Neural Embeddings Rank: Aligning 3D Latent Dynamics with Movements

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Presentation Overview

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A novel dimensionality reduction method.

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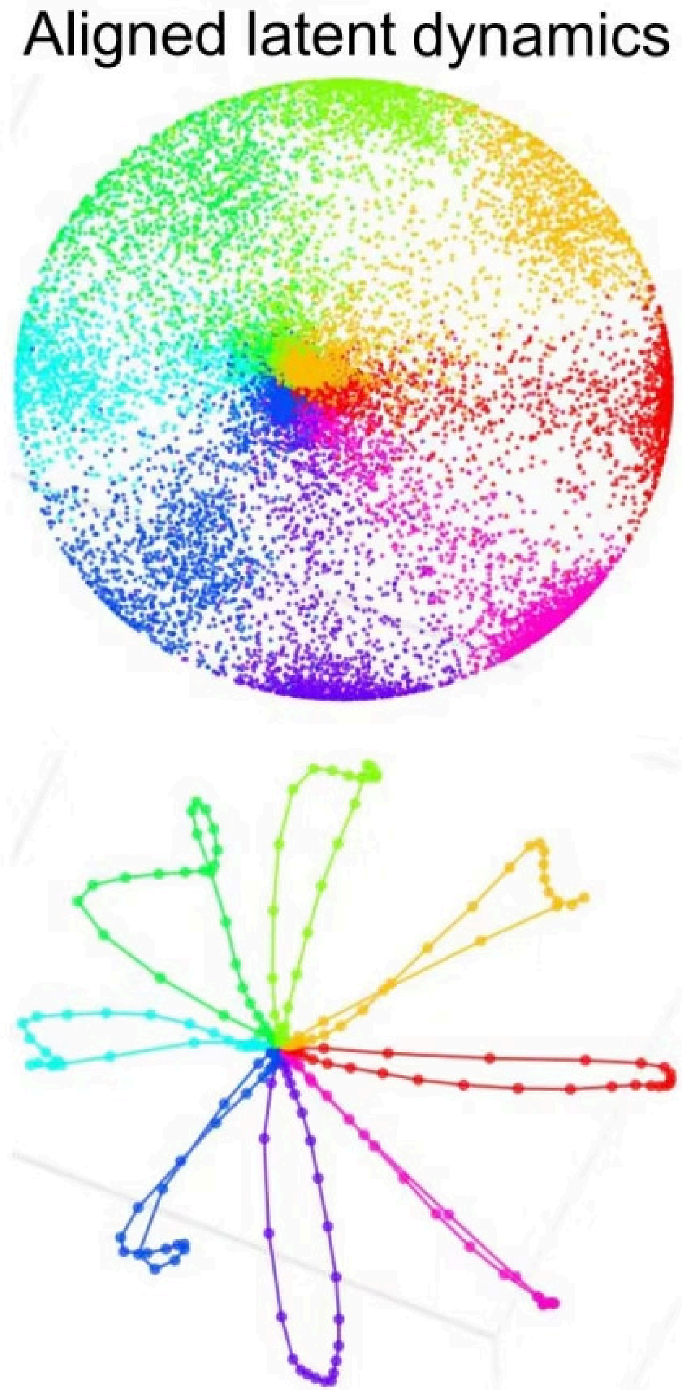
Implications and limitations of NER.



The Challenge: Aligning Neural Dynamics with Movement

High-Dimensional Data

Simultaneously recorded neurons generate complex, high-dimensional data that is difficult to interpret.

Visualization & Comparison

Existing methods struggle to reduce dimensionality while maintaining clear, movement-aligned latent dynamics.

Decoding Limitations

Traditional decoders face issues with long-term recordings and cross-animal applications due to changing neural identities.

The goal is to extract latent dynamics most informative about movements.

