Incremental Traversability Assessment Learning using Growing Neural Gas Algorithm

Jan Faigl* and Miloš Prágr

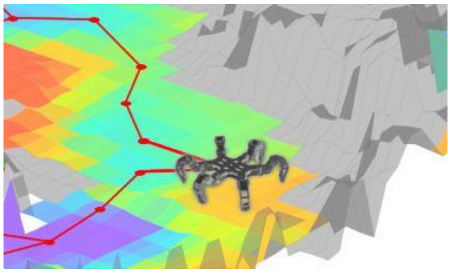
Department of Computer Science, Faculty of Electrical Engineering
Czech Technical University in Prague
Technická 2, 166 27, Prague 6, Czech Republic
*Corresponding author: Jan Faigl (faiglj@fel.cvut.cz)
{faiglj,pragrmi1}@fel.cvut.cz,
WWW home page: https://comrob.fel.cvut.cz/

Abstract. In this paper, we report early results on the deployment of the growing neural gas algorithm in online incremental learning of traversability assessment with a multi-legged walking robot. The addressed problem is to incrementally build a model of the robot experience with traversing the terrain that can be immediately utilized in the traversability cost assessment of seen but not yet visited areas. The main motivation of the studied deployment is to improve the performance of the autonomous mission by avoiding hard to traverse areas and support planning cost-efficient paths based on the continuously collected measurements characterizing the operational environment. We propose to employ the growing neural gas algorithm to incrementally build a model of the terrain characterization from exteroceptive features that are associated with the proprioceptive based estimation of the traversal cost. Based on the reported results, the proposed deployment provides competitive results to the existing approach based on the Incremental Gaussian Mixture Network.

Keywords: Terrain Characterization, Multi-Legged Walking Robot

1 Introduction

The problem studied in this paper is arising from robotic data collection missions where an autonomous robot is requested to repeatably visit a set of locations to measure some phenomena of interest [3]. During such a mission, the robot not only collects the requested data measurements, but it also experiences the terrain. Hence, the experience can be exploited in finding more efficient paths through the environment, and thus improve the mission performance. This might be especially suitable for multi-legged robots that can traverse rough terrains [1], but they suffer from low stability and high energy requirements when traversing difficult terrains [6]. Therefore, we aim to incrementally learn a model of the traversability assessment that can be instantly utilized in the evaluation of the seen but not yet visited areas, to support planning cost-efficient paths. Our motivational deployment is visualized in Fig. 1.



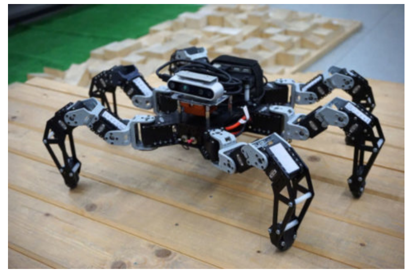


Fig. 1. Example of the traversability assessment model used in path planning for a hexapod walking robot. The gray areas are parts of the operational environment mapped so far, and the traversability cost is visualized by the respective color of the areas, where hard to traverse parts are in red and low-cost parts are in blue.

Existing approaches to terrain characterization can be categorized into terrain classification and traversability assessment using a continuous function. The traversability assessment for path planning is of our particular interest; however, we consider assessment only of passable terrains, and thus we rely on prior binary classification to traversable and untraversable areas. The estimation of the motion cost can be based on locally observed properties [14] and modeling of such a spatial phenomenon can be performed by the Gaussian Process (GP) based regression, e.g., to create continuous occupancy [9] or elevation maps [16]. However, GPs are computationally demanding to be directly utilized in online decision-making and incremental model learning. Therefore, in our previous work [12], we employed the Incremental Gaussian Mixture Network Model (IGMN) [10] to learn a cost of transport model that is then utilized in the cost prediction using exteroceptive sensing of robot surroundings.

Although the IGMN provides a satisfiable performance in the cost estimation suitable for path planning [12, 13], we aim to explore other possibilities to combine terrain classification with terrain traversability learning in a computationally efficient way. Motivated by recent advancements in the application of the Growing Neural Gas (GNG) algorithms in online labeling [2], time series classification [8], online anomaly detection [15] using motion and appearance features [17] and clustering data streams [5], we tackled the studied problem using the original GNG algorithm [4] proposed by Bernd Fritzke in 1994. The only modification is in adding a new node if the current winning unit is not close enough [11] instead of growing every fixed number of adaptations.

