Surface Type Classification for Autonomous Robots Using Temporal, Statistical and Spectral Feature Extraction and Selection

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Outline

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Introduction

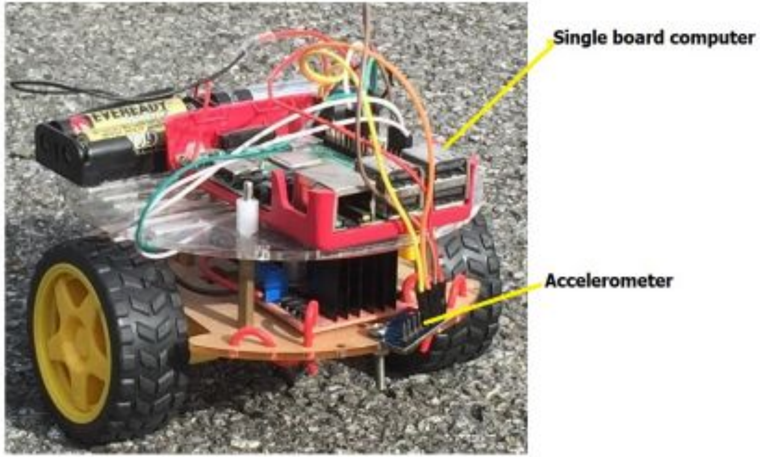


Fig. 1: Experimental Setup [1]

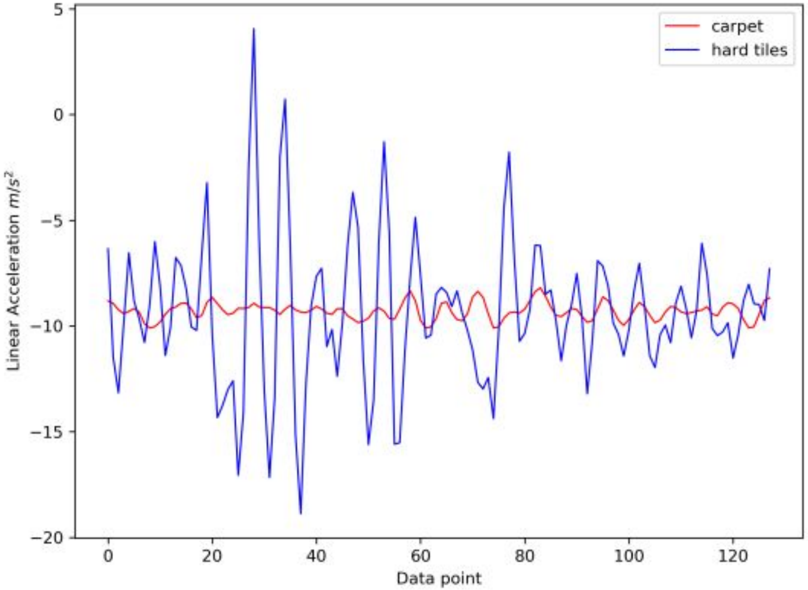


Fig. 2: Variation of one of the measures recorded by the IMU for two classes. [2]

Related works

- Luo et al. have developed a framework that classifies surfaces into five types such as smooth wood, rough foam, smooth foam, thick carpet, and thin carpet using four time-domain features i.e., mean of amplitude, integral of absolute value, variance and root mean square [3].
- Brooks and Iagnemma looked into a technique for a robot to learn to classify outdoor surfaces using vibration and traction sensors and then utilize that knowledge to learn to detect the type of terrain ahead using an inbuilt camera [4].
- Krzysztof used multiple sensors and cameras combined for terrain classification and negotiation [5].
- Kertész classified indoor surfaces using sensors from legged walking robot [6].

Motivation

- Necessity of surface detection in **real-time** for autonomous robots
- In a **complex human-living interior** environment
- Extracted features and their domains were limited in previous studies.

Materials and Methods

- Dataset Description
- Feature Extraction
- Preprocessing
- Feature Selection
- Classification
- Experimental Settings and Evaluation Metrics

Dataset Description

- Sensor data from autonomous navigating robots to classify indoor surfaces taken from a previous study [2].
- XSENS MTi-300 IMU sensor used to capture data.
- 9 different surface types: hard tiles with large space, hard tiles, soft tiles, fine concrete, concrete, soft polyvinyl chloride (PVC), tiles, wood, and carpet.
- Accelerometer data - 3 channels - X, Y and Z axis.
- Gyroscope data for angular rate in 3 channels - X, Y, and Z axis.
- Internally estimated orientation - 3 channels for vector and 1 channel for scaler for 4 attitude quaternion channels.

