Filtered Random Hybrid Strokes (FRHS): Filtering Time-Series Considering Velocity Profile

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Keywords: Random Hybrid Strokes, Kinematic Theory, Handwriting, Early Dementia Identification, Bi-LSTM.

Abstract: This paper proposes an improvement to the data augmentation technique, Random Hybrid Stroke (RHS), widely used in handwriting analysis for the early detection of dementia. This improvement involves the application of a filtering method to handwriting time series, redefining the concept of a 'stroke' based on insights derived from kinematic theory. Specifically, a trait is considered as the segment joining successive local mini- mum and local maximum points with respect to the lognormal velocity profile. Experimental evaluations wereconducted using a dataset consisting of 23 different writing tasks (Mini-COG, MMSE, etc.) for the early detection of dementia using K-Fold cross-validation with K set to 10. The proposed improvement demonstrates promising results, showing an increase in performance over a wide range of writing tasks and representing a significant contribution, in particular, for the Mini-COG, MMSE and Trail Matrix Tests.

1 INTRODUCTION

The progressive deterioration of brain cells gives rise to noticeable impacts on memory, thinking, behav- ioral, and emotional skills. Such brain cells' deterio- rations is collectively characterized as dementia [1](Pat- terson, 2018),(Gauthier et al., 2022). This condi- tion often progresses into more severe forms, such as Alzheimer's Disease (AD), Parkinson's Disease (PD), or Lewy Body Dementia. The prevalence of Alzheimer's disease is on a steady rise, with approx- imately one new case reported every three seconds, according to the World Alzheimer Report (Patterson,2018).

The impairment of brain cells results in increased difficulty performing daily life activities due to cog- nitive, functional, and behavioral decline (Impedovo and Pirlo, 2018),(De Stefano et al., 2019). Among these activities, handwriting is profoundly affected by the degradation of brain cells (De Stefano et al., 2019).

Handwriting, being a complex biometric trait, serves various analytical purposes, ranging from se- curity (Zhang et al., 2016)(Faundez-Zanuy et al., 2021) (Castro et al., 2023b) to health (Gattulli et al., 2022),(Gattulli et al., 2023),(Dentamaro et al., 2021a),(Dentamaro et al., 2021b),(Erdogmus and Kabakus, 2023),(D'Alessandro et al., 2023).

The evaluation of a patient's health status can be conducted by utilizing a diverse set of data sources. The set of data sources include images of hand- writing tasks (Lemos et al., 2018) , such as draw- ing and writing text (offline handwriting) (Dentamaro et al., 2021a), (Impedovo et al., 2012), time-series data associated with pen movements during handwrit- ing tasks (online handwriting) (Gattulli et al., 2022), (Cilia et al., 2022), (Angelillo et al., 2019b) and also videos capturing gait (Dentamaro et al., 2020) (Cheriet et al., 2023), audio recordings (Dentamaro et al., 2023), among others.

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Bello, S., Monaco, A., Musti, L., Pirlo, G. and Semeraro, G.
Filtered Random Hybrid Strokes (Frhs): Filtering Time-Series Considerding Velocity Profile.
DOI: 10.5220/0012567500003654

In *Proceedings of the 13th International Conference on Pattern Recognition Applications and Methods (ICPRAM 2024)*, pages 961-968
ISBN: 978-989-758-684-2; ISSN: 2184-4313

This work is focused the analysis of online handwriting considering the health domain. The online handwriting analysis allows a non-invasive analysis through the use of digital tablets and digital pens (Gat- tulli et al., 2022) (Cilia et al., 2022), (Angelillo et al., 2019a).

More in detail, tablets are capable to capture pentip movements on-surface, as well as in-air movements (within a range from the tablet surface that varies accordingly to the tablet), saving simpler informations as x and y coordinates, pressure on the surface, button-status (if the pen is touching ”1” or not ”0” the surface), timestamp and more complex in- formation as velocity, azimuth and altitude (Gattulli et al., 2023) (Impedovo and Pirlo, 2018) (Faundez- Zanuy et al., 2021).