In the rest of the paper, we specify the problem context and report on our early evaluation results and comparison of the GNG with the IGMN.

2 Problem Specification

The studied problem is to estimate the traversal cost based on the experience of the robot with terrain traversing. The considered terrain characterization is a combination of exteroceptive signals, which allows predicting the cost from range measurements, with proprioceptive measurements characterizing the robot experience with the terrain. The robot operational environment is modeled as the 2.5D elevation map to store the elevation and RGB color information that is utilized to compute the exteroceptive part of the terrain descriptor. In particular, we utilize a terrain feature descriptor that consists of three shape features [7] and two appearance features. The shape features s_1, s_2, and s_3 are defined as

$$s_1 = \frac{\lambda_1}{\lambda_3}, \quad s_2 = \frac{\lambda_2 - \lambda_1}{\lambda_3}, \quad s_3 = \frac{\lambda_3 - \lambda_2}{\lambda_3}, \tag{1}$$

where $\lambda_1 \leq \lambda_2 \leq \lambda_3$ are the eigenvalues of the covariance matrix of the elevation in a particular area of interest. The appearance part of the descriptor consists of the ab channel means of Lab color space denoted a_1 and a_2. Finally, the traversal cost is characterized by the experienced stability cost c determined as the square root of the robot roll variance for 10 s period measured by the onboard attitude heading reference system running at 400 Hz. The model descriptor is thus six dimensional vector $\boldsymbol{d} = (s_1, s_2, s_3, a_1, a_2, c)$ and the traversability assessment is based on the model inference to predict c using $\boldsymbol{d}_{sa} = (s_1, s_2, s_3, a_1, a_2)$.

During the mission, the robot builds a map of its surroundings, traverse the terrain, and its experience with the terrain can be represented as a sequence of n descriptors that is further called trail $\mathcal{T}$, i.e., $\mathcal{T} = (\boldsymbol{d}(1), \ldots, \boldsymbol{d}(n))$. Every single descriptor $\boldsymbol{d}(k)$ is utilized to incrementally update the model $\mathcal{M}(k)$

$$\mathcal{M}(k) \leftarrow \mathrm{learn}(\mathcal{M}(k-1), \boldsymbol{d}(k)) \tag{2}$$

that can be immediately used to assess a set of descriptors characterizing seen but not yet visited areas, e.g., organized in a grid map, $\mathcal{G} = \{(x_i, y_j, \boldsymbol{d}_{sa}(i,j)) \mid 1 \leq i \leq w, 1 \leq j \leq h\}$, where x_i and y_j are the spatial coordinates of the corresponding exteroceptive measurements $\boldsymbol{d}_{sa}(i,j)$ for the $w \times h$ large grid map. Since the measurements might not be available for every cell of the map, the number of descriptors $m = |\mathcal{G}|$ can be $m \leq w \cdot h$.

The evaluation of the learned model and its generalization to other environments can be based on measuring the difference between the predicted values of c for the grid map $\mathcal{G}$ and the ground truth values. However, it is nearly impossible to establish the ground truth, because it would require a precise and complete traversing of all areas of the particular environment, but most importantly the measured experience depends on many factors, and it is generally a random variable. Therefore, we consider a reference value of the predicted cost determined by the computationally demanding GPs using the whole particular trail $\mathcal{T}$ denoted as $\mathcal{M}^{\mathcal{T}}_{\mathrm{GP}}$. For each k-th descriptor of the trail, $\mathcal{M}(k)$ is used to assess $\mathcal{G}$, and we measure the performance of the incrementally learned model as the evolution of the root-mean-square error (RMSE) to the GP-based predictor

$$RMSE(k) = \sqrt{\frac{\sum_{\boldsymbol{d}_{sa} \in \mathcal{G}} \left(\mathrm{predict}(\mathcal{M}(k), \boldsymbol{d}_{sa}) - \mathrm{predict}(\mathcal{M}^{\mathcal{T}}_{\mathrm{GP}}, \boldsymbol{d}_{sa})\right)^2}{m}}. \tag{3}$$

