Human-AI Shared Control via Frequency-based Policy Dissection

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Abstract

Human-AI shared control allows human to interact and collaborate with AI to accomplish control tasks in complex environments. Previous Reinforcement Learning (RL) methods attempt the goal-conditioned design to achieve human-controllable policies at the cost of redesigning the reward function and training paradigm. Inspired by the neuroscience approach to investigate the motor cortex in primates, we develop a simple yet effective frequency-based approach called Policy Dissection to align the intermediate representation of the learned neural controller with the kinematic attributes of the agent behavior. Without modifying the neural controller or retraining the model, the proposed approach can convert a given RL-trained policy into a human-interactive policy. We evaluate the proposed approach on the RL tasks of autonomous driving and locomotion. The experiments show that human-AI shared control achieved by Policy Dissection in driving task can substantially improve the performance and safety in unseen traffic scenes. With human in the loop, the locomotion robots also exhibit versatile controllable motion skills even though they are only trained to move forward. Our results suggest the promising direction of implementing human-AI shared autonomy through interpreting the learned representation of the autonomous agents. Demo video and code will be made available at https://metadriverse.github.io/policydissect.

1 Introduction

In recent years, autonomous agents trained from deep Reinforcement Learning (RL) achieve huge success in a range of applications from robot control [62, 50], autonomous driving [7, 29], to the power system in smart building [40]. Despite the capability to effectively discover feasible policy under unknown system dynamics in a model-free setting [60], the lack of generalizability [14] in unseen environments hinders the real-world deployment of learning-based neural policy. Furthermore, it remains difficult to understand the internal mechanism and the decision making of the neural network [30, 71], especially when abnormal behaviors happen [10, 70, 45]. The lack of transparency and controllability greatly limit the application of the end-to-end neural controllers in safety-critical systems.

One potential direction to make the neural controller safer and more trustworthy is incorporating human into the control loop, which we refer as human-AI shared control. With human involvement, the performance and the safety of the shared autonomy systems can be substantially improved [48, 15, 49], even on new tasks and unseen environments. Human-AI shared control has been implemented in various forms, such as enforcing intervention [28, 46] or providing high-level commands [15] to the AI models. Previous work also explores goal-conditioned reinforcement learning as a form of human-AI shared control, where a high-level goal is fed as an input to the policy during training [53, 2, 15, 25]. Thus the behavior of the learned agent can be controlled by varying the input goal [43, 36, 72]. However, training goal-conditioned policy requires additional modification of the
neural controller, algorithm, and the reward function, while the human control only happens at the goal level, still lacking interpretability and control of fine-grained movement.

In this work we develop a minimalist approach called **Policy Dissection**, to enable human-AI shared control on autonomous agents trained on a wide range of tasks. Policy Dissection does not impose assumption on the agent’s training scheme, and it requires neither retraining the controller’s network nor modifying the environment. Policy Dissection achieves human-AI shared control by firstly dissecting the internal representations of the learned policy and aligning them with specific kinematic attributes, and then modulating the activation of the internal representations to elicit the desired motor skills. Policy Dissection takes the inspiration from neuroscience studies on motor cortex of primates: exerting electrical stimulation on different areas of motor cortex can elicit meaningful body movements. A stimulation-evoked map can be built to reveal the relationship between the evoked body movement and the motor neurons located in different areas of motor cortex [21, 20, 33]. In order to replicate the stimulation-evoked map of a neural controller, the proposed Policy Dissection follows a frequency analysis and matching strategy, associating the kinematic attribute and the unit activation. The procedure of building stimulation-evoked map by Policy Dissection is shown in Fig. 2. Concretely, we first roll out the given policy for several episodes. After collecting a set of time series of the activities of all units, kinematics and dynamics, we identify the units whose activities align with the kinematic and dynamic attributes in a way that there is the lowest frequency discrepancy between the specific units and the kinematic attributes in the frequency domain. The stimulation-evoked map between units and attributes is thus built and used to modulate the activation intensity of identified units so that the desired motor skills can be elicited. Therefore, Policy Dissection constructs an interpretable control interface on top of the trained agent for human to interact with and evoke certain behaviors of the agent, thus achieving human-AI shared control.

We evaluate the proposed method on several RL agents ranging from locomotion robots to autonomous driving agents in simulation environments. Experimental results suggest that meaningful motor primitives emerge in the internal representation. As shown in Fig. 1, novel behaviors can be deliberately evoked by activating units related to certain motor primitives, even though they are not the necessary behaviors to solve the primal task. In the quantitative evaluation, we use the human-AI shared control system enabled by Policy Dissection to improve the generalization in test-time unseen environment and achieve task transfer. In an autonomous driving task, we first train baseline agents under mild traffic condition and evaluate the driving policy on new test environments containing unseen near-accidental scenes. Different to the poor performance of the baseline agent in these new environments, the human-AI shared control system achieves superior performance and safety guarantee, with 95% success rate and almost zero cost. In quadrupedal locomotion task, a robot with only proprioceptive state input can avoid obstacles with shared control, even though its primal task is moving forward. These results show that the proposed Policy Dissection not only helps understand
Figure 2: Overview of the proposed Policy Dissection. Taking Ant robot as an example, it first identifies the connection between unit activation and kinematic attributes (painted in the same colors). After that human can activate units to evoke desired behaviors by stimulating one or more motor primitives. For example, stimulating motor primitive related to yaw rate makes the Ant spin, while activating motor primitive related to velocities in different axes brings moving-up or deceleration.

the learned representations of the neural controller, but also brings the intriguing potential application of human-AI shared control.

