KIHT: Kaligo-based Intelligent Handwriting Teacher

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***Abstract*—Kaligo-based Intelligent Handwriting Teacher (KIHT) is a bi-nationally funded research project. The aim of this joint project is to develop an intelligent learning device for automated handwriting, composed of existing components, which can be made available to as many students as possible. With KIHT, we specifically address the challenging task of using inertial sensors to retrace the trajectory of a pen without relying on external reference systems. The nearly unlimited freedom to let the pen glide over the paper has not yet provided a satisfactory solution to this challenge in the state-of-the-art methods, even with sophisticated algorithms and AI approaches. The final phase of the project is now being launched and together with partners from industry and academia, we are taking a holistic approach by considering the entire chain of components, from the pen to the embedded processing system, the algorithms and the app.**

***Index Terms*—Embedded Systems, AI accelerator, hardware/software co-design, Handwriting Recognition**

I. Introduction

Established handwriting and digital media exist without much overlap. The development of numerous digital pens has not changed this much. Studies have repeatedly shown that handwriting leads to higher quality results than typing a text [1]. For example, in several studies, the authors found that students who took notes on laptops performed worse on conceptual questions than students who took notes by hand [2].This means that without handwriting, a knowledge society loses one of its most powerful tools. Until now, the learning process of handwriting had to be continuously checked and monitored by a teacher or parents. By using suitable computer programs and an electronic pen, it is made possible to accompany this learning process automatically. This enables individual assistance for each student and gives the teacher more time and freedom to support the children. The main goal of the KIHT project is the development of a hardware-software combination of an electronic pen and its firmware and drivers, which can be used with any tablet computer to bring handwriting into the digital domain. While tablet-specific electronic pens exist, they need pen-specific circuitry in the tablet and are limited to on-screen writing. There is yet no low-cost product in the market that co-operates with any mobile device and writes on paper. Writing on paper is preferred because of superior haptics and any lack of latency. The software part of the project covers the reconstruction of the pen trace in coordinates from inertial data which is transferred wirelessly from the pen. The use of a tablet computer makes it possible to adapt the exercises individually for each pupil and to synchronize and save the data automatically. The project consortium consists of two universities and two companies located in Germany and France: Universite de Rennes (INSA Rennes) is responsible for the design and development of the deep learning AI that reconstructs online handwriting trajectories from the pen developed by the STABILO International GmbH. Karlsruhe Institute of Technology develops various concepts for the integration of AI algorithms adapted to the embedded hardware and Learn&Go extends their App Kaligo to teach students how to write and spell using a tablet and the electronic pen. This article provides an overview of the project and its progress after the successful completion of the initial planning stage and the first end-to-end tests: Starting from the sensor technology, the AI algorithms, the integration of these into the pen, and finally the interaction with the app. The final phase of the project is now being launched and this paper demonstrates a complete pipeline for handwriting reconstruction from IMU sensors. We plan to distribute the complexity of the overall system across both the software and hardware, enabling fast and efficient AI execution. With a target price for the electronic pen of around half the price of an Apple Pencil, the planned intelligent learning device should be made accessible to as many users as possible.

This work was funded by the German Federal Ministry of Education and Research (BMBF) under grant number 01IS21097A (KIHT).

II. Handwriting and Pen

a) Importance of Handwriting Motor Skills: While the faithful reproduction of letter shapes is widely accepted to be essential for legible writing, the importance of motor skills is much less appreciated. Routine handwriting is characterized by a smooth course of velocity over time with just one maximum of velocity within a stroke [3]. If words are written repeatedly, experienced writers retain the characteristic execution of the movement over all runs. Writing movements of this kind are understood by Mai and Marquardt to be automated [4]. Non-automated movements, on the other hand, are characterized by several maxima in the course of velocity, so they are executed with several motion impulses per stroke.

