Mapping Self-Motion Information in the Posterior Parietal Cortex

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Introduction

Efficient fluid navigation of familiar environments is a critical cognitive task for many species. Prey species must be able to avoid predation, foraging species must be able to exploit abundant sources of food, and humans routinely rely upon built paths, sidewalks, and roads. Many researchers recognize the importance of spatial information processing, and much prior research has focused on how this is accomplished in the brain, but some questions still remain unanswered.

It is known how an animal is able to track its position in the space of an environment. The Medial Entorhinal Cortex contains grid cells, head direction cells, and grid by head direction cells with each being modulated by velocity (Sargolini et al., 2006). These cells map the observable environment in tessellated triangle patterns unique to each cell. Convergent inputs from the Entorhinal Cortex to the Hippocampus allow the Hippocampus to map the environment more sparsely than grid cells. Mapping of bodily positions is observed in Hippocampal neurons whose activity is localized to particular areas of the immediate environment. These cells are termed 'place cells' and their activity is dependent on the spatial relationships between the animal and visual cues, but also heavily impacted by the integration of self-motion information (Cressant, Muller, & Poucet, 1997; Foster, Castro, & McNaughton, 1989; Terrazas et al., 2005).

It is hypothesized that the Parietal Cortex plays an active role in the translation of spatial location information into motor action plans (Byrne et al., 2007; Whitlock et al., 2008). Lesions to the Parietal Cortex of rats, monkeys, and humans result in impaired coordination of complex action sequences (Kolb and Walkey, 1987; Kesner et al., 1991; Save et al., 1992; Save and Moghaddam, 1996; Li and Andersen, 2001;Newsome and Pare, 1988; Mesulam, 1981). Data collected from the parietal cortex of monkeys has shown that these neurons map spatial attention, location of sensory stimuli, and motor plans (Duhamel et al., 1992; Colby and Goldberg, 1999; Buneo et al., 2002; Snyder et al., 1998; Andersen et al., 1985). Suggestive of similar functions for the parietal cortex in rodents, lesions to the rat parietal cortex result in impaired recognition of changes in spatial distributions of objects (Save et al., 1992; DeCoteau and Kesner, 1998). These data suggest that the Parietal Cortex may have an important role in integrating observed environmental stimuli with coordination of action sequences.

Taking lesion studies a step further, multi-electrode recording from Posterior Parietal Cortex cells in freely behaving rats has demonstrated that just under half of these cells are tuned to discrete states of motion, and a majority of these correspond to acceleration state, when an animal is freely foraging in an open arena (Whitlock et al. 2012). However, when a rat is traversing a familiar route towards a specific goal, the majority of Parietal Cortex neurons track the position of the animal along the route, irrespective of behavior or placement of the maze in the recording environment (Nitz 2006).

Although it is known that the Hippocampus and Entorhinal Cortex utilize self motion information to create spatial maps of an environment, the question still remains for the parietal cortex: what factors related to route position drive spatially modulated Parietal Cortex firing patterns? Two hypotheses were put forth to answer this question. Firstly, the Parietal Cortex may be integrating strictly spatial information over time, projected from the Hippocampus, through the Retrosplenial Cortex to create spatially driven maps of familiar routes. Secondly, the Parietal Cortex may also be using projections from the Thalamus, containing self-motion information, to create an allocentric map of the route that is driven by sensory information. It is possible that a combination of both self-motion and spatial information are taken together in order to track an animal’s progression along a familiar navigational epoch. These hypotheses in mind, a preliminary analysis of data gathered in the Posterior Parietal Cortex of rats traversing familiar routes was conducted using a generalized linear model with both spatial and self-motion predictive factors.

Analyses

All statistical analyses were conducted with Matlab software and utilized the built-in statistics toolbox whenever possible.

Linearization of Path Traversals

After path traversals were sorted into *clean* and *interrupted* runs (per the procedure described in ‘selection of path traversals’) the position of the animal at each moment in time along clean runs was binned into 206 and 221 linear position points along the space of the W and the Top Hat mazes, respectively. Using two differently colored LED head mounted lights and an overhead camera, four factors of self-motion were extrapolated and binned with these position points. Velocity, acceleration, head-direction, and angular velocity were labeled self-motion factors. Four descriptors of the space of the maze were defined as the position along the maze, and the probability of being at the apex of a right turn, left turn, or center of a straight, respectively.

