Semi-Supervised Gated Recurrent Neural Networks for Robotic Terrain Classification

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Abstract—Legged robots are popular candidates for missions in challenging terrains due to their versatile locomotion strategies. Terrain classification is a key enabling technology for autonomous legged robots, allowing them to harness their innate flexibility to adapt to the demands of their operating environment. We show how highly capable machine learning techniques, namely gated recurrent neural networks, allow our target legged robot to correctly classify the terrain it traverses in both supervised and semi-supervised fashions. Tests on a benchmark dataset shows that our time-domain classifiers are well capable of handling raw and variable-length data with small amount of labels and outperform frequency-domain classifiers. The classification results on our own extended dataset opens up a range of high-performance behaviours that are specific to those environments. Furthermore, we show how raw unlabelled data is used to improve significantly the classification results in a semi-supervised model.

Index Terms—Deep learning methods, legged robots.

I. INTRODUCTION

Log-inspired legged robots offer advantages when walking in extreme environments with their ability to adapt to instantaneous conditions including undulation, slope, roughness, and terrain types. This is possible by changing gaits, foot-tip arc shapes, footfall placement, stride length, etc., to tune their behaviour and overcome the challenges presented by their environment. Compared to other types of robots, they have more flexibility to effectively couple their hardware and software configuration to the specifics of the terrain.

An important step to fully harnessing these myriad degrees of behavioural freedom is terrain classification; the ability for a robot to correctly gauge the type of terrain it is on, and thus enact an appropriate response to overcome the challenges of that terrain. A plethora of previous approaches focus on terrain classification with legged robots using various methods with varying levels of accuracy [1]–[5].

In this work, we focus on the use of modern, highly capable deep learning methods, namely gated recurrent neural networks, to perform this classification in both supervised and semi-supervised schemes. Our main contributions are:

- A deep learning model for terrain classification via proprioceptive sensing, which significantly outperforms state of the art frequency-domain approaches.
- Alleviating the challenges of pre-processing methods applied on long and variable length time-series data by proposing models capable of handling raw data.
- Comparison of gated RNN models, LSTMs and GRUs, for terrain classification given raw variable-length data.
- Extensive testing, both on the published benchmark PUT dataset [6], [7] covering indoor terrains, and another large, outdoor dataset (QCAT) collected by the authors.
- The first semi-supervised model for robotic terrain classification capable of dealing with raw and variable-length data, showing comparable performance to fully supervised methods, with much less annotated data.

This work covers three entries of a recent collection of Grand Challenges [8]. Our approach significantly outperforms the frequency-domain models in legged terrain classification [6], and offers the potential for legged robots to generate high-performance behavioural responses that are customised to their environments. Moreover, to the best of our knowledge, this is the first study that investigates a semi-supervised model that can directly use raw and variable-length time-series data for robotic terrain classification.

II. RELATED WORK

Legged robot locomotion in rough and unstructured terrain can be addressed either by purely reactive methods or

1 Biohybrid and bioinspired robots, Navigation and exploration in extreme environments, and Fundamental aspects of AI for robotics.

2 Dataset: https://doi.org/10.25919/5f88b9c730442
Source code:https://github.com/csiro-robotics/deep-terrain-classification.git
deliberative methods. Reactive methods [9]–[11] adapt to new terrain types by changing locomotion parameters or body configuration accordingly. While these methods typically incur low processing overheads, the actual adaptation process can be slow as the robot has to walk over the new terrain for the changes to trigger. Therefore, there is a risk of the robot entering terrain beyond it’s locomotion capability before it is identified, potentially stranding the robot in a local minima.

Deliberative methods first classify the type of terrain [1]–[5], then switch to appropriate behaviours rather than adapting reactively. Proprioceptive sensing and visual perception are often used to gain information about the terrain through the robots’ joints, force sensors attached to the feet, inertial measurement units (IMUs), and cameras. These inputs are then fed in to machine learning frameworks to classify the type of terrain. Methods based on visual perception may fail in the presence of large variations in illumination intensity, dust, fog, smoke, or seasonal changes in color perception.

Variable length input sequences are frequently encountered with legged robots, e.g., when the robot walks at different speeds with variable step frequencies; if not addressed, the classification results will only be valid when the robot is walking at the speed used during the training phase. As such, state of the art methods in proprioceptive sensing are dominated by frequency domain classifiers that transfer raw time-series data into frequency descriptors [6], [12], [13], as the transform makes the input data insensitive to the length of the input sequence. Recent neural approaches [6] used an FFT-based pre-processor to overcome problems faced by neural network-based methods when processing variable length sequences.