Introducing Neural Embeddings Rank (NER)

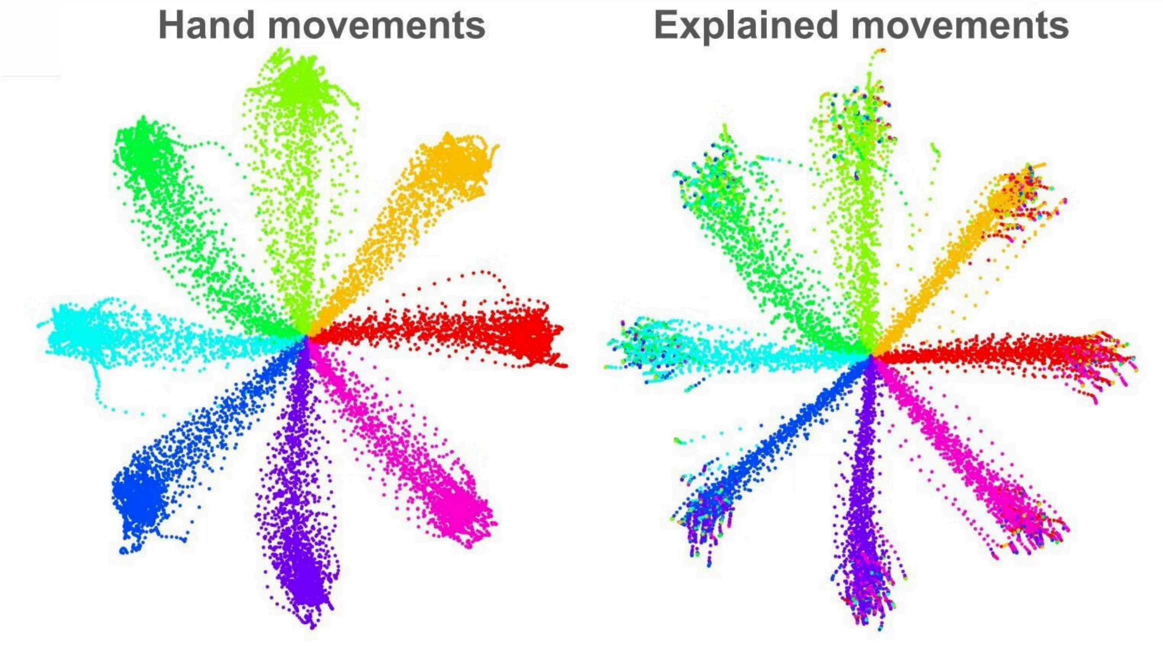


Figure 1: Comparison of hand movements and the NER approach to contrasting embeddings.

Key Innovation

NER embeds neural dynamics into a 3D latent space, contrasting embeddings based on movement ranks to align them with continuous movement labels.

Addressing Challenges

- Handles high dimensionality and class imbalance.
- Learns regression-aware representations for continuous movements.
- No additional hyperparameters needed compared to CEBRA.

NER vs. CEBRA: The Core Difference

NER is inspired by previous studies and uses similar data sampling and neural feature encoding as CEBRA. The key difference lies in the loss function.

CEBRA's Approach

CEBRA treats each embedding in a batch as a discrete class. For an anchor, it contrasts with its augmented embedding as a positive pair and a batch of randomly sampled embeddings as negative pairs.

$$l^{(i)}_{CEBRA} = -log\frac{exp(sim(v_i, v_j)/\tau)}{\sum N_{n=1} exp(sim(v_i, v_n)/\tau)}$$