Calculation of Predictive Factors

Each initial predictive factor was calculated in relationship to the pixels on the overhead camera and sorted into position bins for each maze. The W maze was assigned 206 position bins while the Top Hat was assigned 221 position bins, according to the length of each maze. The velocity factor is more accurately described as ‘speed’ since this value was calculated irrespective of direction. This speed was defined as the distance traveled (in pixels) every .08 of a second. After binning of the velocity values, the acceleration of the animal was calculated as the change in velocity from each bin to the next. Similar to the velocity being calculated from the pixels of the camera, the head direction was calculated by use of the two head mounted LEDs. Head direction was estimated using three sequential points; the average angle between consecutive points over two intervals was taken as the head direction of the animal and binned into the track position value of the center point. In order for the generalized linear model function to handle this value appropriately, the head direction angle was represented by both the cosine and sine of the angle with respect to view of the camera. After binning of the head direction values, the angular velocity was calculated as the change in head direction averaged across the preceding and following 3cm (5 bins) at each point. Position along the maze was represented by the numbers 1-206 and 1-221 for the W and Hat mazes, respectively (these corresponding to the position bins for each maze). The probability of being at the apex of a turn, or the center of a straight was defined using a gaussian distribution with center at each specified turn apex (or center of straight), and spread of 41 position points, normalized to produce values between 0 and 1.

Implementation of Generalized Linear Model

In order to determine the degree to which particular factors of self motion, or spatial location along a route, are most important for the firing patterns of cells recorded in the parietal cortex, the eight aforementioned factors were included in the implementation of a generalized linear model (GLM). Again, the self-motion factors were the velocity, acceleration, head direction, and angular velocity of the animal at each position bin, while the route-space factors were the position along the route, the probability of being at the apex of a turn (left and right separately), and the probability of being at the center of a straight. Along with these factors, two summary factors were used to represent relative the contribution of all self-motion variables, and all track variables, respectively (self-motion variables being the first four, and route position variables being the latter four). The model was restricted to all runs of a particular direction (inbound or outbound) for a single recording, with each cell having its own GLM. Implementation of this generalized linear model allows for simultaneous comparison of all ten of these predictor factors for their contribution to the firing rate of each cell.

After creation of the model with all ten predictor factors, the model was tested for correlation to the firing rate of the cell it modeled. Secondly, a new model for each predictor was created by removing only the predictor factor of interest, and the importance of this variable was measured by computing the difference in correlation between the model with all predictors and the model with one predictor removed. Therefore, eleven generalized linear models were created for each cell - that is one GLM including all ten predictors, and a single GLM for when each of the ten predictors are removed individually.

Determination of Relative Contributions of each Predictor

Correlations between each model and the firing rate of the cell were computed using the Matlab function *corrcoef*, which calculates correlation coefficients between two matrices. This is in order to show the relative necessity of each predictor for the firing rate of each cell according to the direction of path traversal in a single recording. After correlations were computed between the firing rate and each model, the difference in correlation between the total model, and each lesser model were computed. The relative contribution of each predictor to the firing rate of each cell is shown as the difference in correlation between the total model and the model with each respective predictor removed. A test for significance was conducted on each of these correlation values to determine if an actual difference was observed.

Conclusion of Significance

In order to test for significance, a Kolomogorov-Smirnov test with a significance level of 0.01 was used to determine if there was an absolute difference between the correlation of the total model and the firing rate of the cell and the difference between the correlations of each model and the total model. Each predictor factor was said to significantly contribute to the firing rate of the cell if the difference between the correlation of the total model and the firing rate of the cell and the correlation between the model without the predictor factor of interest and the firing rate of the cell, was deemed significant by the Kolomogorov-Smirnov test.

