SLIP PREDICTION FOR EXPLORATION ROVER BASED ON TRANSFER LEARNING

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ABSTRACT

This paper addresses the problem of slip prediction for exploration rovers. When an exploration rover is operated on terrains of fine-grained sand, especially on slopes, it is important to accurately and precisely predict vehicle slippage for avoiding entrapment. However, the prediction of vehicle slippage is challenging especially, when predicting slip on possibly risky terrains since for such terrains no or only scarce traverse data is usually available for prediction. To address the problem, this paper proposes a slip prediction method based on transfer learning. The proposed method utilizes limited data on low risk terrain of the target environment and boosts the prediction accuracy by leveraging traverse experiences on multiple types of terrains.

1 INTRODUCTION

Several surface exploration missions using manned and unmanned rovers have been operated on the Moon and Mars thus far. Those rover missions have made great contributions of important scientific findings. The target areas of earlier missions were mainly on benign terrains although some vehicles occasionally drove on inclined terrains. NASA's Curiosity Mars rover, on the other hand, is targeting at ascending to the low layer of Mount Sharp. Future rover missions are expected to traverse challenging terrains such as walls of lunar craters, slopes of loose regolith.

One of the problems in traversing such terrains is slippage of rovers [1, 2]. The rover slippage can become significant on sandy terrains, especially on slopes, inducing high sinkage and making the rover entrapped into the sand. Therefore, it is important to detecting risky terrains that induce such critical slip and then to select safe routes for successful operations.

However, accurate and precise prediction of the vehicle slippage is highly difficult due to complicated vehicle-terrain interactions. Vehicle behaviors are generally affected by many factors such as terrain geometry (slope and roughness), surface type (sand, cohesive soil, rocks, bedrock, or mixture of these), and surface accumulated condition (compacted or not, accumulation depth, and moisture content) [3].

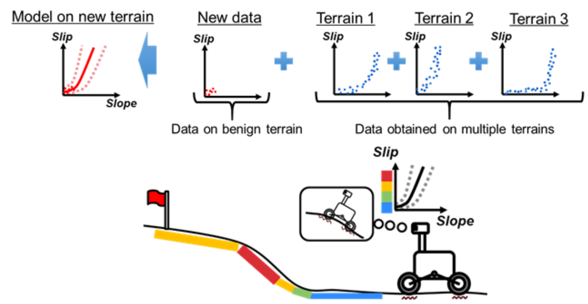


Figure 1: Concept of the proposed slip prediction on possibly risky terrains.

Several research so far have proposed slip prediction algorithms [4, 5, 6]. While these methods are somewhat promising, sufficient traverse data on target environments are essentially required for an accurate prediction of the traversability of the terrains. If the rover targets at ascending steep slopes, it is required to take risks for obtaining traverse data of that possibly hazardous terrains. Usually during a mission, however, a rover typically avoids risky terrains for the mission safety. Therefore, traverse data on such terrains might be only scarcely or even never available. This makes the slip prediction of steep slopes challenging.

This work addresses the above problem which inherent in rover slip prediction. Especially, the present work is aiming at improving the prediction accuracy of the slippage on challenging terrains of new environments from in-situ traverse data on relatively safe area (Fig. 1). The present study proposes a slip prediction method based on multi-source transfer Gaussian process regression (MSTGPR). The proposed method leverages traverse experiences on multiple terrains, which might be obtained either on Earth or during a mission, and improves prediction accuracy on possibly risky terrains of the target mission environment where no in-situ traverse data is available beforehand for prediction.

This paper is organized as follows. First the transfer learning-based slip prediction method is proposed in Section 2. Next, the proposed method is evaluated using a synthetic slip-slope dataset in Section 3. Section 4 summarizes this paper and mentions future works.

2 PROPOSED METHOD

This section proposes a slip prediction method based on transfer learning. Transfer learning [7] is a learning method that applies knowledges or learned models in one or more applications/tasks (source domains) to the model learning for another application/task (target domain). By appropriately transferring the model information from the source domain, transfer learning can improve the performance in the target domain when the target training data is limited.