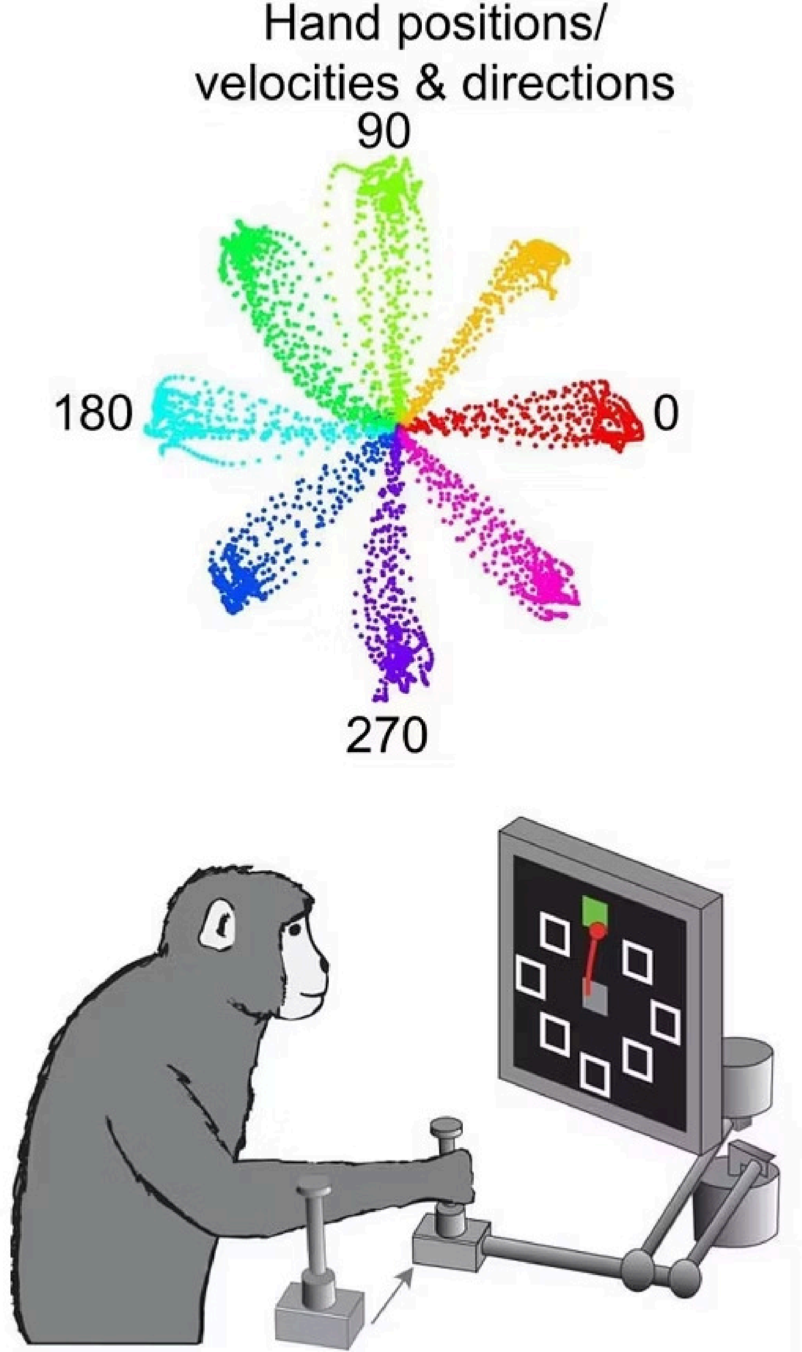
Where sim(,) is similarity (e.g., negative L2).

NER's Approach

NER ranks two batch of embeddings according to their continuous labels. It contrasts an anchor with its augmented or first embedding as a positive pair and the remaining embeddings as negative pairs, repeating this process.

$$l^{(i)}_{NER} = \frac{1}{2N-1}\sum 2N_{j=1, j\neq i} - log\frac{exp(sim(v_i, v_j)/\tau)}{\sum_{v_k \in S_{i,j}} exp(sim(v_i, v_k)/\tau)}$$

Where S_{i,j} denotes embeddings of lower ranks than v_i in terms of label distance relative to v_i.



Experimental Design

1

Subjects & Tasks

Two monkeys (H & C) performed center-out reaching tasks using a planar manipulandum.