Discussion

Significant Predictive Factors of Cell Firing Rates

Figure 1 illustrates, for 119 cells, which predictive factors were shown to be significant for the firing rate patterns of each cell (see ‘conclusion of significance’ for description of significance testing). Each row represents a single cell, while each column represents an individual predictive factor, with columns five and ten being summary statistics. Columns five and ten represent summary predictive factors for the preceding four columns. The fifth column (‘all self-motion variables’) will be significant if any of the self-motion predictive factors are significant. Therefore, this column represents a summary of the velocity, acceleration, head direction, and angular velocity values in the model. Likewise, the last column will be significant if any of the preceding four predictive factors (route progression, probability of being at the apex of a left, right, or center of straight) are found to be significant. The design of Figure 1 allows for the GLM to speak directly to the two hypotheses; that is whether spatial information, self-motion information, or a combination of the two are necessary for creating route maps in the Parietal

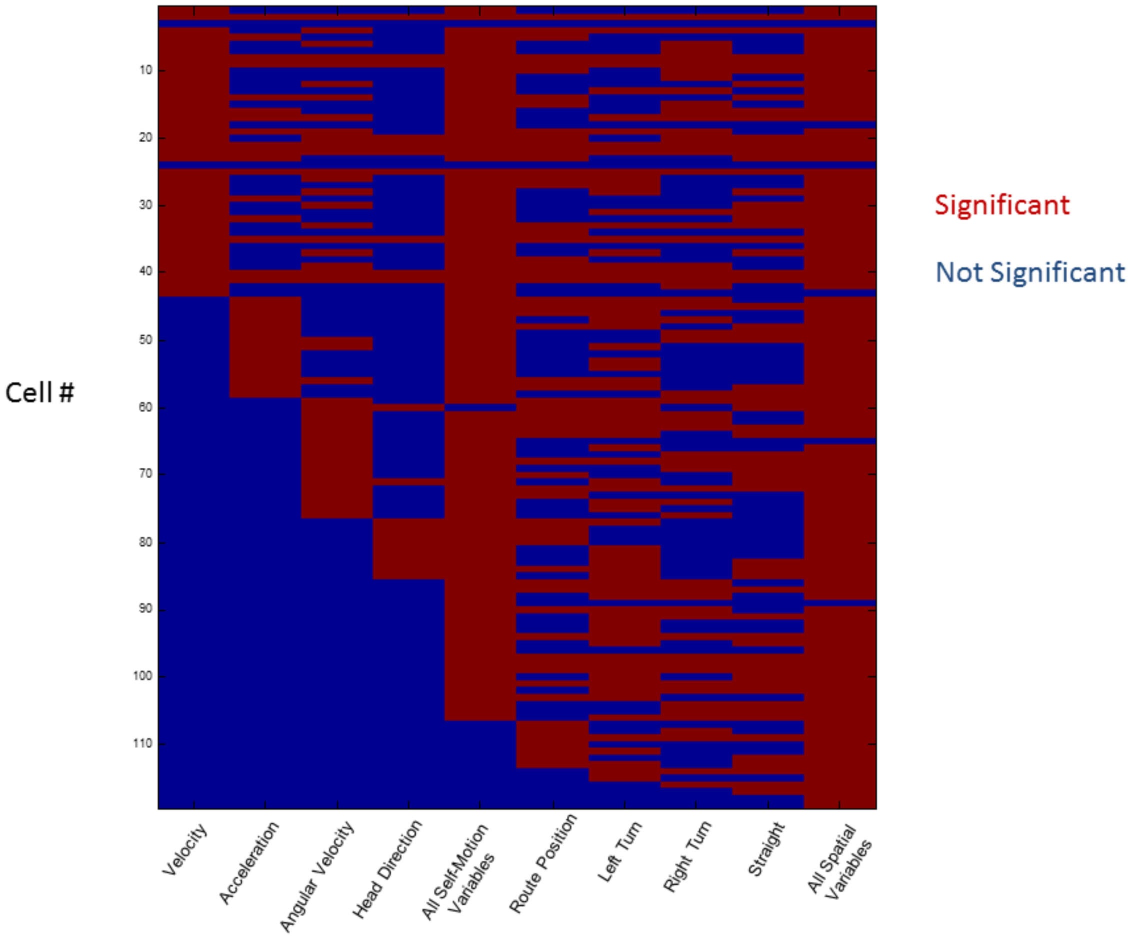
Cortex. From this preliminary GLM analysis, it is suggested that both self-motion and spatial information are important for the firing patterns of a majority of cells in the Parietal Cortex.

