Original Research Article

Decoding the Direction of Arm Movements using Long Short-Term Memory and Poisson State Space Model Algorithms

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ABSTRACT

Brain-computer interfaces (BCIs) allow for decoding neural signals associated with intended movements and converting that to commands that can control external hardware, including prosthetics. This can help individuals with paralysis who lack the ability to voluntarily control their limb movements. This study aims to investigate decoding the direction of arm movement from single-neuron non-human primate recordings obtained during a center-out reaching task. The intended direction of movement was decoded from a population of directionally tuned neurons using two decoding algorithms: Long Short-Term Memory (LSTM) and another algorithm known as the Poisson State Space Model (POSSM). LSTM learns spike patterns directly from the data, while POSSM uses a framework specifically tuned to neuronal firing dynamics. The results demonstrated that the POSSM achieved relatively higher decoding accuracy when compared to LSTM, suggesting that the neural activity in the dataset follows patterns suited to the Poisson model's assumptions. POSSM is a relatively novel algorithm, and this manuscript represents an early attempt to adopt it in a motor decoding task. The results suggest that it outperforms LSTM. These findings may inform the design of more accurate and efficient brain–computer interface systems and support future advancements in motor rehabilitation strategies.

Keywords: Poisson State-Space Model (POSSM); Long Short-Term Memory (LSTM); Single-neuron decoding; Brain-computer interface; neural decoding; motor cortex

INTRODUCTION

In the United States (US) alone, nearly 5.4 million people live with some form of disability due to paralysis. Every year, around 18,000 new cases of Spinal cord injury (SCI) contribute to the millions of paralyzed individuals (1). Beyond the number of those already affected, many struggle to provide for themselves financially. 50% of SCI survivors live in poverty, and they also burden the United States healthcare system by around $40.5 billion annually. This is a problem that extends beyond the United States.

Paralyzed individuals adapt to daily life using combinations of medical and technological support systems. They must go through physical and occupational therapy (OT) to help maintain muscle strength, prevent stiffness, and learn new ways to perform daily tasks. Assistive devices, such as wheelchairs, help with

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mobility. Speech-recognition and eye-tracking software help people use computers, allowing them to control adaptive home systems and communicate. BCI systems provide hope for individuals with mobility limitations to become active members of society.

Single-neuron recordings provide one of the most direct windows into motor encoding. This signal is characterized by a high signal-to-noise ratio (SNR) compared to other means of signal acquisition, like an electroencephalogram (EEG). There are some trade-offs that come with these types of BCIs; as intracortical BCIs, single-neuron recordings require the use of microelectrode arrays that require invasive surgery to implant.

Decoding motor control using invasive BCIs like electrocorticography (ECoG) or intracortical microelectrode arrays was previously reported. For example, Jang *et al*. used an ECoG BCI to decode multiple types of hand movements by analyzing cortical activity patterns and demonstrated that high-resolution invasive recordings can be used to differentiate motor tasks with great accuracy (2). Similarly, Ajiboye *et al.* were able to successfully restore hand movement in a paralyzed patient using an intracortical BCI. These systems have been successful in the partial restoration of hand control (3). However, these methods require surgery, which increases the risk-to-benefit ratio and, thus, makes it less accessible.

Knowledge of single neurons in the context of how the motor cortex encodes movement is growing rapidly. Previous work has shown that individual neurons are tuned to specific parameters like movement direction, force, or velocity (4). Examining the firing rates of populations of neurons allows researchers to predict the intended movement of the limb in controlled experiments. Real-time control remains a challenge: neural signals are sparse; recordings can be unstable if electrodes shift, or neurons drop out.

Single-unit recordings from the motor cortex during a center-out reaching task were used to evaluate two decoding algorithms, including the Poisson State-Space Model (POSSM) and Long Short-Term Memory (LSTM), to map neuronal spiking patterns onto intended hand movement directions. POSSM is a hybrid architecture that combines individual spike tokenization developed by AHW Ryoo *et al*. This paper aims to evaluate the use of POSSM, as a relatively novel algorithm, to decode the direction of movement. It also aims to compare that to the performance of LSTM. This analysis could be used to guide the development of future BCI systems.