2

Neural Recordings

96-channel Utah arrays in M1, PMd, and S1 captured neural activity.

3

Data Processing

Spike sorting and dimensionality reduction to 3D latent dynamics.

4

Decoding

Linear and kNN decoders used to predict hand velocities, positions, and directions.

NER's Superior Performance

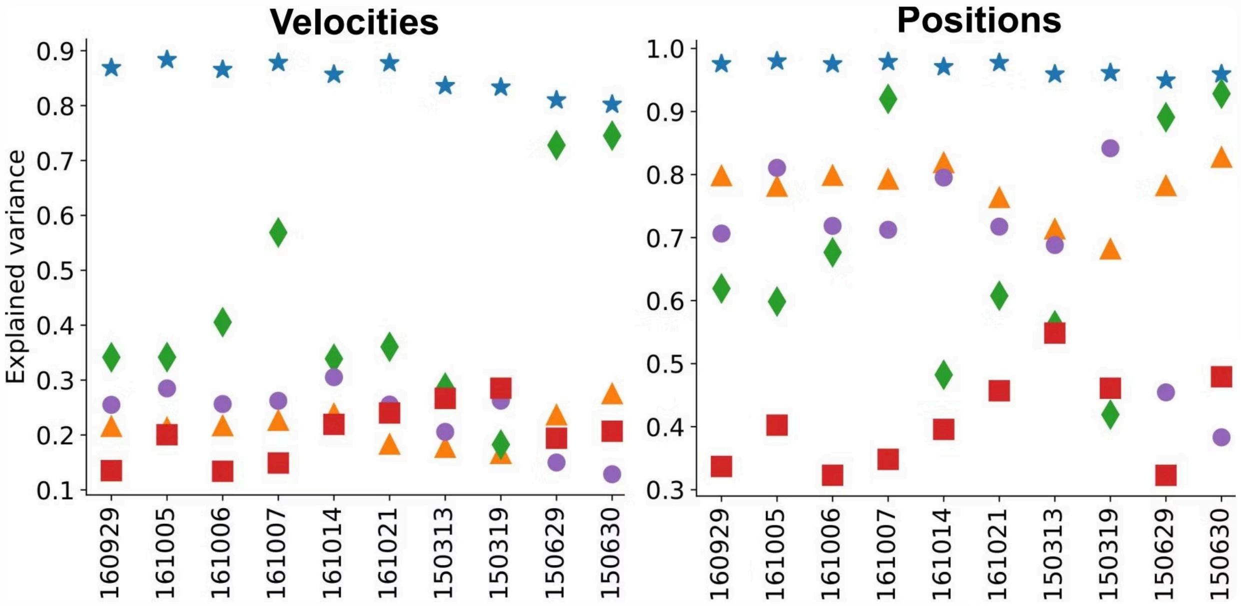


Figure 4: Explained variance of movements in M1.

Movement-Aligned Latent Dynamics

NER consistently revealed neural embeddings aligned with movement in M1, PMd, and S1, forming clear pinwheel structures.

High Explained Variance

NER explained 86% of velocity variance and 97% of position variance using linear decoders, significantly outperforming other methods.

