Graphomotor Evolution in the Handwriting of Bengali Children Through Sigma-Lognormal Based-Parameters: A Preliminary Study

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Abstract. Handwriting has a natural evolution throughout child development. It is expected that the higher their educational level, the more fluent their handwriting. This paper is the first study in graphomotor evolution in Bengali children. This study is focused on the handwriting of the first five letters learnt in Bengali (Bangla) schools in Kolkata, India. We selected between three and six participants within three different classrooms and applied the Sigma-Lognormal model to their handwriting by using the iDeLog method. We present conventional and novel parameters extracted from the lognormality analysis of their handwriting. An assessment of extracted parameters is carried out with meaningful statistical differences observed within their handwriting evolution. Our results adds to the growing list of evidence supporting the lognormality principle of graphomotor evolution in children.

1. Introduction

Among the different modelling-techniques associated with rapid movement, handwriting generation in children has already been analytically represented using the Kinematic Theory of rapid human movements and its associated Sigma-Lognormal model. In Duval et al. (2015) three groups of kindergarten children between 3 and 6 years old executed simple and oblique traces, with 10 lognormals approximated in average terms. Such trajectories were reconstructed with a sum of lognormals through the Sigma-Lognormal model. The study showed that lognormality patterns in velocity profiles were related to the age of the children with signal-to-noise-ratio in velocity SNR_v, number of lognormals $NbLog$ and the ratio between them $SNR_v/NbLog$ statistically assessed. Similar parameters were discussing in Laniel et al. (2019) to determine the fine motor control in healthy and attention deficit/hyperactivity disorder children. Other similar patterns and characters were executed by children in Plamondon et al. (2013). The authors discussed a combination of classical and Sigma-lognormal features to assess the handwriting evolution of three groups of children aged between 3 and 6 years old. Apart from observing successful writing reconstruction performances related to the rapidity, fluidity and regularity in childrens handwriting, the authors statistically determined which parameter can better identify children in a classroom. Additionally, iterative tools and applications for learning to write are discussed in Plamondon et al. (2018) on the basis of Sigma-Lognormal model.

In this paper, our contribution is twofold. Firstly, we present novel and classical Sigma-Lognormal parameters to study handwriting fluidity. Some features can be extracted directly from the Sigma-Lognormal decomposition, however, others are related to geometrical relationships with trajectory, virtual target points, and the relationship between lognormals that represents elementary neuromuscular movements. For these purposes, iDeLog (Ferrer et al. (2018)) was deemed to be a suitable option for extracting such parameters. Secondly, a preliminary study of these parameters within Bengali handwriting is provided. Children from different classrooms enrolled in a school based in Kolkata, India wrote the first learnt letters in this script. Results showing the childrens' graphomotor evolution with Sigma-Lognormal parameters are obtained and discussed from statistical analysis.

The paper is organized as follows: Section 2 makes a short description of the iDeLog method for extracting the Sigma-Lognormal parameters; Section 3 introduces the experiments and the study whereas Section 4 is devoted to the data analysis results. Final remarks are given in Section 5.

2. iDeLog method for Sigma-Lognormal model: a short review

A novel framework to implement the Kinematic Theory of rapid movement and its Sigma-Lognormal model is iDeLog (Ferrer et al. (2018)), which has been developed in MATLAB. This method decomposes a spatiotemporal trajectory as a sum of temporally overlapped circumferences. It also divides the trajectory into strokes, where j is the index of the stroke. Then, iDeLog estimates the virtual target points tp_{j_1} and

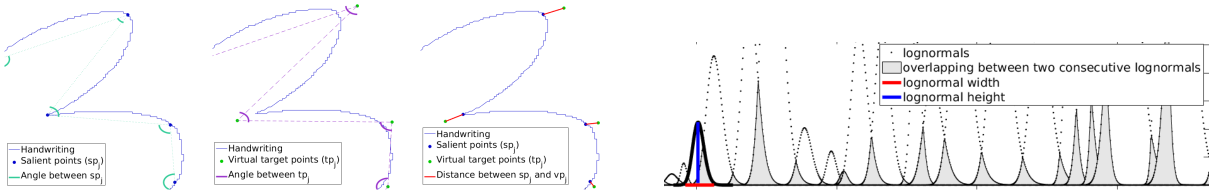

Fig. 1. The novel parameters in both handwriting velocity and trajectory. Left: parameters p_4, p_5, p_6. Right: parameters p_7, p_8, p_9.