Learned movements are carried out automatically, that is, completely planned in advance and then no longer consciously controlled or corrected in detail. They are controlled by the cerebellum and the motor cortex and require no visual control

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[5]. Thus, the task of writing a sentence with eyes closed and then with eyes open will show the same automated motion profile. In less experienced writers, however, writing is associated with conscious hand-eye coordination. This leads to less automated movements. The cerebrum, which is responsible for controlling cognitive movements, then takes control of this non-automated motion execution. This conscious movement control not only leads to significantly slower writing, but also heavily burdens the brain's working memory and makes it difficult to focus on spelling or content at the same time.

Automated handwriting is essential for success in school as it allows the student to follow the lesson while taking notes at the same time. Note-taking considerably improves the proportion of what has been learned, especially if the notes are created by handwriting [2]. According to another study [1], handwritten papers contain 38% more relevant concepts compared to typed papers, indicating an improved creativity when using a pen rather than a keyboard. Askvik et al. show that handwriting is vital to facilitate and optimize learning [6].

b) Computer-supported Handwriting Education: Learning to write has two aspects: One is to learn and be able to reproduce letter shapes, the other is the development of muscle memory to be able to write fast and efficiently.

The first aspect is taught by a multitude of apps on mobile devices, of which Kaligo from the French company Learn&Go is one of the best. Most apps only allow to trace letter shapes with the finger, whereas the more serious apps use the special electronic pens which come with more expensive tablet computers. This, however, restricts the availability of those apps to a select subset of users.

In order to lower the barriers to computerized handwriting instruction and to also cover the second aspect of handwriting learning, we propose to use an instrumented pen which writes on paper and transmits movement information to a wirelessly connected computer. By using the Bluetooth® 5 protocol, practically all current mobile devices can be pen-enabled.

c) The Electronic Pen: It is not possible to observe the writing process in detail with the naked eye, since the eyes can only track motion of up to a speed of about 1.5 Hz, but writing takes place at up to 6 Hz [7]. The registration and analysis of writing movements using kinematic motion analysis provide insights into the graphomotoric process that can not be detected by mere observation. Therefore, STABILO has developed an instrumented pen that captures handwriting movements in detail and precisely describes their structure in terms of their acceleration, maximum speed and braking phases. Such a measurement also shows that the kinematic characteristics of the handwriting motion of various skilled writers show surprising uniformity [3].

By adding an inertial measurement unit (IMU), a force sensor, a radio module and a battery to a pen, STABILO has created an electronic pen (see Figure 1) which is well equipped to measure writing movements in much greater detail than could be observed before.

Specifically, the inertial sensor is the LSM6DSO by ST Microelectronics, the magnetometer is the ALPS HSCDTD008A,

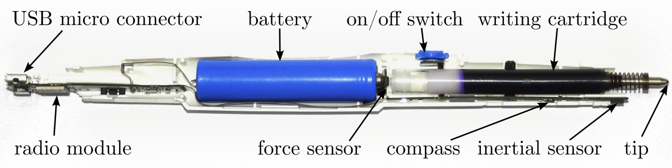

Fig. 1. Current model of the electronic pen with one half of the body removed.

the force sensor is the ALPS HSFPAR003A and the radio module is the muRata WSM-BL241 which is based on the Nordic nRF52832. This part includes a Cortex M4F microcontroller running at 48 MHz which is used for reading the sensor data, processing it for wireless transfer and running the Bluetooth stack.

d) Data Processing: In order to enable this pen to also measure the movement of the tip, conventional methods of sensor fusion as used in robotics or indoor navigation proved inadequate. While the large scale movements in indoor navigation show clear, easy to interpret patterns, the small scale in handwriting leaves the sensor data with a poor signal to noise ratio and additional localisation techniques such as triangulation using the signal strength at several receivers [8] cannot be used. Simple integration of the inertial data fails due to excessive drift, so an alternative method of tracking the pen tip had to be found.

Thankfully, the recent development of deep neural networks offers an opportunity, and early experiments [9] showed promising results.

III. AI Algorithms Based on Deep Learning

Handwriting trajectory reconstruction is commonplace in many set-ups (pen and tablet, camera based system). In tracking systems, Inertial Measurement Unit (IMU) sensors are gaining popularity as a cost-effective solution, despite their tendency to produce noisy signals. Interestingly, IMUs can also be effectively utilized with a pen for tablets and a different pen for traditional paper handwriting. However, there has been relatively limited attention directed towards the reconstruction of online handwriting trajectories using IMU signals.