The model inference provides a prediction of the traversal cost as a continuous variable, and its particular value depends on many factors. Therefore, models learned by different techniques would unlikely provide the identical value of the predicted traversal cost as the reference GP-based model. Hence, we can take advantage of the learned GP-based model that provides the variance of the learned random variables, and we can consider a model is well approximating the GP-based reference if the predicted value is close to the predicted mean value of the GP-based model. Thus, for each particular descriptor $\boldsymbol{d}_{sa} \in \mathcal{G}$, we can estimate the mean $\mu(\boldsymbol{d}_{sa}) = \text{predicted}(\mathcal{M}_{\text{GP}}^{\mathcal{T}}, \boldsymbol{d}_{sa})$ and its variance $\sigma^2(\boldsymbol{d}_{sa})$. Then, we can consider that the predicted value by the model $\mathcal{M}$ is correct with respect to the reference model $\mathcal{M}_{\text{GP}}^{\mathcal{T}}$ if its distance from $\mu(\boldsymbol{d}_{sa})$ is shorter than two times of the standard deviation, i.e., the predicted value fits about 95% values of the corresponding distribution represented by the GP. Based on this idea, the model correctness quality indicator R_c can be defined as the ratio of the number of the correctly estimated traversal costs to the total number of the descriptors in $\mathcal{G}$

$$R_c(\mathcal{M}) = \frac{|\{\boldsymbol{d}_{sa}|\boldsymbol{d}_{sa} \in \mathcal{G} \text{ and } |\,\text{predict}(\mathcal{M}, \boldsymbol{d}_{sa}) - \mu(\boldsymbol{d}_{sa})| \leq 2\sigma(\boldsymbol{d}_{sa})\}|}{|\mathcal{G}|} \cdot 100\%. \tag{4}$$

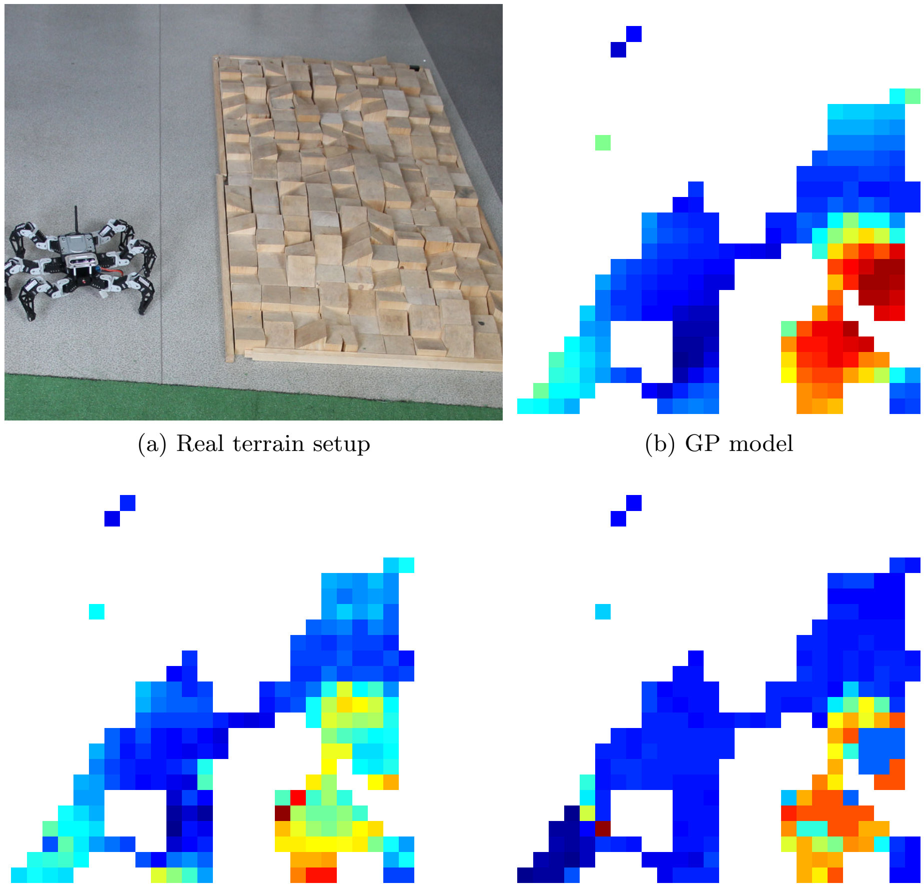
Finally, we can further exploit explicitly labeled terrains and learn individual GP-based model for each particular terrain type using only the corresponding parts of the trails for the specific (human labeled) terrain types. In the evaluation of the testing grid map $\mathcal{G}$, we can use all learned models to predict the traversal cost, but the value with the lowest variance (i.e., with the highest confidence of the predicted value) is considered to be the reference traversal cost for the particular descriptor. Such a compound model of individual GPs for particular terrain types is denoted $\mathcal{M}_{\text{GP}}^{tt}$ and it can be used in (4) as the reference GP-based model. Note that such an evaluation is possible only if the explicit labels of the terrain types for the specific parts of the trails are available, which is not the case of the incremental learning in the motivational deployment, but labels are available for evaluation of the examined learning methods.