Supervised Recurrent Neural Networks (RNNs) have been used for robotic terrain classification since they can capture temporal features from raw time-series data [14], [15]. They directly use the raw data stream as input rather than accumulating data over time and transferring to either frequency or temporal descriptors making these models better candidates for real-time classification. In both [14], [15], RNNs achieved a superior performance than SVMs on frequency based features for a dataset with 2345 small fixed-length (100 time-steps) samples and for a dataset with only 136 large fixed-length (400 time-steps) samples. In this paper, we rigorously investigate the performance of two types of supervised RNNs for robotic terrain classification given large variable-length samples (maximum lengths of two datasets: 1291 time-steps and 662 time-steps) from two different datasets.

RNNs are widely used in natural language processing tasks as a next step predictor, since they predict what comes next in a sequence [16]–[19]. Here, RNNs are used in an unsupervised paradigm as data labelling is not required during training. Semi-supervised learning combines supervised and unsupervised learning to address a major drawback of supervised models, an extensive reliance on hand-annotated datasets. Semi-supervised learning has been widely studied for image classification, natural language processing, and video prediction, and achieved outstanding results with small amounts of labelled data [20]–[25].

Applications of semi-supervision for robotic terrain classification are underrepresented in the literature. A semi-supervised Laplacian Support Vector Machine (SVM) was recently proposed for a relatively small dataset (1584 samples for 6 different types of terrains); this method could achieve higher accuracy than a traditional Laplacian SVM [26]. Ten time-domain features were used as input, including number of sign variations in a sample, sample mean, sample variance, an auto-correlation function of a sample, an impulse factor. Therefore, this method does not deal with raw data, and requires many hand crafted features to function. Furthermore, the proposed method cannot deal with variable-length datasets such as PUT and QCAT because the length of data needs to be set in advance to extract time-domain features.

We are therefore motivated to investigate the utilisation of RNNs as semi-supervised models for terrain classification, to handle raw and variable-length time-series data. We propose a semi-supervised method that incorporates unsupervised RNNs and supervised RNNs, and test on two datasets (indoor and outdoor). We demonstrate (i) our time domain representation outperforms recent frequency-domain representations, and (ii) semi-supervision provides equivalent performance to state of the art algorithms, while requiring less labelled data.

III. BACKGROUND

Recurrent Neural Networks (RNNs) are a prevalent machine learning technique for dealing with time-series data. An RNN takes an external signal \( x_t \) and the previous hidden state \( h_{t-1} \) as input, and outputs the current hidden state \( h_t \) as:

\[
h_t = f(Wx_t + Uh_{t-1})
\]

where \( W \) and \( U \) are learnable parameters and \( f \) is a non-linear activation function. One advantage of RNNs is their ability to work with variable-length input sequences. RNNs are able to learn a distribution over a variable-length sequence by learning the distribution over the next input [27]. Early RNN models had difficulties dealing with long-term dependencies in data [28], [29], which led to the development of architectures with more direct memory mechanisms including memory registers, and gated activation functions replacing simple non-linear activation functions. Here, we focus on two popular implementations; Long Short-Term Memory (LSTM) [30] and Gated Recurrent Unit (GRU) [27].

A. Long Short-Term Memory

An LSTM cell (Fig. 2(a)) comprises a memory cell \( c_t \), an input gate \( i_t \), a forget gate \( f_t \), and an output gate \( o_t \) as:

\[
h_t = o_t \tanh(c_t)
\]
\[
o_t = \sigma(W_o x_t + U_o h_{t-1})
\]
\[
c_t = f_t c_{t-1} + i_t \tilde{c}_{t-1} \\
\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1}) \\
f_t = \sigma(W_f x_t + U_f h_{t-1}) \\
i_t = \sigma(W_i x_t + U_i h_{t-1})
\] (2)

The input, forget, and output gates control how much new information is memorized, how much old information is forgotten, and how much information is output from the memory cell.