We have excluded orientation channel data because it has a scarce correlation with surface type suggested by the previous study [2].

Dataset Description

The distribution of the surfaces is not even throughout the dataset (see Fig. 1). There is a severe class imbalance issue and we have handled the issue using class weights in out training procedure.

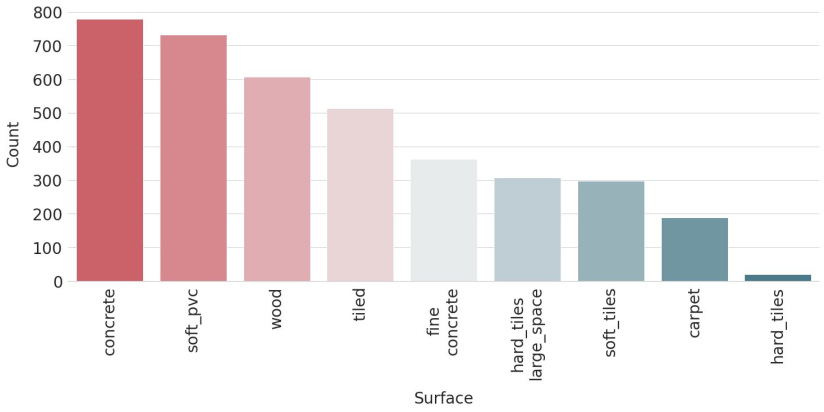


Figure 3 Surface type distribution in the dataset

Feature Extraction

- **Spectral Domain:** spectral characteristics of a signal in a relatively short period of time.
- **Temporal Domain:** long-term dynamics of a signal over time.
- **Statistical Domain:** basic statistics of the signal.

Feature Extraction

time series = 6 (x, y, z from accelerometer and gyroscope)
feature from one time series = 199
total number of features = 199x6 = 1194

All types of features extracted are summarized in Table I. For constructing feature sets from sensor data, we have used the time series feature extraction library (tsfel) [7].

Table I
EXTRACTED FEATURES FROM DIFFERENT DOMAINS

Domain	Features
Temporal domain	Autocorrelation, Centroid, Mean absolute differences, Mean differences, Median absolute differences, Median differences, Distance, Sum of absolute differences, Total energy, Entropy, Peak to peak distance, Area under the curve, Absolute energy, Maximum peaks, Minimum peaks, Slope, Zero crossing rate
Statistical domain	Histogram, Interquartile range, Mean absolute deviation, Median absolute deviation, Root mean square, Standard deviation, Variance, Kurtosis, Skewness, Maximum, Minimum, Mean, Median, ECDF, ECDF Percentile, ECDF percentile count, ECDF slope
Spectral domain	FFT mean coefficient, Wavelet absolute mean, Wavelet standard deviation, Wavelet variance, Spectral distance, Fundamental frequency, Maximum frequency, Median frequency, Spectral maximum peaks, Maximum Power Spectrum, Spectral Centroid, Decrease, Kurtosis, Skewness Spread, Slope, Variation, Spectral Roll-off, Roll-on, Human Range Energy, MFCC, LPCC, Power Bandwidth, Spectral Entropy, Wavelet Entropy, Wavelet Energy

