CRRL: Learning Channel-invariant Neural Representations for High-performance Cross-day Decoding

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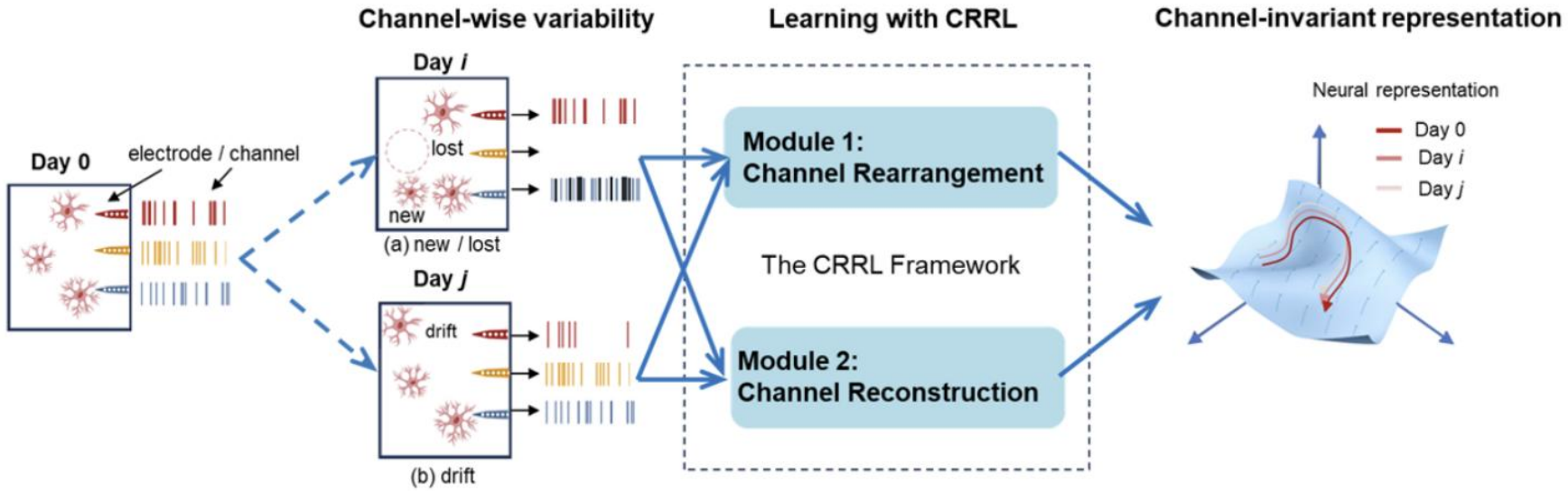
Background & Motivation

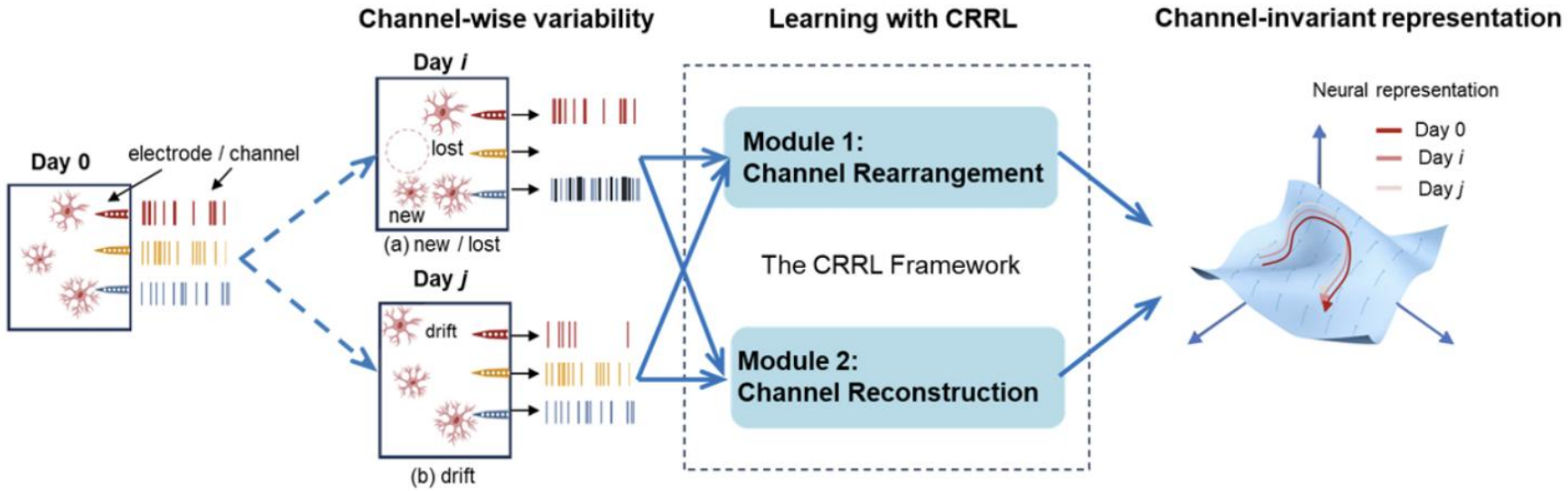
The channel-wise variability can stem from diverse reasons.
First, the appearance of new neurons and the disappearance of existing neurons can happen across different experimental days.
Second, the movement of neurons or electrodes can also drift in the recorded neural signals at each channel.