### B. Gated Recurrent Unit

A GRU unit (Fig. 2(b)) consists of a reset gate \( r_t \), and an update gate \( z_t \), which reset and update the memory content adaptively.

\[
h_t = (1 - z_t) h_{t-1} + z_t \tilde{h}_t \\
z_t = \sigma(W_z x_t + U_z h_{t-1}) \\
\tilde{h}_t = \tanh(W x_t + U (r_t \odot h_{t-1})) \\
r_t = \sigma(W_r x_t + U_r h_{t-1})
\] (3)

where \( \odot \) denotes element-wise multiplication. GRUs can be considered as an adaptive leaky integrator neuron [31] in which \( z_t \) is a user-defined constant value.

### C. RNN for Terrain Classification

As shown in previous sections, GRUs have a simpler structure and fewer learnable parameters, and are therefore computationally more efficient compared to LSTM. However, it has been shown that RNN performance critically depends on the task and dataset [32]. We evaluate both GRUs and LSTMs on two terrain classification datasets in this paper. Prior work evaluated LSTMs on the PUT dataset [6], [7] but reports poor results on the raw data, producing predictions not much greater than random chance. Instead they developed methods in the frequency domain [6] with 80.39\% accuracy, and fixed data windowing methods using a one dimensional Convolutional Neural Networks (CNNs) input layer [7] fed into LSTMs which achieved 96.89\%, at the cost of data windowing. Using the PUT dataset, the authors slid a fixed-sized window (size of 70) with a stride of 50 to reduce the overall size of each sample. This poses two major challenges to the model. First, the proposed method may not be easily applied to other datasets as the window size and the stride size are adjustable parameters, and potentially sensitive to the characteristics of each dataset. Another major issue is how to do real-time evaluation with the model given that it needs a relatively long history of data (70) to be fed to the window, and how to perform the stride in real-time given the large size of the stride (50) used during training of the model. The extra hyper-parameter search for numbers of CNNs may also add to the complexity of the proposed method.

### IV. Method

#### A. Robots and Datasets

We collected the outdoor dataset for terrain classification (QCAT) using our robotic test platform (DyRET). Our aim was to test our proposed supervised and semi-supervised models on both the previously-introduced indoor dataset (PUT) and the outdoor dataset. Details of the two datasets are provided in Table I.

1) PUT Dataset (Indoors): The PUT dataset [6] was collected using a six-legged robot equipped with a Force/Torque (F/T) sensor on one of its legs, sampled at 200 Hz. The robot walked at three different speeds, in six walking directions, on six different artificial indoor terrains (sand, rubber, concrete, artificial grass, wood chipping and gravel). Eighty steps are completed for each combination of speed, direction, and terrain, giving a total of 8640 steps in the whole dataset.

2) Test Platform: We used the open-source Dynamic Robot for Embodied Testing (DyRET) platform [33] (Fig. 1) to collect the data. DyRET is a mammal-inspired robot weighing about 5 kg, built specifically to facilitate machine learning research on real-world robots [33]. Control is via position controlled Robotis servomotors and a high level spline-based gait controller [34]. The robot is equipped with individual directional force sensors (OptoForce OMD-20-SH-80 N) on each foot, reporting force on three axes at 100 Hz. An Attitude and Heading Reference System (XSens MTI-30) reports linear acceleration, rotational velocity and orientation at 100 Hz.

3) QCAT Dataset (Outdoors): The QCAT dataset was collected at different locations on CSIRO’s QCAT site in Brisbane, Australia, in November 2019. Fig. 3 shows the different environments comprising the dataset: a concrete road, grass, gravel, mulch, a dirt path, and sand. Data collection involved walking with a fixed gait, but with three different step-frequencies (0.125 Hz, 0.1875 Hz and 0.25 Hz) and two different step lengths (80 mm and 120 mm), for a total of six different speeds tested per surface. The robot walks forwards for eight steps, with ten repeats for a total of 80 steps per speed and surface. To avoid overspecialisation to certain features of the terrain type, each repeat occurs on a different part of the terrain. The dataset consists of the force sensors’ measurements (12 dimensions: 4 sensors x 3) and the IMU sensor’s measurements (10 dimensions: 3 of linear accelerations, 3 of angular velocities, and 4 of orientations).