The proposed method learns the slip prediction model of the new traverse environment (target domain) by using the slip data on benign terrains of that environment and pre-obtained slip data on multiple terrain types (source domains). Specifically, this study builds the target slip model as a weighted sum of the slip models for the source domains $\{S_i\}$ $(i = 1, \dots, N)$ as in Eq. 1.

$$f^{(T)}(\boldsymbol{x}) = \sum_{i=1}^{N} w_i f^{(S_i)}(\boldsymbol{x}) \quad (1)$$

Here $\boldsymbol{x}$ represents the input feature vector of the terrain geometry, such as pitch, roll, and surface roughness. w_i represents the weight for the i-th source model. While any algorithms can be applied to learn the base source model $f^{(S_i)}(\boldsymbol{x})$ and the weight w_i, this study utilizes multi-source transfer Gaussian process regression (MSTGPR) [10], a variant of Gaussian process regression (GPR) [8] for multi-source transfer learning.

This study assumes that traverse data on multiple terrain types have been obtained beforehand, for example either by pre-flight traverse tests on the Earth or during earlier mission stages. This study also assumes that the rover can estimate its slippage from its onboard sensory information.

2.1 Gaussian Process Regression

GPR is a nonparametric approach to lean a regression model which does not require to assume any specific forms for the model (e.g., linear, polynomial, or exponential), and the model shape is determined based on training data. In addition to this, GP can express the prediction uncertainties as variances along with the predictive means. Because of these features, GPR is suitable for modeling the vehicle slippage which shows complicated behaviors depending on the target terrain geometry and surface type. The work by Cunningham et al. [6] shows the effectiveness of GPR for modelling rover slippage.

The GPR-based slip prediction assumes that the slip measurement y is given by the following form:

$$y = f(\boldsymbol{x}) + \varepsilon \quad (2)$$

where $\boldsymbol{x}$ denotes the terrain geometry and ε denotes the observation error that follows a zero-mean Gaussian distribution. $f(\boldsymbol{x})$ is the latent function that represents the rover slip behavior. $f(\boldsymbol{x})$ follows the Gaussian distribution which is determined by the mean $m(\boldsymbol{x})$ and covariance function $k(\boldsymbol{x}, \boldsymbol{x}')$.

Given the training data $\boldsymbol{D} = \{\boldsymbol{X}, \boldsymbol{y}\}$, the joint distribution of the latent function and the measurements $\boldsymbol{y}$ can be learned by tuning the hyperparameters of the model.

In the prediction step, the predictive slip at the point $\boldsymbol{x}_*$ is given by $f(\boldsymbol{x}_*) \sim p(f|\boldsymbol{D}) = \mathcal{N}(f|m, v)$ where the predictive mean $m(\boldsymbol{x}_*)$ and variance $v(\boldsymbol{x}_*)$ are given by Eqs. 3-4, respectively.

$$m(\boldsymbol{x}_*) = \boldsymbol{K}(\boldsymbol{x}_*, \boldsymbol{X})(\boldsymbol{K}(\boldsymbol{X}, \boldsymbol{X}) + \beta^{-1}\boldsymbol{I})^{-1}\boldsymbol{y} \quad (3)$$

$$v(\boldsymbol{x}_*) = \boldsymbol{K}(\boldsymbol{x}_*, \boldsymbol{x}_*) - \boldsymbol{K}(\boldsymbol{x}_*, \boldsymbol{X})(\boldsymbol{K}(\boldsymbol{X}, \boldsymbol{X}) + \beta^{-1}\boldsymbol{I})^{-1}\boldsymbol{K}(\boldsymbol{X}, \boldsymbol{x}_*) \quad (4)$$

Here $\boldsymbol{X}$ and $\boldsymbol{y}$ denotes the n training inputs and measurements, respectively. $\boldsymbol{K}(\cdot, \cdot)$ denotes the covariance matrix evaluated with the pairs of the training input points or the prediction point $\boldsymbol{x}_*$. β denotes the precision against the measurement noise ε, and $\boldsymbol{I}$ denotes an $n \times n$ identity matrix.

