Behavioral Representation in Mouse Visual Cortex

Final Report

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***Abstract*—This project aims to investigate how the neural activity in the visual cortex of mice is related to their facial behaviors and locomotion. Using the dataset that record the activity of approximately 10,000 neurons simultaneously across multiple cortical depths, along with motion energy analysis to track the facial behaviors of the mice, we seek to identify which types of behaviors are represented by the neurons and how these representations are encoded in the neural activity. By testing different decoding models, we aim to gain insights into the information processing strategies used by the brain. This project has the potential to provide important insights into the neural basis of mouse behavior, which could have implications for our understanding of human behavior.**

***Index Terms*—Neural activity, Visual cortex, Information processing, Decoding models**

I. Motivation

The study of neural decoding is a fascinating field of research that can provide valuable insights into the workings of the brain. In [1] Hires et al. investigated the nonlinear response properties of neurons in the primary auditory cortex of awake primates. This study highlights the importance of understanding the nonlinear behavior of neurons and how it can impact sensory perception and processing. In [3], Quian Quiroga and Panzeri provide a comprehensive review of information theory and decoding approaches for extracting information from neuronal populations. One particular area of interest is the neural decoding of mice, which are commonly used in neuroscience research due to their small size, ease of handling, and genetic manipulability. In this project, we aim to investigate how the neural activity in the visual cortex of mice is related to their facial behaviors, such as whisking and grooming, as well as their locomotion.

To achieve this goal, we will use the dataset that recording the activity of approximately 10,000 neurons simultaneously across multiple cortical depths in the visual cortex of the mice. The dataset also contain the facial behaviors of the mice using motion energy analysis, which involves using principal components analysis to extract the most informative features of the facial movements.

By combining these two sources of data, we hope to gain a better understanding of the relationship between neural activity in the visual cortex and the facial behaviors of the mice. Specifically, we will be looking for patterns in the data that can help us identify which types of behaviors are represented by the neurons, and how these representations are encoded in the neural activity. We will also be testing different models to see how well they can decode the facial behaviors from the neural activity, which will give us insights into the information processing strategies used by the brain.

Overall, this project has the potential to provide important insights into the neural basis of mouse behavior, which could have implications for our understanding of human behavior as well.

II. Dataset

To conduct our research, we will utilize a publicly available dataset that records the activity of around 10,000 neurons simultaneously across multiple cortical depths in the visual cortex of mice. The 3-dimensional positions of the neurons recorded are shown in Fig. 1. This dataset was collected using a cutting-edge technique called two-photon calcium imaging, which enables real-time monitoring of neuronal activity while the mice engage in different behaviors, such as running, grooming, moving whiskers. This was done to study the neural activity patterns that occur during natural behavior. Additionally, the dataset also contains the facial behaviors of the mice using motion energy analysis, Singular value decomposition was implemented to extract 1000 most informative features of their facial movements.

The dataset had a total of 8 fields viz, the neural response data; the running speed of mice; timecourses,and spatial masks of extracted behavioral SVDs; 3-D position of each neuron in the brain; statistics about each neuron; pupil area, and eye position tracker data. The representations of each field can be found in fig. 2. Further details about this dataset can be found in [2]

In this project, the dataset was split into training and testing datasets. The training data contains 5000 samples, and testing dataset has about 2000 samples.

III. Problems to address

The primary goal of this project is to investigate the relationship between the neural activity of mice and their facial behaviors and motion. To achieve this, we will be using the dataset that contains activities of thousands of neurons in the