#### B. Supervised Terrain Classification

We tested supervised LSTMs and GRUs for the PUT and QCAT datasets to see whether gated RNNs can deal with both a variable-length indoor dataset and a variable-length outdoor natural environment dataset. Fig. 4(a) shows how an RNN can be

|                | QCAT dataset | PUT dataset |
|----------------|--------------|-------------|
| Number of surfaces | 6            | 6           |
| Number of speeds   | 6            | 3           |
| Number of directions | *1*         | 6           |
| Sample rate        | 100 Hz       | 200 Hz      |
| Number of sensors   | 4            | 1           |
| Steps per combination | 80          | 80          |
| Total number of samples | 2880        | 8640        |
| Walking duration    | 222 min      | -           |
used for this task. The model takes an external signal $x_{1:T}$ from time step 1 to $T$ during forward computation and only outputs $y$ at time-step $T$. The model does not need to output at every time-step because the whole $x_{1:T}$ belongs to one class. This is different from a regression task where a regression model outputs a different signal at each time-step. As both datasets have variable-length sequences, $T$ has a different value for each sequence. The output $y$ is computed by softmax, which produces a distribution over the terrain classes.

C. Semi-Supervised Terrain Classification

We tested semi-supervised RNNs for both datasets to examine their performances when only a small portion of annotated data was provided. The proposed model stacks a classifier model above a predictor model (Fig. 4(b)). More specifically, we stacked unsupervised RNNs, supervised RNNs, and Fully Connected Layer (FCL) neural networks. First, the unsupervised RNNs, referred to as predictor RNNs, are trained by taking the current signal $x_t$ (Force/Torque signals for PUT and IMU signals for QCAT) as input and predicting the next step signal $x_{t+1}$ and the RNN output $y$ was used for the predictor loss function:

$$L_{loss}^p = \frac{1}{T-1} \sum_{t=1}^{T-1} (x_{t+1} - y_t)^2 + \lambda \sum_{n=1}^{N_p} (\theta^n)^2$$

where $C$ is the total class number and the second terms on the right show $L2$ regularization terms for $N$ learnable parameters of the classifier model and the predictor model.

As neither dataset has an independent set of test samples available, we apply $k$-fold cross-validation to reduce bias. Following commonly-used settings, we set $k$ to 5 and 10 in our experiments [35], [36]. The training hyper-parameters such as number of neurons in each layer, the initial learning rate (0.001), the mini-batch size, dropout percentage (20%), and the $\lambda$ were found heuristically.

A. RNNs Trained on the PUT Dataset

We evaluated GRUs and LSTMs for classifying the terrains in the PUT dataset. The mean and Standard Deviation (SD) results of models trained by a simple loss function (Eq. 4 with $\lambda$ set as 0) are shown in Table II. The Minimum (Min) accuracy among $k$ models and Maximum (Max) accuracy among $k$ models are also given. First, the most standard and straightforward architectures of GRUs and LSTMs are compared, then we added more complexity to the superior RNN to achieve higher accuracy. GRUs consistently outperform LSTMs, a trend which is repeated for 10-fold Cross-Validation (CV) models. The 10-fold models are noted to always have a better mean accuracy than 5-fold learning model by decreasing the learning rate and retraining the whole model with classifying data, referred to as a Feature Extracting (FE) + Fine Tuning (FT) semi-supervised learning model. Both models were compared on PUT and QCAT datasets.

V. Results

We conducted our experiments to examine how gated RNNs perform in terrain classification tasks for legged robots in both supervised and semi-supervised fashions. The first experiment investigates GRUs and LSTMs for classifying terrains in the (indoor) PUT dataset, and the second experiment does the same on the outdoor QCAT dataset. The last experiment examines semi-supervised RNNs for both datasets.

In our all experiments, each dimension of the input data is normalized to zero mean and unit standard variation. The cross entropy between the ground truth data $\hat{y}$ and the RNN output $y$ was used for the classifier loss function whereas the mean square error between the next step signal $x_{t+1}$ and the RNN output $y$ was used for the predictor loss function:

$$L_{loss}^c = \sum_{c=1}^{C} \hat{y}_c \log y_c + \lambda \sum_{n=1}^{N_c} (\theta^n)^2$$

$$L_{loss}^p = \frac{1}{T-1} \sum_{t=1}^{T-1} (x_{t+1} - y_t)^2 + \lambda \sum_{n=1}^{N_p} (\theta^n)^2$$

where $C$ is the total class number and the second terms on the right show $L2$ regularization terms for $N$ learnable parameters of the classifier model and the predictor model.