2 Related Work

**Human-AI Shared Control.** Existing methods on human-AI shared control can be roughly divided into two categories. The first category is to have human in the control loop to train learning systems and then execute without human in test time [73]. By incorporating human into the training, previous works successfully improve the performance on visual input control tasks such as Atari game [1, 51, 64]. Robotic control tasks also benefit from human feedback [28, 39, 58, 46, 65]. The other category is to have human in both training and test time to accurately accomplish human-assistive tasks. A series of works study this problem based on the Atari Game [48, 52, 8, 31]. In addition, the human-AI shared control system is built on autonomous vehicle [19], robotics arm [27] and in multi-agent setting [31]. The reported results on various tasks reflect the effectiveness and efficiency of training and coordination with human-assistive AI.

**Neural Network Interpretability.** There is a growing interest in AI community to understand what is learned inside the neural network. Previous interpretability methods mostly focus on explaining the networks trained for visual tasks [74, 56, 11, 75, 38]. Various empirical studies have found that meaningful and interpretable structures emerge in the internal representation when trained for the primal tasks. For example, object detectors emerge in scene classifier [6], and disentangled layout and attribute controllers emerge from image generation model [67]. Manipulating the output image of deep generative models is achieved by editing the disentangled hidden features [5, 57, 66]. On the other hand, visuomotor control tasks can also acquire visual understanding to explain the behavior chosen by agent with visual input through saliency map [59, 3, 47, 12, 26, 22].

**Neuroscience Inspired Control.** The complex behaviors shown by recent autonomous agents prompt researchers to develop new analysis methods. As a source of inspiration, neuroscience provides useful tools [44, 33], and effective procedures [24, 18, 42] for understanding animal brains which are also like black-box systems. Recent works try to develop neural network-based policies from the perspective of neuroscience [17, 4, 69, 13]. In a closely related work on understanding learned agent, Merel et al. [42] use RSA [34] with CKA [32] similarity index to reveal that behaviors spanning multiple timescales are encoded in distinct neural layers. Apart from providing the neuroscientific tools, many concepts from neuroscience, such as motor primitive also inspire researchers to design generalizable controllers [63, 61, 41].

3 Policy Dissection Method

Policy Dissection aims at deriving human-controllable policy from a well-trained RL agent. It has two unique features to enable human-AI shared control: First, it operates on a well-trained RL agent without re-training or modifying the original reward/environment and the policy architecture. We only need to roll out the agent for several episodes and log its neural activity and kinematic attributes. Based on the collected records, certain units and kinematic attributes will be aligned. Thus our
Figure 3: We first rollout the trained policy for several episodes and record the neural activities and track kinematic attributes, such as velocity and yaw rate. After applying the frequency matching to identify motor primitives, we can align units with many kinematic attributes. The curves of kinematic attributes and the unit activation in the same motor primitive are painted in the same colors. For clarity, we only show the result of one recorded episode and a proportion of units, and the curves of units are sorted by their amplitude.

method is non-intrusive to the primal task and trained model, and applicable to a wide range of environments. Second, Policy Dissection can discover generalizable motor skills that even the agent is not trained to perform. As shown in Fig. 1, the Ant robot can be steered to move up/down even it is only trained to move forward as fast as possible in the primal task. We will introduce the three essential steps of the Policy Dissection method in detail.

3.1 Monitoring Neural Activity and Kinematics

Since multi-layer perceptron (MLP) is the most common network architecture used in many RL tasks, we assume the neural controller is a MLP, which has \( L \) hidden layers and all layers have the same number of \( I \) hidden units. We denote a neuron by \( l, i \) as \( z^{l,i} \), where \( l = 1, \ldots, L \) is the index of layer and \( i = 1, \ldots, I \) is the neuron index in each layer, and its output at time step \( t \) is \( z^{l,i}_t \). The agent’s kinematic attributes are represented by \( s^j \), \( j = 1, \ldots, J \), where \( J \) is the total number of attributes. We define the motor primitive as the unit \( m^j \in \{ z \} \) that steers the agent and causes transition of the kinematics. We assume that each kinematic attribute \( s^j \) has a corresponding motor primitive \( m^j \) to drive the attribute to desired state, and thus there are also \( J \) motor primitives. Our goal is to discover motor primitive \( m^j \) by associating the units with certain kinematic attribute. As shown in Fig. 3, we take the Ant robot as an illustrative example. Policy Dissection starts by rolling out the pretrained agent for several episodes and tracking the activation of all units as well as the the kinematics, such as yaw rate and velocity. We record the \( I \cdot L \) time series \( \{ z^{l,i}_t \} = \{ z^{l,i}_1, z^{l,i}_2, \ldots \}^{l \cdot L} \) measuring the neural activities and \( J \) time series of kinematic attributes \( \{ s^j_t \} = \{ s^j_1, s^j_2, \ldots \}^J \) for further analysis.

