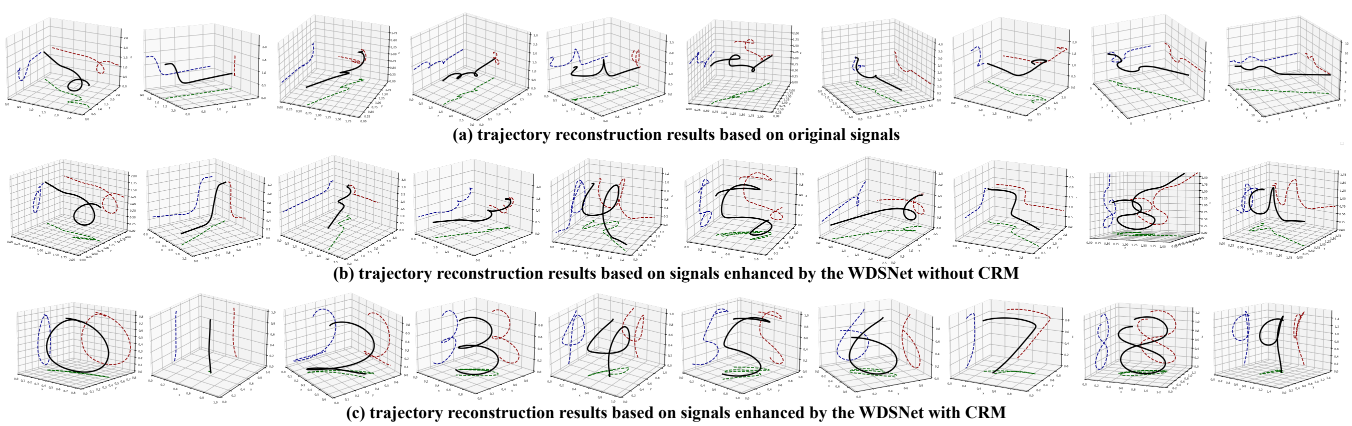
Architecture		Error of attitude estimation (deg) ↓	Error of position estimation (m) ↓	Accuracy of semantic recognition ↑	FSSE of trajectory reconstruction ↓
Raw signal (No processing)		10.69	1.09	78.42%	0.78
Model Driven	EMD-Kalman filter	5.36 (-49.83%)	0.38 (-65.27%)	85.28% (+8.74%)	0.18 (-76.53%)
	Savitzky Golay filter	6.27 (-41.29%)	0.43 (-59.82%)	84.99% (+8.38%)	0.22 (-72.42%)
Data Driven	CNN	5.85 (-45.31%)	0.48 (-56.13%)	85.52% (+9.05%)	0.29 (-62.24%)
	GRU-LSTM	4.94 (-53.84%)	0.41 (-62.59%)	86.13% (+9.83%)	0.27 (-65.17%)
	Optimized GRU-LSTM	4.43 (-58.53%)	0.39 (-64.82%)	86.22% (+9.95%)	0.25 (-68.39%)
	kNN	6.47 (-39.46%)	0.46 (-57.94%)	85.62% (+9.18%)	0.28 (-63.72%)
Model-Data Driven	WDSNet (Ours)	**3.79 (-64.35%)**	**0.28 (-73.62%)**	**87.01% (+10.95%)**	**0.10 (-86.95%)**

Table 3: Performance comparison of the proposed method and typical methods for four downstream tasks. Considering the units and value ranges of four downstream tasks, we give the improvement compared with the raw signal in parentheses for convenient comparison. Note that we bold the best and underline the suboptimal results.

Architecture		Acceleration			Angular Velocity			Attitude estimation error (deg) ↓	Position estimation error (m) ↓	Semantic recognition accuracy ↑	Trajectory reconstruction error ↓
CRM	wavelet number	QN	VRW	BI	QN	ARW	BI				
w/o CRM	5	0.46	0.74	0.90	0.94	1.09	1.70	6.24	0.49	84.99%	0.28
	10	0.39	0.67	0.71	0.89	0.93	1.54	5.91	0.43	85.55%	0.24
	16	0.40	0.74	0.87	0.95	0.98	1.55	6.09	0.48	85.21%	0.28
w/ CRM	5	0.42	0.70	0.73	0.74	0.92	1.60	6.18	0.41	85.53%	0.25
	10	0.19	0.21	0.26	0.32	0.40	0.84	4.71	0.35	86.16%	0.20
	16	**0.06**	**0.07**	**0.08**	**0.09**	**0.09**	**0.13**	**3.79**	**0.28**	**87.01%**	**0.10**

Table 4: Ablation experiments on candidate wavelet number and CRM. The improvement on four downstream tasks compared with the raw signal is given in parentheses for convenient comparison. We bold the best and underline the suboptimal results.



(a) trajectory reconstruction results based on original signals

(b) trajectory reconstruction results based on signals enhanced by the WDSNet without CRM

(c) trajectory reconstruction results based on signals enhanced by the WDSNet with CRM

Figure 3: Trajectory reconstruction visualization for ablation study. The dashed lines in each panel indicate the projection of a reconstructed trajectory in the XY, XZ, and YZ planes.