Long-Term & Cross-Hemisphere Decoding

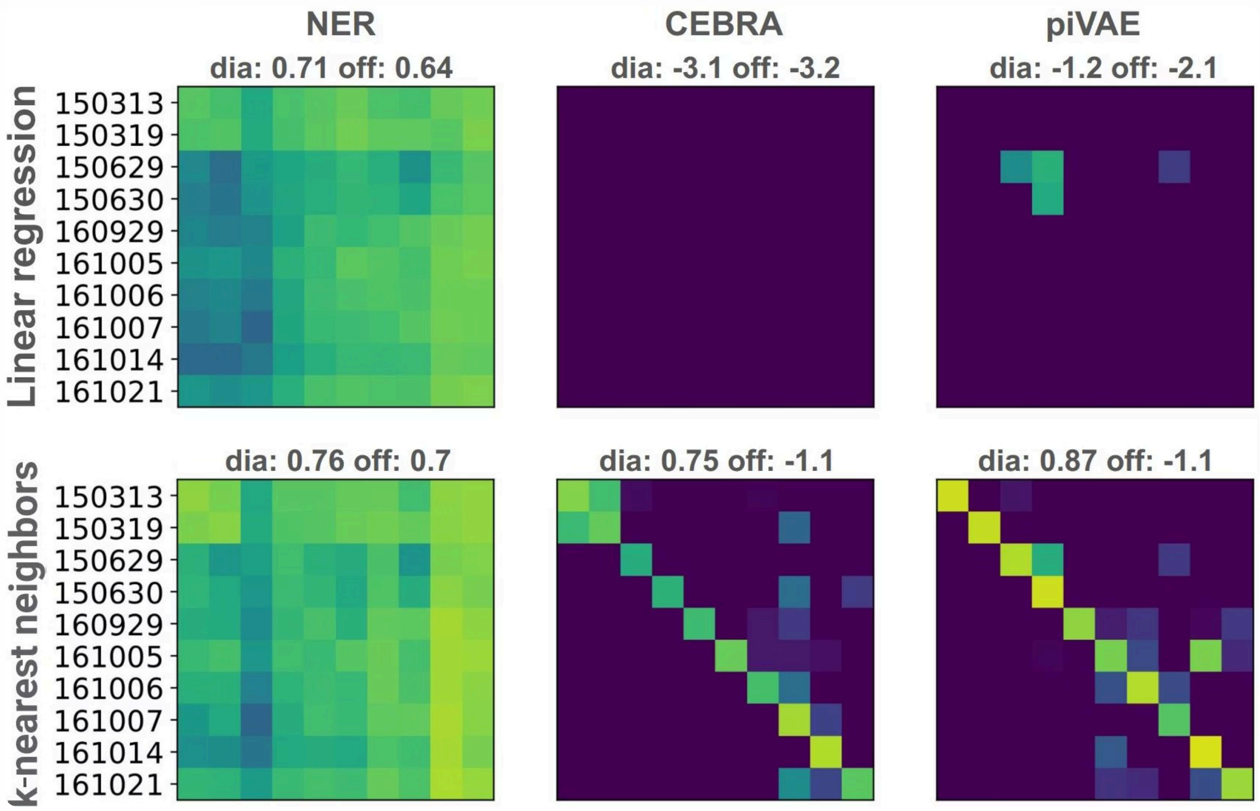


Figure 5: Decoding performance across time and brain hemispheres in M1.

Robust Decoding

NER, with a linear decoder, successfully decoded hand velocities, positions, and directions across different sessions (over a year) and hemispheres.

Performance remained comparable to within-session decoding (e.g., 64% vs. 71% for velocity).

Outperforming Competitors

CEBRA and piVAE struggled with cross-session decoding, especially with linear decoders, highlighting NER's superior generalizability.