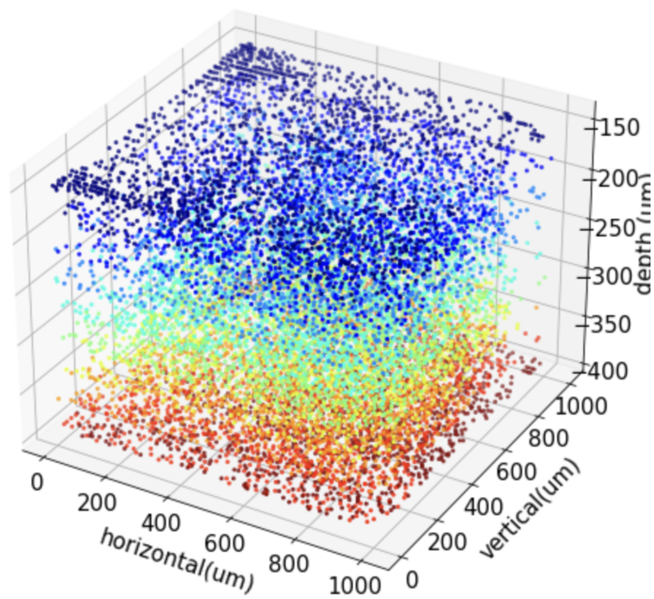

Fig. 1. Three-dimensional position of neurons.

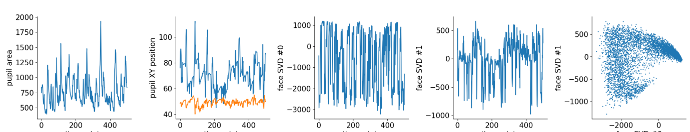

Fig. 2. Representation of different dataset fields.

visual cortex of mice, along with motion energy analysis to track their facial movements to train various decoding models to predict the mouse's pupil area, eye position, and motion energy from the neural activity.

The first step in this project is to train a linear decoder to predict the mouse's pupil area from the neural activity. We will then add an L2 penalty to improve the fit of the model. We will also be computing the decoding accuracy from neurons at different cortical depths to identify which depths are most informative for predicting pupil area.

Next, we will be training a decoder to predict the mouse's eye position from the neural activity. This will involve building a new model that can capture the complex relationship between neural activity and eye position.

In addition to predicting pupil area and eye position, we will also be training a decoder to predict the motion energy of the mouse from the neural activity. This will involve building a non-linear decoder that can capture the complex relationship between neural activity and motion energy. We will also cluster the facial movements from these predictions to better understand the represented behaviors.

Overall, this project seeks to gain insights into the neural mechanisms that govern mouse behavior, with the potential for future applications in understanding human behavior.

IV. Methods

In this project, we implemented several linear and non-linear decoders to predict the pupil area, eye position, and motion energy. We used sklearn to create the linear decoder, and tensorflow to create the non-linear decoder. For each step of project, we used data that was normalized using standard scalar method. To avoid overfitting and reduce the dimensionality of the data for computation, we implemented principal component analysis to project the data to 1000 components. We split the overall dataset into training dataset and testing dataset, training dataset contains 5000 samples, and testing dataset contains 2018 samples, when we were fitting the decoder, we implemented the 4-fold cross-validation.

A. Pupil Area

The pupil area tracker data contains information about variation in pupil area across time, the data is shown in fig. 3. The data is single dimensional. In this part, we implemented different decoders to predict the pupil area tracker data using neural activities. Furthermore, we explore the weight values of different neuron in ridge regression, try to find which neurons contain the most information about pupil area. In this step, we set the standard to distinguish the informative neuron for the pupil area prediction, that is, if the weight value of a neuron larger than mean value of all weights plus the standard deviation of all weights, this neuron is seen as informative neuron.

Furthermore, we also compute the decodding accuracy from neurons at different cortical depth. In this dataset, all neurons are divided into six different depths, that is, 390μm to 360μm, 360μm to 330μm, 330μm to 300μm, 300μm to 270μm, 270μm to 240μm and 240μm to 210μm. We implemented ridge regression to neurons locate at different depth separately, and compute the mean squared error, tried to figure out neurons locate at which depth carry the most information about pupil area.

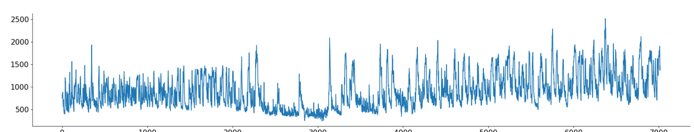

Fig. 3. Pupil area tracker data.

B. Eye Position

In this dataset, the eye position is represented in 2-dimensional coordinate system, containing information about eye movement in the X-axis and Y-axis.The eye position data is shown in fig. 4. In this part, we implemented "MultiOutputRegressor" in sklearn to predict two-dimensional position. In the dataset, there are some position values recorded as infinite value, we ruled out all those values before trained the decoder.