We also investigated fine-tuning of the whole FE semi-supervised model as Feature Extracting (FE) semi-supervised learning because the predictor RNNs are used as feature extractors.
CV models. However, SD values are smaller for some of the 5-fold CV models. Table III shows results of the models trained by loss with the $L_2$ regularization term (Eq. 4) in which $\lambda$ was set to 0.01. The performance of GRUs is improved by adding the regularization term, which is not always the case for LSTMs. One notable aspect is that even small GRUs (50 units) achieved a reasonable accuracy of 89.47%. This can be vital for using the classifier on memory constrained embedded systems. The main result of note is that the more complex architecture (RNNs+FCLs) achieved a mean accuracy of 93.2%, which is significantly better (12.81%) than the model reported in [6], and 27.1% better than the best results obtained by a conventional machine learning algorithm (SVMs), reported in [6]. The more complex architecture consists of GRUs plus Fully Connected Layers (FCLs) with dropouts [37], and learning rate decay was used during its training phase. The notable network achieved 95.39% maximum accuracy, whereas its minimum accuracy is 92.06%. This difference shows the importance of using cross-validation and reporting mean and standard deviation of all CV models. We then implemented SVM and Fully Connected Neural (FCN) models found in [6] given Frequency Domain (FD) features and test them using 10-fold CV. The results are given in Table III. The difference between maximally and minimally accurate models for both SVM and FCN again emphasizes the importance of cross-validation. The mean accuracy of our RNNs+FCLs architecture is 13.97% better than the FCN models and 27.1% better than the SVM models (10-fold CV).

The overall results show that RNNs are capable of dealing with raw PUT data without reducing the temporal size or transferring from the time-domain to the frequency domain. Our results therefore suggest that gated RNNs are capable of dealing with long sequences specially when datasets are not too complex such as PUT. This also positions GRUs as a leading candidate for learning terrain classifiers in this context. We later show the importance of keeping the temporal resolutions for RNN models (Fig. 6).

Using a straightforward architecture, we show that our RNN implementation performs significantly better than previously reported results given the raw data [6], [7]. E.g. 50 LSTMs with no regularization and a fixed learning rate achieved a mean accuracy of 83.68%, compared to 18% in the literature. We suggest a possible reason for poor performance observed in previous results. Variable-length samples in the PUT dataset use zero-padding to equalize the lengths of all samples to the maximum length. If the length of each sample is not considered during training of RNN models, it will be set as the maximum length, and the final accuracy will decrease because padded zeros affect both forward computation and back-propagation through time during training. In Eq. 1, the value of current hidden states $h_t$ depends on values of both input $x_t$ and previous hidden states $h_{t-1}$, therefore zero values of input $x_t$ will not necessarily result in zero values of current hidden states $h_t$. This means padded

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**TABLE II**

| CV Models | Mean% | SD% | Min% | Max% |
|-----------|-------|-----|------|------|
| 10-fold CV | 50 GRUs | 87.68 | 1.02 | 85.84 | 89.06 |
|           | 50 LSTMs | 83.68 | 1.06 | 81.35 | 84.99 |
|           | 100 GRUs | 90.15 | 1.11 | 88.30 | 91.42 |
|           | 100 LSTMs | 85.33 | 1.39 | 82.64 | 87.67 |
|           | 400 GRUs | 92.13 | 0.48 | 91.42 | 92.81 |
|           | 400 LSTMs | 90.43 | 0.39 | 89.6 | 91.43 |
| 5-fold CV | 50 GRUs | 82.93 | 1.13 | 84.93 | 88.04 |
|           | 50 LSTMs | 81.86 | 0.76 | 80.47 | 82.73 |
|           | 100 GRUs | 90.92 | 0.6 | 89.49 | 90.94 |
|           | 100 LSTMs | 83.98 | 0.67 | 83.21 | 85.2 |
|           | 400 GRUs | 91.42 | 0.77 | 90.24 | 92.54 |
|           | 400 LSTMs | 89.67 | 0.74 | 88.95 | 91.1 |