The objective of this work is to introduce an enhancement to the data augmentation technique known as Random Hybrid Stroke (Gattulli et al., 2022) (Zhang et al., 2016). This enhancement involves ap- plying a filtering method to the handwriting time- series, altering the definition of a stroke based on in- sights derived from the Kinematic Theory.

The organisation of this work is as follows: Section 2 provides an overview of related work in the field so as to explain the insight behind this pa- per. Section 3 explains the methods employed in this study. The dataset is discussed in detail in Section 4. Section 5 presents the experimental set-ups, benchmarking results and a comprehensive discussion. Finally, Section 6 focuses on the conclusions drawn from the study.

2 RELATED WORKS

2.1 Kinematic Theory in Handwriting Analysis

The integration of kinematic theory represented a sig- nificant milestone in the evolution of handwriting analysis. Studies such as (Plamondon, 1995) and (O’Reilly and Plamondon, 2009) laid the foundation for understanding the kinematic aspects of motor con- trol in writing and they formulated the matematical model of the kinematic theory called Sigma Log- Nomral (ΣΛ). Of particular interest is the concept that the result of writing, i.e. a graphic sign as characters of numbers, is considered to be composed of primi- tives called strokes . Indeed, accordingly to kinematic theory (Plamondon, 1995), (Ferrer et al., 2018), these primitives are identified through their velocity profile. Each stroke, in fact, has a lognormal velocity profile, characterised by a bell-shaped pattern. This discovery in kinematic theory is of fundamental importance, as it can be applied to any movement performed by hu- mans, as, for example, in the analysis of walking fromvideos (Dentamaro et al., 2020) (Castro et al., 2023a) (Dentamaro et al., 2021c). In the context of writing, in a sequence of strokes that make up a graphic stroke, such as letters and numbers, each stroke is delimited by its minimum points in velocity profile.

2.2 Random Hybrid Stroke (RHS)

Zhang X (2016) introduced the Random Hybrid Stroke (RHS) technique to improve handwriting anal- ysis in the context of security (Zhang et al., 2016). RHS is based on random sampling of fixed-length stroke sub-sequences, making the stroke sequences independent of user and writing task, thus showing promise in user identification. In the work of Zhang X. (2016), a different concept of stroke was also adopted, defining it as the segment joining two suc- cessive points. Furthermore, strokes are distinguished as real or imaginary, depending on whether the seg- ment was traced entirely on the tablet or partly or en- tirely at a distance from the tablet. The innovation of the RHS technique lies in its ability to perform data augmentation to facilitate the training of deep learn- ing models, instead of different SoA technique that focus on generate artificial data sampling the data dis- tribution, as the LICIC (Dentamaro et al., 2018)

2.3 Proposed Enhancement

In the study conducted by Gattuli V (2022), the Random Hybrid Stroke (RHS) technique was used to analyse handwriting with the specific aim of detecting early signs of dementia. The work conducted by Gat- tulli V. (2022) made it possible to transfer a technique that originated in the context of safety into the con- text of health, in accordance with Faundez-Zanuy’s (2021) statement that there are competing tasks in handwriting analysis that belong to both the safety and health domines (Gattulli et al., 2022) (Faundez- Zanuy et al., 2021). Thus, the application of the RHS allowed for the augmentation of data in such a way that deep learning architectures could also be used.

The central aspect of this work concerns the devel- opment of a filtered version of hybrid random traits. This enhancement focuses on refining the definition of stroke through a filtering process applied to the time series of coordinates and pressures. The filtering procedure involves the identification and selection of successive local maxima and minima in the time se- ries. These specific points play a crucial role as they indicate the beginning, the point of maximum veloc- ity and the conclusion of a stroke. Consequently, the definition of a run, initially proposed by (Zhang et al.,2016), is redefined as the segment located between two consecutive important points.

The primary objective of this redefined approach is to improve the performance and effectiveness of early dementia detection in the field of handwriting analysis.