Relative Contributions of Each Predictor

Before significance tests can be conducted on the difference in correlations between models, the actual difference in correlation must be calculated. Figure 2 shows the difference in correlation between the full model, and each respective sub-model, for a single cell. Therefore, this graph represents the relative contribution of each predictive factor for the firing rate of the cell. In the case of this single cell, velocity is the only significant predictive factor of the firing rate pattern. Plots such as this one were created for most cells included in the current GLM analysis. More exemplars can be found in the appendix. However, due to time constraints, the relative contribution of each predictor on all cells that are included in the analysis, have not been analyzed in depth.

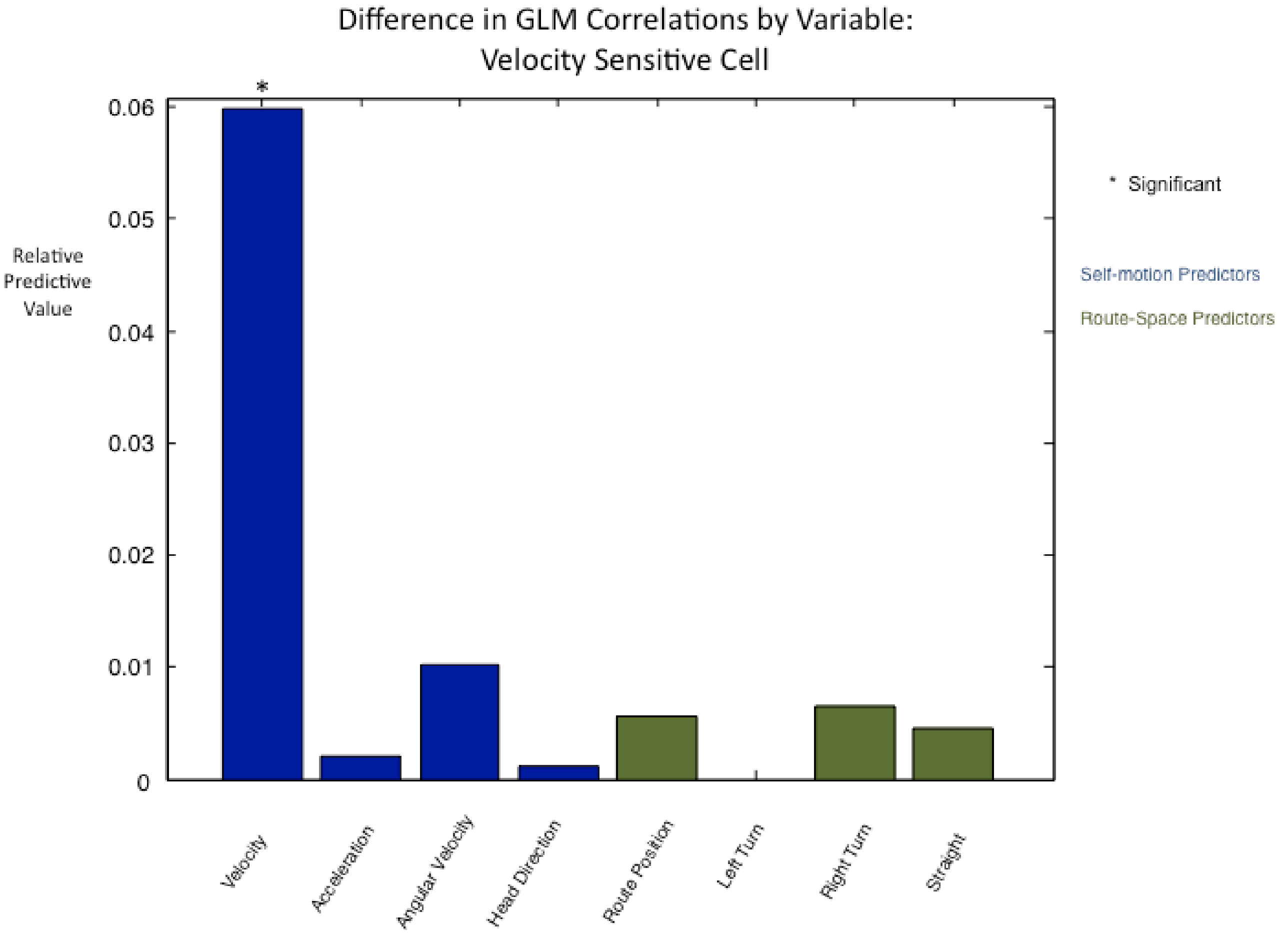
Although not deeply considered, many figures such as this exemplar have been looked at preliminarily, and general trends can be discussed. Firstly, cells that exhibit significant values in correlation differences for multiple predictive factors are quite common. This can be seen in Figure 1 as well as in Figures 3 and 4 (found in the appendix). In many such figures for individual cells, a range of values for each predictive factor are observed. That is, many cells have multiple significant predictive factors with varying degrees of relative contributions to the cell's firing rate. Figure 2 illustrates a cell that is strongly sensitive to velocity in particular, whereas many cells have been observed to be relatively similarly sensitive to three or more predictive factors. Secondly, it can be seen from this figure that the differences in correlation between each predictor and the total model are low. This is due to a low total correlation value for each GLM. The highest correlation value observed between a full model and an individual cell's firing rate was just over .5.