3 Evaluation Results

The experimental evaluation of the GNG in terrain assessment learning has been performed for a hexapod walking robot in a set of laboratory terrains that consists of flat ground, black fabric, artificial turf, wooden blocks, and wooden stairs. Each terrain type has been traversed four times and a single $\mathcal{T}_{\text{all}}$ of all concatenated trails has 827 descriptors. The evaluation is performed for a grid $\mathcal{G}$ created for a different setup with slightly modified terrain types, see Fig. 2.

The GNG algorithm [4] has been implemented in C++, and both the learning and inference take a fraction of millisecond, and it is practically negligible. The utilized parameters according to notation in [4] are $\epsilon_b = 0.2$, $\epsilon_n = 0.1$, $a_{max} = 10$, $\alpha = 0.5$, $d = 0.995$, and new node is added if the Euclidean distance of the new measurement $\boldsymbol{d}$ to the nearest unit exceeds 0.15.

In addition to the GP-based model, we compare the GNG with the IGMN [10] that is supervised approximation of the EM algorithm that incrementally constructs the Gaussian mixture model, adjusts its components and parameters



(a) Real terrain setup (b) GP model

(c) IGMN model (d) GNG model

Fig. 2. A snapshot of the robot on wooden blocks and visualization of the assessment of the reference $\mathcal{G}$ using the full GP-based model and learned IGMN and GNG for $\mathcal{T}_{\mathrm{all}}$.

based on each presented training sample. New components are inserted during the learning process and must prove their relevance by accumulating sufficient posterior probability to be retained by the mixture. The IGMN has been utilized in our previous work [12] and here, we use the same setup with the maximal number of components limited to ten, the grace period $v_{\min} = 100$, minimal accumulated posterior $sp_{\min} = 3$, and scaling factor $\delta = 1$, but with terrain descriptor $\boldsymbol{d}$. Due to its implementation in Python, it is a bit more computationally demanding, and it operates in a fraction of second, which is, however, still satisfiable for deployment in online path planning.

The performance of the predictors has been evaluated using (3) for the whole trail $\mathcal{T}_{all}$, but also for four individual trails $\mathcal{T}_1$, $\mathcal{T}_2$, $\mathcal{T}_3$, and $\mathcal{T}_4$ with the terrain sequence of black fabric, wooden blocks, flat, stairs, and artificial turf. Besides, we consider four additional trails with shuffled terrain types denoted $\mathcal{T}_{r_i}$. The evolution of the RMSE is depicted in Fig. 3, Fig. 4, and Fig. 5. In addition to

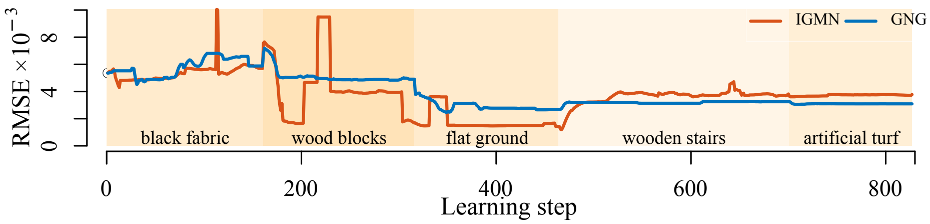


Fig. 3. Evolution of $RMSE(k)$ for particular learning step – each learning step the whole grid map $\mathcal{G}$ is assessed using the currently learned model.