**TABLE III**

| CV Models | Mean% | SD% | Min% | Max% |
|-----------|-------|-----|------|------|
| 10-fold CV | SVM (FD) | 66.1 | 1.64 | 64.0 | 69.0 |
|           | FCN (FD) | 79.23 | 0.97 | 77.47 | 80.58 |
|           | 50 GRUs | 89.47 | 0.79 | 88.3 | 90.77 |
|           | 50 LSTMs | 83.63 | 1.85 | 81.22 | 87.34 |
|           | 100 GRUs | 90.71 | 0.87 | 89.7 | 92.49 |
|           | 100 LSTMs | 85.79 | 1.64 | 83.58 | 88.52 |
|           | 400 GRUs | 92.35 | 0.78 | 90.67 | 93.86 |
|           | 400 LSTMs | 88.3 | 1.49 | 85.74 | 91.0 |
|           | RNNs+FCLs | 93.2 | 0.89 | 92.06 | 95.39 |
| 5-fold CV | 50 GRUs | 88.44 | 1.06 | 86.86 | 90.08 |
|           | 50 LSTMs | 83.07 | 0.46 | 82.31 | 83.6 |
|           | 100 GRUs | 89.99 | 0.68 | 88.95 | 90.88 |
|           | 100 LSTMs | 85.44 | 0.38 | 85.09 | 86.11 |
|           | 400 GRUs | 91.91 | 0.41 | 91.26 | 92.38 |
|           | 400 LSTMs | 85.34 | 1.95 | 83.7 | 89.06 |

$^3$SD, Min, Max, and CV abbreviate standard deviation, minimum and maximum accuracy among $k$ RNN models, and cross validation, respectively.
zeros can deteriorate the performance of RNNs if not handled properly.

We rigorously tested both GRUs and LSTMs on the raw PUT dataset without windowing, training on multiple subsets of the data using k-fold cross-validation and reliably demonstrate high performance results using our RNN implementations. Prior work [6], [7] showed results for a single 90/10 train/validation split (without a holdout test dataset or using cross-validation) in which the model may be overly biased and overfitted. We implemented frequency-domain models based on [6] using k-fold cross-validation (avoiding bias) and compared their performances with our proposed models. The proposed models demonstrated superior results, without the requirement to transfer or window the data.

B. RNNs Trained on the QCAT Dataset

We evaluated GRUs and LSTMs for classifying the terrains on the outdoor, variable-length QCAT dataset. Models were trained on data collected by the force sensors (OptoForce sensors), and the IMU (Xsens). IMUs measure movement and orientation, which is affected by many factors other than the surface it walks on. It is also susceptible to noise, which may make the data harder to work with. Force sensors on the feet are more expensive and mounting them can be mechanically and electrically challenging. They are not available on many platforms due to this, but the advantage is that they are in direct contact with the surface, which may reduce noise.

Table IV show results achieved by GRUs and LSTMs using four force sensors and trained via regularized loss (Eq. 4). Similar to the PUT dataset, GRUs again outperform LSTMs. The best network (96.6% of accuracy) is 10-fold CV models with FCL. Using the best network, the mean accuracy of 288 test samples with respect to their sequence lengths was measured. The mean value of $T$ was 523 steps. The model achieved the mean accuracy of over 60% given only 50% of the sequence length and over 70% given only 60% of the sequence length. This suggests that the proposed model can be applied in real-time terrain classification.

We also consider a robot that relies either on a single force sensor, or solely on the IMU. As discussed earlier, force sensors are expensive and many platforms do not have them, demonstrating our method working with a more accessible, reduced sensory payload therefore has merit.

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**TABLE IV**

| Classification Accuracy for QCAT Dataset With Regularization Loss for Training of Networks\(^3\) |
|------------------|---------|--------|--------|--------|
|                  | Mean%   | SD%    | Min%   | Max%   |
| 10-fold CV       |         |        |        |        |
| 50 GRUs          | 87.71   | 2.28   | 84.37  | 92.01  |
| 50 LSTMs         | 80.56   | 0.96   | 78.82  | 81.94  |
| 100 GRUs         | 89.58   | 1.24   | 88.19  | 92.36  |
| 100 LSTMs        | 82.29   | 1.15   | 80.56  | 84.38  |
| 350 GRUs         | 93.02   | 1.62   | 90.97  | 96.53  |
| 350 LSTMs        | 85.97   | 1.64   | 82.29  | 87.85  |
| RNNs+DCL         | 96.6    | 0.89   | 95.49  | 98.61  |
| 5-fold CV        |         |        |        |        |
| 50 GRUs          | 86.6    | 1.54   | 85.07  | 89.41  |
| 50 LSTMs         | 81.46   | 1.64   | 79.17  | 83.33  |
| 100 GRUs         | 87.71   | 1.03   | 86.46  | 88.72  |
| 100 LSTMs        | 83.82   | 1.67   | 80.9   | 85.42  |
| 350 GRUs         | 91.28   | 1.05   | 90.1   | 92.88  |
| 350 LSTMs        | 83.19   | 1.21   | 81.25  | 85.07  |