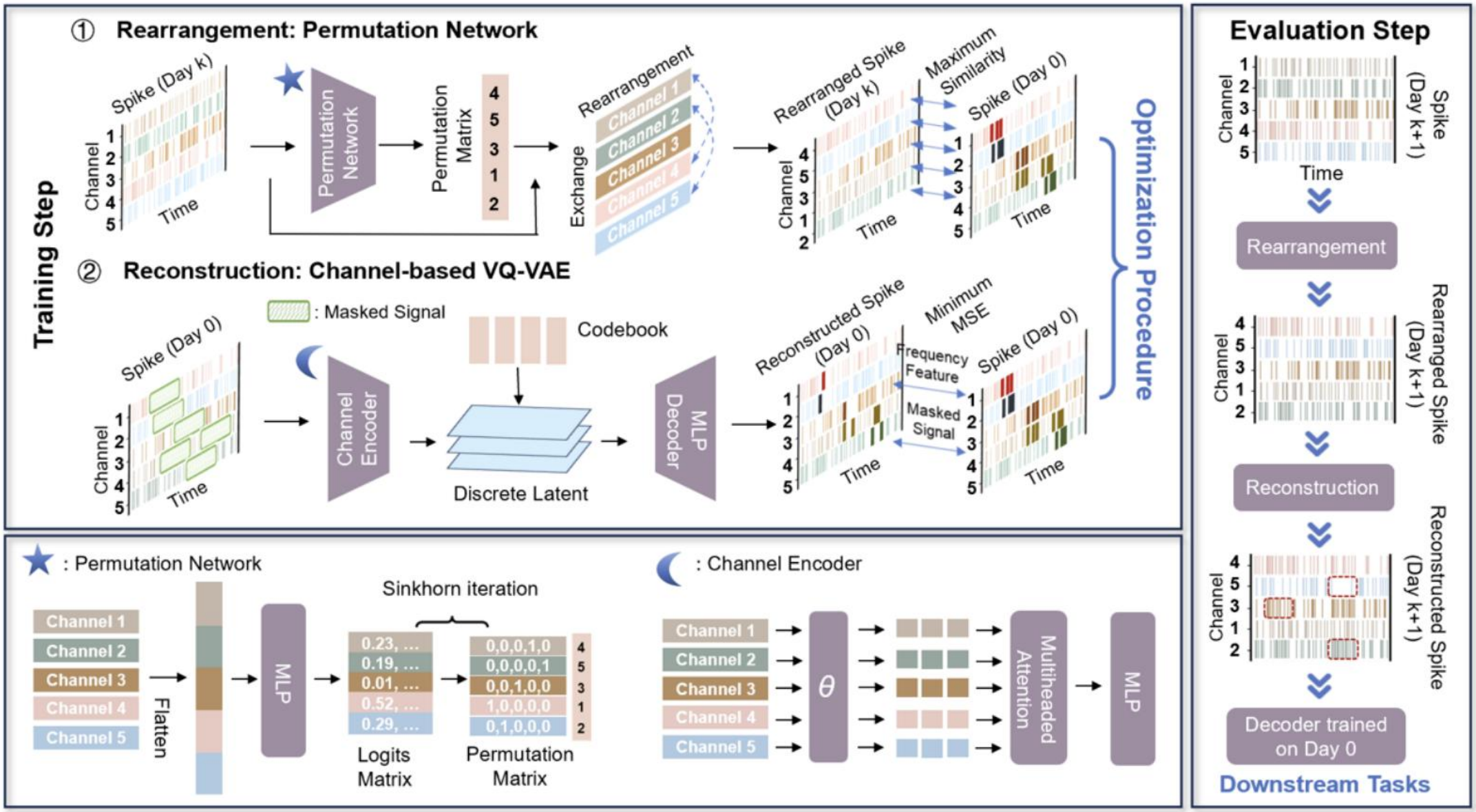
Background & Motivation

Existing studies addressed this problem from several aspects.

