Enhancing Ground Maneuverability Through Robot Adaptation to Complex Unstructured Off-Road Terrains

Sriram Siva[1], Maggie Wigness[2], John G. Rogers[2], Hao Zhang[1]
[1]Department of Computer Science, Colorado School of Mines, Golden, CO 80401, USA
[2]US Army Research Laboratory (ARL), Adelphi, MD 20783, USA
sivasriram@mines.edu, maggie.b.wigness.civ@mail.mil, john.g.rogers59.civ@mail.mil, hzhang@mines.edu

Abstract

While a robot navigates on complex unstructured off-road terrains, the robot's expected behaviors cannot always be executed accurately due to setbacks such as wheel slip and reduced tire pressure. In this paper, we propose an approach for enhancing robot's maneuverability by consistent behavior generation that enables a ground robot's actual behaviors to more accurately match expected behaviors while adapting to off-road terrain. Our approach learns offset behaviors that are used to compensate for the inconsistency between the actual and expected behaviors without explicitly modeling various setbacks. Experimental results in complex unstructured off-road terrains demonstrate the superior performance of our proposed approach to achieve consistent behaviors.

Introduction

Off-road field environments, as seen in Fig. 1, are challenging for autonomous ground robots to navigate as the terrain exhibits a wide variety of charecteristics and cannot be modeled beforehand. The capability of adapting navigational behaviors to these complex unstructured off-road terrains is essential for robots to successfully complete navigation tasks.

Robot terrain adaptation is then an essential capability for robots to adapt their navigational behaviors according to off-road terrains. Although, the research problem of robot terrain adaptation has been widely investigated over the past several years, the challenge of how to generate consistent navigational behaviors for robot terrain adaptation has not been well addressed.

In this paper, we present our research on enhancing robot's maneuverability through consistent behavior generation that enables a robot's actual navigational behaviors to match the expected behaviors while adapting to a variety of unstructured off-road terrains. Our approach learns robot offset behaviors to compensate for the inconsistency between the actual and expected navigational behaviors without explicitly modeling the setbacks, while also adaptively navigating over various terrain. In addition, our approach is able to integrate multi-modal features to characterize terrain and automatically estimate the importance of these features.

Experiments are conducted for robot navigation scenarios over complex off-road terrains to validate our approach.

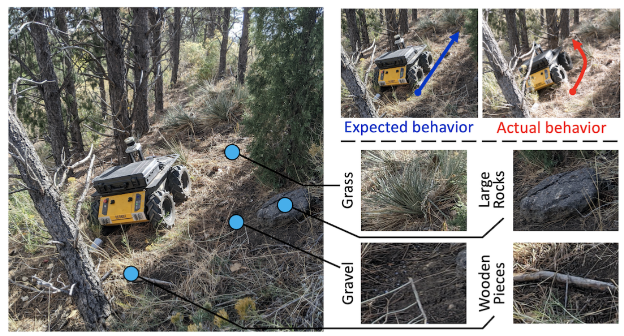

Figure 1: Motivating scenarios for robot terrain adaptation. When ground robots are deployed in this environment, their actual behaviors often do not match the expected behaviors, e.g., due to wheel slip. Thus, requiring the capability of generating consistent navigational behaviors.