3.2 Associating Units with Kinematic Attributes

Observing the neural activity and kinematics recording in Fig. 3, it can be found that several repeated patterns of changing kinematics appear in different frequency when executing the policy, which is reminiscent of animal behavioral research [21, 20, 33]. It suggests that the motor skills has its predominant frequency component [42], controlling fast kinematics and slow kinematics. Since neural activation signals also encode distinct frequency information, this resemblance inspires us to process time series of both neural activity and kinematic attributes in frequency domain, where the difference of predominant frequency between two signals can be clearly revealed and the phase discrepancy of two time series are eliminated. As a consequence, this allows us to associate kinematic attributes with units whose activity best matches the corresponding motor primitives.
In Policy Dissection, all time series are transformed into the frequency domain through Discrete-time Short-time Fourier transform (STFT):

\[
\text{STFT}(d, \omega|\mathbf{x}) \equiv \sum_{t=-\infty}^{\infty} x_t W(t-d)e^{-j\omega t}.
\]

STFT splits the time series \( \mathbf{x} = [x_1, x_2, \ldots] \) into a sequence of temporal window and \( d \in [1, +\infty] \) denotes the time step of the center of the temporal window. STFT then conducts Fourier transform in each temporal window. \( \omega \in [0, +\infty] \) denotes the frequency. To reduce spectral leakage and reserve the frequency information as much as possible, the window function \( W(t) \) used in Policy Dissection is blackman window. Moreover, the window length is 64 with hop length 16. We apply STFT instead of naive Fourier transform since it can retain temporal information by breaking the time series into several overlapping chunks of frames. This feature is important since in the following frequency matching we focus on the similarity of resulting spectrograms as well as the temporal correlation of two signals. We use the spectrogram to characterize a measurement:

\[
\text{SG}(d, \omega|\mathbf{x}) \equiv |\text{STFT}(d, \omega|\mathbf{x})|^2.
\]

After obtaining the spectrograms for all kinematic attributes and neural activities, frequency discrepancy can be computed for each neuron-kinematics pair \((\mathbf{z}^{l,i}, \mathbf{s}^j)\):

\[
\text{Dis}(\mathbf{z}^{l,i}, \mathbf{s}^j) = \sum_{d} \sum_{\omega} \| \text{SG}(d, \omega|\mathbf{z}^{l,i}) - \text{SG}(d, \omega|\mathbf{s}^j) \|_2.
\]

For each kinematic attribute, frequency matching is applied to select the unit with minimal average discrepancy as the motor primitive responsible for the variation of kinematics:

\[
m^j = \arg\min_{\mathbf{z}^{l,i}} \frac{1}{N} \sum_{N} \text{Dis}(\mathbf{z}^{l,i}, \mathbf{s}^j),
\]

where \( N \) is the number of collected episodes. We build \( \{(m^j, s^j)\}, j = 1, \ldots, J \) as the stimulation-evoked map, which further enables human to evoke certain behaviors by activating one or more motor primitives.

### 3.3 Steering Agent via Stimulation-evoked Map

Human-AI shared can be fulfilled via the stimulation-evoked map. As shown in Fig. 2, we stimulate certain motor primitives that are tightly coupled with certain kinematics such as spinning (increasing yaw rate) and deceleration (decreasing linear velocity). In this section, we discuss the implementation details of the process to elicit the desired behaviors.

**Identifying Correlation Coefficient.** The correlation between activation value of motor primitives and the kinematics attributes needs to be determined. As shown in Ant robot of Fig. 1, activating the neurons controlling y-axis movement with positive value can drive the Ant move left, and a negative value makes the Ant move right.

We compute the correlation coefficient through spectral phase discrepancy. Since motor primitives have their own predominant frequency component responding to specific kinematic attributes responding in similar frequency, we first find the predominant frequency component:

\[
\omega^* = \arg\max_{\omega} \sum_d \| \text{SG}(d, \omega|m^j) - \text{SG}(d, \omega|s^j) \|_2.
\]

At each window of STFT, we can compute the phase discrepancy of the transforms of \( m^j \) and \( s^j \) at the predominant frequency \( \omega^* \). The average phase discrepancy at all temporal windows is across \( N \) collected episodes:

\[
p^j = \frac{1}{D \cdot N} \sum_d \sum_{N} [\Phi(\text{STFT}(d, \omega^*|m^j)) - \Phi(\text{STFT}(d, \omega^*|s^j))],
\]
where $D$ is the number of temporal windows and $\Phi$ is the function retrieving the phase. We then normalize $p^j$ to get correlation coefficient $\rho$ between $m^j$ and $s^j$ as

$$\rho^j = 1 - \frac{|2p^j|}{\pi}.$$  \hspace{1cm} (7)

A positive $\rho^j$ indicates we can amplify the kinematic attribute $s^j$ by stimulating the motor primitive $m^j$ with a positive value.

**Identifying Unit Output.** Suppose we want to amplify the scale of kinematic attribute $s^j$, the output value $v^j$ for motor primitive $m^j$, namely the activation of $m^j$, can be determined by:

$$v^j = k^j \rho^j,$$ \hspace{1cm} (8)

where $k^j$ is a custom constant decided manually for each motor primitive.

**Combining Motor Primitives.** Some behavior requires stimulating one or more motor primitives to evoke. Taking the Ant robot shown in Fig. 2 as the example, moving towards y-axis can be implemented by two kinematic attributes including increasing $V_y$ and heading towards y-axis. Therefore, we activate two corresponding motor primitives selected by Eq. 4 with value calculated by Eq. 8 to make the agent move towards y-axis. The overall policy dissection workflow is in Appendix B.

