Tactile Sensing for Ground Classification

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Abstract:
This paper describes the ground classification procedure for a six-legged walking robot. The terrain is classified according to the information gathered with the 6-DOF torque-force sensors. The statistical description of the obtained signals allow to obtain compact representation of the contact type for each 6-DOF component. Namely, the 4-element vector [variance, skewness, kurtosis, fifth moment] was used. Subsequently Discriminant Analysis was applied separately for classification of each component of the 6-DOF vector. The signal which gives the best classification rate was established. The obtained result provides the information for the design of the new contact sensors for the robot feet.

Keywords: *walking robot, torque-force sensor, compliant ground, classification*

1. Introduction

Walking robots to work reliably in outdoor environment have to adopt their gait parameters to the type of the surface they are walking on. The information on the terrain could be obtained using tactile probing.

So far the terrain classification was performed mainly for the wheeled robots as it is was described in several articles [2, 12, 14]. The authors use accelerometers to measure vibrations during the movement of the robot to identify the terrain type. The series of articles [3--6] describes the research where an inclined tactile probe with accelerometer was used for surface identification. In their articles authors were showing the results of testing several data classification methods to obtain reliable classification results. Some research in tactile probing was also conducted for the walking robots. Early work was presented in [8, 9]. Further research on this topic was described in [6], where the robot RHex uses inertial and actuator cues for environment identification. In the latest research [7], the robot uses vibrations of the legs to classify several types of the terrain. The topic of the compliant ground and its influence on the locomotion patterns is also investigated in a human brain research. The work on this issue was reported in [10, 11].

In our research we are focused on the on-line terrain classification. The purpose of our investigations is to allow the robot to identify several types of terrain while walking. In consequence the robot would obtain the information required to change the type of the gait accordingly to the characteristics of the ground. The main contribution of this paper is the experimental validation of the feasibility of the on-line terrain classification. Moreover, the obtained results allow to indicate which components of the 6-DOF generalized force vector of the contact should be chosen for the classification purposes. This information could also be used for designing the robot foot contact sensors.

Fig. 1. *Messor robot while walking on the artificial grass*

2. Tactile Sensing for Ground Classification

2.1. Experimental Setup

The experimental setup consists of the Messor which is a biologically inspired six-legged walking robot. Its trunk has the following dimensions: width 26 cm and length 30.6 cm, while the segments of the

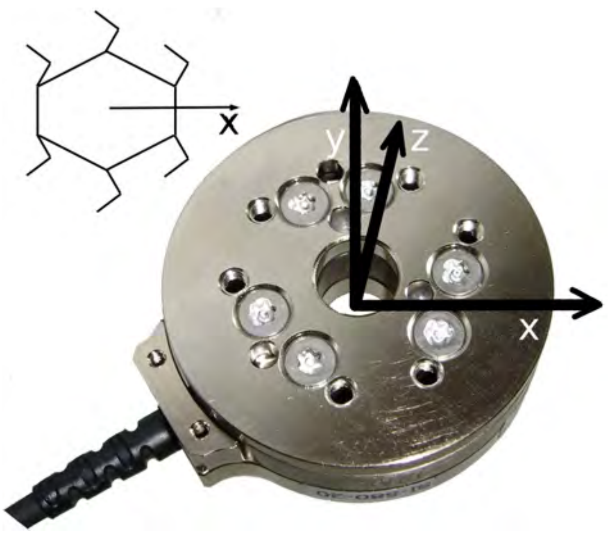

Fig. 2. *ATI Mini45 F/T transducer*

Fig. 3. Types of terrain: soft ground (a), artificial grass (b), gravel (c), pebbles (d), sand (e)

