



HAL
open science

Domain adaptation for pen trajectory reconstruction from kinematic sensors

Florent Imbert, Yann Soullard, Romain Tavenard, Eric Anquetil

► **To cite this version:**

Florent Imbert, Yann Soullard, Romain Tavenard, Eric Anquetil. Domain adaptation for pen trajectory reconstruction from kinematic sensors. SIFED 2023 – Symposium International Francophone sur l'Écrit et le Document, Jun 2023, Paris, France. hal-04125711

HAL Id: hal-04125711

<https://inria.hal.science/hal-04125711>

Submitted on 12 Jun 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

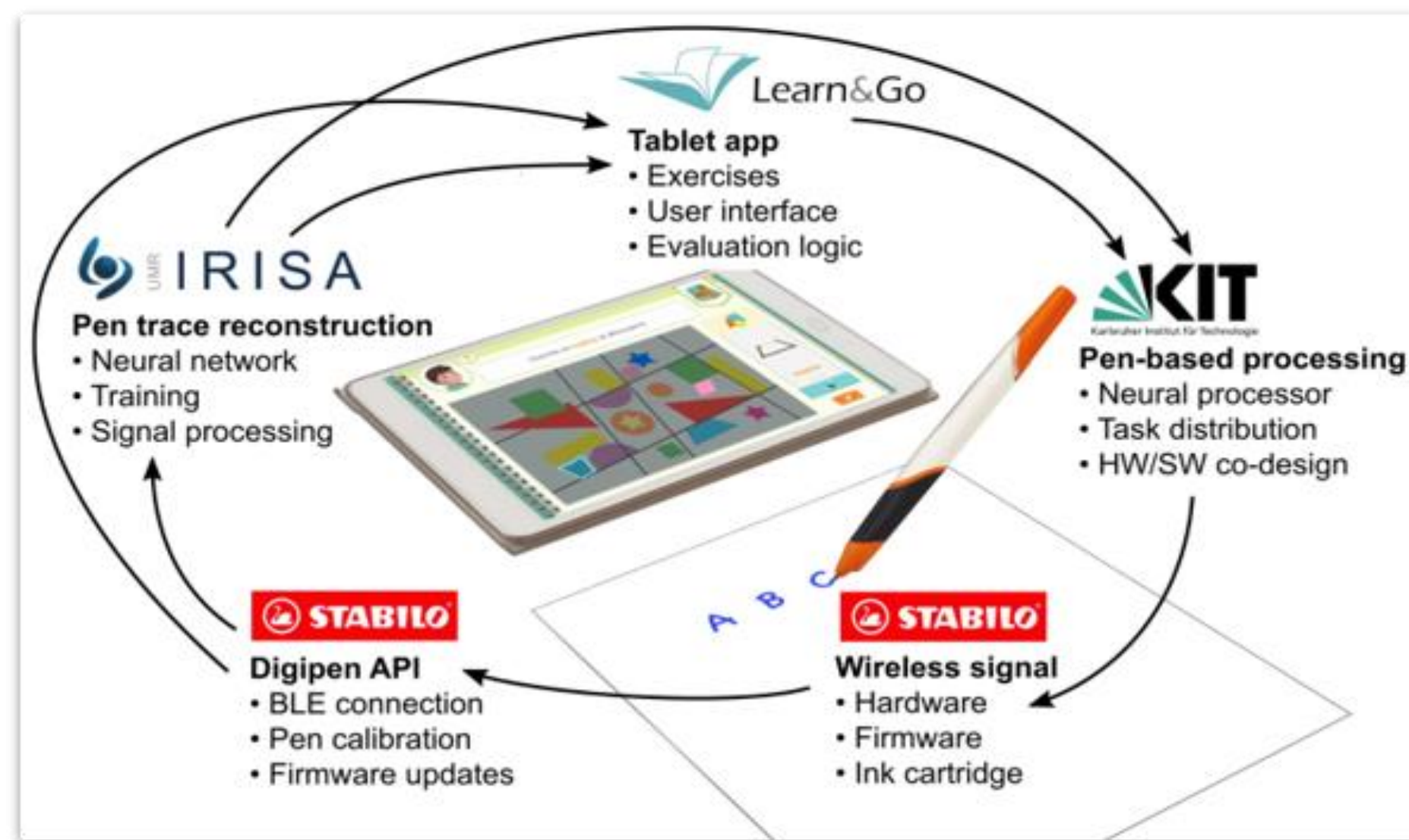


Distributed under a Creative Commons Attribution 4.0 International License

Domain adaptation for pen trajectory reconstruction from kinematic sensors

1. Context

An ANR bilateral Franco-German project



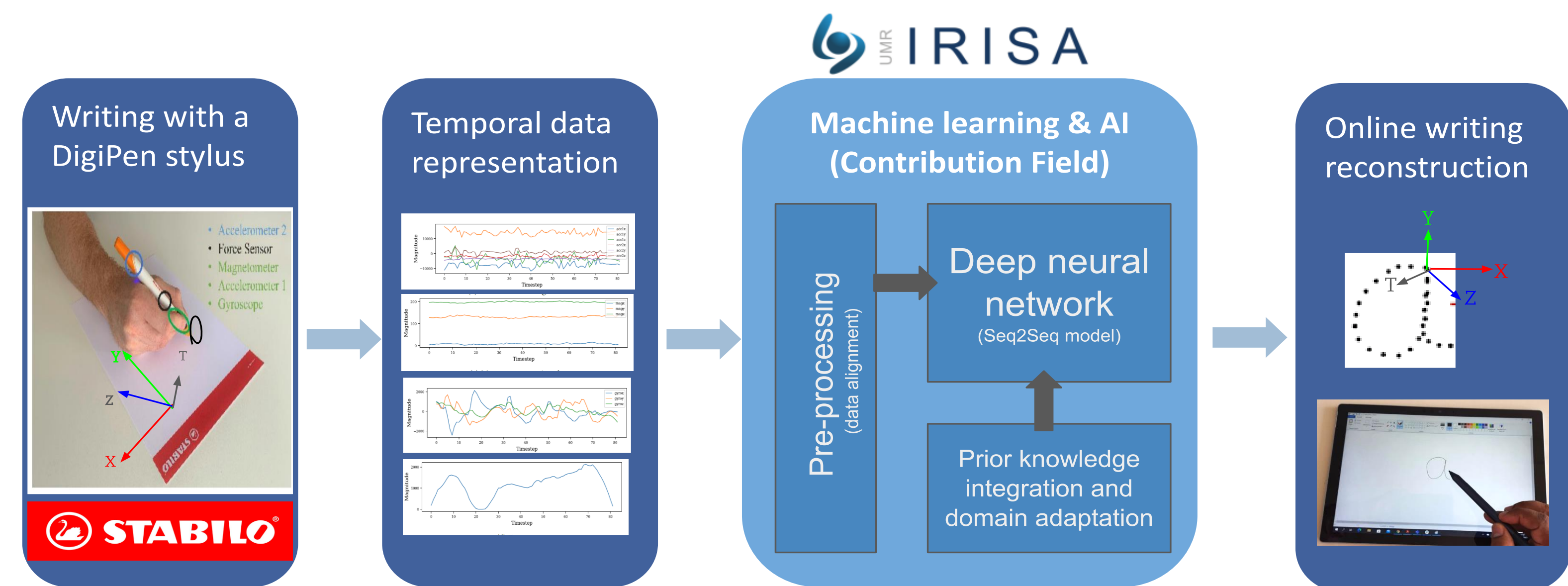
Goals

Development of a complete system (hardware + software) to **reconstruct the trajectory** of a digital pen equipped by inertial measurement units (IMU).

Partnership

2 academics collaborators and 2 industries collaborators.