Figure 1) Significance Tests



There are a number of reasons why low correlation values may be observed. Each GLM was applied to the *actual* firing rates of the cell it tested, and a certain amount of noise-that can not be accounted for in the GLM-is expected in the actual firing rates of neurons. The probability distributions for the spatial predictors could also be more accurately defined. Due to time constraints, an arbitrary gaussian distribution was chosen to represent the likelihood of being at the apex of a turn or the center of a straight. Certainly, this was a thoughtful process taking into account the characteristics of each maze, and the way that the animals run the mazes, but no further testing was conducting regarding the optimal description of these predictors for cell firing rates. It is also possible that an unrelated predictor factor not considered in this analysis could significantly improve the model, but these predictors were specifically chosen because of their implication by the literature.

Figure 2)



Taking the GLM Further

The programs written in order to implement this Generalized Linear Model analysis allows for efficient and in-depth categorization of the contributing information types necessary for the regular function of single neurons. Functioning as a preliminary analysis, the GLM can allow for (theoretically) an unlimited number of cells to be viewed simultaneously and categorized based on what information is significant for their firing rates. For more in-depth analyses on the single neuron level the GLM can show the relative contribution of each predictive factor to the firing rate of each cell.

This is an incredibly robust test, and (relative to its output) only a very small amount of analysis has been conducted on its results-due to time constraints for this particular project. The current state of the model allows for more analysis at the individual neuron level over time. However, the GLM can still be improved through more testing.

Mentioned in the previous section, there are a few rough edges to this model that could be smoothed with minimal changes. The model could be applied to average firing rates, as opposed to actual firing rates in order to remove some effect of noise expected in neuronal signals. Considering the predictor factors related to turns and straight portions of the maze, the gaussian distributions could be rigorously manipulated in order to find the optimal representations of the space of the maze. Both of these could easily be manipulated and could possibly have a significant effect on the model.

More tests for the validity of the model could be conducted. So far, the correlation is the only measure of goodness of fit, and this was only tested on data the model had taken into consideration. It would be beneficial to leave some trials (for each cell) out of the model's consideration in order to test how well it predicts data not initially taken into account.

Experimental Procedures

All procedures fell within the guidelines of the National Institutes of Health and approved Institutional Animal Care and Use Committee protocols.

Behavioral Training

Two adult Sprague-Dawley rats (n=2) were trained to traverse outbound and inbound directions of two mazes. The first maze, termed the 'W' maze, consists of four straight paths segmented by three turns of approximately 120 degrees. Termed the 'Top Hat' maze, the second maze consisted of five straight segments separated by four 90 degree turns (see figure). Each maze was a raised platform six inches above the floor of the recording room, slightly wider than the width of the animals, approximately 4 feet in length, with some variability in length due to the difference in turn sequences. Behavior was motivated by food restriction. Body weights were not permitted to drop below 80% of free-feeding weights and typically remained above 85%. Training took place over 2–3 weeks, with total path traversals being few the first days of training, but increasing to at least 20 traversals per maze per session in the latter weeks. Once each animal achieved such proficiency in a low light setting, 2-3 days of training in complete darkness was provided. Following surgery and recovery, one recording was made per day for a total of twelve recordings in each animal.

Surgery

Microdrives fabricated in the laboratory containing twelve tetrodes were implanted over the posterior parietal cortex. Target coordinates, relative to bregma, were posterior 4.0 mm, lateral 2.3 mm. A craniotomy was made over each target site, the dura excised, and the tetrode tips moved into the brain to an initial depth of 0.5 mm. Rats were permitted to recover for 5 days after surgery.