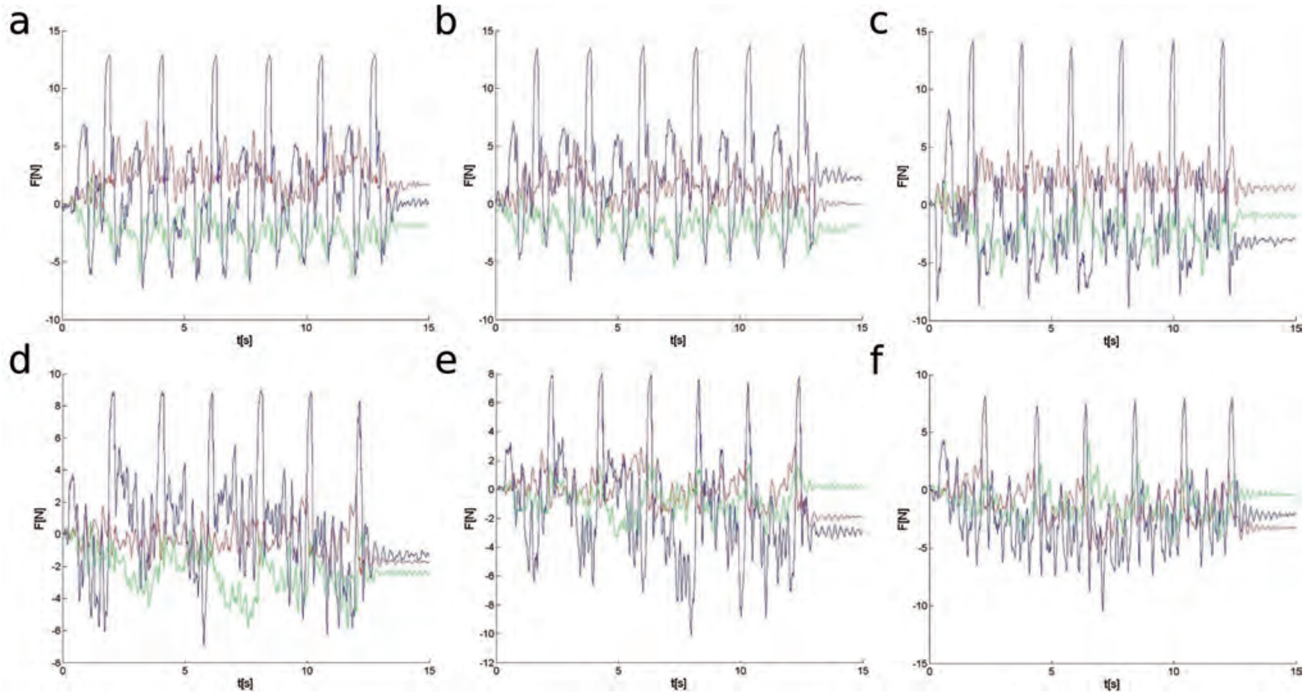

Fig. 4. Components of the contact force vector for the robot walking on: soft ground (a), artificial grass (b), solid ground (c), gravel (d), pebbles (e), sand (f). Each component is marked with a color: red - F_x, green - F_y, blue - F_z

leg are: coxa 5.5 cm, femur 16 cm, tibia 23 cm. The detailed description of the robot could be found in [13]. The machine is shown in Figure 1. The robot foot is equipped with 6-DOF torque-force sensor and has the spherical shape. The applied ATI Mini45 F/T transducer is shown in Figure 2. The sensor allows to measure forces of the magnitude up to 290 N (resolution = 1/8 N) and to measure torque of the magnitude up to 10 Nm (resolution = 1/376 Nm).

In the experiment the robot is walking straight with the wave gait. The direction of the robot movement is aligned with the x-axis of the torque-force sensor for the robot legs in their initial position. The orientation of the coordinates frames of the robot and the transducer was shown in Figure 2. The step length is equal to 6 cm, and the walking speed is equal to 2.79 cm/s. The testing set comprise six types of terrain: soft ground - rubber paver tiles, artificial grass, solid ground - concrete floor, gravel, pebbles and sand. The testing set was shown in Figure 3, solid ground is the concrete pavement surrounding the ground probes.

Each experiment trial consisted of 6 steps. 10 trials for each terrain type were performed. Example of the force and torque signals obtained from the transducer while the robot was walking on each type of the terrain was shown in Figure 4 and Figure 5 respectively. Each plot represents signals for different type of terrain. Each component of the force and torque vector was marked with appropriate colors. As it can be seen in Figure 4 (F_z signal - blue line) the measurements are starting when the robot foot is on the ground. The initial force resulting from the weight of the robot is assumed to be neutral value - 0. In the F_z signal six peaks with positive value could be observed. These are representing six steps performed by the robot.