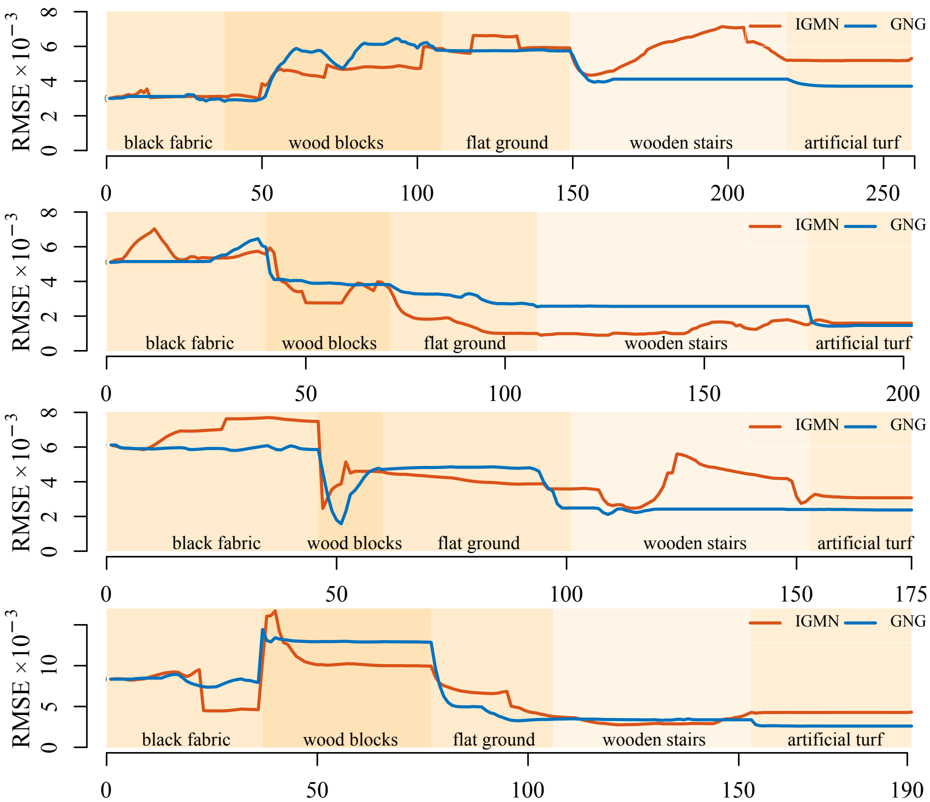


Fig. 4. Evolution of $RMSE(k)$ for individual trails $\mathcal{T}_1$–$\mathcal{T}_4$ from top to bottom.

the RMSE, we consider the correctness ratio R_c defined in (4) for evaluation of the final learned models per particular method and individual trails. Since the trail $\mathcal{T}_{all}$ can be considered as the most information-rich, the used reference GP-based model is learned from $\mathcal{T}_{all}$. The results are depicted in Table 1.

A similar evaluation can be performed for the compound reference model consisting of the individual GP-based models for the particular terrain types denoted $\mathcal{M}^{tt}_{\mathrm{GP}}$, see the two bottom rows in Table 1. In this case, the number of the correctly estimated traversal costs is overall noticeably smaller than for a single GP-based model using $\mathcal{T}_{all}$. The two reference GP-based models are compared in Fig. 6 regarding the predicted traversal cost and estimated variance.