METHODS AND MATERIALS

Data collection

The neural recordings used in this study were obtained from the primary motor cortex (M1) of macaque monkeys performing a center-out reaching task. The dataset was originally collected using a multielectrode Utah array and made publicly available in Stevenson *et al*. Neural data from 143 motor cortex neurons across 80 trials were used (5). Behavioral data were collected using a manipulandum, which is an exoskeleton device that fits over the arm and constrains movement to a two-dimensional plane. The manipulandum functions similarly to a joystick operated by the entire arm (Figure 1). The behavioral task followed the center-out reaching paradigm described by Georgopoulos *et al*. (4). In each trial, the subject maintained the cursor on a central target for 500 ms before a peripheral target appeared at one of eight possible locations arranged in a circle around the center. An instructed delay period of 1000-1500 ms followed, during which the subject was required to wait for a “go” cue. Upon receiving the cue, the subject moved the cursor toward the peripheral target and held it there for 500 ms to complete the trial. The spike trains were binned in twenty millisecond windows over a two second period from minus one to plus one second around the go cue, resulting in 100-time bins per trial.

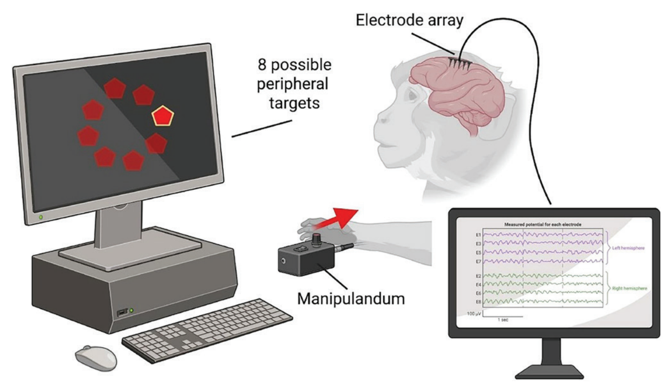

Figure 1. *Experimental setup for center-out reaching task used to collect data for POSSM and LSTM testing. Neural activity was recorded from the motor cortex using an intracortical microelectrode array while the subject performed a two-dimensional reaching task using a manipulandum. Spike activity was recorded during this task and the data was used to train and evaluate the LSTM and POSSM decoding algorithms.*

The neural activity was recorded using an intracortical microelectrode array, an invasive BCI system. It allows for precise measurement of single-neuron spikes from the motor cortex (6).

The dataset was provided in a preprocessed format, and no additional artifact rejection or spike filtering procedures were required. Spike counts were binned into fixed 20 ms windows, and bins with zero spikes were retained to preserve the natural sparsity of neural firing activity.

Machine learning to decode movement

LSTM

The LSTM model is a type of deep learning algorithm that is learnt from examples. It analyzes neural spike sequences to find patterns associated with specific movement directions. LSTM processes data step by step and remembers important features and forgets patterns that become irrelevant as it goes through the data points. Through training, it can recognize certain rhythms and combinations of spikes that correspond to directions, thus allowing it to derive movement directions from new spike sequences. LSTM was applied to decode movement direction by analyzing spike sequences recorded from motor cortex neurons during the center-out reaching task.

LSTM has been applied in several other recent studies in neural decoding. In Liu *et al.* for instance, LSTM demonstrated that it could accurately decode motor cortex activity and extract movement-related information directly from raw spike data (7). Through a similar process, LSTM was trained on spike sequence data from motor cortex neurons to learn patterns for specific hand movement directions.

For each trial the binned spike counts were arranged into a matrix of size neurons by time bins, and each matrix was treated as a temporal sequence input to the LSTM network. Movement direction was encoded as one of eight classes corresponding to 8 evenly spaced target directions from 0 to 315 degrees. The LSTM model was trained at 70 percent of the trials and evaluated on the remaining 30 percent that were held out during training. We used a single bidirectional LSTM layer with 100 hidden units followed by a dropout layer with a probability of 0.3 and a fully connected SoftMax output layer that mapped to the eight movement directions. The network was trained with the Adam optimizer using a mini batch size of 16, a maximum of 100 epochs, gradient clipping with a threshold of 1, and an initial learning rate of 0.005.