In this work, the emphasis is on the challenging task of trajectory reconstruction from IMU sensors in the Digipen and we aim to advance trajectory reconstruction using deep neural networks. We introduce a novel and complete pipeline for handwriting trajectory reconstruction from IMU sensors, including preprocessing, a neural network architecture inspired by Temporal Convolutional Networks (TCN), and an evaluation protocol based on the Fréchet distance [10].

1) Related works: Only a handful of works have ventured in the domain of handwriting trajectory reconstruction using IMU signals with deep learning techniques. Wehbi et al. [11] propose a multi-writer approach dealing with the STABILO Digipen, which generalizes the works of Ott et al. [12] with a monowriter approach. In [11], the authors propose a Convolutional Neural Network architecture for trajectory reconstruction with a linear interpolation to match the sensor data with the tablet ground

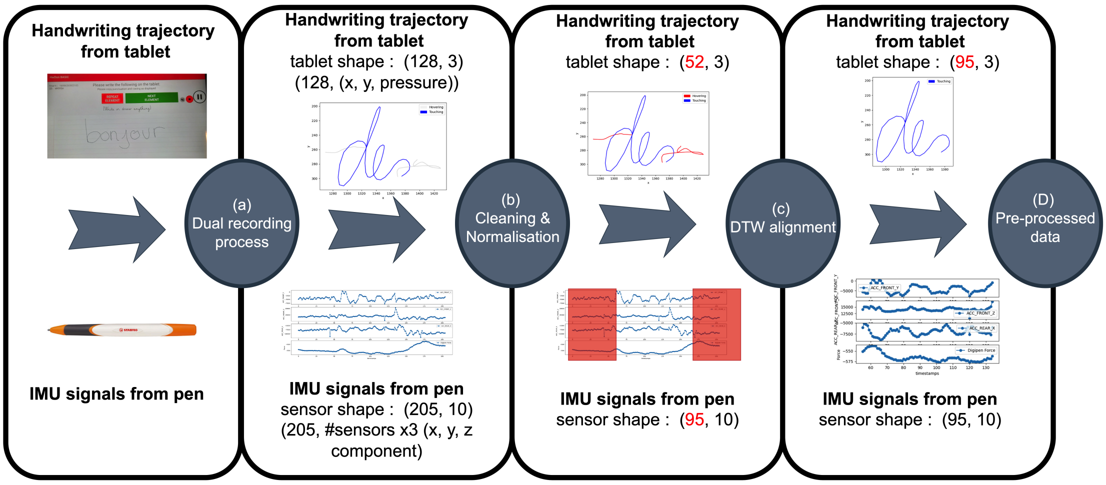

Fig. 2. Our preprocessing pipeline.

truth for training the network. Experiments are carried out with an earlier version than ours of the STABILO Digipen (version 5.5).

2) Trajectory reconstruction pipeline: Here, we perform the trajectory reconstruction using Deep Learning from IMU sensors. On the one hand, IMUs allow trajectory acquisition whatever the medium used by a writer. On the other hand, deep learning methods are well defined to extract, from the IMU sensors, complex features that will be helpful to build the trajectory reconstruction. However, training examples are required to efficiently train a neural network model, which requires the acquisition of labeled data using a tablet. This leads to many challenges.

a) Main challenges: First, one major hurdle lies in the discrepancy between the sampling rates of the stylus and the tablet. This does not allow to match the input IMU sensors directly with the tablet ground truth trajectory to train a model. To partially address this, the Samsung S7 FE tablet and Digipen v6.3 were chosen for data collection, due to closed sampling rates. Second, the orientation of the pen also emerges as a critical factor, as it directly influences pen sensor values. The Digipen design incorporates ergonomic features to facilitate proper finger placement, ensuring that the stylus maintains a consistent orientation. Third, performing a trajectory reconstruction involves modeling pen movements even when the pen is not in contact with the surface (hovering parts). During hovering parts, the tablet discontinues recording because the pen is too far from the surface and thus there is no ground truth that can be related to the input sensors. Finally, accelerometer drift or asynchronous timestamps in the transmitted kinematic data are additional hurdles to the data collection process. To address those challenges, we propose a complete processing chain based on preprocessing, a neural network model and an evaluation protocol.