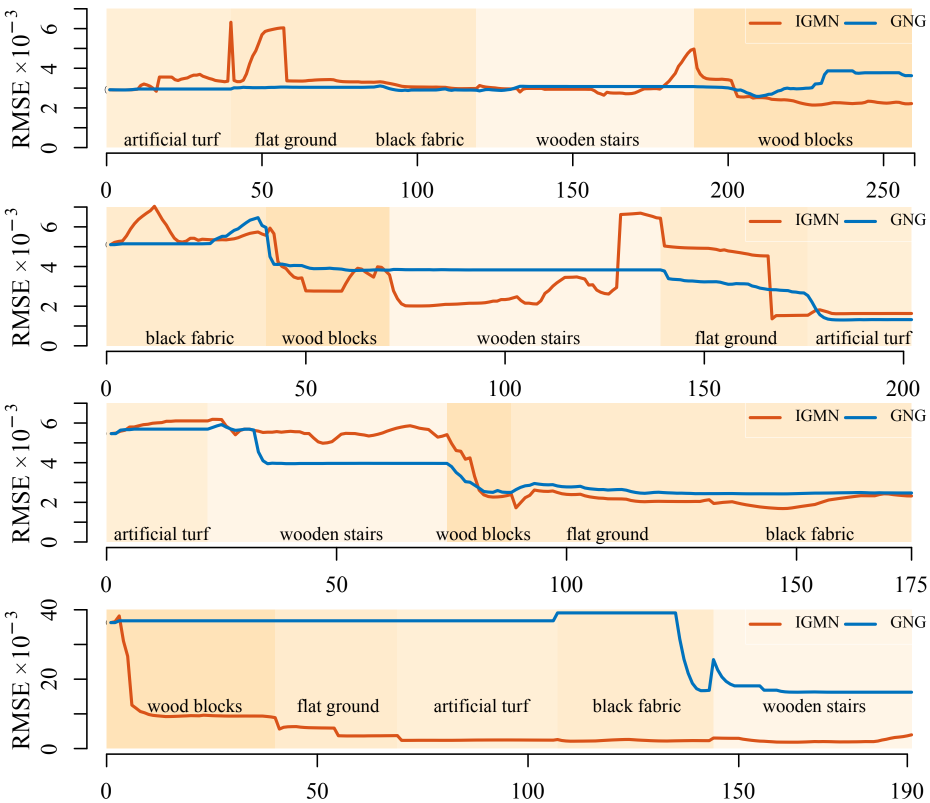
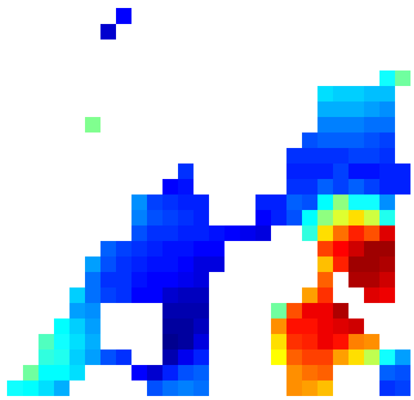


Fig. 5. $RMSE(k)$ for the trails $\mathcal{T}_{r_1}$–$\mathcal{T}_{r_4}$ with a random order of the terrain types.

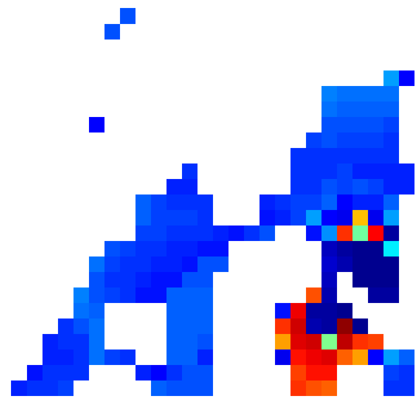
Table 1. Correctness ratio R_c according to the reference models $\mathcal{M}_{\mathrm{GP}}^{\mathcal{T}_{all}}$ and $\mathcal{M}_{\mathrm{GP}}^{tt}$

Reference Model	**Method**	**Trail**								
		$\mathcal{T}_{all}$	$\mathcal{T}_1$	$\mathcal{T}_2$	$\mathcal{T}_3$	$\mathcal{T}_4$	$\mathcal{T}_{r_1}$	$\mathcal{T}_{r_2}$	$\mathcal{T}_{r_3}$	$\mathcal{T}_{r_4}$
$\mathcal{M}_{\mathrm{GP}}^{\mathcal{T}_{all}}$	IGMN	0.72	0.70	0.86	0.99	0.87	0.82	0.99	0.98	0.88
	GNG	0.71	0.82	0.91	1.00	0.96	0.82	0.82	0.94	0.82
$\mathcal{M}_{\mathrm{GP}}^{tt}$	IGMN	0.52	0.16	0.53	0.56	0.18	0.23	0.31	0.62	0.18
	GNG	0.66	0.53	0.61	0.71	0.26	0.47	0.68	0.73	0.24