Subsequently the signal from each trial was divided into separate steps of the robot gait. Initial and final steps were removed from the data set to obtain measurements from the regular robot walk, not in transient states. Final data set consist of six subsets of 36 steps for each type of terrain which gives 216 six-dimensional vectors of signals. The example of the single step response for each type of terrain was shown in Figure 6.

2.2. Features Selected for Classification

Further the single step signal in time domain for each 6-DOF component was transformed into features vector comprising four elements:

1) variance;
2) skewness;
3) kurtosis;
4) fifth moment.

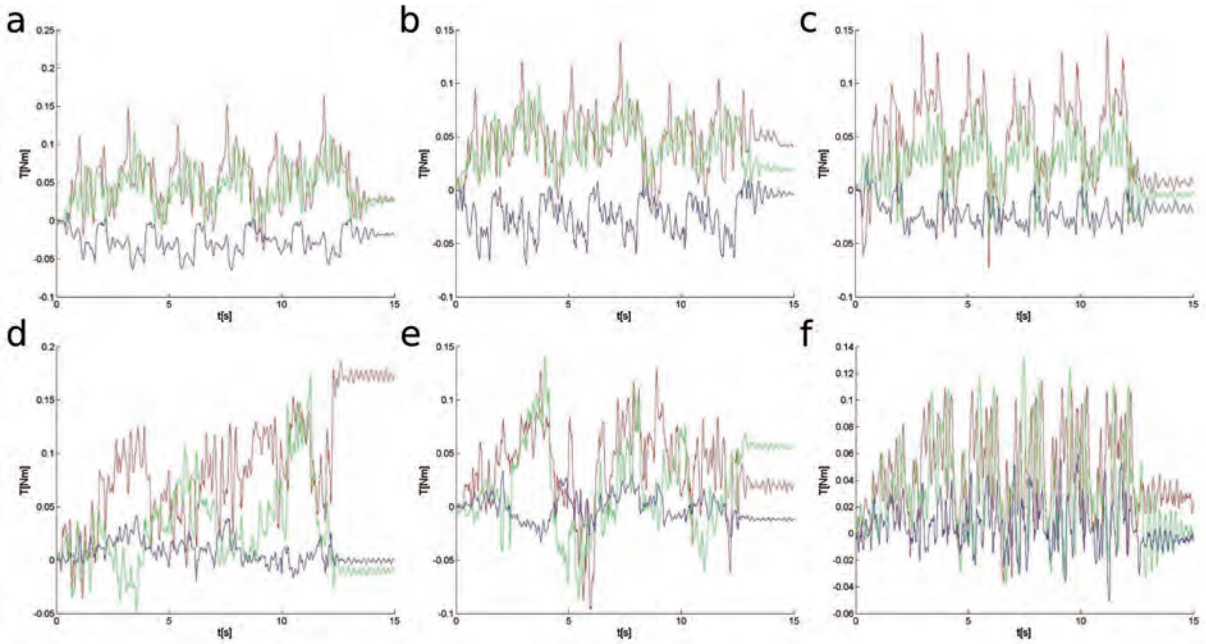

Fig. 5. *Components of the contact torque vector for the robot walking on: soft ground (a), artificial grass (b), solid ground (c), gravel (d), pebbles (e), sand (f). Each component is marked with a color: red -* T_x*, green -* T_y*, blue -* T_z