b) Data Preprocessing: We describe the data preprocessing steps undertaken in the training phase of the pipeline (Figure 2). The signals are initially divided into spans corresponding to individual written samples, and timestamps are added as an additional channel (Figure 2 (a)). Irrelevant sections of the input signals, specifically the start and end pen-up movements, are removed (Figure 2 (b)). Further, the signals are normalized by their maximum values to facilitate interoperability between different Digipen versions (Figure 2 (a)). In the test phase, preprocessing is limited to the cleaning and normalization of sensor data. To map the sensor data accurately to the displacement vectors of the handwriting trajectory, the (x, y) channels of the handwriting trajectory are used to compute displacement vectors $(\Delta x, \Delta y)$. Addressing the different sampling rates between the stylus and the tablet is essential to have a temporal alignment to learn how to generate a (relative) position from sensor values acquired at a given time. Dynamic Time Warping (DTW) alignment is employed to find an alignment path between the timestamps of the stylus and the tablet (Figure 2 (c)). To account for transmission time delays and mismatched timestamps, a method is applied to synchronize the data. Notably, the DTW approach is favored over linear interpolation [11] for keeping the dynamics of the writing as much as possible. Then we split the data into strokes during the training phase. The goal is to train the neural network model on touching strokes only, specifically where information is most consistent. Touching strokes are identified based on predefined thresholds related to force values.

c) Neural Network Model: This section focuses on the neural network model designed to predict displacement vectors of handwriting trajectories based on preprocessed sensor data. If Wehbi et al. [11] have chosen a CNN architecture, we propose to choose a Temporal Convolutional neural Network (TCN). Dilated convolutions play an essential role in handwriting reconstruction, since from a graphomotor point of view, a movement is conditioned by its past trajectory. Such convolutional layers allow to increase the receptive field without increasing the number of weights trained in the network. Our network architecture (Figure 3) is based on 4 blocks of a non-causal TCN followed by 2 dense layers. The use of a TCN

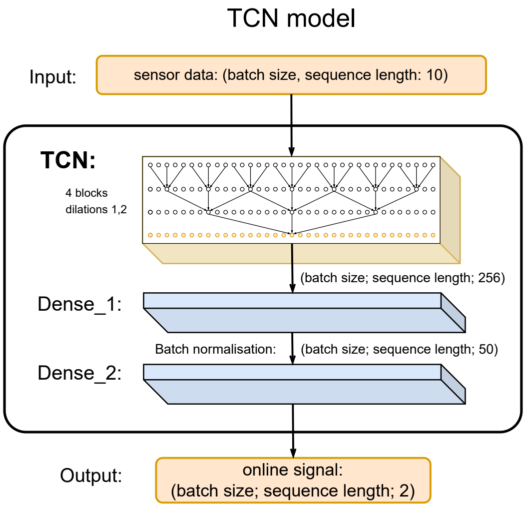

Fig. 3. Our TCN model [10].

has the advantage of being faster to train and less prone to vanishing gradient than LSTM networks, especially in the case of long sequences [13]. Each TCN block is composed of 2 convolutions with dilation 1 and 2 respectively and a kernel size of 3. The choice of parameters results in a receptive field of 49. The network remains light as it contains less than 1M of parameters so it can be trained with a limited amount of data. During training, the model is trained to minimize the Mean Square Error (MSE) between sensor value predictions and DTW-aligned tablet trajectory. The training process involves utilizing the ADAM optimization, a batch size of 16 and a learning rate of $10e^{-3}$.

d) Post-Processing: The post-processing stage in the pipeline is consistent across both training and test phases. It focuses on reconstructing the predicted handwriting trajectories by accumulating values from the predicted displacement vectors. For evaluation purposes, we normalize the scale of reconstruction and ground truth between 0 and 1, without distorting them. Then we recenter ground truth and prediction, and we use the Fréchet distance as a metric. The Fréchet distance is well defined to evaluate the model performance as it measures the distance between two curves by taking into account the location and ordering of the points along the curves.