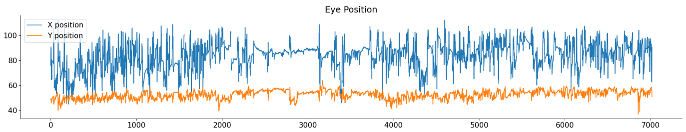

Fig. 4. Pupil area tracker data.

C. Motion Energy

In this dataset, the motion energy is defined as the absolute value of difference between two consecutiva frames. As shown in fig. 5. For computational consideration, singular value decomposition was implemented to reduce the dimension of the motion energy. The first two components of singular value decomposition are shown in fig. 6.

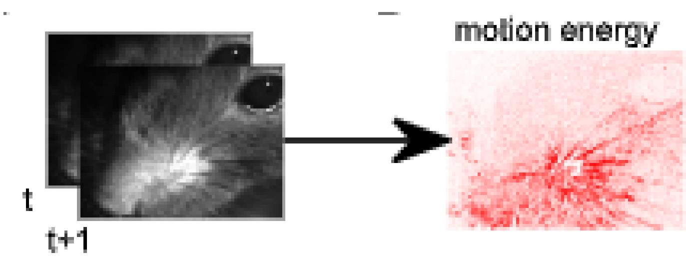

Fig. 5. The motion energy.

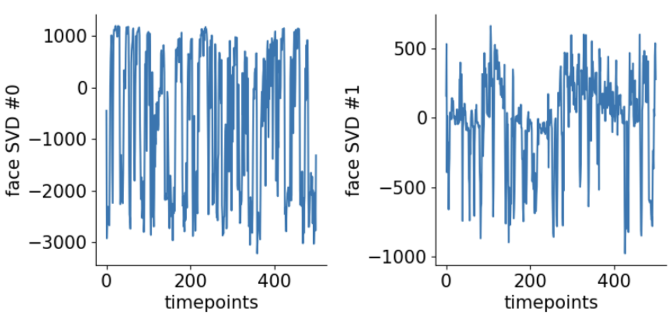

Fig. 6. the first two components of motion energy.

In this part, we trained both linear and non-linear decoder to predict the motion energy. We used mean squared error to evaluate the prediction results. The euation used to compute mean squared error can be expressed as equation (1):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x - x')^2 + (y - y') \tag{1}$$

Where x and y are the ground truth x position and y position, x' is the predicted x position and y' is the predicted y position.

Furthermore, to compare the prediction results comprehensively, we implemented K-means to cluster all the prediction, and compare the cluster results with ground truth.

V. Results

A. Pupil Area Prediction

The pupil area prediction results are shown below. The prediction results of linear decoder, linear decoder with ridge penalty, and non-linear decoder are shown in fig. 7, fig. 8, fig. 9 respectively.

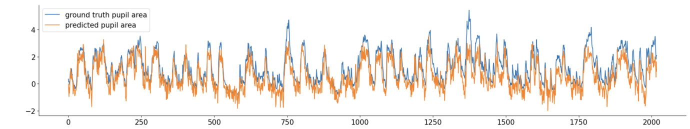

Fig. 7. The prediction result of linear decoder.

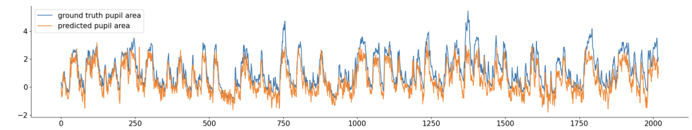

Fig. 8. The prediction result of linear decoder with ridge penalty.

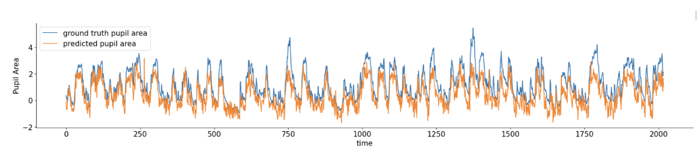

Fig. 9. The prediction result of non-linear decoder.