**TABLE V**

| Classification Accuracy for QCAT Dataset With IMU Sensor With Regularization Loss for Training of Networks\(^3\) |
|------------------|---------|--------|--------|--------|
|                  | Mean%   | SD%    | Min%   | Max%   |
| 10-fold CV       |         |        |        |        |
| 50 GRUs          | 90.07   | 1.77   | 87.5   | 93.06  |
| 50 LSTMs         | 83.06   | 2.46   | 78.82  | 87.5   |
| 100 GRUs         | 93.06   | 1.27   | 91.32  | 95.49  |
| 100 LSTMs        | 84.44   | 2.52   | 78.47  | 88.19  |
| 350 GRUs         | 94.37   | 1.68   | 90.97  | 96.88  |
| 350 LSTMs        | 85.0    | 2.11   | 81.25  | 88.19  |
| RNNs+DCL         | 96.63   | 1.17   | 94.44  | 98.26  |
| 5-fold CV        |         |        |        |        |
| 50 GRUs          | 88.61   | 1.11   | 87.15  | 90.28  |
| 50 LSTMs         | 80.83   | 1.43   | 78.47  | 82.64  |
| 100 GRUs         | 90.63   | 1.29   | 88.19  | 92.01  |
| 100 LSTMs        | 83.23   | 1.02   | 81.6   | 84.55  |
| 350 GRUs         | 92.7    | 0.87   | 91.32  | 93.92  |
| 350 LSTMs        | 84.03   | 2.17   | 82.12  | 87.33  |

We achieved a mean accuracy of 87.74% when using only one force sensor. Using an IMU sensor (Table V), we see remarkably high mean accuracy (96.63%) that is slightly better than the one achieved by the four force sensors (96.6%). The results suggest that GRUs are capable of dealing with noise in the input signal, showing that our classification models are widely applicable across many robot platforms. Trends are consistent with previous results obtained using force sensors. Notably, more of the 5-fold CV models had less variance than the 10-fold CV models. We also investigated the models given both IMU and force inputs and
observed that they could achieve the accuracy of 97.64 ± 1.03%. Given the remarkable accuracy obtained by IMU or force sensors, it does not seem necessary to have both types of sensors for terrain classification, although more investigations are required to ascertain the limits of this, or applicability to different types of robots. Overall, results show that our proposed supervised method can be successfully deployed for outdoor terrain classification given data from different proprioceptive sensors (F/T and IMU), and it can successfully deal with variable-length data.

C. Semi-Supervised Learning

Supervised RNNs achieved high accuracy for classifying the different terrains across both datasets. However, the process of data collection for supervised models is tedious. For data annotation, either the robots need to walk on different types of terrains separately, or one needs to post-hoc hand-label the data. The effort can be reduced if only a portion of data needs to be annotated for comparable performance, so we proposed semi-supervised RNNs for the terrain classification. Because GRUs outperformed LSTMs in all previous experiments, only GRUs are used in the following experiments. IMU data is only used for the QCAT dataset given our previous promising results with this ubiquitous sensor.

We investigated 5 different splits of predicting/classifying data. In Fig. 5, 5% means the whole dataset was randomly divided into two: 90% of data was used as the predicting data and the remainder was classifying data. Using 2-fold cross-validation to lower classifier bias, the classifying data (10% of the whole data) was randomly split into two. Therefore, the supervised model (classifier RNNs and FCL) was only trained by 5% of the whole data, and evaluated on the other 5%. As 5% of the data was used for training of the supervised model, we called these models ‘5%’. We tested the classifiers on the remaining 90% of data, which are referred as test accuracy. Similarly, ‘25%’ means the whole dataset was randomly divided into two: 50% predicting data and 50% classifying data. All networks were trained by 25% of the data, evaluated on 25%, and tested on 50%. To compare the semi-supervised models with supervised models and show the effect of the predictor RNNs in the semi-supervised models, we trained supervised classifiers using the classifying data.

Test accuracy results (Fig. 5) shows the superior performance of semi-supervised models over supervised models. The gap between their percentage accuracy is significantly larger for a smaller amount of labels, and becomes smaller as more labels are provided during training. QCAT supervised model accuracy is notably lower (49.31% and 61.85%) than PUT results (71.93% and 82.38%) when networks are trained by 5% and 10% labels, possibly because PUT has more samples which more adequately train the models.