3 METHODS

In this section is described the used method to per- form the experiments of this work. Specifically, it was used a Bi-Directional Long Short Term Memory with Self-Attention (Vaswani et al., 2017) (Bi-LSTM) us- ing the two versions of Random Hybrid Stroke (RHS) (Zhang et al., 2016) technique.

3.1 Random Hybrid Strokes

The Random Hybrid Strokes technique is based on the processing of handwriting data. The data must be time-series containing position coordinates (x, y) and button status (0 for in-air movements and 1 for on- surface movements). An example of the time-series is given in Eq. 1, and its graphical representation is shown in Figure 1. The time-series are pre-processed to obtain information about strokes, defined as the line between two points, rather than mere position and button status.

$$S = [(x1, y1, bs1), (x2, y2, bs2), ..., (xn, yn, bsn)] \quad (1)$$

Hence, the difference between successive pairs of co- ordinates and the multiplication of button status are computed.

$$\Delta S = [(\Delta x1, \Delta y1, \tilde{b}s1), ..., (\Delta xn, \Delta yn, \tilde{b}sn)] \quad (2)$$

where $\Delta xi = xi \quad xi{-}1$, $\Delta yi = yi \quad yi{-}1$, and $\tilde{b}si = bsi$ bsi 1. This leads to obtaining two types of strokes: real strokes, where $\tilde{b}si$ is 1, representing

strokes drawn on the surface, and imaginary strokes, where $\tilde{b}si$ is 0, representing strokes drawn with at least one of the two points with button status as 0. Finally, random sub-sampling from the stroke sequences ∆S is performed. This results in a set of fixed-length stroke sub-sequences, represented in Eq. 3.

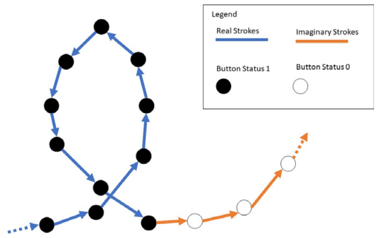

Figure 1: Example of handwriting trait. In the images points with different button status (”1” or ”0”) are rappresented as black and white points. Strokes between points are high- lighted if ”real strokes” or ”imaginary” strokes accordingly to the description.

3.2 Filtered Hybrid Strokes

In this work, is proposed an upgrade of RHS. Such upgrade is inspired by the Sigma-LogNormal (ΣΛ) Model(O’Reilly and Plamondon, 2009) of the human movement and the Kinematic Theory (Plamondon, 1995). The Sigma-LogNormal analyze the velocity profile of a timeseries of coordinates and ensemble with the Kinematic-Theory state that when a person perform a movement, as drawing a single straight line, the velocity profile is similar to a Normal distribution. Similarly, in this work the time-series of coordi- nates is firstly transformed looking the velocity pro- file of the movement performed by the pen. Secondly, only local maxima and local minimum are collected by the velocity profile and then the referencing coor- dinates and button status. The intuition is that in this way it is possible to maintain only the most significant point to use for the reaming steps of Random Hybrid Strokes (explained above).

An example is reported in Figure 2.

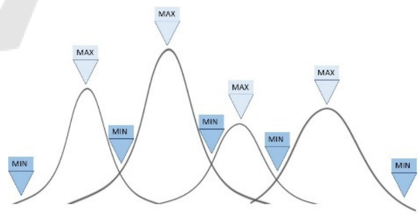

Figure 2: In the figure are represented the log-normal of the velocity profile of strokes. Hence, a stroke is identified between successive local minimum. The highlighted points

$$RHSi = [\Delta S[i,i{+}size], \Delta S[j, j{+}size], ...] \quad (3)$$

where i and j indicate different starting points from the n points, and size represents the length of sub- sequences. In conclusion, the Random Hybrid Stroke technique uses both imaginary and real strokes, giv- ing the name ”Hybrid” to this technique. It considers strokes as data information, hence the term ”Stroke,” and employs random sub-sampling of fixed lengths of the stroke series, giving rise to the term ”Random.”are them that are selected during the filtering.

3.3 Deep Learning

The used model to perform experiments using both RHS-based techniques is a Bi-Directional Long Short Term Memory with Self-Attention (Bi-LSTM).