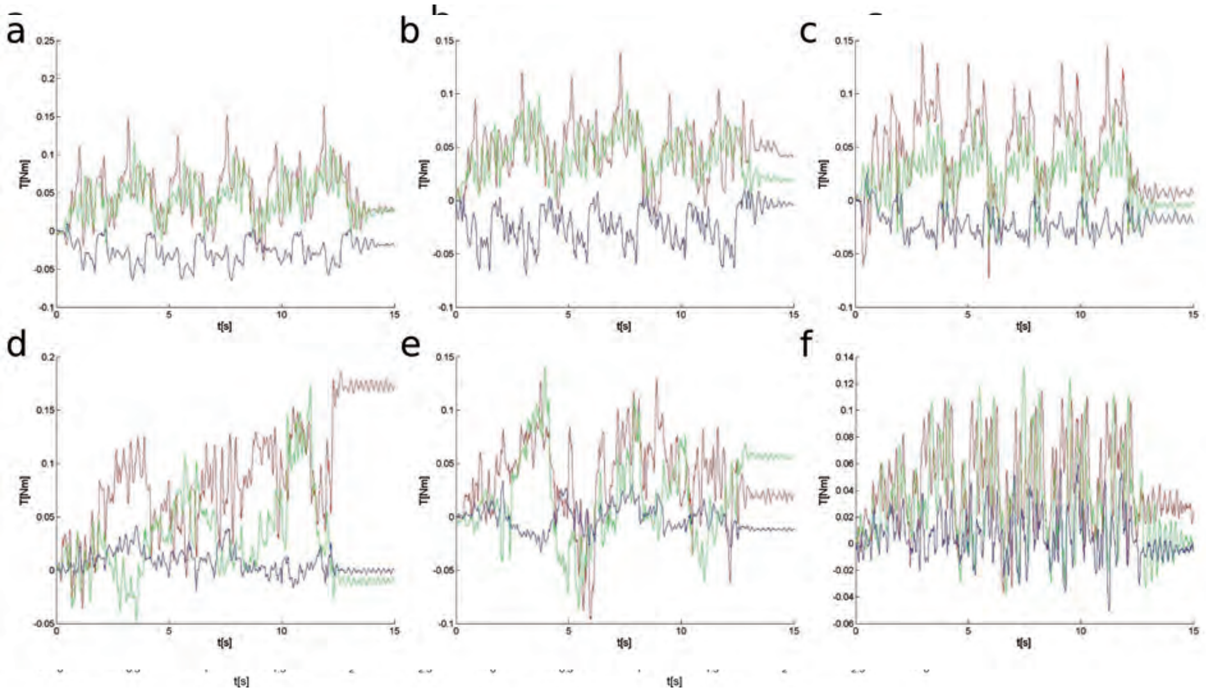

Fig. 6. *The force (a,b,c) and torque (d,e,f) signals of the 6-DOF generalized force vector of contact for the single step for each type of terrain: red - soft ground, green - artificial grass, blue - solid ground, cyan - gravel, magenta - pebbles and yellow - sand*

The features were extracted from the time window (single step) of size W (2.15 s). The selection of features was inspired by the previous research reported in [5, 14]:

The example plot of three selected features (variance, skewness, kurtosis) for each signal is shown in Figure 7. For the visualization purposes only 3-D vector was chosen. In mentioned above figures the red crosses represent the features vector for the soft ground, green circles for the artificial grass, the blue star for the solid ground, the cyan dots for gravel, the magenta squares for pebbles and yellow diamonds for sand. In the figures it could be seen that the clusters of points are distinguishable. Additionally distribution of points representing features vector could be compared with the time domain response of the same signals shown in Figure 6.

2.3. Classification Process

Using the group of points obtained in previous section the Discriminant Analysis (DA), described in [1],