Approach

We extract multi-modal features from multiple sensors installed on the robot (e.g., visual camera, LiDAR, and IMU) while traversing over a terrain. We concatenate all features extracted at time point t into a vector and denote it as $\mathbf{x}^{(t)} \in \mathbb{R}^q$, where $q = \sum_{j=1}^{m} q_j$, q_j is the dimensionality of the j-th feature modality, and m is the number of modalities. We represent features extracted from a sequence of consecutive c time points as a data instance $\mathbf{x} = [\mathbf{x}^{(t)}; \ldots ; \mathbf{x}^{(t-c)}] \in \mathbb{R}^d$, where $d = c \times q$. We further denote the set of n data instances for training our approach as $\mathbf{X} = [\mathbf{x}_1, \ldots , \mathbf{x}_n] \in \mathbb{R}^{d\times n}$. We use $\mathbf{Y} = [\mathbf{y}_1, \ldots , \mathbf{y}_n] \in \mathbb{R}^{r\times n}$ to denote the expected navigational behaviors (e.g., velocity, motor torque, and steering angle) of the robot associated with $\mathbf{X}$, where $\mathbf{y}_i \in \mathbb{R}^r$ is a vector of r behavior control variables corresponding to $\mathbf{x}_i$. We estimate the robot's behaviors $\mathbf{y}_i$ using $\mathbf{x}_i = [\mathbf{x}_i^{(t)}; \ldots ; \mathbf{x}_i^{(t-c)}]$, taking into account the history of c observations. Then, we formulate the problem of navigational behavior estimation as: $\min(\mathbf{w}) \|\mathbf{Y} - \mathbf{W}^\top \mathbf{X}\|_F^2$. Here $\mathbf{W} \in \mathbb{R}^{d\times r}$ is a weight matrix indicating the importance of feature modalities towards generating navigational behaviors and $\|.\|_F$ is the Frobenius norm.

To generate consistent navigational behaviors, our approach monitors the difference between the actual and the expected navigational behaviors caused by the setbacks, and

Table 1: Quantitative results for scenarios when robot traverses over unstructured off-road terrain shown in Fig. 2.

	Failure Rate (/10)			Traversal Time (s)			Inconsistency			Jerkiness (m/s^3)		
Terrain	MM-LfD	TRAL	**Ours**	MM-LfD	TRAL	**Ours**	MM-LfD	TRAL	**Ours**	MM-LfD	TRAL	**Ours**
Gr-M.Rock	7	2	**1**	**19.7**	27.5	23.1	17.28	14.54	**12.31**	80.56	58.36	**51.93**
Gr-L.Rock	9	3	**3**	27.4	29.4	28.8	101.26	68.87	**51.16**	40.51	28.22	**24.55**
M.Terrain I	1	0	**0**	18.2	19.4	18.9	5.38	4.91	**3.39**	83.17	70.36	**68.55**
M.Terrain II	7	4	5	**18.1**	30.2	28.5	95.47	80.43	**78.82**	77.49	52.51	**47.93**

computes an offset to reduce this difference without explicitly modeling all the setbacks. Formally, we denote the actual behaviors executed by the robot as $\hat{\mathbf{Y}} = [\hat{\mathbf{y}}_1, \dots, \hat{\mathbf{y}}_n] \in \mathbb{R}^{r \times n}$, where $\hat{\mathbf{y}}_i \in \mathbb{R}^r$ denotes the actual behaviors executed by the robot when observing $\mathbf{x}_i$. We define that the actual behaviors $\hat{\mathbf{y}}_i$ is composed by the expected behaviors $\mathbf{y}_i$ and the offset behaviors $\mathbf{v}_i \in \mathbb{R}^r$, i.e., $\hat{\mathbf{y}}_i = \mathbf{y}_i + \mathbf{v}_i$. The offset behaviors $\mathbf{v}_i$ is computed as $\mathbf{v}_i = \mathbf{U}^\top \mathbf{e}_i$, where $\mathbf{e}_i = [(\hat{\mathbf{y}}_i^{(t)} - \mathbf{y}_i^{(t)}); \dots; (\hat{\mathbf{y}}_i^{(t-c)} - \mathbf{y}_i^{(t-c)})] \in \mathbb{R}^{rc}$ denotes a vector of differences between actual and expected behaviors in the previous c time steps. $\mathbf{U} = [\mathbf{u}^1, \dots, \mathbf{u}^r] \in \mathbb{R}^{rc \times r}$ is the weight matrix, and $\mathbf{u}^j \in \mathbb{R}^{rc}$ indicates the importance of $\mathbf{e}_i$ towards generating the j-th element in $\mathbf{v}_i$. Then, generating consistent navigational behaviors can be formulated as:

$$\min_{\mathbf{U},\mathbf{W}} \|\hat{\mathbf{Y}} - \mathbf{W}^\top \mathbf{X} - \mathbf{U}^\top \mathbf{E}\|_F^2 + \lambda_1 \|\mathbf{W}\|_M + \lambda_2 \|\mathbf{U}\|_T \quad (1)$$

where $\mathbf{E} = [\mathbf{e}_1, \dots, \mathbf{e}_n] \in \mathbb{R}^{rc \times n}$. The first term of Eq. (1) is a loss function to model the actual behavior by considering both $\mathbf{X}$ and $\mathbf{E}$ to achieve consistent navigational behaviors. The second term is a regularization term termed as the feature modality norm, that groups together weights within a feature modality and enforces sparsity among different modalities, thus, identifying the most descriptive features for behavior generation. Finally the last term is a regularization term called the temporal norm, designed to explore which time steps in the historical data are more important for generating the offset behaviors.