Table 1: Classes division of “HAND-UNIBA” and its Balanced version.

HAND-UNIBA		Balanced HAND-UNIBA	
Class	N° Patients	Class	N° Patients
Healthy	56	Healthy	49
Mild	17	Diseased	49
First	32		

This model is characterized by the use of two layer of LSTM that analyse the time-series in two different time-direction: forward and backward, differently form other work as (Impedovo et al., 2019). Than the Self-Attention is applied in order to retain the most significant information. Finally, a Dense Layer is used to extract the prediction in ”healthy” or ”pa- tient”. The whole structure is represented in Figure 3

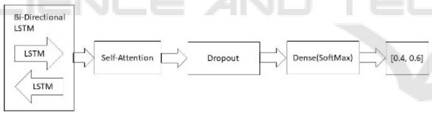

Figure 3: In the figure are represented the deep learning model used in this work. It is a Bi-Directional Long Short Term Memory with the Self-Attention

4 DATA

In this work is used the Balanced version of ”HAND- UNIBA” data-set used in the previous work [early de- mentia]. Such version was obtained firstly, merging in a single class (patient or diseased) person with mild or fist-stage dementia, and secondly selecting the same amount of healthy person from the original data-set. In this way, the Balanced version of ”HAND- UNIBA” data-set, referred also as ”Balanced-Hand”, contain 49 healthy and 49 diseased person. Such in- formation are also reported in Table 1.

Each one of the 98 patients has performed 23 tasks. Multiple tasks were conducted because in this way it could be possible to encompass both cognitive and functional assessments. The recorded tasks belonged to various categories, including the Mental

5 RESULTS

In this section the experimental set-ups and obtained results are presented and discussed.

Regarding the labeling phases, patients with the disease are assigned the class label ”1”, while healthy patients are designated as the class with the label ”0”. Then, it is applied One-Hot Encoding.

All the experiments were performed utilizing the same data-set, patient label encoding, and a consistent methodology for the training/testing phases, specifi- cally employing K-Fold Cross Validation with K set to 10.Such experimentation was performed 10 times to average the evaluation metrics, providing a more robust assessment of the proposed method.

The division into folds is applied to the users. Subsequently, during training, each Random Hybrid Stroke (RHS) is considered separately. However, dur- ing the testing phase, all predictions for a single user are averaged, and then an argmax is applied to iden- tify the predicted class.

In terms of the model architecture, the Bi-directional Long Short-Term Memory (Bi-LSTM) was configured with 30 units for each LSTM, 2 units, and Softmax as the activation function for the Dense Layer. The training of the model utilized a batch size of 32, employed Adam as the optimizer, and binary cross-entropy as the loss function.

In the domain of neural degenerative disease prediction, classification errors are of paramount importance. Hence, metrics, such as precision (Eq 4) and recall (Eq 5), are useful to evaluate if the model is capable of predicting the correct class, avoiding behaviors like giving the same prediction always (precision) and determining if the model can distinguish between the two classes (recall). The terms in equations 4 and 5 are: TP for True Positive (for correctly predicted instances of the positive class), FP for False Positive (for instances of the negative class predicted as positive), FN for False Negative (for instances of the positive class predicted as negative).

$$precision = \frac{TP}{TP + FP} \quad (4)$$

$$recall = \frac{TP}{TP + FN} \quad (5)$$

Table 2: Tasks and their descriptions.