POSSM

POSSM is a mathematical algorithm used to calculate neural spike activity by modeling the likelihood of spikes occurring for each movement direction. The model picks up how frequently each neuron tends to fire when the subject moves in different directions, such as up, down, or sideways. During decoding, the model uses the Poisson probability formula to calculate how likely it is that the observed spikes correspond to each possible direction. Each moment in time contributes data which helps update the probabilities until the movement ends. The direction with the highest overall likelihood is chosen as the decoded output. This approach is effective for real-time motor decoding applications.

Our framework follows the state-space modeling approach by Ryoo *et al.* who demonstrated that Poisson-based models can achieve real-time neural decoding performance by combining statistical modeling with efficient temporal updating (8). Since POSSM is based on known firing rate statistics, it can provide stable and interpretable results. It is effective for real-time motor decoding and performs well even with smaller datasets or variable neural signals.

For the Poisson model, we computed the average firing rate for each neuron and each movement direction by summing spikes over the full two second window and dividing by the window duration, then averaging across all trials with the same direction. At each time bin we computed the Poisson log likelihood of the observed spike counts under each direction specific firing rate and accumulated these log likelihoods over time. The decoded direction at any time was taken as the direction with maximal cumulative log likelihood, and the final predicted direction for the trial was the value at the end of the two second window.

Evaluation Metrics

The performance of the model was evaluated using classification accuracy, precision, recall, specificity, and F1 scores. Confusion matrices were generated to visualize the relationship between the true and predicted movement directions. Accuracy was computed as the proportion of correctly classified trials out of the total number of trials. Precision and recall were calculated per class and averaged across directions. Specificity measured the proportion of correctly identified negative cases for each direction. The F1 score was computed as the harmonic mean of precision and recall providing a balanced measure of classification performance.

RESULTS

After implementing LSTM and POSSM to predict hand movement direction from single-neuron activity during the center-out reaching task, performance was evaluated and displayed on confusion matrices, which demonstrate the relationship between true movement directions and predicted directions.

Figure 2 shows the confusion matrix (CM) for the LSTM Temporal Decoder. The LSTM model demonstrated moderate decoding accuracy, correctly identifying several movement directions, but at the same time, getting many of them incorrect. The accuracy fluctuates in different runs; however, the average accuracy of five runs was around 66%.

It achieved a precision and recall of approximately 0.647, which demonstrates moderate success in predicting the correct movement direction. The specificity was 0.925, indicating that it was able to correctly identify most directions without confusion. Its harmonic mean of precision and recall, F1-score, of 0.615 confirms its consistent but not optimal performance.

Figure 3 shows the CM for the Temporal POSSM Decoder. The POSSM model achieved higher overall accuracy compared to LSTM, with most predictions aligned at the diagonal, indicating 86% accuracy. This suggests that the POSSM method is able to capture neural firing patterns associated with each movement direction, making it a more reliable movement decoder. This is supported by its precision of 0.882, recall of 0.831, specificity of 0.980, and F1 score of 0.840, indicating consistently high classification performance (Figure 4).

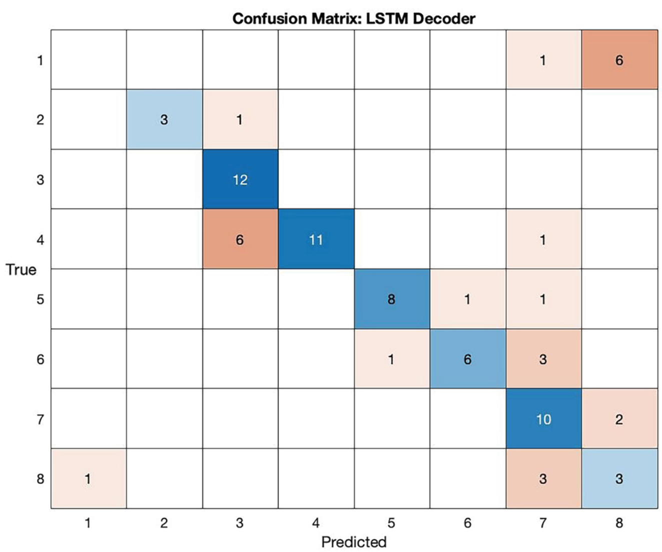

Figure 2. Confusion matrix demonstrating the prediction accuracy of LSTM. Rows represent true movement, and columns represent predicted directions. Diagonal values indicate correct classifications, while off-diagonal values represent misclassifications. The matrix reflects moderate decoding performance.