Results show the effectiveness of fine-tuning for semi-supervised learning, as those models outperform the FE semi-supervised models in all cases. Accuracy is slightly lower for 25% (92.24% accuracy) than 20% (91.86% accuracy) for PUT dataset, and it is really close for QCAT. This is likely because predictor RNNs are trained on less data (50%) for the former model, although its classifier model had access to 5% more labels, suggesting that a balance between amounts of training data for the supervised and unsupervised model may be needed to achieve the highest possible accuracy using semi-supervised models. The overall results indicate that semi-supervised learning is an effective learning method when few labels are available, addressing a major shortcoming of supervised learning, especially for terrain classification where extensive annotations may be difficult to procure.

We visualised the temporal evolution of hidden states of a GRU given 720 testing samples of different lengths (T). Principal Component Analysis (PCA) reduced the GRU hidden state dimension (200 GRU units) to two principle components. Fig. 6 displays the PCA results at time-step t = 10%T, 40%T, 70%T and T for QCAT dataset. Dirt, mulch, and gravel classes are seen to be the most challenging for the network due to similarities between these classes (Fig. 3). Sand and concrete are the most separable classes for the network due to their contrasting mechanical properties. The figure also shows how the hidden states of the same classes are mostly clustered together over time. This emphasizes the importance of the data temporal resolution for terrain classification tasks.

We investigated other possible architectures for semi-supervised learning, which were shown to be effective in tasks such as image classification or NLP. Our first approach replaced classifier RNNs with fully connected layers. Second, we removed the predictor RNNs, pre-trained RNNs and fully connected layers for the one-step prediction task, and fine-tuned the whole network for the classification task. We also replaced the predictor RNNs with auto-encoder RNNs, meaning that the unsupervised RNNs were trained on the current signal x_t (F/T signals for PUT and IMU signals for QCAT) and predicted the the same time step signal x_t. Preliminary results suggest that none of the aforementioned semi-supervised methods are effective for the robotic terrain classification (PUT and QCAT). They under-performed the supervised models, although more detailed analysis and investigations are needed to have a conclusive statement.

We rigorously tested our proposed semi-supervised models on the raw variable-length PUT (indoor) and the raw variable-length QCAT (outdoor) datasets. Results on both datasets show the superior performance of the proposed method when only a small amount of annotated data is available. The presented results also demonstrate that the proposed semi-supervised models can be used with different proprioceptive sensor modalities (F/T and IMU). This suggests that the proposed method can be used on a wide variety of robotic platforms incorporating such sensor modalities.

VI. CONCLUSIONS

We utilized supervised and semi-supervised gated RNNs for the robotic terrain classification. Our classifiers were first evaluated on the PUT dataset composed of time-series data with variable lengths that were collected in an indoor environment. RNN models given time-series dataset significantly exceeded the accuracy rates of the SVM and the fully connected neural model using frequency-domain transferred data. Furthermore, we achieved high accuracy rates by RNN classifiers on our own dataset composed of time-series data with variable lengths that were collected in an outdoor environment. The results obtained from both datasets suggest that a GRU outperforms LSTM for proprioceptive terrain classification. The results also
show the importance of the data temporal resolution for terrain classification. In the second experiment, we showed that IMU sensors, available on many robot platforms, may be a sensor of choice for terrain classification. We introduced the first deep semi-supervised models for robotic terrain classification, and showed that they are capable of directly dealing with raw and variable-length time-series data. Results indicate that semi-supervised models outperformed supervised models remarkably when only small amounts of annotated data are available, suggesting that less annotated data is required for terrain classification, and thus larger usable datasets can be easily made available. Future work may focus on the generalization capability of the proposed semi-supervised model to unseen terrains and unseen gaits. For example, the unsupervised RNNs can be fine-tuned online by new data from new terrains or new gaits without data annotation. The generalization capability of the model may improve continually as the robot continues to walk on the new terrain or with a new gait. Our dataset is relatively large, covering a broad range of 6 terrains representing the majority of outdoor environments encountered by legged robots. As such, we see the transfer of our models for downstream multi-terrain locomotion tasks as readily attainable, e.g., to trigger controller or morphological adaptation. The DyRET platform used is engineered specifically to allow for such morphological adaptation. The results also open up an interesting future extension of the current work: a transfer learning between robot platforms, meaning that a different robot will be used for training the unsupervised model with no annotated data. To that end, IMUs may lead to more transferrable models as their readings are less platform dependant than sensor data. This would also work for different gait on a single robot.

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