3) Results: For training our neural networks, we use the KIHT dataset composed of 106 different writers and 18854 samples from the following categories: characters, words, equations, geometric shapes, and sentences. The test set is composed of 344 samples from 10 different users not seen during the training phase. Note that the IRISA-KIHT-S dataset, a subpart of the KIHT dataset (30 writers) on which similar results are obtained, is available publicly for research purposes[1].
We obtain the following qualitative (Figure 4) and quantitative results (Table I), results are divided into 3 categories: mono-strokes, multi-strokes and global to allow comparison of reconstruction with and without hovering. We achieve a good

[1]More information here : https://www-intuidoc.irisa.fr/irisa-kiht-s-dataset/

TABLE I
AVERAGE FRÉCHET DISTANCE OF OUR PIPELINE.

Type	Fréchet distance	Number of samples
Mono-stroke sample	0.11	54
Multi-stroke sample	0.19	290
Global	0.18	344

reconstruction of the touching part of the handwriting which is confirmed by the mono-stroke score in (Table I), and a degraded reconstruction for hovering parts as seen in the multi-stroke score (Table I). These are due to the lack of ground truths for these parts and a great variability in the nature of hovering parts.

IV. HARDWARE/SOFTWARE CO-DESIGN

Deployment of the Neural Networks (NNs) onto embedded devices, such as the STABILO Digipen, is a quite challenging task. On one hand, modern NNs have a complex, multilayered structure, using hundreds of thousands parameters in order to be able to generalize. On the other hand, the computational resources, memory capacity and power budget of the tiny battery-powered embedded devices are very limited. Hence, to be able to perform the inference stage on the embedded device, the NN has to be first tailored for the target hardware. This can be achieved using different NN optimization techniques such as quantization, activation function approximation and pruning [14]. They allow to significantly reduce the model size and needed computational resources by sacrificing a slight portion of the reconstruction accuracy.

a) Quantization: For the model quantization we considered both Post Training Quantization (PTQ) and Quantization-aware Training (QAT). PTQ is a method of weight quantization, which is applied to the already trained NN and reduces the precision of the weights. Being straight-forward and very efficient, such method leads to the prediction accuracy decreases due to introduced round-off errors. QAT takes into account the weight precision during the NN-training. This approach allows to find more suitable weight values for the given weights resolution and to improve the prediction accuracy of the NN, pertaining to the reduced model size.

However, gained accuracy comes with the cost of retraining of the neural network. Performing training with quantized weights can take longer than training the original network and the training procedure is more prone to the validation loss oscillation. Several techniques allow to tackle this problem like a Straight-Through Estimator (STE) and retraining the quantized with PTQ network, what allows to converge the training process faster. In [15] and [16] we show, that quantization of the Long Short-Term Memory (LSTM)-based NNs for time-series classification task leads only to a slight accuracy loss.

b) Approximate computing: Further network optimizations can be achieved with a use of approximate computing techniques, which leverages different algorithms and methods to replace the full precision float arithmetical operations with their less precise counterparts. It allows to reduce the usage of the Floating-Point Unit (FPU) of the Microcontroller Unit