2.2 Multi-Source Transfer Gaussian Process Regression

In MSTGPR, the correlation between a source domain and the target domain is captured in addition to the correlation between data points [9, 10]. The transfer covariance function $k_*(\boldsymbol{x}, \boldsymbol{x}')$, given Eq. 5, is introduced for this purpose.

$$k_*(\boldsymbol{x}, \boldsymbol{x}') = \begin{cases} \lambda_i k(\boldsymbol{x}, \boldsymbol{x}') & \boldsymbol{x} \in \boldsymbol{\mathcal{X}}^{(S_i)} \,\&\, \boldsymbol{x}' \in \boldsymbol{\mathcal{X}}^{(T)}\ or \\ & \boldsymbol{x} \in \boldsymbol{\mathcal{X}}^{(T)} \,\&\, \boldsymbol{x}' \in \boldsymbol{\mathcal{X}}^{(S_i)} \\ k(\boldsymbol{x}, \boldsymbol{x}') & otherwise \end{cases} \quad (5)$$

In Eq. 5, $\lambda_i \in [-1, 1]$ denotes the similarity coefficient between the source domain S_i and the target domain T, with a higher λ_i representing a higher similarity.

Based on the transfer covariance function, the covariance matrix for a single transfer GPR is defined as Eq. 6.

$$\widetilde{\boldsymbol{K}}_{S_iT} = \begin{bmatrix} \boldsymbol{K}_{S_i} & \lambda_i \boldsymbol{K}_{S_iT} \\ \lambda_i \boldsymbol{K}_{TS_i} & \boldsymbol{K}_T \end{bmatrix} \tag{6}$$

Here $\boldsymbol{K}_{S_i}$ and $\boldsymbol{K}_T$ are the covariance matrices of the individual domain S_i and T, respectively, whereas $\boldsymbol{K}_{S_iT} = \boldsymbol{K}_{TS_i}^T$ is the covariance matrix between the two domains.

Given the source domain data $\boldsymbol{D}^{(S_i)} = \{\boldsymbol{X}^{(S_i)}, \boldsymbol{y}^{(S_i)}\}$ and the training data of the target domain $\boldsymbol{D}^{(T)} = \{\boldsymbol{X}^{(T)}, \boldsymbol{y}^{(T)}\}$, the joint distribution of the latent function $f^{(S_i,T)}(\boldsymbol{x})$ and the measurements $\boldsymbol{y}^{(S_iT)} = \{\boldsymbol{y}^{(S_i)}, \boldsymbol{y}^{(T)}\}$ can be learned by tuning the hyperparameters in the covariance function and the similarity coefficient λ_i.

The predictive slip of the target domain is given by $f^{(S_i,T)}(\boldsymbol{x}_*) \sim p\left(f^{(S_i,T)} | \boldsymbol{D}^{(S_i)}, \boldsymbol{D}^{(T)}\right) = \mathcal{N}(f^{(S_i,T)} | m^{(S_i,T)}, v^{(S_i,T)})$ with the predictive mean and variance represented by Eqs. 7-8, respectively.

$$m^{(S_i,T)}(\boldsymbol{x}_*) = \boldsymbol{K}_*(\boldsymbol{x}_*, \boldsymbol{X})\left(\widetilde{\boldsymbol{K}}_{S_iT} + \boldsymbol{\Lambda}\right)^{-1} \boldsymbol{y}^{(S_iT)} \tag{7}$$

$$\sigma^{(S_i,T)}(\boldsymbol{x}_*) = \boldsymbol{K}(\boldsymbol{x}_*, \boldsymbol{x}_*) + \beta_T^{-1} - \boldsymbol{K}_*(\boldsymbol{x}_*, \boldsymbol{X})\left(\widetilde{\boldsymbol{K}}_{S_iT} + \boldsymbol{\Lambda}_{S_i,T}\right)^{-1} \boldsymbol{K}_*(\boldsymbol{X}, \boldsymbol{x}_*) \tag{8}$$

Here $\boldsymbol{\Lambda}_{S_i,T} = \begin{bmatrix} \beta_{S_i}^{-1} \boldsymbol{I}_{n_{S_i}} & \boldsymbol{0} \\ \boldsymbol{0} & \beta_T^{-1} \boldsymbol{I}_{n_T} \end{bmatrix}$ with β_{S_i} and β_T being the precisions against the measurement noise in the source S_i and target domains, respectively.

