is similar.:

F1, G1 (Step 1): Processing a single custom stroke: Normalization, Smoothing. The custom stroke is first normalized – its size and position are adjusted to the standard form so that the comparison with the reference is invariant to the scale and place of writing. Then the normalized stroke is smoothed, for example, using the Catmull-Rum spline, to eliminate small vibrations and obtain a clearer representation of the intended trajectory.

F1, G1 (Step 2): Loading the reference path. The corresponding reference for a given line or continuous letter is extracted.

F2, G2: Matching a custom stroke with a reference path. The processed custom stroke is directly compared with the reference path. The results of this comparison (data on similarities and differences) are transferred to the general deviation calculation unit (I).

Processing for the path H (Discontinuous letter):

This path is designed to analyze letters consisting of several separate strokes, and includes more complex logic:

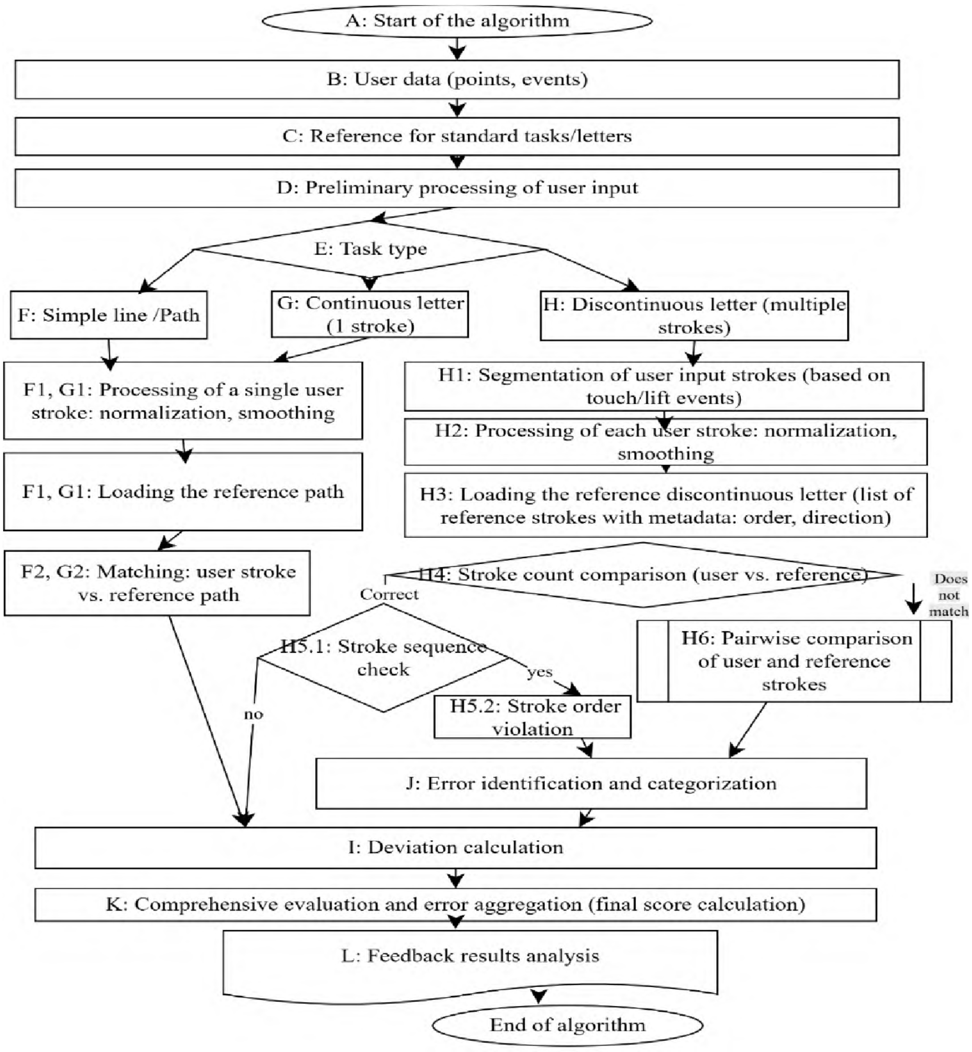

Figure 2. Error analysis algorithm

H1: Segmentation of user input into strokes. All user input for a given letter is divided into separate strokes. Stroke boundaries are used for events when the tool is lifted off the screen (ACTION_UP) and then touched again (ACTION_DOWN).

H2: Processing each custom stroke: Normalization, Smoothing. Each identified custom stroke undergoes an individual normalization and smoothing procedure, similar to that described in F1, G1 (Step 1).

H3: Loading a discontinuous letter reference. A reference is loaded, which for such letters is a list of individual reference strokes, including metadata about their correct execution order and, possibly, direction.

H4: Comparing the number of strokes (user and reference).