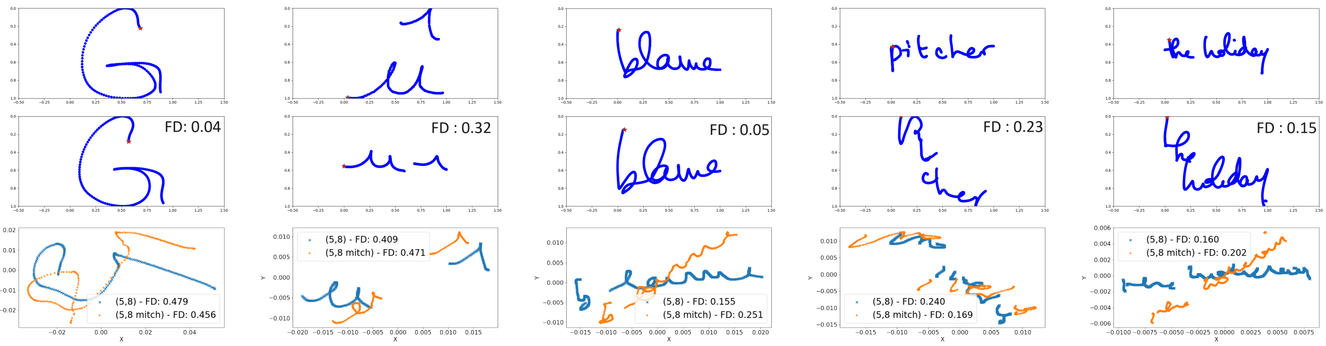

Fig. 4. Our reconstruction after our pipeline, with ground truth on the first line, prediction of the original model on the second line, and prediction of the optimized models on the third line, each with the associated Fréchet distances. Letters and words with mono strokes and multi strokes are shown.

(MCU) or even to perform the computations on the platforms without FPU at all. In our previous work [16] we present the design of the LSTM hardware accelerator based on the Mitchell's logarithmic multiplier and demonstrate, that the accuracy of the time-series classification does not significantly decrease using approximate computing.

c) TCN Optimization: Applying the previously mentioned optimization techniques to regression networks is a challenging task, since the regression quality is more affected by the reduced weight and arithmetic operation precision due to high amount of predicted classes. In our work [17] we show that it is still possible to apply these techniques without significant precision loss. We quantized candidate NNs from [11] using the PTQ and QAT. For QAT we initialized the networs with the baseline models weights and trained the networks using QKeras. The data sets, used for retraining are identical to those ones used for the original precision models. Retrained quantized networks achieve comparable to the baseline model precision, for example, the (3,8) fixed point quantized TCN-49 achieves the average Frechet distance of **0.21** on the test data set, requiring only the fourth of the original memory space for the weights - **460 KB** of ROM. In the Figure 4 we present examles of the reconstructed trajectories from the optimized TCN-49 networks after QAT and Mitchell's approximation of multiplication.

V. App Integration

a) Kaligo App: The “Kaligo handwriting and spelling app” is a digital workbook providing feedback during the handwriting and spelling learning process [18]. It targets children ranging from three to eight years old and even older for those who present special needs that might be related to neurological disorders such as dysgraphia, dyslexia or other disorders that might prevent them from achieving an automated handwriting and/or spelling. The Kaligo App today works with pen-based tablets and offers 14 different types of exercises, among which 6 are dedicated to the handwriting of strokes, shapes, numbers, or words in capital, lowercase or cursive letters. For those 6 exercises, the strokes are collected while written on a pen-based tablet and analysed in order to give an on-line confident and meaningful feedback in real time to the writer.

The engine analysing the collected strokes is based on the work described in [19]. It produces a score reflecting the handwriting quality based on three different aspects: shape, order and direction. The score is given to the writer in the shape of a color-scale indicator drawn under each gesture with the following color code: very good (green with yellow star), good (green), average (orange), and incorrect (red), see Figure 5 (a) (b). When the feedback indicates the gesture as “average” or “incorrect”, the writer is given the opportunity to compare his attempt with the model, see Figure 5 (c). In the meantime, results from the handwriting analysis are also available on the on-line Teacher Portal where teachers can monitor the progress of their students and create dedicated lessons, see Figure 5 (d). The integration of the trajectory reconstruction pipeline in the Kaligo App allows it to use the data collected by the inertial measurement unit while performing Kaligo writing exercises on paper with the electronic pen. The trajectory reconstruction pipeline provides the Kaligo App with strokes in formats that it can use after minor adaptations (like resizing). The goal here is to give the same on-line confident and meaningful feedback as those currently given by the handwriting analysis in the Kaligo App when the strokes are collected on the tablet. The future Kaligo App will also show on the tablet the reconstructed strokes written on paper with the electronic pen.