2. Handwriting reconstruction

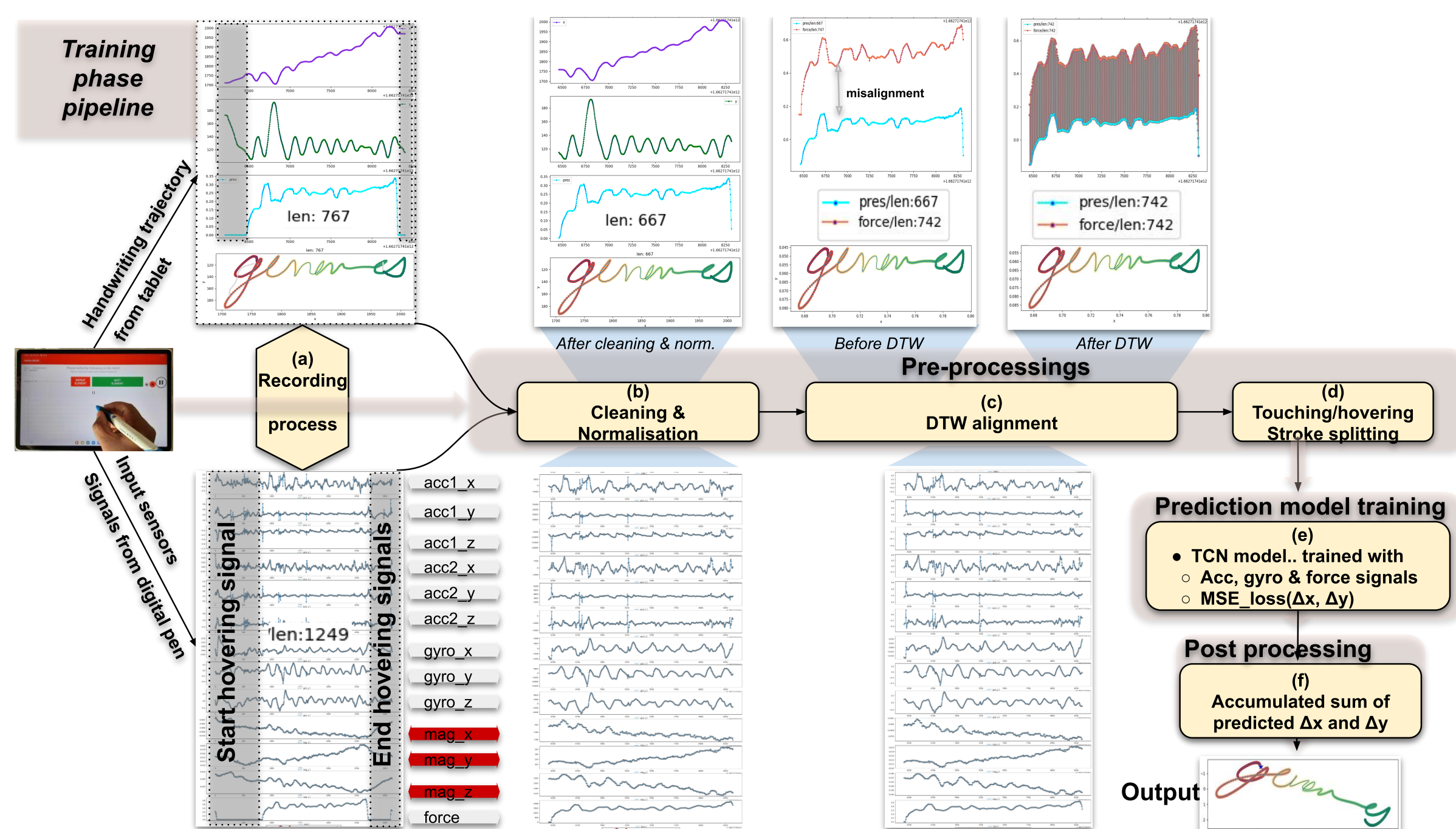


IMUs: Front and rear accelerometers, gyroscope, magnetometer, force sensor