tp_j, the starting and ending angle of the circumference θ_{sj} and θ_{ej}, and the lognormal parameters t_{0_j}, μ_j, σ_j and D_j for each stroke, j. After this first solution, the algorithm iterates moving the target point to improve the representation of the spatiotemporal trajectory by the Sigma-Lognormal transform.
The values μ_j and σ_j are obtained by means of minimizing the velocity profile and the estimated lognormals by means of a Levenberg-Marquardt algorithm (LMA). The parameter t_{0j} is obtained as $t_{0j} = t_{min,j} - 0.5$ where $t_{min,j}$ is the velocity minima in which the stroke starts. Moreover, the iDeLog method estimates the virtual targets points tp_j from the salient point sp_j. The closer is the angle of the vertex sp_j, calculated with sp_{j-1} and sp_{j+1}, the further is tp_j from sp_j. iDeLog accomplishes a refinement algorithm to optimize the position of the virtual target points tp_j to improve both the reconstructed trajectory and velocity profile. The improvement is carried out by means of an iterative Least Mean Square (LMS) algorithm applied stroke by stroke in the same order than the original movement.

2.1 Sigma-Lognormal parameters for handwriting evolution

The handwriting decomposition with Sigma-Lognormal model is an appropriate technique to study the evolution of handwriting in children (Duval et al. (2015); Plamondon et al. (2013)). Beyond the six parameters to define each of lognormal function in the handwriting, it is possible to calculate extended parameters to further explore the physical relationships with handwriting evolution. In this paper we have studied the following additional nine parameters:

- p_1 is the variance distribution of the lognormal functions, σ_j.
- p_2 is the mean distribution of the lognormal functions, μ_j.
- p_3 denotes the amplitude of the elementary movement, D_j, which is a geometrical relationship from circular trajectories that define the writing action plan.
- p_4 refers to the distance between salient points and its corresponding virtual target point. The larger the distance, the more fluent the handwriting
- p_5 is the angle between salient points (Ferrer et al. (2017)). The more acute the angle, the more fluent the handwriting.
- p_6 contains the angle between virtual target points with an interpretation as for p_5.
- p_7 stores the overlapping area between two consecutive lognormals. The greater the area the more fluent the handwriting as the writer does not pause in every stroke traced.
- p_8 refers to the height or maximum of the peaks of the bell-shaped lognormal functions. The higher their values, the more speed used for tracing the strokes.
- p_9 contains the widths of the individual lognormal functions. The larger their values, the more time was spent for tracing a stroke.

The novel parameters defined above are illustrated in Figure 1.

3. Study and experiments

3.1 Participants and data collection

Fifteen Bengali children from Kolkata participated in this study. Six children were enrolled in the kindergarten 2 (KG2) classroom (aged between 4 and 5), six from Grade 2 (G2) classroom (ages 6 to 7) and, finally three from Grade 5 (G5) classroom (ages 9 to 10). The task was to write twice the first five letters that native Bengali children learn. As they were the first letters learnt, it is expected that their production was automated and intrinsic. Participants wrote in a worksheet, which included the first five letters printed on the top of the sheet.
To register their on-line handwriting, the worksheet was placed over a Wacom tablet, so the participants could write with an inked pen and receive visual feedback. The Wacom tablet was configured at 5080 dpi and a 135 Hz sampling rate. We analysed the letters from the second writing attempt since children may be more confident with the task and familiar with the work environment.
From the obtained writing sequences, we concatenated the pen-down data of their handwriting, applied a cubic splines resampling at 200 Hz and smoothed by a Chebyshev filter. The resulting concatenated handwriting string for each participant was analysed with iDeLog. It is worth noting that iDeLog is

especially convenient for modelling trajectories and velocities of long and complex handwriting (Ferrer et al. (2018)). In total, nine long pieces of handwriting were analysed.