Selection of Path Traversals for Analysis

To simplify data analyses, and the path of the animal was linearized, and outbound and inbound laps were separately defined. In order to restrict the analyses to what would be termed 'familiar routes' the initial step in the linearization process was to define uninterrupted path traversals. Using a guided user interface in Matlab, position records were examined on a lap-by-lap basis. Uninterrupted traversals lacked evidence for reversal of direction or a full stop of any duration. For all paths, a minimum of six uninterrupted path traversals was required for inclusion of the recording session in data analyses.

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Appendix

Figure 3)

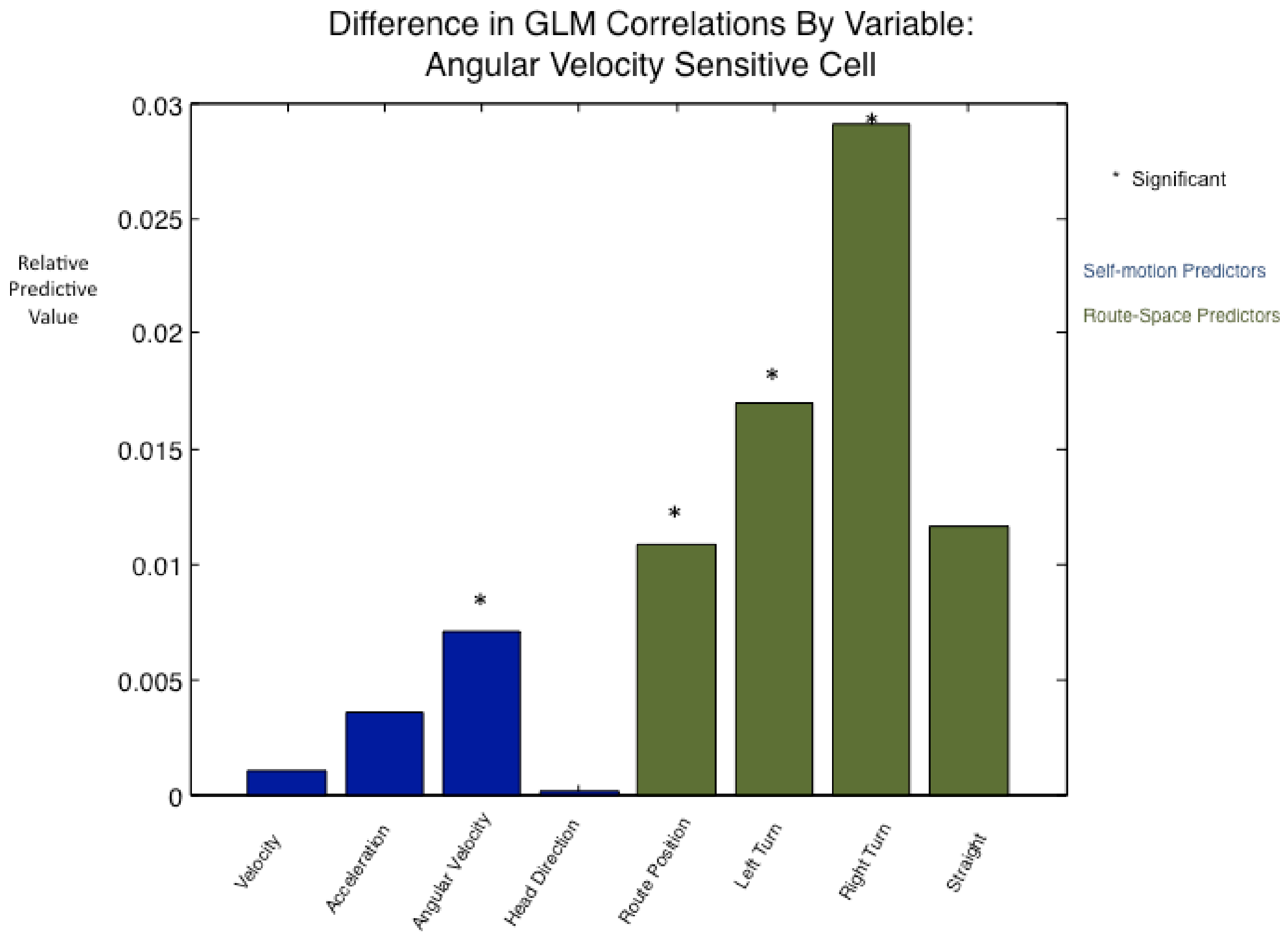

Figure 4)