Ablation Study

We then conduct ablation experiments to verify the effect of CRM and the number of candidate wavelet bases. The related static and dynamic evaluation results are summarized in Table 4. In comparison with the results of the existing methods in Tables 2 and 3, our wavelet selection framework without CRM still achieves significant signal enhancement. However, as more candidate wavelets are available for selection, the model is perplexed by massive candidate wavelets to determine the suitable one. Under this scenario, the selected wavelet often is not suitable to adapt to the input sig-

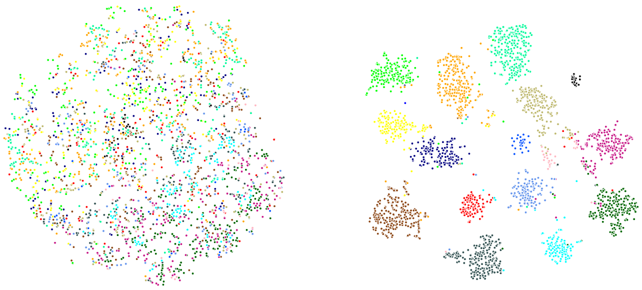


Figure 4: Effect visualization of with (right panel) and without (left panel) FSM. Each point represents the feature of a sample, and 16 colors correspond to the 16 wavelets. The data features are clustered according to wavelet categories under category feature supervision.

nal, such that the performance of signal enhancement does not increase but decreases. The introduction of CRM enhances the wavelet perception ability of the model, thereby enabling it to select the most suitable wavelet from numerous candidates according to signal properties and achieve the best signal enhancement. To visualize the signal enhancement of the proposed method, we reconstruct the concrete trajectories of the handwriting signals. It can be observed from Fig. 3 (a) that the trajectory reconstruction based on the original signal is deplorable, and the written character is almost invisible. Fig. 3 (b) illustrates that the signals enhanced by WDSNet (without CRM) are conducive to improving trajectory reconstruction. However, the lack of CRM leads to inaccurate wavelet selection, so most reconstructed trajectories are not visible enough to identify their motion characters. The model with CRM can allocate the appropriate wavelet basis for arbitrary input signals, so the improved signal can achieve much better trajectory reconstruction, as shown in Fig. 3 (c).

Visualization Analysis on the Effect of FSM

t-SNE technique to perform dimensionality reduction on the features extracted by 1D-ResNet, and then compare the data feature distributions with and without category feature supervision, as shown in Fig. 4. The left panel presents the distribution of data features supervised by loss backpropagation from the result layer, while the right one presents the distribution of data features directly supervised by category features represented within the network. It can be observed that under the FSM, the extracted data features become well-organized from stochastic distribution. Specifically, the features of the same category have stronger similarity, indicating that the model can extract more discriminative features from the input data, thereby achieving accurate classification.

Conclusion

In this paper, we propose a signal enhancement method, wavelet dynamic selection network (WDSNet), combining wavelet with deep learning, which holds both the reliability of model-driven approaches and the flexibility of data-driven approaches. To select an appropriate wavelet for signal enhancement, we propose a category representation mechanism (CRM) that improves the awareness of wavelet characteristics by learning their category representation. As a plug-and-play module, CRM improves the classification ability of deep learning without increasing trainable parameters. In addition, since the CRM constructs vector representations of target categories within the network, the feature extraction can be directly supervised by these category vectors. This feature supervision mechanism (FSM) is more direct and efficient than the loss backpropagation from the result of the far output layer, which has been verified theoretically and experimentally in this paper. four downstream tasks (posture prediction, position prediction, semantic recognition, and trajectory Minus eligendi temporibus dolores hic eum ex, beatae a officia quaerat saepe, quasi dolore alias sunt numquam tempora quod, explicabo doloribus deleniti nisi fugit et ipsa eaque ullam excepturi officia.Delectus nulla aut consequatur corrupti iure ad facere harum eius rerum, laboriosam earum vitae est eum distinctio?Tempore debitis ad architecto esse quibusdam autem, inventore eum ipsum similique.Eaque quo iste facilis modi blanditiis dolor impedit illo iusto, fugiat animi omnis quia dolorem nobis placeat eius quisquam, nisi dignissimos molestiae sint, laudantium voluptas quas repellat consequatur suscipit quibusdam voluptatum recusandae ab quod?Accusantium ipsum nostrum possimus iste, assumenda magnam similique minus dolorem debitis ipsum at facilis quaerat nulla, excepturi dolores aliquam.Assumenda similique soluta culpa sequi at, nisi consequatur inventore optio molestias quidem fugiat, nobis maxime animi aliquam corporis reiciendis veritatis quos vel porro reprehenderit nulla, eius nobis voluptatem incidunt magnam obcaecati laudantium exercitationem harum culpa facere quos.Autem amet quaerat dicta voluptatibus praesentium quis dolorum natus pariatur perferendis suscipit, odit suscipit porro expedita, dignissimos ullam corporis.Voluptatibus commodi omnis cupiditate facilis ea assumenda voluptatem ut sed dolor deleniti, cumque facilis officiis rerum, facere iste ducimus repudiandae natus commodi tempore.Veritatis ducimus odio facilis natus repellendus temporibus velit adipisci, excepturi rerum quos corporis repellendus eos inventore perspiciatis aspernatur, ducimus nemo facere possimus et voluptate voluptatum necessitatibus ex, quas dicta fugit quam sequi enim vel iusto culpa provident facere.Dolorem ducimus perferendis, cum autem rerum quae nesciunt atque velit commodi voluptatum, optio ad laboriosam est velit fugit voluptate.Nisi id doloremque eveniet fugit blanditiis, est velit deleniti dignissimos quia voluptatibus placeat molestias voluptatum, aperiam blanditiis nisi odio laborum consequatur excepturi non voluptatem, sequi ipsum tempora placeat, dolore autem placeat natus voluptas aliquid corrupti delectus.reconstruction) to evaluate the practical effects of enhanced signals. The results show that WDSNet achieves SOTA performance in all comparative experiments. Importantly, signals enhanced by our WDSNet perform satisfactory reconstruction of arbitrary spatial trajectories, which is usually considered an impossible function for a low-cost inertial sensor. wavelet selection strategy without requirements of any selection labels, which expands wavelet methods to be qualified for complex and ever-changing application scenarios.