Preprocessing

Scaling to a normalized value is necessary for many machine learning classifiers

- Standard Scaling

$$z_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

- Min-Max Scaling

$$z_i = \frac{x_i - min(x)}{max(x) - min(x)} \tag{2}$$

Feature Selection

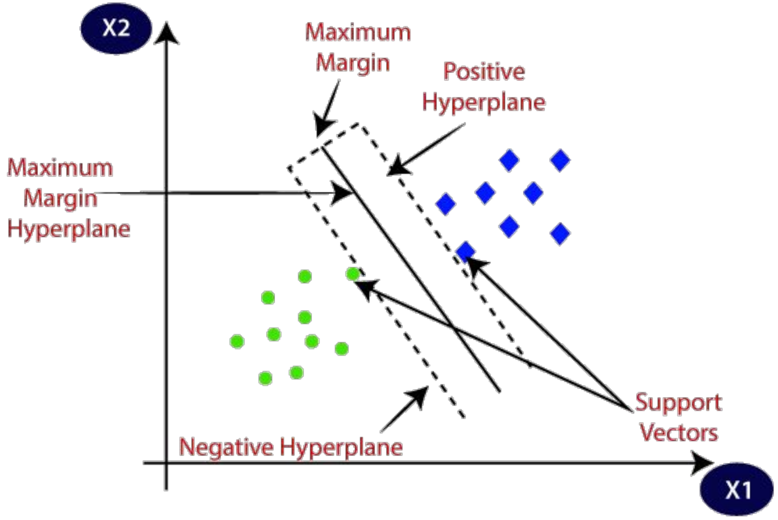
Feature Selection

- Variance Thresholding

$$Variance, \sigma^2 = \frac{\sum(x_i - \mu)^2}{N} \qquad (3)$$

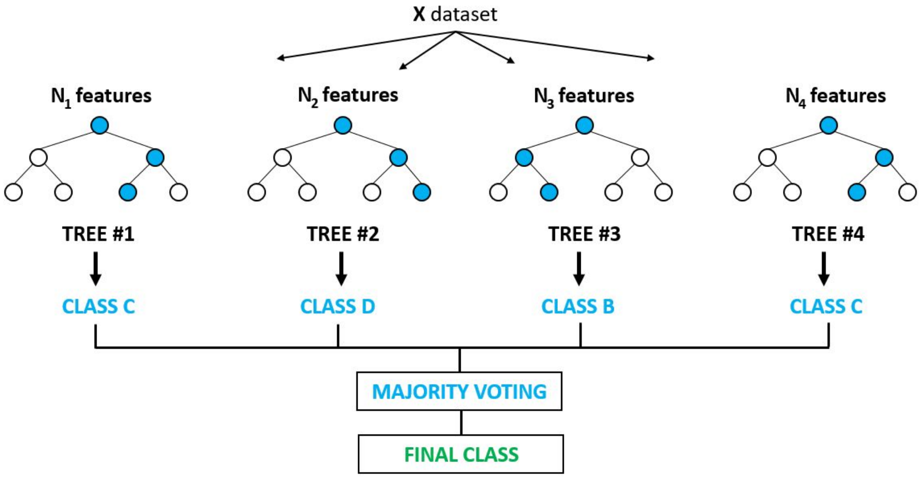
$$\sigma^2 > th*(1-th)$$

Classification Method



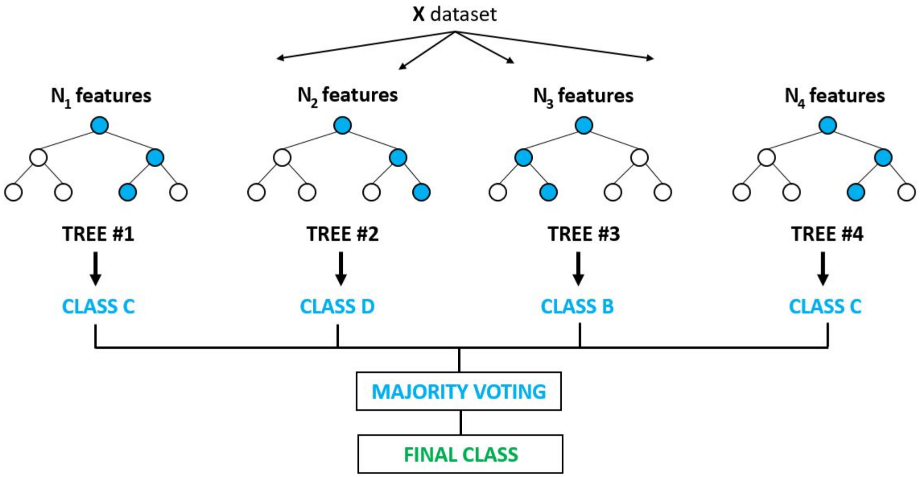
Support Vector Machine (SVM)

Classification Method



Random Forest (RF)

Classification Method



Extremely Randomized Trees (ERT)

Experimental Settings and Evaluation Metrics

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{8}$$

$$TPR = \frac{TP}{TP + FN} \tag{9}$$

$$FPR = \frac{FP}{FP + TN} \tag{10}$$

Results

Classifier Selection

Table II
CLASSIFIER SELECTION

Classifier	Scaling					
	Raw Data		Standard Scaled Data		Min-Max Scaled Data	
	Acc (%)	Time	Acc (%)	Time	Acc (%)	Time
Support Vector Machine	31.36±1.11	34.78	68.90±2.19	23.80	65.77±2.94	22.15
Random Forest	75.12±2.49	8.78	75.19±2.52	8.76	75.40±2.68	8.69
Extremely Randomized Trees	75.88±2.14	2.40	75.96±2.06	2.44	75.88±2.22	2.45