1. **The first group** is the data alignment approaches. However, it required that a subset of the channels should be stable across different days.
2. **The second group** attempts to improve the robustness of cross-day neural decoding by using more data. These large-scale methods implicitly account for differences in neurons or channels, but require higher training costs.



Method


Training Step
① Rearrangement: Permutation Network
Spike (Day k)
Channel
Time
Permutation Network
Permutation Matrix
4 5 3 1 2
Rearrangement
Exchange
Channel 1
Channel 2
Channel 3
Channel 4
Channel 5
Rearranged Spike (Day k)
Maximum Similarity
Spike (Day 0)
② Reconstruction: Channel-based VQ-VAE
: Masked Signal
Codebook
Spike (Day 0)
Channel Encoder
Discrete Latent
MLP Decoder
Reconstructed Spike (Day 0)
Minimum MSE
Frequency Feature
Masked Signal
Optimization Procedure
: Permutation Network
Sinkhorn iteration
Flatten
MLP
0.23, ...
0.19, ...
0.01, ...
0.52, ...
0.29, ...
0,0,0,1,0
0,0,0,0,1
0,0,1,0,0
1,0,0,0,0
0,1,0,0,0
Logits Matrix
Permutation Matrix
: Channel Encoder
θ
Multiheaded Attention
MLP
Evaluation Step
Spike (Day k+1)
Rearrangement
Rearranged Spike (Day k+1)
Reconstruction
Reconstructed Spike (Day k+1)
Decoder trained on Day 0
Downstream Tasks

Experiment

Table 1: Ablation study on simulation dataset.

R^2/acc	w/o RA	w/o RC	RA + RC
New/lost neuron (5 %)	0.83/99.1	0.72/92.7	**0.92/99.5**
New/lost neuron (10 %)	0.81/96.1	0.69/89.3	**0.87/99.3**
Shuffled channel (5 %)	0.15/55.1	0.85/92.1	**0.89/98.0**
Shuffled channel (10 %)	0.05/48.3	0.77/87.5	**0.86/98.2**
Changed function (5 %)	0.66/80.8	0.45/64.7	**0.73/91.4**

Table 3: Ablation Study on Real Neural Datasets.

	Component		Center-Out (C)			ISO (J)			Key (G)		
	RA	RC	[5, 10)	[10, 20)	[20, 40)	[5, 10)	[10, 20)	[20, 40)	[5, 10)	[10, 20)	[20, 40)
CRRL	✓	-	0.73/68.1	0.61/64.6	0.57/63.5	0.44/57.7	0.41/48.3	0.41/52.5	0.35	0.31	0.32
CRRL	-	✓	0.73/66.4	0.64/57.6	0.52/53.2	0.47/62.2	0.36/53.0	0.32/49.3	0.38	0.33	0.26
CRRL	✓	✓	**0.75/77.1**	**0.68/70.5**	**0.65/66.8**	**0.51/66.3**	**0.48/61.5**	**0.43/62.2**	**0.41**	**0.37**	**0.35**

Experiment

Table 2: The performance of regression and classification prediction which compares with different cross-day decoding methods.

R^2/acc	Model	Task	Number of days since day 0					
			0	[5, 10)	[10, 20)	[20, 40)	[40, 65)	[65, 100)
Center-Out (C)	Stabilizedbci	Trajectory/ Direction	0.84/86.5	0.59/56.6	0.52/50.7	0.45/44.8	-/-	-/-
	SD-Net			0.73/69.3	0.65/62.5	0.62/63.3	-/-	-/-
	NoMAD			0.55/48.4	0.58/50.6	0.41/37.9	-/-	-/-
	CRRL (Ours)			**0.75/77.1**	**0.68/70.5**	**0.65/66.8**	-/-	-/-
Center-Out (M)	Stabilizedbci	Trajectory/ Direction	0.68/73.1	-/-	0.38/51.6	0.34/43.7	-/-	-/-
	SD-Net			-/-	0.45/62.0	0.39/52.0	-/-	-/-
	NoMAD			-/-	0.33/39.5	0.26/29.7	-/-	-/-
	CRRL (Ours)			-/-	**0.51/63.5**	**0.45/57.4**	-/-	-/-
ISO (J)	Stabilizedbci	Trajectory/ Direction	0.73/92.5	0.38/57.4	0.32/53.1	0.23/35.0	0.20/36.5	0.17/29.1
	SD-Net			0.42/65.2	0.35/58.6	0.28/44.2	0.25/43.8	0.20/34.5
	NoMAD			0.44/65.2	0.45/**62.4**	0.37/40.8	0.28/37.5	0.31/39.7
	CRRL (Ours)			**0.51/66.3**	**0.48**/61.5	**0.43/62.2**	**0.46/48.6**	**0.47/51.1**
ISO (S)	Stabilizedbci	Trajectory/ Direction	0.75/94.4	0.33/43.3	0.35/47.2	0.24/40.9	0.18/25.0	<0 /14.8
	SD-Net			0.40/56.5	0.37/53.7	0.36/53.7	0.32/45.6	0.24/35.9
	NoMAD			0.34/53.3	**0.40**/51.2	**0.38**/45.0	0.37/44.1	0.29/31.3
	CRRL (Ours)			**0.43/57.2**	0.39/**56.6**	0.35/**54.5**	**0.37/54.1**	**0.30/45.2**
ISO (J)	ADAN	EMG	0.71	0.66	0.60	0.56	0.54	0.48
	Cycle-GAN			0.68	0.65	0.63	0.59	0.50
	CRRL (Ours)			**0.70**	**0.66**	**0.69**	**0.65**	**0.61**
Key (G)	ADAN	EMG	0.46	0.26	0.21	0.18	<0	-
	Cycle-GAN			0.27	0.25	0.20	0.09	-
	CRRL (Ours)			**0.41**	**0.37**	**0.35**	**0.32**	-