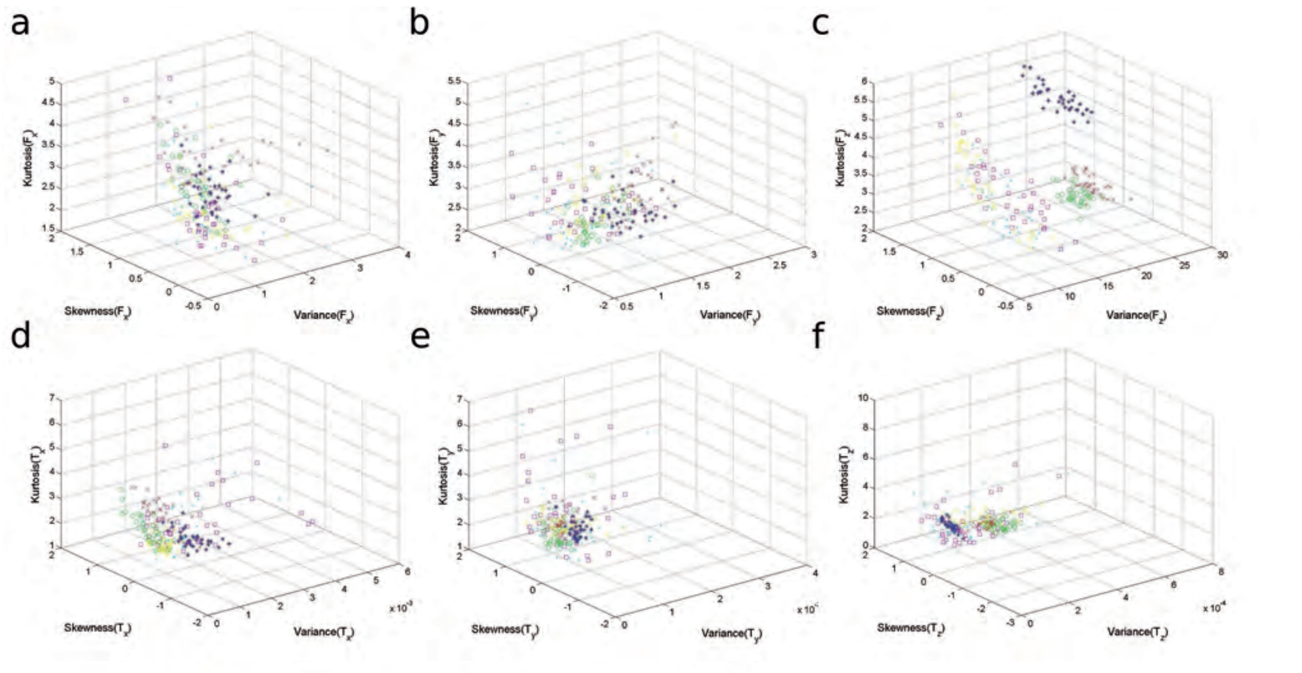

Fig. 7. *Cloud of points for the features obtained from the force (a,b,c) and torque (d,e,f) signals of the 6-DOF generalized force vector of contact for the single step. The markers for each type of the terrain are: red cross - soft ground, green circle - artificial grass, blue star - solid ground, cyan dot - gravel, magenta square- pebbles and yellow diamond - sand*

was used in order to obtain the separation between the clusters of points and in consequence to build the classifier. In the classification process the training set consisted of 156 points (26 for each group - terrain type) and the sample set comprised 60 points (10 for each group - terrain type). The target set was prepared beforehand for the known training set.

In the presented research three types of the discriminant function were applied to solve the classification problem. First method uses the linear function - Linear Discriminant Analysis (LDA) where a multivariate normal density, with a pooled estimate of covariance is fitted to each group. Next the quadratic function was applied to obtain Quadratic Discriminant Analysis (QDA), where multivariate normal densities with covariance estimates stratified by group is fitted. Finally discriminant function with Mahalanobis distances with stratified covariance estimates was applied to the classification process. The results of the obtained error for the training data are shown in Table 1 and graphically presented in Figure 8. As it can be seen the best performance was obtained for signal F_z and the Quadratic Discriminant Analysis.

Tab. 1. *Misclassification Error*

	F_x	F_y	F_z	T_x	T_y	T_z	F_zT_z
l	0.56	0.46	0.23	0.39	0.54	0.44	0.15
m	0.65	0.46	0.26	0.58	0.72	0.61	0.18
q	0.47	0.44	0.21	0.32	0.43	0.35	0.10

3. Experimental Results

The data presented in Table 1 suggest that the QDA should be used in further investigations. However by looking at confusion matrices for the testing set it can

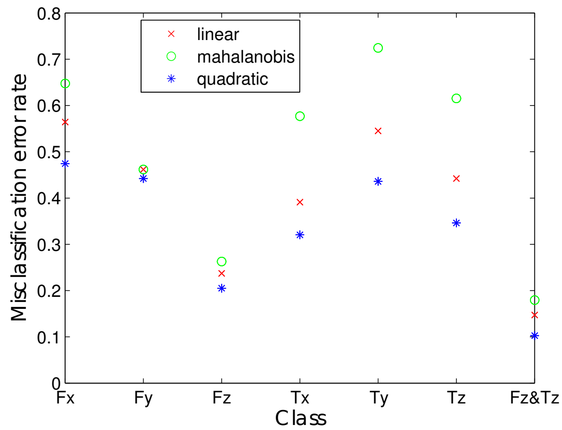

Fig. 8. *Misclassification error rate for the training data*

be seen that the better classification performance was obtained for the LDA. The QDA is better fitted to the training data but the LDA has in this case better generalization properties. The confusion matrices for LDA were shown in Tables 2, 3, 4, 5, 6, 7.