If the number of strokes drawn by the user does not match the reference one, the algorithm proceeds according to the scheme to Block H6: Step-by-step comparison of the user's strokes and the reference. This implies an attempt to perform an analysis based on the available data, perhaps to identify missing or superfluous strokes, or for the best possible comparison. The results of such a comparison are then sent to the error identification unit (J).

If the number of strokes matches, the check continues in Block H5_1: Checking the sequence of strokes. It analyzes whether the time order of custom strokes corresponds to the prescribed order in the reference.

If the sequence is correct ("yes"), then the analysis process proceeds to Block I: Calculation of deviations, where a detailed comparison of each pair of matched strokes (user and reference) will be carried out.

If the sequence is broken ("no"), this is recorded as an error in Block H5_2: The stroke order is broken, and information about this error is transmitted directly to Block J: Error identification and categorization.

General stages of analysis (Blocks I, J, K, L):

After the custom strokes (or stroke) are compared with the reference ones (for paths F, G, or a successful branch H), or if the analysis has moved on to processing structural errors (from H4/H6, H5_2), the following general steps are performed:

I: Calculation of deviations. This block quantifies the differences between the actual spelling and the reference for the compared strokes. Metrics are calculated, such as: the average and maximum distance from the points of the user curve to the reference line, the difference in angles between the segments, deviations in the starting/ending points of the strokes, as well as possibly more complex metrics of curve similarity (for example, the Frechet distance). For multi-stroke letters, the relative position and proportions of strokes can also be analyzed here.

J: Identification and categorization of errors. Based on the calculated deviations (from block I) and information about structural errors (for example, an incorrect number of strokes from H4/H6 or a violation of the order from H5_2), the algorithm identifies and classifies specific types of errors. Examples of categories: significant distortion of the shape, going beyond the contour, incorrect direction of movement, incorrect number or order of elements, violation of proportions.

K: Comprehensive assessment and aggregation of errors (Calculation of ErrorCount / Final Score). All identified errors and their severity are aggregated into a single comprehensive assessment. This can be a numerical indicator, such as ErrorCount (the total number of errors, as in the user's CSV file), or the percentage of accuracy (for example, calculated using the formula $P = (1 - E/n) \times 100\%$), or a more detailed error profile. At this stage, weights can be applied for different types of errors depending on their criticality.

L: Analysis results / Feedback. The final assessment and information about specific errors (possibly with recommendations for their correction) are generated to provide feedback to the user directly in the application, as well as for saving and subsequent use in reports for parents and teachers.

Based on the types and number of errors, the application can give the user specific hints (for example, "Start this line a little higher", "Lead the line more smoothly", "You missed one element").

Conclusions

The most important stage was the development of algorithms for digital processing of user input. Each interaction with the screen was recorded as a sequence of coordinate points, touch time, pressure parameters, and type of input device. These data were transformed into polygonal chains describing the trajectory of movement. In order to improve the accuracy of visual analysis and subsequent assessment of the smoothness of movement, approximation and smoothing methods were used, in particular, interpolation using the Catmull–Rom spline. A comparative analysis of the user trajectory with the reference template was carried out based on an assessment of deviations in the shape, order and direction of graphic elements. Mathematical models based on the use of piecewise linear functions were implemented, which made it possible to formalize trajectories in the form of parametric descriptions suitable for quantitative analysis. The developed metrics included indicators of angular deformation, dispersion of segment lengths, curvature, and smoothing coefficient.

References:

1. Al Kendi, W., Gechter, F., Heyberger, L., & Guyeux, C. (2024). Advancements and Challenges in Handwritten Text Recognition: A Comprehensive Survey. Journal of Imaging, 10(1), 18. https://doi.org/10.3390/jimaging10010018
2. Amruth, A., Mohanty, M., Vimal, C., Ramanan, R., & Beena, B. (2024). Advanced Handwriting Recognition System for Handwritten Scripts With AutoCorrect Feature. 1–9. https://doi.org/10.1109/icccnt61001.2024.10724995
3. P.B., Likhitha, L.K., & Rajesh, D.S. (2021). Handwritten Digit Recognition Using Deep Learning. International Journal of Scientific Research in Science and Technology, 7(4), 153–158. https://doi.org/10.32628/CSEIT217439
4. Wehbi, M., Hamann, T., Barth, J., & Eskofier, B. M. (2021). Digitizing Handwriting with a Sensor Pen: A Writer-Independent Recognizer. https://doi.org/10.1109/ICFHR2020.2020.00061
5. Rane, D., Verma, P., & Lahiri, U. (2022). How Good is your Drawing? Quantifying Graphomotor Skill Using a Portable Platform (pp. 409–422). https://doi.org/10.1007/978-3-031-22131-6_31
6. Dinehart, L.H. (2014). Handwriting in early childhood education: Current research and future implications. Journal of Early Childhood Literacy, 15(1), 97-118. https://doi.org/10.1177/1468798414522825
7. Barker, J. (2022). Characteristics and Graphomotor Skills of Young Children's Writing and Drawing on a Tablet Screen. 23(3), 273–296. https://doi.org/10.22154/jcle.23.3.12
8. Ceccacci, S., Taddei, A., Del Bianco, N., Giaconi, C., Forteza Forteza, D., & Moreno-Tallón, F. (2024). Preventing Dysgraphia: Early Observation Protocols and a Technological Framework for Monitoring and Enhancing Graphomotor Skills. Information, 15(12), 781. https://doi.org/10.3390/info15120781
9. Šafárová, K., Mekyska, J., Urbánek, T., Galáž, Z., Mucha, J., Zvončák, V., & Bednářová, J. (2022). Grafomotorické dovednosti. https://doi.org/10.5817/cz.muni.m280-0257-2022
10. Kopnova, O.L., Aytymova, A.M., Abildinova, G., Safaraliev, B.S., Koleva, N.S., & Panova, M. (2024). Assessment of the level of formation of graphomotor skills of preschool and primary school students using graphic tablets. Sovremennye Naukoёmkie Tehnologii, 1(5), 154–159. https://doi.org/10.17513/snt.40021
11. Devillaine, L., Lambert, R., Boutet, J., Aloui, S., Brault, V., Jolly, C., & Labyt, E. (2021). Analysis of Graphomotor Tests with Machine Learning Algorithms for an Early and Universal Pre-Diagnosis of Dysgraphia. Sensors, 21(21), 7026. https://doi.org/10.3390/S21217026
12. Tayebi Arasteh, S., Kalisz, A. Conversion Between Cubic Bezier Curves and Catmull–Rom Splines. SN COMPUT. SCI. **2**, 398 (2021). https://doi.org/10.1007/s42979-021-00770-x