The comparison of mean squared error is shown in table I, from which we can find non-linear decoder can give the most accurate prediction, which indicates that the relation between neuron activities and pupil area is non-linear.

We also observed the locations of neurons that contain most information about the pupil area. The neurons have the weight value larger than mean value of all weight values plus the standard deviation of all weight values in ridge regression are seen as informative neuron. There are totally 1157 neurons are informative for the pupil area prediction. Their locations are shown in Fig. 10.

Furthermore, we also compute the decoding accuracy from neurons at different cortical depth. In this dataset, all neurons are divided into six different depths, that is, 390μm to 360μm, 360μm to 330μm, 330μm to 300μm, 300μm to 270μm, 270μm to 240μm and 240μm to 210μm. We implemented ridge regression to neurons locate at different depth separately, and compute the mean squared error, tried to figure out neurons locate at which depth carry the most information about pupil area. The prediction results are shown in Table II. From the table, we can find the deeper neurons give better prediction, which means deeper neurons carry more information about pupil area.

B. Eye Position Prediction

In this part, we trained both linear decoder and non-linear decoder, the prediction results are shown in Fig. 11. The

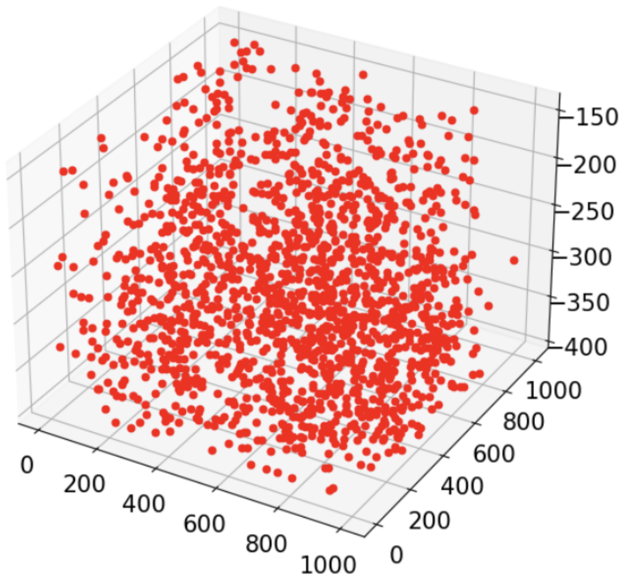

Fig. 10. The locations of the most informative neurons.

TABLE I
THE COMPARISON BETWEEN DIFFERENT DECODERS

Methods	MSE(Training)	MSE(Testing)
Linear decoder	0.0759	0.6347
Linear decoder with ridge penalty	0.0045	0.6196
Non-linear decoder	0.0011	0.5309

comparison of mean squared error is shown in Table III. By comparing the results, we can find non-linear decoder can give a better prediction results, which indicates that the relation between neural activities and eye position is more likely non-linear.

TABLE II
PREDICTION RESULTS USING NEURONS LOCATES AT DIFFERENT DEPTH

Depth (μm)	MSE
360	0.8937
330	0.8897
300	0.9057
270	0.9286
240	1.0397
210	1.0396
180	1.1637
150	1.2780

TABLE III
THE COMPARISON BETWEEN DIFFERENT DECODERS

Methods	MSE on Training Dataset	MSE on testing
Linear decoder	0.3183	0.9120
Non-linear decoder	0.0011	0.8309