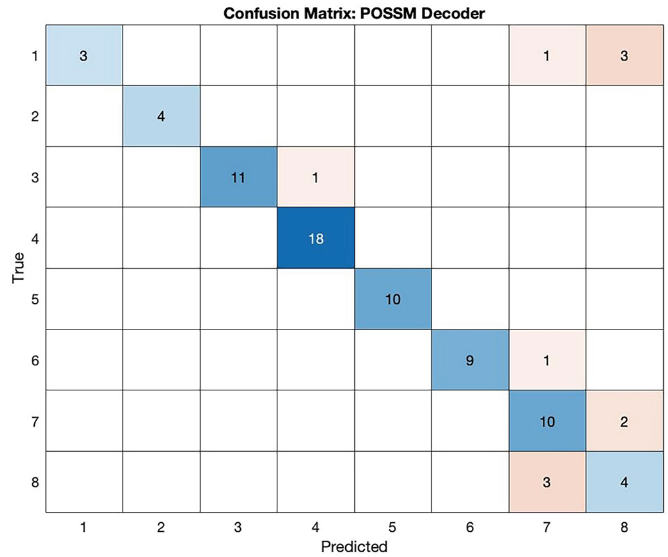

Figure 3. Confusion matrix demonstrating prediction accuracy of POSSM. Rows represent true movement directions, and columns represent predicted directions. The matrix reflects stronger classification performance in comparison with LSTM.

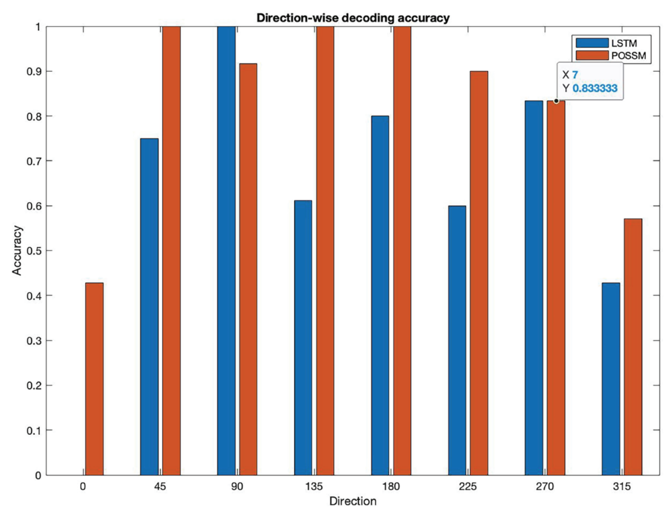

Figure 4. Accuracy per direction for LSTM and POSSM. Each bar represents classification accuracy for a specific movement direction. POSSM consistently achieved higher accuracy across most directions, indicating stronger direction-specific decoding performance.

DISCUSSION

While single-neuron recordings provide very precise data, it is very complex and requires careful decoding. Neural spikes are sparse, and electrodes can sometimes record unstable activity if a neuron shifts or if the electrode drifts over time. Interpreting single-neuron data requires preprocessing, because although the data encodes precise motor intentions, it can also be influenced by background firing and interneuron variability.

The POSSM and LSTM decoding algorithms were evaluated. Each approach relied on different assumptions about directional encoding. POSSM uses a mathematical framework that assumes each neuron has a preferred movement direction and that its firing follows a Poisson pattern, meaning spikes occur randomly but with an average rate that depends on direction. This assumption aligns with well-established properties of motor cortical neurons, which often exhibit directionally tuned firing rates that can be approximate by Poisson statistics when spikes are modeled as count processes within fixed time bins. Due to the way this model incorporates actual firing statistics, it is relatively efficient at capturing directional patterns without extensive training. This makes POSSM a good fit for relatively small or moderate data sets, where neural activity follows consistent and direction-specific firing patterns. Due to the model's simplicity, the probability of overfitting is reduced, and stable performance can be achieved.