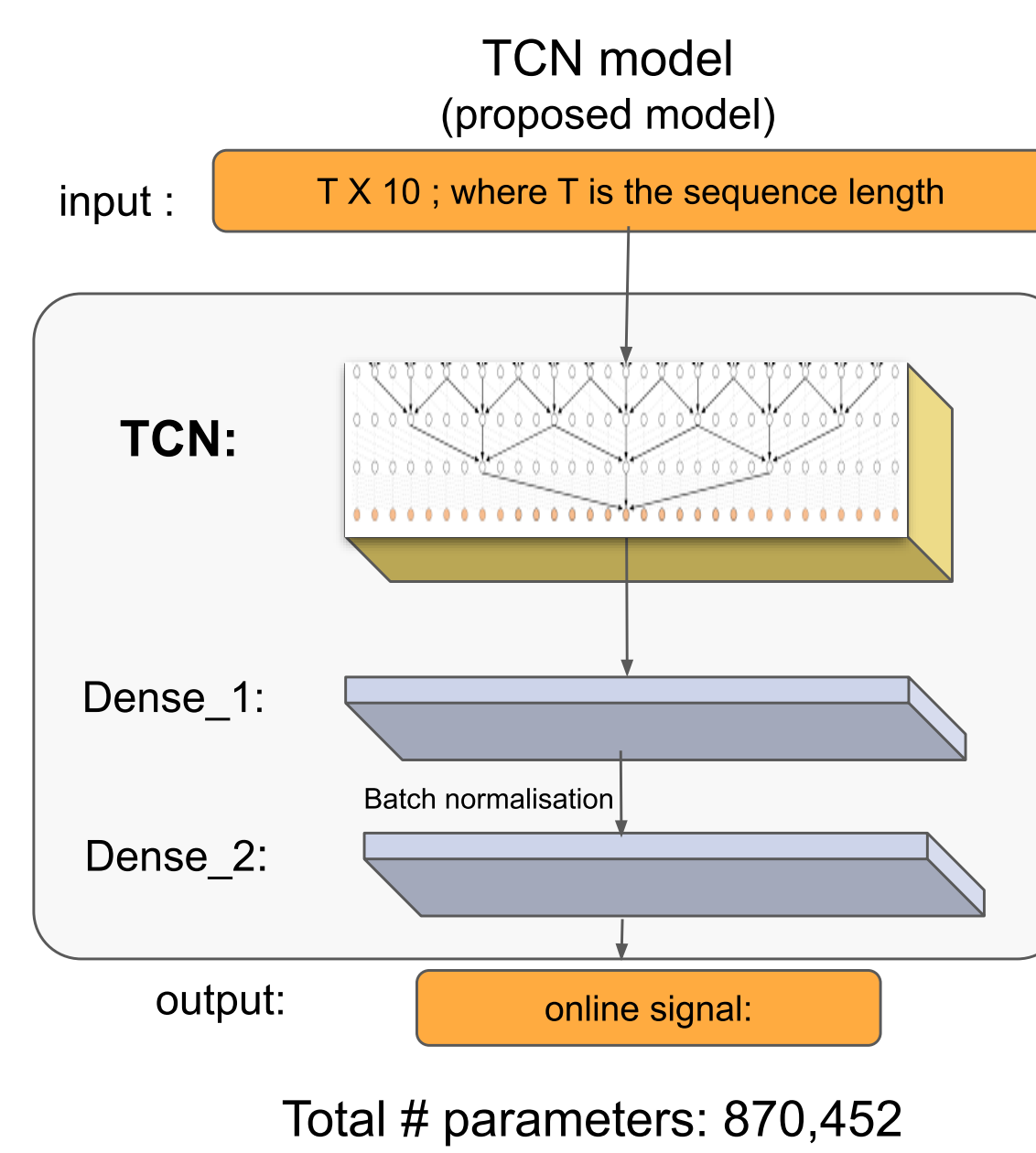
Challenges:

- Design a sequence-to-sequence neural network
- Reconstruct online trajectory from relative signals
- Writing on any surface