## 4 Experiments

We first apply policy dissection to an autonomous driving task to study the learning dynamics in Sec. 4.2. We demonstrate that the emergent pivotal motor primitives are highly correlated with the success of policy learning. In Sec. 4.3, we show a novel application of the shared autonomy: improving the test-time generalization, where Human-AI shared control can be an alternative to overcoming the generalization gap between training and unseen test-time environment. The experiment demonstrates our method finds not only the correlation but causality between unit output and kinematics. In Sec. 4.4, we conduct experiments on quadrupedal robot and demonstrate that a quadrupedal robot trained to traverse complex terrain with only proprioceptive state can transfer to accomplish obstacle avoidance task with a bit human effort, even it does not have any information of the surrounding. Lastly, more qualitative demonstrations in Sec. 4.5 show that our method can be generalized to various environments and autonomy tasks.

### 4.1 Experimental Setting

The qualitative experiments are conducted on the Ant and Walker in MuJoCo [62] and the Bipedal-Walker [9] following the general setting. The quantitative experiments of human-AI shared control are conducted on MetaDrive and Pybullet-AI environments introduced as follows:

**MetaDrive.** We train agents to accomplish autonomous driving task in the safety environment of MetaDrive [37]. In this task, the goal is to maneuver the target vehicle to destination with low-level continuous control actions. An episode terminates only when the vehicle arrives the destination, drives out of road, or collides with the sidewalk. The observation of autonomous vehicle consists of map, navigation, lidar, and state information such as speed and heading.

**Pybullet-A1.** The legged robots locomotion experiments are conducted on the Pybullet-Unitree-A1 [16] robot. We follow the same environment setting used by Locotransformer robot [68], including terrain shape, obstacle distributions, sensors, reward definition, and termination condition. Two agents are trained. One “insensible” agent with only proprioceptive state is trained to walk on uneven terrain, while the other agent with Locotransformer is directly trained to avoid obstacle. The shared control system will be built on the “insensible” agent, where human subjects help the agent sidestep obstacles.

**Training Set and Test Set.** As shown in Fig. 5, for both autonomous driving and robot locomotion tasks, we prepare training set and held-out test set. For driving task, the test set is used to benchmark the test-time generalizability of human-AI shared control system and AI-only control system. We train autonomous driving policies in 50 different environments where the traffic condition is mild and all traffic vehicles and target vehicle can drive smoothly towards their destinations. No obstacles are in these environments. In testing time, the trained agents will be evaluated in the other 20 unseen
Figure 5: Examples of training and test scenes used in the generalization experiment. In MetaDrive SafetyEnv, the held-out 20 test scenes are more complex compared to 50 training scenarios. For quadruped robot locomotion task, the robot is trained to traverse open but bumpy terrains and tested on the terrain full of obstacles where obstacle avoidance ability is needed to reach the destination.

maps with higher traffic density. Besides, obstacles like traffic cones and breakdown vehicles will scatter randomly on the road. In this case, the target vehicle needs to be maneuvered delicately. We compare the performance and safety of the trained policy in two scenarios: runs in the test set solely, and runs with the human-AI shared control system built from Policy Dissection.

The primal task for legged robot is to move toward one direction as fast as possible. We design the test environment to be a forest-like environment where tree obstacles are randomly scattered. Therefore, though the overall goal is still to move forward, the agent needs extra effort to sidestep obstacles in the test environment.

Evaluation Metrics. For driving task, we evaluate agents on all the 20 test environments, and report the ratio of episodes where the agent arrives at the destination as the success rate. Also, Out of Road rate can be calculated if the termination is caused by driving out of road. For benchmarking the safety of agents, the collision to vehicles, obstacles, sidewalk and buildings raises a cost $+1$. In addition, human attention cost is a huge concern of human-AI shared control system. We quantify this using human involvement, which is measured by the number of environment steps when the human subject presses keys for activating units, or controls throttle, brake, and steering wheel. We average the sum of reward, cost and human involvement on 20 environments as episodic return, episodic cost and human involvement. The evaluation process above will be repeated 5 times for each agent, and we report the average value and std for all metrics. For the locomotion task, we use moving distance to measure the performance. Moving distance is the displacement of robot on specific direction, i.e. x-axis. The evaluation is also repeated for 5 times on the exclusive test environment.

All experiments without human are repeated 5 times with different random seeds. $N = 5$ episodes are used for applying Policy Dissection. For experiments involving human subject, we repeat each experiment with 5 human subjects. For driving task, all human subjects have driving license. Human subject can pause the experiments if any discomfort happens. No human subjects were harmed in the experiments. Human subjects have signed the experiment agreement and get compensation.

4.2 Policy Dissection for Understanding Learning Dynamics

In this section, we verify the correlation between motor primitives and relevant kinematic attributes. We first train PPO [54] agent on the MetaDrive's training environments and then conduct Policy Dissection on the trained policy and find two motor primitives in which Primitive 1 is associated with Speed and Primitive 2 associated with Side Distance. We then plot the evolution of the frequency discrepancy between the identified motor primitives and the kinematics alongside with the macroscopic measure of the learning progress in Fig. 6.

