Sensor-to-Trace : Self-Supervised Learning for Multi-Domain Handwriting Reconstruction from Stabilo DigiPen's Sensor Signals

Job opportunity from Institut de Recherche en Informatique et Systèmes Aléatoires (IRISA), Rennes, France

Position	Internship
Location	IRISA lab, SHADoc team 263 avenue du Général Leclerc, 35000 Rennes (France)
Duration	6 months
Desired start date	February 1, 2027
Supervisors & Contacts	Eric Anquetil eric.anquetil@irisa.fr Yann Soullard yann.soullard@univ-rennes2.fr

Keywords

> Self-supervised learning, Deep learning, Handwriting reconstruction, IMU sensor signals, Trajectory reconstruction, Time series matching metrics, Stabilo Digipen

Subject

Handwriting remains a natural and ubiquitous means of interaction, yet its accurate, real-time digitization still poses significant challenges. While most of electronic styluses are marketed in conjunction with tablets, digital pens have been developed to enable writing on paper, while keeping a digital trace. These pens integrate a camera to capture the writing trace and require the use of special dot papers. In recent years, STABILO has designed a new pen, called Digipen, with the goal to write on any surface (tablet, paper, board,...). This pen integrates IMU sensors (accelerometers, gyroscope, pressure sensor) to capture the pen's trajectory. Beyond note-taking, it offers promising applications in education, supporting handwriting learning on paper while allowing fine-grained digital analysis of the ductus and written content.

Previous research works using this pen have shown promising results for handwriting trace reconstruction, notably through a mixture-of-experts approach separating the 2D writing trace from 3D pen-up trajectories [Imbert et al., 2025], and a multi-head network handling signal variability caused by friction differences across surfaces (e.g. tablet and paper) [Imbert et al., 2026].

However, these systems perform well only on their training domain (short texts, adults, tablet) and generalize poorly to new contexts such as children's handwriting, writing on paper, or other patterns (mathematical expressions, unrestricted drawing). This is mainly due to limited annotated data that are available in training and due to the high variability of signals between different domains. A preliminary work explored various self-supervised learning strategies, such as generative approaches based on masking Zerveas et al. [2021] and contrastive approaches as Pöppelbaum et al. [2022], to learn features of interest in signals. The self-supervised-based process is illustrated in Figure 1 : it is a two-step approach in which a model is first trained on a pretext task, where supervision is derived from data itself (step 1 in the figure), and the learned representations are then transferred to the downstream target task (step 2 in the figure) Zhang et al. [2024]. The goal is twofold : 1) to exploit additional unsupervised data in the pretext task, and 2) to build features from another task that helps and strengthens the target task. We have shown that self-supervised learning enhance trace reconstruction on adult tablet data.

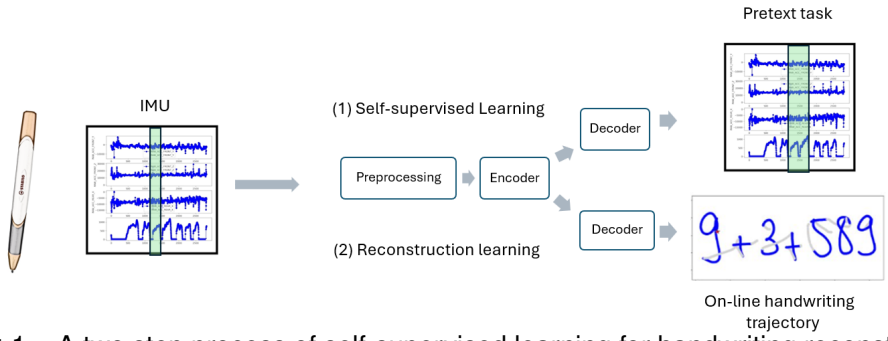


FIGURE 1 – A two step process of self-supervised learning for handwriting reconstruction.

During this internship, we will explore two main avenues for improving existing systems. First, building on the preliminary study, we will investigate the benefit of **self-supervised learning in a multi-domain learning** framework. To this end, we will rely on a multi-head neural network architecture recently developed within the team Imbert et al. [2026], based on a Temporal Convolutional Network and Squeeze-and-Excitation-based attention, with the goal to process data from various domains : adult or children's handwriting, on tablet or on paper. To this end, architectural evolutions may be implemented. In particular, we will seek to improve the repositioning of the pen after a pen-up movement, whose the lack of labeling during training and the high variability of signals significantly impact the quality of the trace reconstruction. In a second step, we will explore **new ways of assessing the quality of the reconstruction**. Currently, the Fréchet distance has shown better agreement with the visual rendering of the reconstructed trace than other metrics such as the Root Mean Square Error (RMSE) or the Dynamic Time Warping (DTW). However, the Fréchet distance has also limitations, and we will seek to strengthen the analysis with additional metrics which could be extended to serve as a loss function during training.

If it is successful, **this work may lead to a scientific publication and, subject to funding, a PhD thesis can be considered** as a continuation of this internship in partnership with the Stabilo company and the Karlsruhe Institute of Technology (Germany) with the goal to jointly design the next generation of the Digipen.

Références

Florent Imbert, Eric Anquetil, Yann Soullard, and Romain Tavenard. Mixture-of-experts for handwriting trajectory reconstruction from imu sensors. *Pattern Recognition*, 161 :111231, 2025.

Florent Imbert, Yann Soullard, Eric Anquetil, Alexey Serdyuk, and Tanja Harbaum. A multi-head network based on squeeze-and-excitation for reconstructing the handwriting trajectory of an imu-based digital pen. *Pattern Recognition Letters*, 2026. ISSN 0167-8655. doi : https://doi.org/10.1016/j.patrec.2026.10.004. URL https://www.sciencedirect.com/science/article/pii/S0167865526003752.

Johannes Pöppelbaum, Gavneet Singh Chadha, and Andreas Schwung. Contrastive learning based self-supervised time-series analysis. *Applied Soft Computing*, 117 :108397, 2022.

George Zerveas, Srideepika Jayaraman, Dhaval Patel, Anuradha Bhamidipaty, and Carsten Eickhoff. A transformer-based framework for multivariate time series representation learning. In *Proceedings of the 27th ACM SIGKDD conference on knowledge discovery & data mining*, pages 2114–2124, 2021.

Kexin Zhang, Qingsong Wen, Chaoli Zhang, Rongyao Cai, Ming Jin, Yong Liu, James Y Zhang, Yuxuan Liang, Guansong Pang, Dongjin Song, et al. Self-supervised learning for time series analysis : Taxonomy, progress, and prospects. *IEEE transactions on pattern analysis and machine intelligence*, 46 (10) :6775–6794, 2024.

Expected skills

- Expected courses : Machine Learning, Deep Learning
- Skills :
  - Python programming
  - At least one experience with a deep learning environment (PyTorch, Keras, TensorFlow)

How to apply

- CV
- Master's or engineering school grades