Experiment

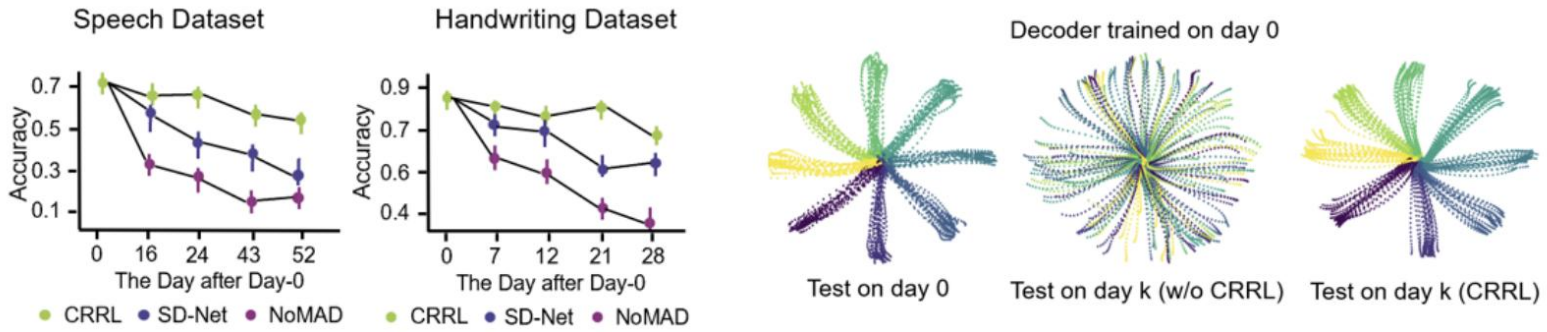


Figure 3: (Left) we compare our CRRL with two baseline methods (SD-Net and NoMAD) on speech and handwriting datasets. We evaluate the performance using the classifier trained on day 0 data. (Right) we use CRRL to decode the hand trajectory across days. First, we use the regressor trained with the data from day 0 to evaluate the performance. In the middle figure, this regressor completely loses its decoding ability on day k data. However, through CRRL, the regressor recovers its performance, which is close to the performance on day 0 data.

Experiment

Table 4: Comparison with large-scale models including POYO-1 and NDT2 Multi. PT is the pretrain model and FSS is the few shot setting,

Method	Monkey C	M1-A	M2
POYO-1 + Full finetune	0.9683 ± 0.01	-	-
NDT2 Multi + FSS	-	0.59 ± 0.07	0.43 ± 0.08
CRRL w/o PT	0.8715 ± 0.03	0.42 ± 0.13	0.31 ± 0.07
CRRL PT + Full finetune	**0.9750 ± 0.02**	**0.63 ± 0.08**	**0.55 ± 0.13**

Table 5: Plugin-in experiment.

R^2	Day 7	Day 30	Day 56
ADAN	0.26 ± 0.04	0.18 ± 0.05	<0
Cycle-GAN	0.27 ± 0.02	0.20 ± 0.03	0.09 ± 0.02
RA + ADAN	0.29 ± 0.02	0.23 ± 0.03	0.14 ± 0.03
RA + Cycle-GAN	**0.33 ± 0.01**	**0.27 ± 0.01**	**0.20 ± 0.02**

Thanks for your attention