For appropriately combining the single TGPR models of multiple source domains in Eq. 1, this study determines the wight w_i for the source domain S_i based on the correlation efficient λ_i as follows [10]:

$$w_i = g(\lambda_i). \tag{9}$$

In summary, the proposed slip prediction method develops the slip model of the target domain based on Eq. 1 by learning the similarity coefficient λ_i along with the TGPR model $f^{(S_i,T)}(\boldsymbol{x})$ from the target training data and the source domain data.

3 EVALUATION

This section evaluates the effectiveness of the proposed transfer leaning-based slip prediction method.

For the evaluation, a synthetic slip dataset shown in Fig. 2 was used. This dataset consists of artificial slip-slope data on eight different terrain types (domains). Each domain data was generated by randomly sampling data points from the probability distributions of

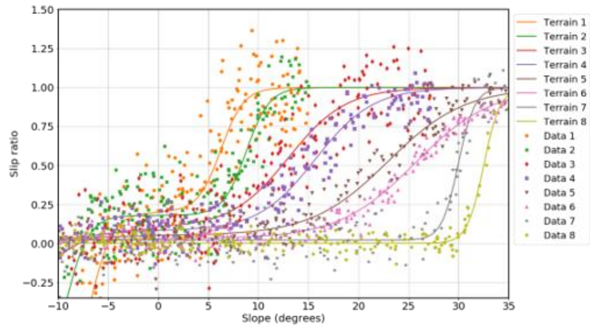


Figure 2: Synthetic dataset for evaluating the proposed slip prediction method. The dataset consists of the slip-slope data of eight terrain types. These data were generated by randomly sampled from noise-added artificial latent slip functions.

the corresponding artificial latent slip functions with some measurement noises. In this study, one of the eight domains was set as the target domain to be predicted, and the rest of all domains were set as the source domains. Among all data, low slope data of the target domain and all source data were used for training the MSTGPR model.

In this evaluation, the covariance function given by Eq. 9 was used for the GPR and MSTGPR.

$$k(\boldsymbol{x}, \boldsymbol{x}') = k_1 \exp(-k_2 |\boldsymbol{x} - \boldsymbol{x}'|^2) + k_3 + k_4 \boldsymbol{x}^T \boldsymbol{x}' \tag{9}$$

This covariance function, which also appears in [11], was selected since it showed better prediction performance than the widely used squared exponential function in this study although the differences were not significant.

The weight for each source domain in Eq. 1 was determined by $w_i = \exp(\lambda_i) / \sum \exp(\lambda_i)$ to assign a higher weight to a source domain with higher similarity to the target domain.

3.1 Evaluation 1

In this first evaluation, this study compared the prediction accuracies (root mean squared errors, RMSEs) of different prediction methods: (a) GPR without transfer, (b) MSTGPR with all sources transferred, and (c) MSTGPR with sources with high similarity transferred.

In this evaluation, the target domain data was split into training and test data as follows: the data points with the slope lower than 10º were used for training and those higher than 10º were used for evaluation. All of the source domain data were used for training of MSTGPR. In the method (a), the slip model of the target domain was learned based on the general GPR described in Section 2.1 using only the training data of the target domain. In (b) and (c), on the other hand, the target slip model was learned based on the proposed MSTGPR of Section 2.2 using both the target domain's training data and the source domain data.

Fig. 3 shows example prediction results of the three methods when the target domain was set to Terrain 3, and Table 1 lists the corresponding RMSEs of these methods.