Abbreviation	Description	User request	Category
CDT	Clock drawing test	Draw a clock with numbers in it, then draw the clock hands at 11.10 a.m	Mini-COG
SW	Sentence drawing test	Think and then write a sentence	MMSE
IPC	Pentagons drawing test	Copy the shape of this design	MMSE
M1	First matrix test	Mark all the numbers "5" in the matrix, without correcting the barriers already made	Trail
M2	Second matrix test	Mark all the numbers "2" and "6" in the matrix, without correcting the barriers already made	Trail
M3	Third matrix test	Mark all the numbers "1", "4" and "9" in the matrix, without correcting the barriers already made	Trail
TMT1	First trail-making test	Connect the circles following the order of the numbers. For example, 1–2-3, and so on. Perform the exercise as quickly as possible and never lift the pen. In case of error,correct immediately	Trail
TMT2	Second trail-making test	Connect the circles alternately following the order of the numbers and the order of the letters of the alphabet. For example, 1-A-2-B-3-C, and so on. Perform the exercise as quickly as possible and never lift the pen. In case of error, correct immediately	Trail
TMTT1	Trail test 1	Connect the circles following the order of the numbers. For example, 1-2-3, and so on. Perform the exercise as quickly as possible and never lift the pen. In case of error,correct immediately	Trail
TMTT2	Trail test 2	Connect the circles alternately following the order of the numbers and the order of the letters of the alphabet. For example, 1-A-2-B-3-C, and so on. Perform the exercise as quickly as possible and never lift the pen. In case of error, correct immediately	Trail
H	Writing the word test	Write the word "Ciao" in italics, resting your wrist on the tablet	Additional tests
VP	Connecting Two verticalpoints tests	Link the vertical points with a straight line four times by going back and forth	Additional tests
HP	Connecting two horizontal points tests	Link the horizontal points with a straight line four times by going back and forth	Additional tests
SC	Square copy task	Copy the square drawing shown	Additional tests
S1	First signature acquisition	Sign your signature here	Additional tests
S2	Second signature acquisition	Sign your signature here	Additional tests
CS	Spiral copying test	Copy the shape of this design	Additional tests
TS	Retrace spiral test	Retrace the shape of this design	Additional tests
CHK	Bank check copying task	Look at the fields on the completed check and copy them back to the blank check below	Additional tests
LE	Write "le" repetitions	Write a sequence of "L" and "E" in italics, for example "LELELELE"	Additional tests
MOM	Writing the word test	Write the word "MAMMA" in italics inside the three boxes, from top to bottom	Additional tests
W	Writing the word test	Write the word "FINESTRA" in italics	Additional tests
DS	Listen and write sentence	Listen and write in italics what you will hear. (The sentence "Oggi e` una bella giornata" will be dictated)	Additional tests

Table 3: Tasks and their descriptions.

Task	N° People Performing the Task	Ratio People Performing the Task
CDT	97	98,98%
SW	98	100%
IPC	97	98,98%
M1	98	100%
M2	98	100%
M3	98	100%
TMT1	96	97,96%
TMT2	82	83,67%
TMTT1	97	98,98%
TMTT2	89	90,82%
H	98	100%
VP	98	100%
HP	98	100%
SC	98	100%
S1	97	98,98%
S2	97	98,98%
CS	97	98,98%
TS	97	98,98%
CHK	98	100%
LE	97	98,98%
MOM	98	100%
W	98	100%
DS	98	100%

Status Assessment of Older Adults (Mini-COG), Mini Mental State Examination (MMSE), Attentional Matrix, Trail Making Test, and several additional assessments. An extended description is in Table 2.

Both versions of HAND-UNIBA data-set contain, for certain task and for certain users, time-series with less than 50 points. Hence, such information were not used to perform experiments. The raw number of people and the percentage of people performing a task is reported in Table 3.In order to consider both metrics (*precision* and *recall*), the *F1-score* (Eq 6) is used, which is the har-monic mean that allows understanding the predictive capability of the model. All three metrics are in the range [0, 1]. Because both classes are considered, the average of *F1-scores*, computed firstly considering the class ”1” as positive and then the class ”0” as positive, is used to compare performance between the proposed method and the previous version.

$$F1 - Score = 2\frac{precision \times recall}{precision + recall} \tag{6}$$

The experimental results are reported in Table 4. Specifically, the column RHS refers to the experiments performed using the original Random Hybrid Strokes technique. Meanwhile, the column FRHS refers to the proposed Filterd Random Hybrid Strokes. Finally, the column Task report the task name. The reported values are the average F1-scores with the associated standard deviation, and the better value are highlighted with bold font.