After computing the optimal values of the weight matrices $\mathbf{W}$ and $\mathbf{U}$ from training data, we can compute the offset behavior as $\mathbf{v} = \mathbf{U}^\top \mathbf{e}$, where $\mathbf{e}$ denotes the difference between the expected $\mathbf{y}$ and the actual behavior $\hat{\mathbf{y}}$. We also predict the offset needed for the next time step to proactively generate behaviors by considering future behavior differences as $\tilde{\mathbf{v}} = \sum_{k=t}^{t-c} \Big(\big(\mathbf{U}^{(k)\top}\big)^{-1} \big(\mathbf{y}^{(k)} - \mathbf{W}^{(k)\top} \mathbf{x}^{(k)}\big) \Big)$. Then our approach allows the robot to generate consistent actual navigational behaviors as:

$$\mathbf{y} = \mathbf{W}^\top \mathbf{x} + [\mathbf{I}_r \quad \mathbf{U}] \, [\tilde{\mathbf{v}} \quad \mathbf{e}]^\top \quad (2)$$

where $\mathbf{I}_r \in \mathbb{R}^{r \times r}$ is an identity matrix.

Experimental Results

We evaluate our approach using a Clearpath Husky robot over complex off-road unstructured terrains. The tracks in these experiments either show transitions between different terrain types (i.e., grass to large rocks and grass to medium rocks) or a mixture of terrain types in real off-road environments (i.e., Mixed Terrain I and Mixed Terrain II), as shown in Fig. 2.

Figure 2: Complex unstructured off-road terrain.

The robot is equipped with an Intel Reasense D435 color-depth camera, an Ouster OS1-64 LiDAR and an array of internal sensors to measure the robot's states (e.g., wheel odometry, inertial readings, motor speed, etc.). Multi-modal features are extracted from sensor data and concatenated to form feature vectors. Training data is provided by human operators who control the robot to traverse terrains as fast as possible while maintaining safety (e.g., no flipping or crashing).

Table 1 presents the quantitative results obtained by our approach and the comparison with multi-modal LfD (MM-LfD) (Wu et al. 2018), and Terrain Representation and Apprenticeship Learning (Siva et al. 2019) (TRAL) methods. 1) *Failure Rate (FR)* during navigation, 2)*Traversal time (TT)* of the robot over a terrain, 3) *Inconsistency* calculated as the error between the expected and actual navigational behaviors and 4) *Jerkiness* calculated as the average sum of acceleration derivative are the four evaluation metrics used to compare the approaches. It is observed that all the methods have a much higher failure rate in the Mixed Terrain II and the terrain of grass to large rocks. Our approach generally performs equally well or significantly better than MM-LfD and TRAL in terms of failure rate. We also observe that both MM-LfD has much small traversal time for successful runs, but has a significantly higher failure rate compared with TRAL and our approach. Our approach clearly outperforms other methods and obtains state-of-the-art performance in terms of consistency and jerkiness.

Acknowledgements

This work was partially supported by ARL's SARA Program W911NF-20-2-0107.

References

Siva, S.; Wigness, M.; Rogers, J.; and Zhang, H. 2019. Robot adaptation to unstructured terrains by joint representation and apprenticeship learning. In *Robotics: Science and Systems*.

Wu, Y.; Wang, R.; D'Haro, L. F.; Banchs, R. E.; and Tee, K. P. 2018. Multi-modal robot apprenticeship: Imitation learning using linearly decayed dmp+ in a human-robot dialogue system. In *International Conference on Intelligent Robots and Systems*.