b) App integration and adaptations: The first version of the working system will focus on the analysis of a cursive letter. In the final version, the goal is to have all the handwriting exercises currently performed on tablet reproduced and adapted for writing with the electronic pen on paper (including the handwriting and analysis of strokes, shapes, numbers, or even full words in capital, lowercase or cursive letters). The writer will no longer perform the exercises on tablet but on paper. The Kaligo App will only remain as an instructor and an evaluator. Therefore it may be used on any mobile device (including mobile phones). The user journey will then be adapted accordingly, see Figure 6.

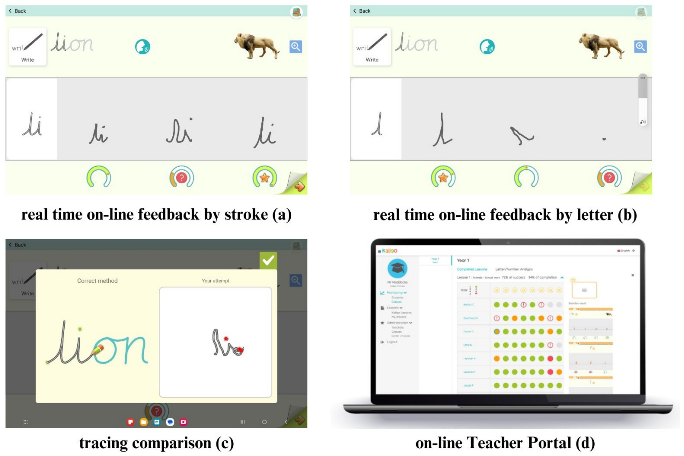

Fig. 5. Kaligo existing handwriting and spelling app environment.

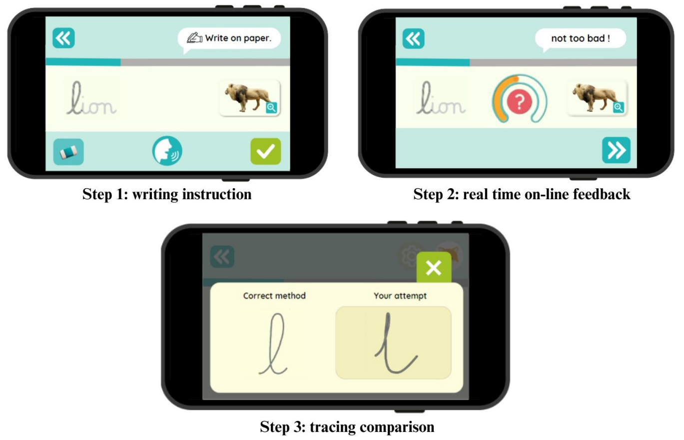

Fig. 6. Adapted app for writing exercises on paper.

VI. Conclusion and Future Work

In conclusion, we propose a complete pipeline for handwriting reconstruction from IMU sensors. Our pipeline is composed of a preprocessing, a TCN-based architecture and an evaluation protocol. Our proposed approach enable good reconstructions of touching parts and outperforms a state-of-the-art approach. Future work will focus on improving the reconstruction of complex hovering parts. Our future objectives also encompass various writing contexts, spanning various mediums such as paper and addressing a wide range of age groups, including learning in a school environment. An inherent challenge lies in the observed bias within the presented tablet data. To mitigate this issue, we are exploring the application of domain adaptation methods as a solution.

Acknowledgment

This work was funded by the German Federal Ministry of Education and Research (BMBF) under grant number 01IS21097A (KIHT). The responsibility for the content of this publication lies with the authors.

This project is financed by the KIHT French-German bilateral ANR project and these four partners, IRISA (France), KIT (Germany), Learn&Go (France) and STABILO (Germany). This work was performed using HPC resources from GENCI-IDRIS (Grant 2021-AD011013148)

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