It is noticeable that the performance difference ranges from about 0.3% to approximately 7%. Specif- ically, the most significant variance occurs in the task cdt, where FRHS outperforms RHS, and in s1, where RHS yields better results than FRHS. RHS demon- strates superior performance in tasks ds, hp, m1, m3, s1, sc, ts, and w. Therefore, in tasks related to dic- tation, connecting two horizontal points four times, the first and third tasks using Attentional Matrix, the first signature, the square copy task, the retracing spi- ral task, and the writing of the fixed word test, RHS emerges as the better alternative.

Table 4: Results obtained from the previous experiments.

RHS		**FRHS**		**Task**
Mean	STD	Mean	STD	
0,55161	0,09186	**0,62234**	0,05778	cdt
0,71060	0,02118	**0,71124**	0,04098	chk
0,64047	0,03287	**0,66566**	0,03388	cs
0,71473	0,01774	0,70250	0,02094	ds
0,65846	0,02043	**0,68427**	0,02908	h
0,66886	0,03534	0,66111	0,02325	hp
0,64749	0,04568	**0,70385**	0,02476	ipc
0,72229	0,02878	***0,72948***	0,02477	le
0,68166	0,02662	0,66744	0,02062	m1
0,72473	0,02962	**0,72706**	0,02072	m2
0,71750	0,02926	0,70536	0,02959	m3
0,68032	0,03348	**0,69668**	0,03497	mom
0,72105	0,01448	0,65310	0,04027	s1
0,70535	0,01171	**0,72960**	0,03038	s2
0,69778	0,02359	0,68690	0,01940	sc
0,69516	0,02177	**0,70934**	0,02039	sw
0,75781	0,01010	**0,76006**	0,01569	tmt1
0,62890	0,02552	**0,66623**	0,01907	tmt2
0,68579	0,02351	**0,70167**	0,03024	tmtt1
0,75652	0,01456	**0,76399**	0,01633	tmtt2
0,63088	0,02028	0,60728	0,01929	ts
0,67202	0,02655	**0,69947**	0,04107	vp
0,71994	0,01958	0,69170	0,02527	w

Considering tasks in the Mini-COG, MMSE, and trail-making tests (*tmt1*, *tmt2*, *tmtt1*, and *tmtt2*), the proposed FRHS demonstrates better performance than the original RHS. Furthermore, FRHS exhibits superior performance in tasks *chk*, *cs*, *h*, *le*, *m2*, *mom*, *s2*, and *vp*.

These results indicate that the proposed method achieves better outcomes for the majority of the handwriting tasks. Additionally, in specific categories such as Mini-COG, MMSE, and Trail Making Test, the proposed method FRHS outperforms the original RHS.

6 CONCLUSIONS

In conclusion, this study introduced a new technique for the early detection of neurodegenerative dis- eases through handwriting analysis. Specifically, the method proposed by this work, a filtered version of the Random Hybrid Strokes technique called Filtered Random Hybrid Strokes (FRHS), aims to improve early dementia prediction performance from hand- writing data.

In fact, the results obtained show that, for most tasks, FRHS outperforms the original RHS. Furthermore, it is noteworthy that the proposed technique improves prediction performance for all writing tasks belonging to the Mini-COG, MMSE and Trail Matrix Test categories.

Hence, the proposed technique not only outperforms the existing approach in terms of f1-scores, but also proves to be particularly good for filtering and data augmentation. Ultimately, FRHS holds great promise for improving early dementia diagnosis and handwriting analysis.

ACKNOWLEDGEMENTS

This article and related research have been conducted during and with the support of the Italian National Inter-University Ph.D. course in Sustainable Develop- ment and Climate Change.

Furthermore, this article and related research have also been conducted with the support and funding of the Ministero della Salute's project ”AmICA: Assis- tenza olistica Intelligente per l'aCtive Ageing in eco- sistemi indoor e outdoor” project, under Traiettoria 1, specifically ”Active Healthy Ageing - Tecnolo- gie per l'invecchiamento attivo e l'assistenza domi- ciliare” (T1-MZ-09).

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