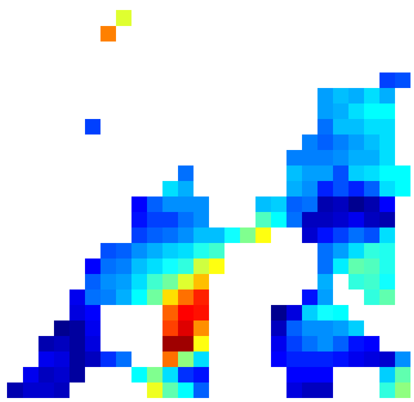
Discussion – The assessments in Fig. 2 indicate that both the IGMN and GNG models partially learned the traversability assessment in comparison to the GP-based model. However, regarding path planning, it is important that the cost is sufficiently distinguishable to avoid difficult terrains, which is satisfied for both models. Regarding the evolution of the RMSE, the GNG performs a bit better in the particular case shown in Fig. 3. On the other hand, it is evident from the individual trails in Fig. 4 and especially with shuffled terrain types in Fig. 5 that particular sequence of the terrains can significantly affect the performance



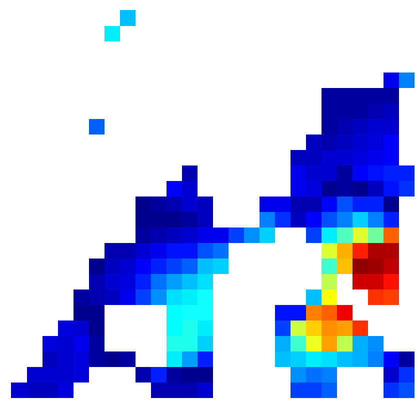
(a) Cost prediction of $\mathcal{M}_{\mathrm{GP}}^{\mathcal{T}_{all}}$ model



(b) Cost prediction of $\mathcal{M}_{\mathbf{GP}}^{tt}$



(c) Variance of $\mathcal{M}_{\mathrm{GP}}^{\mathcal{T}_{all}}$ model



(d) Variance of $\mathcal{M}_{\mathbf{GP}}^{tt}$

Fig. 6. Reference GP-based traversal cost model using the trails $\mathcal{T}_{all}$ with all learning data (right) and compound model based on known terrain types (left). The bottom row visualizes variances of the predicted traversal costs. The lower variances are shown in the dark blue, and it can be observed that the compound model estimates the traversal cost with the overall lower variances. The most unsure prediction is for wooden blocks, see Fig. 2a. A single GP-based model using $\mathcal{T}_{all}$ has the highest variances for the flat ground, and the wooden blocks with the high traversal cost are predicted with the relatively lower variance, but only a few regions have the lowest variance.

regarding the reference GP-based model. It is also not surprising that difficult terrains need several samples to improve the model, see Fig. 5 for the trail that starts with the wooden blocks. Although we employed the GNG algorithm in a very straightforward way, it provides the relatively competitive performance to the IGMN regarding (3), except the trail that starts at wooden blocks (see Fig. 5), which motivates us for further development.

In particular, the results indicate that terrain characterization purely based on a continuous function can provide sporadic results as the real performance of the robot can vary significantly. It is partially addressed in the evaluation using a compound model based on the individual GP-based model for each particular terrain type. Regarding the results visualized in Fig. 6, an advantage of the individual models of the traversal cost per particular terrain types is not clearly supported. Even though there are more parts with the lower variance of the predicted values, there is also the relatively unsure part corresponding to the wooden blocks, where the predicted cost is significantly lower than in Fig. 6a. It is most likely because the terrain descriptor of the wooden blocks is similar to the wooden stairs and considering individual terrain classes reduces the number of samples used in the model learning. Therefore, in our future work, we plan to consider identification of the terrain types and eventually combine the benefits of the both approaches to improve the overall traversal cost prediction. Thus, we aim to investigate techniques of unsupervised clustering to automatically identify possible terrain types and incrementally learn a model of the aggregated traversability cost for such identified terrain classes.

4 Conclusion

We presented evaluation results on a straightforward deployment of the GNG algorithm in incremental traversability assessment learning. We described the problem and evaluation challenges related to the nature of the incremental model learning and simultaneous usage of the model in decision-making for improving the mission performance by a more informed path planning. Although the presented results do not support the GNG is the most suitable technique for the addressed problem, its main benefit is in simplicity and computational efficiency, which allows modeling the traversability cost using tens and hundreds of units in comparison to the fixed number of components in the IGMN, where the size is limited to ten to get a reasonable performance. We consider the added value of this paper in reporting on evaluation results and introducing the methodology for comparing predictors in incremental traversability assessment learning.