3.2 Statistical study

The aim of this study is to determine whether the proposed Sigma-Lognormal parameters can estimate the natural graphomotor evolution in Bengali children. First of all, a test of normality was applied to the data to confirm whether a parametric or non-parametric hypothesis test should be used. We use the Jarque-Bera test, which calculates the skewness and kurtosis of a distribution. It evaluates the null hypothesis which affirms whether a parameter is normally distributed. In our data, the null hypothesis was rejected in all cases ($p < 0.01$), so we conclude that statistical parametric test cannot be used to study our data. Therefore, we use the non-parametric Mann-Whitney U-test to study the equal distribution mean of two samples from a continuous distribution. Moreover, we have used the Kruskal-Wallis non-parametric test to study whether three or more conditions comes from the same distribution.
Thus, in this study we evaluate the following three research questions:

- Q1: *What parameter is more trustworthy to describe the graphomotor evolution of a particular classroom?*
- Q2: *What parameter is more relevant for describing the graphomotor evolution of handwriting in Bengali kindergarten?*
- Q3: *What two classrooms present significantly more similar graphomotor evolution?*

The first question can help to understand the more stable parameters for characterize the handwriting in a classroom. Second question is towards study the parameters that reports better performances in line with the progress in the school. Last question finds the parameters that can differentiate more the graphomotor evolution in two classrooms.

4. Statistical data analysis

This analysis is focused on studying the capacity of using the Sigma-Lognormal model in the analysis of handwriting by children as well as a graphomotor evolution analysis with novel related parameters.

4.1 Reconstruction analysis

The first step was to analyse the quality of the reconstruction. As such, we calculate the mean and standard deviation of the nine Signal-to-noise-ratio values for both velocity and trajectory in dB. We obtained $SNR_v = 17.62_{1.84}$ and $SNR_t = 38.63_{3.71}$. These values suggest that the reconstructed signals can be suitable for the analysis, since they are above 15dB on average (Djioua and Plamondon (2009)). Examining the number of lognormals averages, we have $287.08_{71.74}$ for classroom KG2, $327.25_{38.01}$ for classroom G2 and $133.50_{38.34}$ for classroom G5. At the same time, we can see the average in the ratio $SNR_v/NbLog$ as $0.07_{0.02}$, $0.06_{0.01}$ and $0.13_{0.04}$, for classrooms KG2, G2 and G5 respectively. Similarly, in the case of trajectory, we observe $0.14_{0.04}$, $0.13_{0.02}$ and $0.27_{0.05}$. The higher this value, the fewer lognormals required to trace the same letters, as is the case within classroom G5. Although there are only a few participants within each classroom, these results suggest that the oldest classroom group observed in this study need nearly half the elementary neuromuscular movements for approaching the same task than classrooms KG2 and G2. This observation is repeated in the average handwriting duration per classroom where we calculated $40.37_{8.73}$ s, $43.13_{4.60}$ s and $22.40_{5.79}$ s in classrooms KG2, G2 and G5 respectively. It was observed that there is a disparity of graphomotor evolution within group KG2 according to the standard deviation of number of lognormals and duration.
Furthermore, we have analysed the shimmer and jitter of each concatenated piece of handwriting in each classroom. These features assess the cycle-to-cycle variations between amplitudes and mode of consecutive lognormals respectively (Farrús et al. (2007)). For KG2, G2 and G5 classrooms, the jitter was $0.15_{0.01}$, $0.14_{0.01}$ and $0.17_{0.01}$ respectively. This indicates that children in classroom G5 produced longer and fewer lognormals for the same tasks, as to be expected. The shimmer values were $7.39_{0.69}$, $7.57_{0.68}$ and $7.11_{1.49}$ respectively, which suggest slightly higher amplitude differences in the youngest children.