In the upper plot in Fig. 6, the decreasing discrepancy indicates that Primitive 1 to control speed gradually emerge. With strong negative correlation, the success rate rapidly increases when the discrepancy of speed primitive also rapidly decrease between epoch 20-30. Similarly, in the lower figure in Fig. 6, the decreasing discrepancy between Primitive 2 and side distance shows that the
4.3 Human-AI Shared Control for Test-time Generalization

Using the motor primitives identified above, we can determine the activation value of motor primitive for steering associated kinematics according to Eq. 8. We apply the same process to dissect the policy trained from SAC [23] with same network structure and build a stimulation evoked map for shared control. We then invite human subject to collaborate with the SAC and PPO agents on the test environments with different takeover methods. As shown in Tab. 1, the average human involvement, episodic cost, and success rate on the test environments are reported across policies with or without human involvement. The human involvement greatly improves the performance and safety when deploying the policy in unseen environments where delicate maneuvers such as side-passing and yielding are evoked by human, if necessary, to help finish the task. Compared to naive takeover baseline indicating by $H^n$ where human provide control signals in the whole takeover period, we find that the shared control mechanism enabled by our method only requires a small amount of human budget, since human only needs to activate the neuron at the start of takeover period.

Different from the original PPO policy which is a MLP with 2 hidden layers, 256 units per layer and “tanh” activation function, we also repeat the same experiment for Deep-PPO agent which has 6 hidden layers, and Relu-PPO which has “Relu” as activation function. The results reported in 1 show our method is invariant to the network architectures and RL algorithms.

4.4 Human-AI Shared Control for Task Transfer

In addition to the improved test-time generalization, the stimulation-evoked map enables RL agent to accomplish new task with the help of human. Recent quadrupedal robots trained by RL exhibit promising ability to walk on bumpy terrain via end-to-end control [35]. However, the agent only takes proprioceptive states as input without the observation of surroundings, and thus it can not avoid obstacles by its own. As shown in Fig. 5, we train the agent only to walk on uneven terrain but test it in a new environment full of obstacles. By applying our method, motor primitives related to yaw rate and speed control can be found and serve as the interface for human to steer the “insensible” quadrupedal internal unit of the agent is gradually specialized for controlling side distance. There exists strong correlation between the discrepancy and the out-of-road rate, which can only be reduced by improving the ability to keep side distance. We thus conclude that the pivotal primitives emerge during training.

| Method          | Human Involvement | Episodic Return | Episodic Cost | Success Rate |
|-----------------|-------------------|----------------|---------------|--------------|
| Human           | 405.57 ± 94.79    | 357.21 ± 38.3  | 0.47 ± 0.24   | 0.95 ± 0.03  |
| SAC$^{w/oH}$    | 26.52 ± 1.58      | 342.0 ± 6.25   | 0.42 ± 0.32   | 0.9 ± 0.0    |
| SAC$^{H^n}$     | 2.85 ± 0.22       | 353.19 ± 13.62 | 0.80 ± 0.14   | 0.95 ± 0.03  |
| SAC$^{H^*}$     |                   |                |               |              |
| PPO$^{w/oH}$    |                   |                |               |              |
| PPO$^{H^n}$     |                   |                |               |              |
| PPO$^{H^*}$     |                   |                |               |              |
| Relu-PPO$^{H^*}$|                   |                |               |              |
| Deep-PPO$^{H^*}$|                   |                |               |              |

Table 1: Improvements on the performance and the safety on test environments with human-AI shared control. $H$ indicates “human”. $H^n$ and $H^*$ indicates two takeover methods. $H^n$ requires human to provide steering and throttle in the whole takeover period, while $H^*$ only asks to activate motor primitives at the start of takeover. We also do ablation study on the activation function and number of hidden layers of MLP. The results show our method is general and robust to the policy architecture and RL methods.

| State | Reward | Moving Distance |
|-------|--------|-----------------|
| State$^{w/oH}$ | 18.23 ± 10.55 | 6.55 ± 0.04 |
| State$^{H^*}$  | 413.93 ± 93.33 | 16.94 ± 3.08 |
| State+Vision   | 445.47 ± 190.85 | 18.64 ± 6.45 |

Table 2: Test on Obstacle Avoidance Task.
Figure 7: Qualitative demonstration of Policy Dissection. First row plots the driving results of the trained PPO agent with or without human-AI shared control in three driving cases. Each case plots the trajectories with human involvement, where different colors represent trajectory segments resulted from different motor primitives. Red and orange denote “braking” and “lane changing” respectively. The second row plots more examples of evoking behaviors in different locomotion environments.

robot to avoid obstacles. This forms the “State\(^{w/oH}\)” method. We also include “State+Vision” method [68], which trains a visuomotor policy for legged robot directly in the test environment, enabling it to sidestep obstacles. As shown in Table 2, with human involvement, Policy Dissection successfully transforms the “insensible” policy that is not fit to this task and greatly improves the performance, achieving comparable performance to the agent trained directly for this task.

4.5 Demonstration of Human-AI Shared Control in Diverse Environments

As shown in Fig. 7, in the top-down view we visualize the trajectories of the PPO agent with or without human shared control on the test environment of driving task. Since the PPO agent is trained in the mild traffic density without obstacles, it is incompatible to brake and side-pass. In contrast, with human in the control loop, the lane changing and braking can be deliberately evoked by human, helping the agent solve the near-accidental cases.