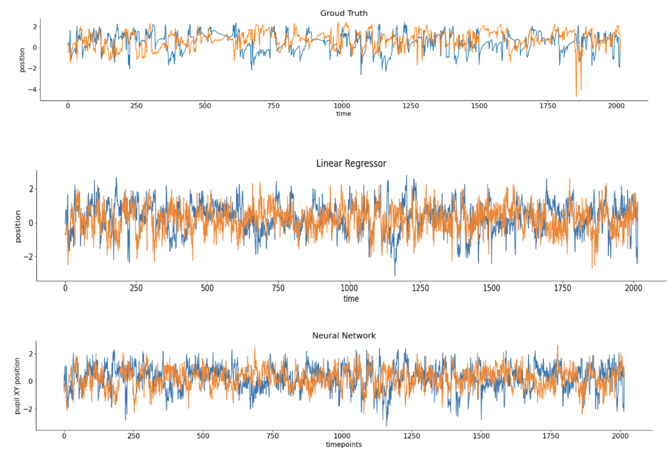

Fig. 11. The eye position prediction results

C. Motion Energy Prediction

In this part, we trained both linear and non-linear decoder to predict the motion energy. The prediction results are shown in Fig. 12, the figure shows the first 500 prediction results of first three components of singular value decomposition. The comparison of mean squared error is shown in table IV. By comparing the results, we can find linear decoder give a better prediction results, which indicates that the relation between neural activities and motion energy is more likely linear.

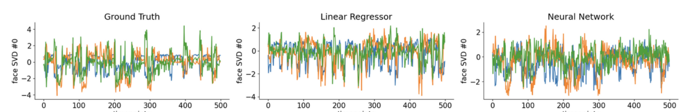

Fig. 12. The motion energy prediction results

TABLE IV
THE COMPARISON BETWEEN DIFFERENT DECODERS

Methods	MSE on Training Dataset	MSE on testing
Linear decoder	0.7317	1.1861
Non-linear decoder	0.8128	1.4119

To evaluate the prediction results comprehensively, we implemented K-means on ground truth data and prediction results, the cluster results are shown in Fig. 13, the figure shows the cluster results of first two singular value decomposition. By comparing the prediction results, we can find that the predicted motion energy shares similar pattern.

VI. DIVISION OF LABORS

In this project, we will be proceeding in 2 parts.

The first part includes building linear decoder with and without L2 penalty to predict mouse's pupil area, and analyzing which neurons in visual cortex are most informative, to compute decoding accuracy from neurons at different cortical

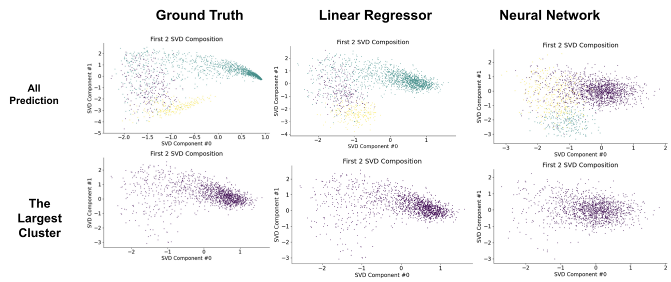

Fig. 13. The clustering results

depth. Furthermore, to train a decoder to predict mouse's eye position and analyze the same.

The second part includes training different linear decoders to predict from neuron activities to motion energy, and analyzing them. Furthermore, we will also train a non-linear decoder to predict same behavior from neuron activities, and compare its performance with linear decoders. We will also cluster facial movements using different methods to understand represented behaviors, and determine which clusters are best predicted by neuron activity.

The first part will be done by Kang Gao, the second part will be done by Aaryan Kumar.

VII. Conclusion

In this project, we trained multiple linear and non-linear decoders to use neural activities collected from mouse visual cortex to predict pupil area, eye position and motion energy. The results showed that in terms of pupil area and eye position, linear decoder performed better than non-linear decoder, which indicates the relations between neural activities and pupil area and eye position are more likely linear. On the other hand, linear decoder surprisingly outperforms the non-linear decoder when predict the motion energy, which indicates the relation between neural activities and motion energy is more likely non-linear. To evaluate the motion energy prediction results comprehensively, we implemented the K-means on both ground truth data and predicted results, the clustering results show that prediction results and ground truth share the similar pattern, which implies the trustworthy of prediction results.

In the process, we find that when we use more than 10000 neurons to predict the behavior that can be expressed as single dimensional variable, overfitting can be an important consideration, in this way, we need use dimension reduction techniques to reduce the dimension of input data.

VIII. Future Work

In the future, we plan to use HMM to discretize the facial movement and determine which states are best predicted by the neural activities by analyzing hidden markov model states, in this way, we can get more insight about the relations between neural activities and face behavior. Furthermore, We will be trying to use time series analysis methods to explore the time related dependencies in the neural activities and behavior.

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