LSTM is a data-driven deep learning model that learns patterns without prior assumptions about neural behavior. It processes spike data sequentially, adjusting many internal weights to discover relationships that predict movement direction. This allows LSTM to model complex, time-dependent firing structures, but it also makes it more dependent on large, high-quality datasets. When data are noisy, limited, or dominated by simple firing rate differences rather than intricate temporal patterns, the LSTM may overfit or fail to generalize effectively. In the dataset, decoding performance seemed to depend more strongly on stable direction-specific firing rates than on complex temporal spike patterns, which may explain why the probabilistic POSSM framework outperformed the LSTM model. The findings concur with other motor cortex literature, which show that neurons in center-out-reaching tasks usually exhibit direction-dependent firing patterns, like cosine-like tuning (4). Structured firing-rate is captured well by POSSM, explaining the effective performance with the dataset.

The Temporal POSSM Decoder performed well; it was able to identify each motion direction, with relatively good accuracy. This suggests strong temporal modeling or possible overfitting on limited data. The LSTM decoder did not perform as well as the POSSM decoder; however, it still performs above random chance, but it struggles to distinguish closely related directions. The confusion pattern indicates that LSTM likely captures some temporal dependencies but with less discriminative power or weaker training. Misclassifications were often for directions that were spatially close to each other, signaling that the model may have had a hard time generalizing fine directional distinctions from the limited training data.

Statistically, POSSM was able to achieve a greater accuracy of 86.3% compared to LSTM's 66.2%, representing an improvement of approximately 20%. This performance difference was also consistent across precision, recall, specificity, and F1 score (Table 1), suggesting that the superiority of POSSM was not limited to a single evaluation metric. While formal statistical significance testing was not performed due to the limited sample size, the magnitude and consistency of the performance gap across multiple metrics indicate a meaningful comparative difference between the two models. Future studies that use larger datasets should incorporate cross-validation with confidence intervals to further quantify statistical significance.

The higher accuracy of the POSSM compared to the LSTM suggests the neural data follow the Poisson distribution. Neurons fired in clear, direction-specific ways that matched the POSSM's underlying model. In contrast, the LSTM may not have had enough data to fully learn these relationships, leading to less consistent predictions. Overall, this highlights that simpler models like POSSM can outperform more complex models when working with limited or well-structured datasets.

Overall, the study was limited in some ways. The

Table 1. *Metrics comparing LSTM and POSSM. Accuracy, precision, recall, specificity, and F1 score were computed on the trials. POSSM demonstrated higher performance across all evaluation metrics compared to LSTM.*

	LSTM	POSSM
Accuracy	0.662	0.863
Precision	0.647	0.882
Recall	0.628	0.831
Specificity	0.925	0.980
F1 score	0.615	0.840

sample size of the data is limited to only 143 neurons, which can constrain generalizability. Another restraint was the small dataset, and limited number of trials. The applications of this study are also limited, as it only focuses on motor arm movement. As a result, it is unclear whether the same performance trends between POSSM and LSTM would persist in more complex, multi-degree-of-freedom movement tasks, such as continuous trajectory decoding, three-dimensional reaching, or simultaneous decoding of position, velocity, and force. There are also a multitude of other algorithms; however, the only two evaluated in this paper were LSTM and POSSM. Future work aims to evaluate the efficiency of a wider range of decoding models beyond just LSTM and POSSM, using datasets with more varied amounts of neuron count and task complexity. Future investigations should also assess model scalability and robustness across different recording conditions, behavioral paradigms, and dataset sizes to better determine the broader applicability of these findings.

CONCLUSION

Comparatively, POSSM is more effective and efficient than LSTM for predicting hand movement direction from single-neuron activity. Through the confusion matrices, it was evident that POSSM achieved a higher accuracy than that of the LSTM; this was likely a result of POSSM's Poisson assumptions which matched the structured, direction-specific firing patterns in the dataset. The findings suggest that simpler probabilistic models may be more effective for low-noise datasets, while deep learning models like LSTM would be more effective for larger and more complex neural data.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests related to this work.

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