4.2 Sigma-Lognormal-based parameter analysis

Our first question (Q1) seeks to validate the robustness of handwriting parameters within classrooms. As we have between three and six participants per classroom, the Kruskal-Wallis test was used, where the null hypothesis is that all children have the same distribution at 1 % of significance level. The results in Table 1 shows that all of the studied parameters reject the null hypothesis for the youngest children. However, for children within classroom G2, the angle between target points (p_6) indicates that the population are similar within a particular classroom. The oldest children have three out of nine parameters that indicate statistical uniformity with their handwriting. Overall, it suggests that the oldest the children

Table 1
Non-parametric Kruskal-Wallis test $p-values$ at 0.01 of significance for Q1 for the studied parameters

Grouping	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9
Within Classroom KG2	1.73e-12	1.78e-06	9.67e-07	9.74e-25	1.35e-10	4.83e-07	3.06e-15	2.25e-06	3.18e-12
Within Classroom G2	1.96e-36	4.58e-09	4.81e-19	3.51e-51	0.00813	**0.0628**	9.68e-61	7.38e-13	4.98e-34
Within Classroom G5	**0.0727**	**0.271**	5.07e-07	2.59e-08	0.00040	0.00307	5.34e-09	8.99e-09	**0.0908**

Table 2
Non-parametric Kruskal-Wallis and Mann-Whitney tests $p-values$ at 0.01 of significance for Q2 and Q3

Grouping	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8	p_9
(KG2, G2, G5)	2.02e-40	4.31e-26	1.33e-38	6.97e-77	2.96e-92	9.92e-62	2.36e-45	7.44e-29	1.25e-40
(KG2, G5)	1.46e-14	1.6e-12	3.69e-23	9.67e-39	4.33e-76	2.44e-56	7.54e-20	7.41e-21	5.21e-15
(KG2,G2)	1.76e-13	1.56e-06	1.04e-05	1.76e-13	**0.0646**	**0.774**	1.27e-11	**0.0203**	3.19e-13
(G2,G5)	8.34e-39	2.45e-26	3.74e-38	4.19e-76	3.01e-81	2.84e-51	1.75e-44	1.99e-28	4.46e-39

the more statistically similarities using the proposed Sigma-Lognormal parameters of their handwritings, this indicating uniformity between the handwriting of children of a similar age.
The second question (Q2) is again assessed with the Kruskal-Wallis test enabling an assessment across the three classrooms. As shown in Table 2, there were significant differences between classrooms for all parameters, especially for p_5, i.e. the distance between salient points and virtual target points ($p = 2.96e-92$). The order of the parameters about statistical significance was found in: $p_5, p_4, p_6, p_7, p_1, p_9, p_3, p_8, p_2$. Note that a low rank number indicates higher significant differences.
The third question (Q3) evaluates whether two groups come from the same distribution. In this way, we have used the Mann-Whitney U-test. We observed in Table 2 that children in classroom KG2 and G2 produce similar outputs for the angle between salient points (p_5), the angle between virtual target points (p_6) and the height of the bell-shaped lognormal peaks (p_8). The major differences between classrooms are observed in classrooms G2 and G5, since their $p-values$ have the lowest results. It suggests a higher improvement in handwriting development which can be associated to a better graphomotor abilities after passing G2.

5. Conclusions

A series of novel, alongside conventional, Sigma-Lognormal parameters are presented in this paper to assess the graphomotor evolution of children in a Bengali school. We present these parameters and their calculation using the iDeLog method (Ferrer et al. (2018)). We have validated the use of Sigma-Lognormal across the handwriting of three groups of children within a Bengali school with fifteen participants. Moreover, statistical data analysis is performed to evaluate the graphomotor evolution of children with these parameters. Our future ideas include extending the number of participants per classroom as well assessing additional Sigma-Lognormal parameters related to the graphomotor evolution. New insights could be also obtained studying letter individually. It is also interesting to analyse pen-ups within the writing sequence since children usually loose attention to the task, especially within those in classroom KG2. Even though our experiments show a range of interesting findings across a number of parameters such as the angle between salient points or target points, more experiments would be necessary to confirm robustness across a wider population. Meanwhile, our results adds to the growing list of evidence supporting the lognormality principle of graphomotor evolution in children.

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