Results

Effect of Scaling Methods and Different Variance Threshold

Table III
SCALING VS VARIANCE THRESHOLD EVALUATION FOR EXTREMELY RANDOMIZED TREES FOR FEATURE SELECTION

Variance Threshold	Scaling								
	Raw Data			Standard Scaled Data			Min-Max Scaled Data		
	# Feat.	Acc (%)	Time	# Feat.	Acc (%)	Time	# Feat.	Acc (%)	Time
None	1194	75.88±2.14	2.15	1194	75.96±2.06	2.15	1194	75.88±2.22	2.08
1.00	1122	76.06±2.20	2.21	1122	76.06±2.23	2.17	1122	75.91±2.41	2.13
0.99	702	76.09±2.24	1.61	1122	76.06±2.23	2.17	389	77.11±1.87	1.17
0.98	559	76.25±2.62	1.42	1122	76.06±2.23	2.17	268	77.80±1.46	1.00
0.97	544	76.30±2.41	1.41	1122	76.06±2.23	2.17	**117**	**78.19±1.72**	**0.72**
0.96	526	76.59±2.16	1.36	1122	76.06±2.23	2.17	56	76.82±1.85	0.60
0.95	513	76.04±1.69	1.35	1122	76.06±2.23	2.17	31	70.31±1.78	0.53
0.90	486	75.88±1.61	1.35	1122	76.06±2.23	2.17	9	58.66±1.46	0.50
0.80	460	73.46±1.71	1.31	1122	76.06±2.23	2.17	-	-	-

Results

Hyperparameter Tuning of ERT

Table IV
HYPERPARAMETER TUNING FOR EXTREMELY RANDOMIZED TREES

Parameter	**Tested values**	**Selected values**
n_estimators	100, 200, 250, 300, 350, 400, 500	300
criterion	gini, entropy	entropy
max_features	None, auto, sqrt, log2	None
class_weight	None, balanced, weighted dictionary	weighted dictionary

Results

Comparison with the state-of-the-art methods

Table V
COMPARISON WITH THE STATE-OF-THE-ART METHOD

Method	Accuracy (%)	AUC score (%)
Lomio et al. (ResNet) [3]	64.95±3.39	92.33±1.16
Lomio et al. (XGB + FCN + ResNet) [3]	68.21±5.12	91.98±1.65
Our method	**80.81±1.00**	**97.25±1.92**

Conclusions

- Utilized time-series dataset for indoor surface recognition consisting of data from multiple sensors.
- Extracted features in temporal, statistical and spectral domains from accelerometer and gyroscope data.
- Classified indoor surfaces with state-of-the-art accuracy using Extremely Randomized Trees.
- Our method comprises a very short time for feature extraction and training which is essential for real-time surface type recognition.

Future works

- Incorporating both indoor and outdoor surfaces.
- Utilizing and extensive study of the features from all three domains and other representations of the signal..
- Still room for improvement before the real-life deployment of the autonomous robots.

References

[1] M. Concon, W. K. Wong, F. H. Juwono, and C. Apriono, “Deep Learning for Terrain Surface Classification: Vibration-based Approach”, CEUR Workshop Proceedings, col. 2786, pp. 237–243, 2021

[2] F. Lomio, E. Skenderi, D. Mohamadi, J. Collin, R. Ghabcheloo, and H. Huttunen, “Surface type classification for autonomous robot indoor navigation,” CoRR, vol. abs/1905.00252, 2019. [Online]. Available: http://arxiv.org/abs/1905.00252

[3] A. Luo, S. Bhattacharya, S. Dutta, Y. Ochi, M. Miura-Mattausch, J. Weng, Y. Zhou, and H. J. Mattausch, “Surface recognition via force-sensory walking-pattern classification for biped robot,” IEEE Sensors Journal, vol. 21, no. 8, pp. 10 061–10 072, 2021.

[4] C. A. Brooks and K. Iagnemma, “Self-supervised terrain classification for planetary surface exploration rovers,” Journal of Field Robotics, vol. 29, no. 3, pp. 445–468, 2012.

[5] K. Walas, “Terrain classification and negotiation with a walking robot,” Journal of Intelligent & Robotic Systems, vol. 78, no. 3, pp. 401–423, 2015.

[6] C. Kertész, “Rigidity-based surface recognition for a domestic legged robot,” IEEE Robotics and automation letters, vol. 1, no. 1, pp. 309–315, 2016.

[7] M. Barandas, D. Folgado, L. Fernandes, S. Santos, M. Abreu, P. Bota, H. Liu, T. Schultz, and H. Gamboa, “Tsfel: Time series feature extraction library,” SoftwareX, vol. 11, p. 100456, 2020.

Any
Questions?

Thank you