3. Pipeline [1]



The architecture

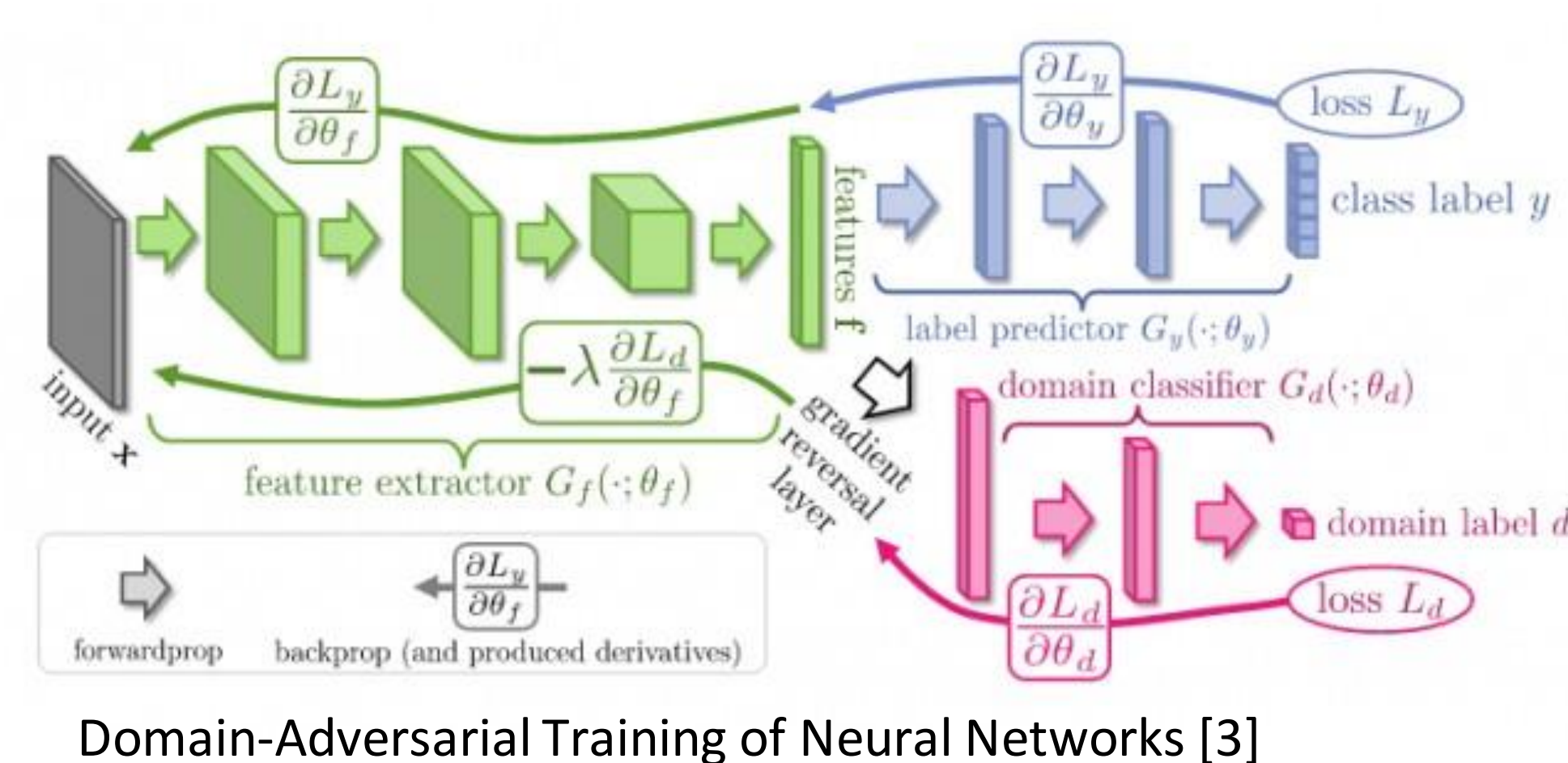


4. Mains challenges

- ✓ Reconstruct the touching strokes
- ✓ Synchronize timestamps
- ✓ Deal with ground truth and sensor data of different sizes
- ✗ Follow the hovering path to reposition the start of the next touching stroke (no label, extra dimension)
- ✗ Learn the z dimension, which is not seen in training (learning on touching only, data acquired on plane surface)
- ✗ Deal with data variability depending on the materials (paper, tablet, etc.), various rubs and noises that impact reconstruction