We provide more qualitative results of human-AI shared control on policies trained in MetaDrive, Pybullet-A1, Ant, Walker and BipedalWalker environments. Please find in the supplemental material for details about identifying motor primitives and evoking these behaviors. We also include a demo video of human-AI shared control in the supplementary material.

5 Conclusion

Inspired by the neuroscience approach to study the motor cortex in primates, we present a simple yet effective method called Policy Dissection to align internal neural representations and kinematic attributes of a given trained policy. The resulting stimulation-evoked map allows human to steer the agent and evoke its certain behaviors. Policy Dissection implements the human-AI shared control systems on top of the models trained from standard RL algorithms without re-training or modification. The human-AI shared control system is quantitatively evaluated in autonomous driving and locomotion tasks, and the result suggests the improvement on test-time generalizability and ability to achieve task transfer. We further provide intriguing demonstrations on various other environments to show the generality of our method and the wider applications of human-AI collaboration.

Limitations and societal impact. Our study finds that a small portion of units are not aligned with any motor primitive. The agent can still accomplish the task even if we set them as zero. More investigation is needed for understanding the role of all units and making the neural policy transparent. Another limitation of Policy Dissection is that we only evaluate this method in continuous control tasks with state vector as input. Wider range of tasks and neural network architecture such as discrete tasks and CNNs can be adopted in future research. One potential negative social impact is that the safety issue remains when deploying the shared control system in real world application. As shown in the autonomous driving experiment, our method derived from empirical study has no theoretical guarantee on the safety of human subject. The unsuccessful collaboration or conflict between human and AI may lead to potential dangers.
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Appendix

A Code and Demo Video.

In the project webpage: https://metadriverse.github.io/policydissect, we provide a demonstrative video showing the Policy Dissection for human-AI shared control and the source code including all trained controllers.

B Workflow of Policy Dissection

Algorithm 1: The workflow of building stimulation-evoked map

\begin{algorithm}
\begin{algorithmic}
\State \textbf{Input}: MLP policy $\pi$ with $L$ layers, $I$ units per layer, environment $\text{env}$, episodes to collect $N$.
\State \textbf{Output}: Motor primitives $m^j$, correlation coefficient $\rho^j$ related to $s^j$, where $j = 1, ..., J$.
\For {$n \leftarrow 0$ to $N$}
\State Executing policy $\pi$ in $\text{env}$, recording $\{z_{l,i}^{j} = [z_{1,i}^{j}, z_{2,i}^{j}, ...]^{L \times I}\}$ and $\{s_{j} = [s_{1,j}, s_{2,j}, ...]^{J}\}$.
\EndFor
\For {$j \leftarrow 0$ to $J$}
\For {$l \leftarrow 0$ to $L$}
\For {$i \leftarrow 0$ to $I$}
\State Calculate frequency discrepancy $\text{Dis}(z_{l,i}^{j}, s_{j})$ following Eq. 3:
\EndFor
\State Determine motor primitive $m^j$ for kinematic attribute $s^j$ according to Eq. 4:
\EndFor
\State Identify correlation coefficient according to Eq. 7:
\EndFor
\end{algorithmic}
\end{algorithm}

C Human Subject’s Comments on Shared Control

The performance of shared controls system is largely determined by the effective coordination between human subject and the AI. Some of our experiment participants report that collaboration with quadrupedal AI is more difficult than with self-driving AI. The possible reason is that human subjects are more familiar with driving vehicles than controlling legged robots. For the shared driving task, human subjects have better global planning abilities about which lane to choose and when to stop. However, for controlling the legged robots on bumpy terrain and avoiding obstacles, some of them didn’t consider how the complex terrain would influence the pose of legged robots and thus had a hard time interacting with the quadrupedal AI. For example, when the robot is moving down from a small slope and is pitching forward, stopping command should be issued cautiously. Otherwise, the agent may roll or flip forward. Therefore, it would be better if human subjects have prior knowledge about the task, so they can collaborate better with the AI trained for this task. How to implement effective human-AI teaming in general is an important but less explored direction.

D Summary of Qualitative Results

We provide a summary on how to identify and use motor primitives to evoke behaviors for the trained agents in different environments.

MetaDrive: Brake. By activating the motor primitive positively related to speed with a negative value, the agent can gradually decrease the speed and still stay in the same lane. The brake can be evoked to avoid collision to obstacles and cut-in vehicles which the agent has never seen in the training phase.

MetaDrive: Lane Changing. Since the agent can observe the distance to left and right side, identifying motor primitives related to sidewalk and yellow solid line can make the distance to side controllable. We use “tanh” as activation function which is symmetric. Therefore identifying only one motor primitive related to one side is enough to evoke lane changing behavior, since, for example, increasing the distance to left side equals decreasing the distance to right side. Lane changing is useful for sidestepping obstacles or moving to another lane with lower traffic density.
Figure 8: Qualitative demonstration of the insensible agents when deployed in test environment with or without human. Facilitated by human, the legged robots can turn left to avoid the collision to the front obstacle, even if it is insensible and trained to move forward as fast as possible.