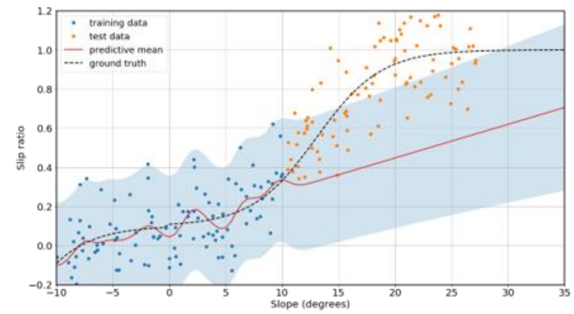
The prediction result of the basic GPR is shown in Fig. 3 (a). The learned GPR model represents to some extent the slip in the range of the training data. However, large prediction errors can be observed with the predictive mean slip significantly underestimated from the true values. In addition, the predicted confidence bound could not capture most of the true slip values. As this result shows, predicting the slippage on high risk terrains out of the training data range is challenging as the prediction is basically an extrapolation problem and the model can be easily overfit to the training data of lower risk terrains.

Fig. 3 (b) shows the prediction model learned based on the proposed method with all source domain model transferred. Compared to the method (a), the RMSE reduced by 41.4%, and the confidence bound covers all test data.

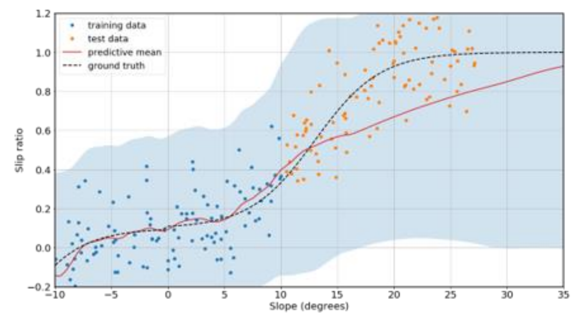
Fig. 3 (c) shows the prediction result based on the proposed method using the slip modes of selective source domains. In this study, the models of the source domains with the learned similarity of $\lambda_i > 0.7$ (Terrains 2, 4, and 5) were used for building the MSTGPR model (Eq. 1). As shown in Fig. 3 (c), the predictive accuracy was improved, and the confidence bound became tighter by selectively transferring the source domain information. The method (c) resulted in the RMSE 53.2% lower than the GPR without transfer and that 20.9% lower than the MSTGPR with all source models transferred.

Table 1: Slip prediction errors (RMSEs) of different regression methods.

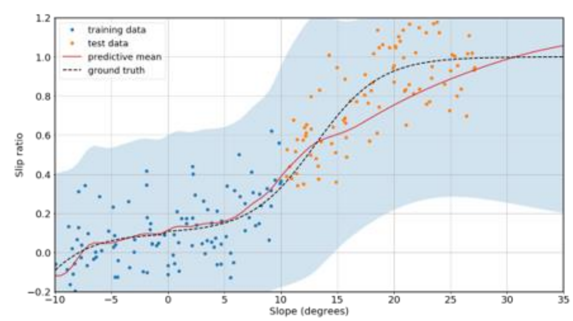
Method	RMSE
(a) GPR (no transfer)	0.432
(b) MSTGPR with all sources transferred	0.253
(c) MSTGPR with selective sources	0.200



(a) GPR (no transfer)