Distinct Dynamics for Different Movements

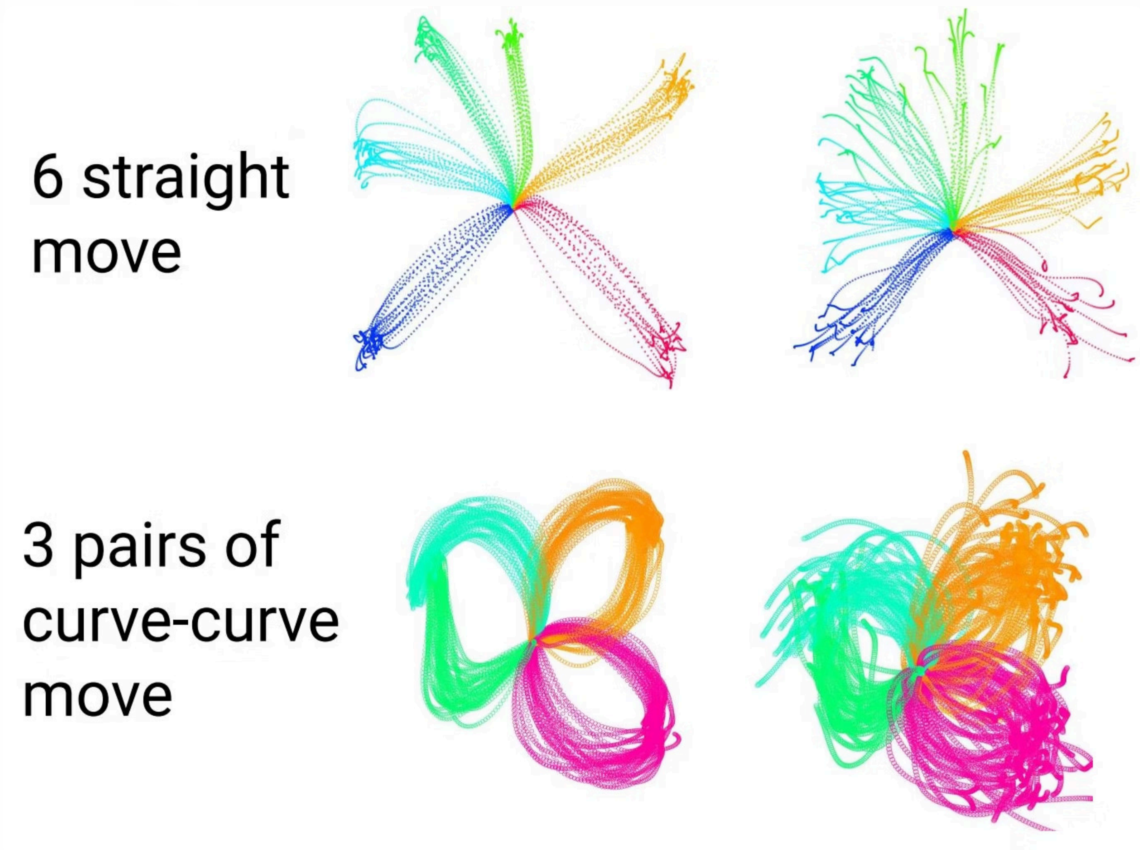


Figure 8: Latent dynamics for straight and curved movements in M1.

Straight vs. Curved Movements

NER effectively differentiated latent dynamics for straight and curved hand movements in M1.

Straight movements showed similar latent dynamics to previous findings, while curved movements produced distinct, separated dynamics.

Robustness Across Movement Types

NER consistently achieved higher explained variance than CEBRA, demonstrating its ability to handle various complex movement types.

Key Takeaways

Superior Alignment

NER effectively aligns low-dimensional latent dynamics with continuous movements.

High Decoding Accuracy

Achieves high variance explanation for velocity and position with linear decoders.

Long-Term Stability

Enables robust decoding across sessions (over a year) and brain areas.

Movement Differentiation

Distinguishes latent dynamics for different movement types, including curved trajectories.

Discussion & Future Directions

Impact on Neuroscience

NER's ability to extract stable, informative latent dynamics opens new avenues for fundamental neuroscience research, especially in probing the stability of neural dynamics.

Brain-Machine Interfaces (BMI)

The method's robust cross-session and cross-subject decoding capabilities, combined with a simple linear decoder, are highly promising for BMI applications.

Broader Applications

NER is not limited to hand movements or electrophysiology; it can be applied to other neural recordings (e.g., calcium imaging) and different types of latent dynamics (e.g., body position, video features).

Limitations & Future Work

Further research is needed for more complex human movements like handwriting and speech, which may require higher-dimensional latent spaces and more advanced ranking methods.

Thank you for your attention!