**Pybullet-A1: Turning Left/Right.** As shown in Fig. 8, the moving direction of legged robot can be controlled by activating the neurons related to yaw or yaw rate. Similarly, negative and positive stimulation makes the agent turn towards opposite direction.

**Pybullet-A1: Stopping.** We can also evoke deceleration or stopping behaviors on the legged robot by controlling the activation of speed-related units. Since a huge deceleration may make the agent roll forward, we also add a pitch control to suppress the possible front flipping.

**Gym-Ant: Stopping.** The ant will stop if motor primitive associated with x-axis speed is activated.

**Gym-Ant: Moving Up/Down.** The ant can move up/down if we activate two primitives respectively related to: 1) Speed of y-axis and 2) heading direction. Similar to evoking legged robot turning behavior, opposite activation values make the agent move in opposite direction.

**Gym-Ant: Spinning.** The ant can spin if we activate units related to yaw rate.

**Gym-Walker: Deceleration.** The agent trained in Walker stops because we stimulate the motor primitives positively associated with velocity with a negative stimulation. As a result, the low-level action sequence for deceleration is executed.

**Gym-Walker: Hopping.** We manage to find the motor primitives associated with torque force. We then disable the movement of the knee in red leg by stimulating the motor primitive with negative value. As a result, the agent hops with only the yellow leg.
**Gym-BipedalWalker: Jumping.** For the agent trained in BipedalWalker, jumping is achieved by stimulating motor primitives related to $V_z$, where Z-axis is upward.

**Gym-BipedalWalker: Front Flipping.** We train the BipedalWalker walking with larger torque, and thus it can jump higher if we activate units associated with $V_z$. BipedalWalker can conduct front flipping, which is the combination of jumping and pitching. This is resulted from combining another motor primitive related to pitch into control. Therefore, the walker jumps with increasing angular velocity, performing front flipping.

**Gym-BipedalWalker: Standing Up from Split.** In addition, a common failure mode of agent trained in BipedalWalker is that the agent performs split and can not stand up when both legs touch the ground. We identify the motor primitives associated with all the motor torques. Stimulating these motor primitives, the agent manages to stand up and continue moving forward.

### E Environment Details

We provide more environment details for MetaDrive and Pybullet-A1 such as the observations, the design of reward functions, and the termination conditions.

#### E.1 MetaDrive

In the driving task, the objective of RL agents is to steer the target vehicles with low-level continuous control actions, namely acceleration, brake, and steering.

**Observation.** The observation of RL agents is as follows:

- A 240-dimensional vector denoting the Lidar-like point clouds with 50m maximum detecting distance centering at the target vehicle. Each entry is in $[0, 1]$ with Gaussian noise and represents the relative distance of the nearest obstacle in the specified direction.
- A vector containing the data that summarizes the target vehicle’s state such as the steering, heading, velocity, and relative distance to the left and right boundaries.
- The navigation information that guides the target vehicle toward the destination. We sparsely spread a set of checkpoints, 50m apart on average, in the route and use the relative positions toward future checkpoints as additional observation to the target vehicle.

**Reward and Cost Scheme.** The reward function is composed of four parts as follows:

$$ R = c_1 R_{disp} + c_2 R_{speed} + R_{term}. $$

The displacement reward $R_{disp} = d_t - d_{t-1}$, wherein the $d_t$ and $d_{t-1}$ denotes the longitudinal movement of the target vehicle in Frenet coordinates of current lane between two consecutive time steps, provides dense reward to encourage agent to move forward. The speed reward $R_{speed} = v_t/v_{max}$ incentives agent to drive fast. $v_t$ and $v_{max}$ denote the current velocity and the maximum velocity (80 km/h), respectively. We also define a sparse terminal reward $R_{term}$, which is non-zero only at the last time step. At that step, we set $R_{disp} = R_{speed} = 0$ and assign $R_{term}$ according to the terminal state. $R_{term}$ is set to $+10$ if the vehicle reaches the destination, $-5$ for crashing others or violating the traffic rule. We set $c_1 = 1$ and $c_2 = 0.1$. For measuring the safety, collision to vehicles, obstacles, sidewalk raises a cost $+1$ at each time step. The sum of cost generated in one episode is episode cost, a metric like episode reward, but reflecting safety instead.

**Termination Conditions and Evaluation Metrics.** Since we attempt to benchmark the safety of shared-control system, collision to vehicles and obstacles will not terminate the episode. The episode will be terminated only when: 1) the agent drive out of the drivable area and 2) the agent arrives the destination. For each trained agent, we evaluate it in 20 held-out test environment and define the ratio of episodes where the agent arrives at the destination as the success rate. The definition is the same for out of road. Also, the average episode reward and cost on 20 test environment produce two metrics: Episodic Reward and Episodic Cost. Since each agent are trained across 5 random seeds, this evaluation process will be executed for 5 agent which has same training setting but different random seeds. We report the average and std on the 4 metrics mentioned above.
E.2 Pybullet-A1

In the quadrupedal locomotion task, the RL training objective is to move forward on bumpy terrain as fast as possible. We use two environments: the one without obstacles as training environment, and the other one with obstacles as test environment. The environment construction, reward definition, tasks are the same as [68]. Its environment has open-source code at: https://github.com/Mehooz/vision4leg. In this work, we only slightly modify the observation as follows:

- IMU recording Yaw, Yaw rate, Pitch and Roll
- Angle of 12 joints
- Torque applied to 12 joints

Containing historical output of these sensors over the last 3 steps, the proprioceptive observation is in 84 dimension. For LocoTransformer baseline method directly trained on test environment, the input is this state vector and first-view depth images in $64 \times 64$ over the last 4 steps.