5. Domain adaptation: 3D and paper

- Acquisition of data :**
 - On an inclined plane in order to get signals with variable z dimension (the height)
 - On paper to obtain data from various materials and signal variability
- Domain adaptation** for data acquired on paper and on inclined plane
 - Goal
 - Build domain-invariant features to tilt and noise in signals
 - By
 - Successive learning of the different colored parts
 - feature extractor (green),
 - label predictor (blue),
 - domain classifier (red)

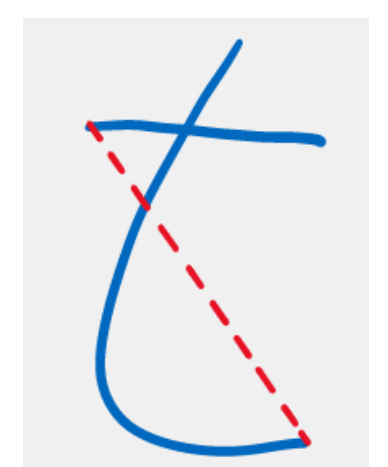


An hybrid loss to penalize hovering

$$L = L_t + \alpha L_h$$

$$L_t = MSE_{t \in touch}$$

$$L_h = \left(\sum_{t \in hov} \Delta x_t - V_{yt} \right)^2$$



6. Preliminary results

- For paper data
 - Ground truth: a, c, d, e, salut
 - Prediction without DANN: (poor reconstruction)
 - Prediction with DANN: (improved reconstruction)
 - Stroke level: (stroke-by-stroke alignment)
- For inclined data
 - Ground truth: Maccabe, meme
 - Prediction without DANN: (poor reconstruction)
 - Prediction with DANN: (improved reconstruction)
 - Stroke level: (stroke-by-stroke alignment)

Domain adaptation to inclined data

Epoch	Lambda	evaluation type	metric type	base model - TCN		DANN		DANN		DANN	
				avg	sd	avg	sd	avg	sd	avg	sd
0.01	label	Fréchet	0.3638	0.145	0.2682	0.1936	0.2823	0.1697	0.2155	0.164	
		RMSE	3.8376	1.9588	2.3127	1.6302	2.5964	1.7103	1.961	1.4674	
	stroke	Fréchet	0.3721	0.1901	0.1972	0.1247	0.2012	0.1304	0.1933	0.1281	
		RMSE	2.8054	1.0438	2.1063	1.454	1.9723	1.3132	1.9928	1.306	

Results analysis

- Domain adaptation improves results qualitatively and quantitatively
- The inclusion of the **third dimension** provides greater **spatial coherence**, which is reflected in improved label scores
- The hovering trajectory is not sufficiently well reconstructed, so we want to fill this gap with a **hybrid loss**.

Florent Imbert

IRISA, Université de Rennes, INSA Rennes

Yann Soullard

IRISA, LETG, Université Rennes 2

Romain Tavenard

IRISA, LETG, Université Rennes 2

Eric Anquetil

IRISA, Université de Rennes, INSA Rennes

Contact

florent.imbert@irisa.fr

References

- Swailh, W., Imbert, F., Soullard, Y. et al. Online handwriting trajectory reconstruction from kinematic sensors using temporal convolutional network. *IJDAR* (2023).
- M. Wehbi, D. Luge, T. Hamann, et al. Surface-free multi-stroke trajectory reconstruction and word recognition using an imu-enhanced digital pen. *Sensors*, 2022.
- Ganin, Yaroslav, et al. « Domain-Adversarial Training of Neural Networks ». In *Domain Adaptation in Computer Vision Applications*, édité par Gabriela Csurka, 189-209. *Advances in Computer Vision and Pattern Recognition*. 2017