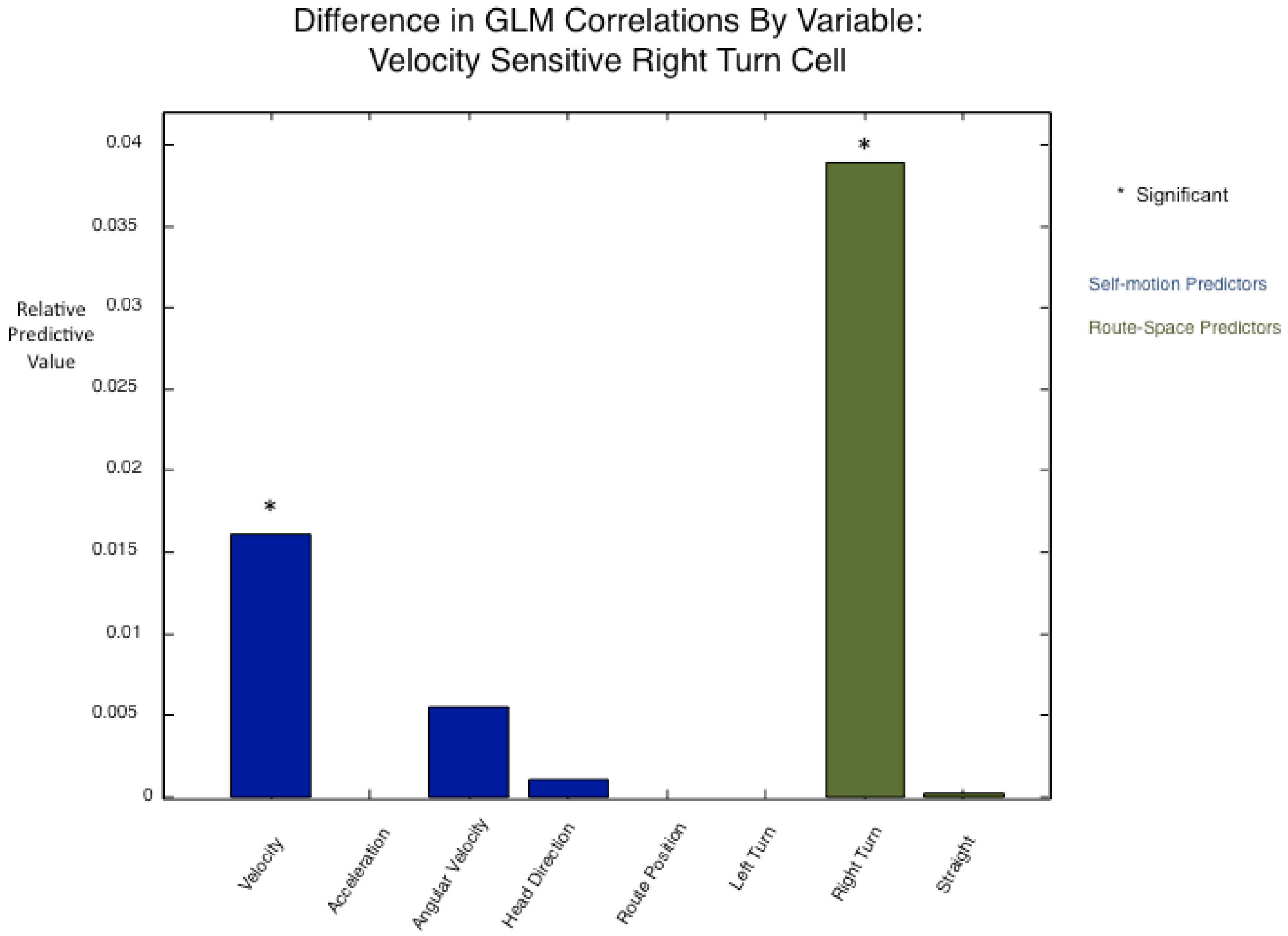
Difference in GLM Correlations By Variable:
Velocity Sensitive Right Turn Cell

Figure 5) Example of Firing Rate and Model Output