Regarding the results, there are still several open questions, but also promising ideas. We aim to further work on combining the continuous traversability assessment function with more explicit terrain classification to improve the performance by recently proposed GNG for anomaly detection in data streams. Moreover, we also plan to consider the explicit sequence of the data measurements and support the terrain classification and traversal cost modeling by multidimensional time series.

Acknowledgments

This work was supported by the Czech Science Foundation under research project No.18-18858S. The authors acknowledge the support of the OP VVV funded project CZ.02.1.01/0.0/0.0/16_019/0000765 “Research Center for Informatics”.

References

1. Bartoszyk, S., Kasprzak, P., Belter, D.: Terrain-aware motion planning for a walking robot. In: International Workshop on Robot Motion and Control (RoMoCo). pp. 29–34 (2017)
2. Beyer, O., Cimiano, P.: Online labelling strategies for growing neural gas. In: Intelligent Data Engineering and Automated Learning (IDEAL). vol. 6936, pp. 76–83 (2011)
3. Dunbabin, M., Marques, L.: Robots for Environmental Monitoring: Significant Advancements and Applications. IEEE Robotics Automation Magazine 19(1), 24–39 (2012)
4. Fritzke, B.: A growing neural gas network learns topologies. In: Neural Information Processing Systems (NIPS). pp. 625–632 (1994)
5. Ghesmoune, M., Lebbah, M., Azzag, H.: A new growing neural gas for clustering data streams. Neural Networks 78, 36–50 (2016)
6. Homberger, T., Bjelonic, M., Kottege, N., Borges, P.V.K.: Terrain-dependant control of hexapod robots using vision. In: International Symposium on Experimental Robotics (ISER). pp. 92–102 (2016)
7. Kragh, M., Jørgensen, R.N., Pedersen, H.: Object detection and terrain classification in agricultural fields using 3d lidar data. In: International Conference on Computer Vision Systems (ICVS). vol. 9163, pp. 188–197. Springer (2015)
8. Nooralishahi, P., Seera, M., Loo, C.K.: Online semi-supervised multi-channel time series classifier based on growing neural gas. Neural Computing and Applications 28(11), 3491–3505 (2017)
9. O'Callaghan, S., Ramos, F.T., Durrant-Whyte, H.: Contextual occupancy maps using Gaussian processes. In: IEEE Int. Conf. Robotics and Automation (ICRA). pp. 1054–1060 (2009)
10. Pinto, R., Engel, P.: A fast incremental gaussian mixture model. PLOS p. e0141942 (2015)
11. Prudent, Y., Ennaji, A.: An incremental growing neural gas learns topologies. In: International Joint Conference on Neural Networks (IJCNN). vol. 2, pp. 1211–1216 (2005)
12. Prágr, M., Čížek, P., Faigl, J.: Cost of transport estimation for legged robot based on terrain features inference from aerial scan. In: IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS). pp. 1745–1750 (2018)
13. Prágr, M., Čížek, P., Faigl, J.: Incremental learning of traversability cost for aerial reconnaissance support to ground units. In: Modelling & Simulation for Autonomous System (MESAS) (2018)
14. Stelzer, A., Hirschmüller, H., Görner, M.: Stereo-vision-based navigation of a six-legged walking robot in unknown rough terrain. International Journal of Robotics Research 31(4), 381–402 (2012)
15. Sun, Q., Liu, H., Harada, T.: Online growing neural gas for anomaly detection in changing surveillance scenes. Pattern Recognition 64, 187–201 (2017)
16. Vasudevan, S., Ramos, F., Nettleton, E., Durrant-Whyte, H., Blair, A.: Gaussian Process modeling of large scale terrain. In: IEEE Int. Conf. Robotics and Automation (ICRA). pp. 1047–1053 (2009)
17. Zhang, Y., Lu, H., Zhang, L., Ruan, X.: Combining motion and appearance cues for anomaly detection. Pattern Recognition 51, 443–452 (2016)