F Learning Curves of Trained Agents

F.1 MetaDrive

Figure 9: Success rate and episode reward of PPO agents on 50 training environments.

Figure 10: Success rate and episode reward of SAC agents on 50 training environments.
F.2 Pybullet-A1 Legged Robots

![Image](image1.png)

(a) Insensible Agent on Training Environment
(b) Visual Input Agent on Test Environment

Figure 11: Training episode reward of two quadrupedal locomotion policies.

F.3 Gym Environment

![Image](image2.png)

Figure 12: The episodic reward during the learning of SAC algorithms in Ant, Walker and Bipedal-Walker tasks. Though we repeat 5 times for each experiment, Policy Dissection is applied to the agent with highest performance to do qualitative study.

G Hyper-parameters

G.1 MetaDrive

Since SAC is not sensitive to the choice of hyperparameters, the learning rate $1e^{-4}$ is also suitable for Deep-SAC (6 Layer) and Relu SAC. For Deep-PPO and Relu-PPO, learning rate should be slightly decreased due to the change of neural network structure. Also note that the number of hidden units is changed to 128 per layer for Deep PPO with 6 layer. This is for keeping the total number of network variables approximate to the network used by default PPO (around 250,000 variables).

| Table 3: SAC/Deep SAC/Relu SAC | Table 4: PPO |
|---------------------------------|-------------|
| Hyper-parameter                 | Value       | Hyper-parameter | Value       |
| Discounted Factor $\gamma$     | 0.99        | KL Coefficient  | 0.2         |
| $\tau$ for target network update | 0.005      | $\lambda$ for GAE [55] | 0.95 |
| Learning Rate                  | $1e^{-4}$   | Discounted Factor $\gamma$ | 0.99 |
| Environmental horizon $T$      | 1500        | Number of SGD epochs | 20 |
| Steps before Learning start    | 10000       | Train Batch Size | 30,000 |
| Activation Function            | “tanh” or “relu” | SGD mini batch size | 256 |
| Prioritized Replay             | False       | Learning Rate   | $3e^{-4}$   |
| Target Network Update Frequency | 1          | Clip Parameter $\epsilon$ | 0.2 |
| Soft Update $\tau$             | $5e^{-3}$   | Activation Function | “Relu” |
| MLP Hidden Units               | 256         | MLP Hidden Units | 256         |
| MLP Layers                     | 2 or 6      | MLP Layers      | 2           |
Table 5: Deep PPO

| Hyper-parameter       | Value |
|-----------------------|-------|
| KL Coefficient        | 0.2   |
| λ for GAE [55]        | 0.95  |
| Discounted Factor γ   | 0.99  |
| Number of SGD epochs  | 20    |
| Train Batch Size      | 30,000 |
| SGD mini batch size   | 100   |
| Learning Rate         | 1e−4  |
| Clip Parameter ϵ      | 0.2   |
| Activation Function   | “tanh”|
| MLP Hidden Units      | 128   |
| MLP Layers            | 6     |

Table 6: Relu-PPO

| Hyper-parameter       | Value |
|-----------------------|-------|
| KL Coefficient        | 0.2   |
| λ for GAE [55]        | 0.95  |
| Discounted Factor γ   | 0.99  |
| Number of SGD epochs  | 20    |
| Train Batch Size      | 30,000|
| SGD mini batch size   | 100   |
| Learning Rate         | 5e−5  |
| Clip Parameter ϵ      | 0.2   |
| Activation Function   | “tanh”|
| MLP Hidden Units      | 256   |
| MLP Layers            | 2     |

G.2 Gym Environments and Pybullet-A1 Legged Robots

Agents of Gym environments (Walker/Ant/Bidepadel Walker) are trained by SAC and share the same hyperparameter setting. Quadrupedal robots are trained by PPO, and we follow the same codebase and configuration used in [68].

Table 7: SAC for Gym agents

| Hyper-parameter                        | Value |
|----------------------------------------|-------|
| Discounted Factor γ                    | 0.99  |
| τ for target network update            | 0.005 |
| Learning Rate                          | 3e−4  |
| Environmental horizon T                | 1500  |
| Steps before Learning start            | 1000  |
| Activation Function                    | “tanh”|
| Prioritized Replay                     | False |
| Target Network Update Frequency        | 1     |
| Soft Update τ                          | 5e−3  |
| MLP Hidden Units                       | 256   |
| MLP Layers                             | 2     |

Table 8: PPO for Legged robots

| Hyper-parameter       | Value |
|-----------------------|-------|
| KL Coefficient        | 0.2   |
| λ for GAE [55]        | 0.95  |
| Discounted Factor γ   | 0.99  |
| Number of SGD epochs  | 3     |
| Train Batch Size      | 16384 |
| SGD mini batch size   | 1024  |
| Learning Rate         | 1e−4  |
| Clip Parameter ϵ      | 0.2   |
| Activation Function   | “tanh”|
| MLP Hidden Units      | 256   |
| MLP Layers            | 4     |