(b) *MSTGPR with all source information*

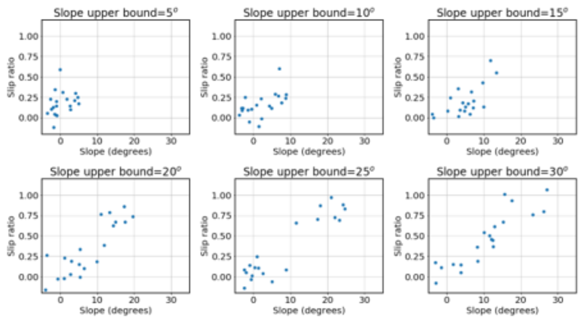


(c) MSTGPR with selective source information

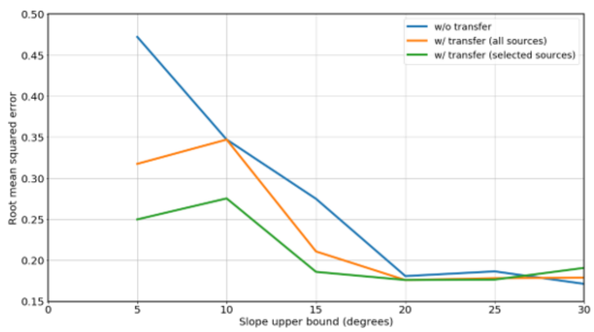
Figure 3: Example results of the slip prediction without and with the knowledge transferred from multiple source domains. The red curve represents the predictive mean whereas the blue shaded area represents the 2-standard deviation around the mean. The black curve represents the true latent slip function from which the data was sampled.

3.2 Evaluation 2

The next evaluation assessed the influence of the input slope range of the training data on the predictive accuracy of the rover slippage. In this evaluation, the upper bound of the slope angle in the target training data was varied from 5º to 30º, and 20 training data were



(a) Training data with various slope upper bounds.



(b) Prediction errors

Figure 4: Comparison of the slip prediction errors of the models learned from training data of different terrain inclination upper bounds.

sampled from the underlying latent function with each selected upper bound, as shown in Fig. 4 (a).

Fig. 4 (b) shows the example relationships between the slip prediction error and the upper bound of the slope in the target training data. Similarly to the previous evaluation, results of three methods (a) GPR without transfer, (b) MSTGPR with all source models transferred, and (c) MSTGPR with selective source models (those with $\lambda_i > 0.5$) were plotted in Fig 4 (b). When learned from the training data with slope upper bound lower than 20º, the GPR without transfer resulted in the highest prediction errors. Within this range, the error could be reduced by using the knowledge of source domains based on the proposed method.

On the other hand, when the models were learned from the training data with the upper slope angle higher than or equal to 20º, no measurable difference can be seen in the prediction errors between GPR and MSTGPR. This is because the prediction accuracy of the GPR could be improve by using the added slip data on higher slopes.

3.3 Discussions

From the above observations, it was shown that the proposed method can improve the slip prediction accuracy when available training data is limited to only those obtained on benign terrains. Additionally, it was also shown that the prediction accuracy of the proposed method can be further improved by selecting source domains with high similarity to the target domain.

On the other hand, if sufficient data is available for learning the prediction model, the improvement by the transfer learning will be very limited. In such situations, simply using the basic GPR is preferable because of its lower computational cost and better learning stability compared to the MSTGPR.

Note that, this paper only shows the results of the case where the target domain was set to Terrain 3 which shows average slip-slope characteristic among all domains. The predictive accuracy of the proposed method differs depending on which domain is chosen as a target, and depending on available source domains to be transferred. For example, as Terrains 1 and 8 are located at the edges among all domains, the proposed method cannot significantly improve the prediction accuracy. How to utilize available source domain data when the slip characteristic of the target domain largely differs from that of the source domains is one of the important future work. One possible strategy is simply avoiding such terrains if high risk is expected.

4 CONCLUSION

This paper proposed a transfer regression method to improve the slip prediction accuracy when in-situ traverse data only on gentle terrains are available for learning the prediction model. Combined with the limited in-situ data, the proposed method leverages traverse experiences on multiple types of terrains to boost the slip prediction accuracy in such situations. The effectiveness of the proposed method was shown using a synthetic slip dataset. The proposed method is especially effective at very early stage of exploration missions.

One of the important future works is to improve the proposed method by incorporating a method to more effectively select and utilize source domain knowledge to transfer. The current approach only uses the slip-slope data for learning the weight for each source domain. Combining other sensory information, such as image textures, may be effective. In addition, in this paper, the proposed method was only evaluated with the synthetic dataset. Currently the authors are planning to conduct traverse experiments of a test rover on various types of terrains to obtain a real dataset.

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