13. Li, J., & Chen, S. (2016). The Cubic α-Catmull-Rom Spline. *Mathematical and Computational Applications*, *21*(3), 33. https://doi.org/10.3390/mca21030033
14. Wu, T., Bai, B., & Wang, P. (2013). Parallel Catmull-Rom Spline Interpolation Algorithm for Image Zooming Based on CUDA. Applied Mathematics & Information Sciences, 7, 533-537. https://www.naturalspublishing.com/Article.asp?ArtcID=1048
15. Tony D. DeRose and Brian A. Barsky. 1988. Geometric continuity, shape parameters, and geometric constructions for Catmull-Rom splines. ACM Trans. Graph. 7, 1 (Jan. 1988), 1–41. https://doi.org/10.1145/42188.42265
16. C. Kong, A. Luo, S. Wang, H. Li, A. Rocha, and A. Kot, "Pixel-inconsistency modeling for image manipulation localization," *IEEE Trans. Pattern Anal. and Mach. Intell.*, vol. 47, no. 6, pp. 4455–4472, 2025. https://arxiv.org/abs/2310.00234
17. C. Yu, X. Zhang, Y. Duan, S. Yan, Z. Wang, Y. Xiang, S. Ji, and W. Chen, "Diff-id: An explainable identity difference quantification framework for deepfake detection," *IEEE Trans. Dependable Secure Comput.*, pp. 1–18, 2024. https://arxiv.org/abs/2303.18174
18. Lyu, S., Pan, X. & Zhang, X. Exposing Region Splicing Forgeries with Blind Local Noise Estimation. Int J Comput Vis 110, 202–221 (2014). https://doi.org/10.1007/s11263-013-0688-y
19. Steve Marschner. Cornell CS4620 Fall 2020. CS 4620 Lecture 14. https://www.cs.cornell.edu/courses/cs4620/2020fa/slides/14splines.pdf
20. Li, Q., Gong, R., & Hase, K. (2024). A Comprehensive Objective Evaluation Method for Handwriting Assistive Devices Using a Tablet and Digital Pen for Individuals with Upper Limb Dysfunction. *Applied Sciences*, *14*(23), 11190. https://doi.org/10.3390/app142311190
21. Begum, N., Akash, M.A.H., Rahman, S., Shin, J., Islam, M.R., & Islam, M.E. (2021). User Authentication Based on Handwriting Analysis of Pen-Tablet Sensor Data Using Optimal Feature Selection Model. *Future Internet*, *13*(9), 231. https://doi.org/10.3390/fi13090231
22. Rahim, M.A., Farid, F.A., Miah, A.S.M., Puza, A.K., Alam, M.N. et al. (2024). An Enhanced Hybrid Model Based on CNN and BiLSTM for Identifying Individuals via Handwriting Analysis. Computer Modeling in Engineering & Sciences, 140(2), 1689–1710. https://doi.org/10.32604/cmes.2024.048714
23. Mekyska, J. et al. (2023). Assessment of Developmental Dysgraphia Utilising a Display Tablet. In: Parziale, A., Diaz, M., Melo, F. (eds) Graphonomics in Human Body Movement. Bridging Research and Practice from Motor Control to Handwriting Analysis and Recognition. IGS 2023. Lecture Notes in Computer Science, vol 14285. Springer, Cham. https://doi.org/10.1007/978-3-031-45461-5_2

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