For the LDA it can be seen that the best performance was obtained for the F_z (Table 4. For this signal it could be observed that the block matrix of 4 submatrices of dimensions 3x3 was obtained. Upper left block concerns three types of terrain: soft ground, artificial grass and solid ground. For these three types of ground good classification rate was obtained. The second block bottom right concerns: gravel, pebbles and sand. For these types of terrain poor classification performance was obtained. Other two blocks of the matrix are filled with zeros, so it is possible to form two subsets of terrain types. Namely, non-friable and friable. In the subset of friable materials it is hard to distinguish between gravel and send basing only on the information about the contact forces. Other good candidate signal but with weaker performance is T_z (Table 7) here the block matrix wasn't obtained but still there are 1.0 and 0.9 values on the diagonal of the matrix.

In the experiments the use of one signal from the transducer for the ground identification could be seen as using weak classifier. In order to improve classification performance the combination of at least two signals could be used to obtain stronger classifier. This assumption was checked for earlier mentioned signal F_z (Table 4) and signal T_z (Table 7). The classifier obtained by combining this two signals has better performance than the classifier for two separate signals as it could be observed in Table 8. In conducted research other signals: F_x, F_y, T_x, T_y, T_z are less informative for the ground classification process as they are not block matrices.

Tab. 2. *Confusion matrix for the testing set for the F_x component of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	0.7	0.1	0.1	0.0	0.1	0.0
gs	0.3	0.6	0.1	0.0	0.0	0.0
sd	0.2	0.1	0.6	0.0	0.0	0.1
gl	0.0	0.3	0.1	0.1	0.1	0.4
ps	0.0	0.0	0.1	0.6	0.0	0.3
snd	0.0	0.1	0.1	0.4	0.0	0.4

Tab. 3. *Confusion matrix for the testing set for the F_y component of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	0.8	0.1	0.1	0.0	0.0	0.0
gs	0.3	0.4	0.2	0.1	0.0	0.0
sd	0.3	0.1	0.5	0.0	0.0	0.1
gl	0.0	0.2	0.0	0.5	0.1	0.2
ps	0.0	0.0	0.2	0.4	0.2	0.2
snd	0.0	0.0	0.0	0.6	0.0	0.4

Tab. 4. *Confusion matrix for the testing set for the F_z component of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	1.0	0.0	0.0	0.0	0.0	0.0
gs	0.3	0.7	0.0	0.0	0.0	0.0
sd	0.0	0.0	1.0	0.0	0.0	0.0
gl	0.0	0.0	0.0	0.3	0.7	0.0
ps	0.0	0.0	0.0	0.2	0.5	0.3
snd	0.0	0.0	0.0	0.8	0.0	0.2

4. Conclusions

In this article the on-line classification of the terrain using the tactile probing was presented. The experiments were conducted on the six legged walking robot. The use of the statistical description of the obtained signals allowed to obtain compact representa-

Tab. 5. *Confusion matrix for the testing set for the T_x component of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	0.7	0.1	0.1	0.0	0.1	0.0
gs	0.3	0.4	0.0	0.0	0.0	0.3
sd	0.0	0.0	0.8	0.0	0.0	0.2
gl	0.1	0.0	0.2	0.4	0.1	0.2
ps	0.2	0.2	0.0	0.5	0.0	0.0
snd	0.0	0.4	0.0	0.1	0.0	0.5

Tab. 6. *Confusion matrix for the testing set for the T_y component of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	0.2	0.1	0.4	0.1	0.0	0.2
gs	0.1	0.8	0.1	0.0	0.0	0.0
sd	0.2	0.0	0.8	0.0	0.0	0.0
gl	0.0	0.3	0.1	0.0	0.2	0.4
ps	0.2	0.1	0.1	0.0	0.2	0.4
snd	0.4	0.1	0.0	0.0	0.1	0.4

Tab. 7. *Confusion matrix for the testing set for the T_z component of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	0.5	0.1	0.0	0.0	0.0	0.4
gs	0.1	0.9	0.0	0.0	0.0	0.0
sd	0.0	0.0	1.0	0.0	0.0	0.0
gl	0.0	0.1	0.3	0.1	0.3	0.2
ps	0.0	0.1	0.2	0.1	0.5	0.1
snd	0.1	0.4	0.3	0.0	0.0	0.2

Tab. 8. *Confusion matrix for the testing set for the F_z & T_z components of 6-DOF contact vector*

	soft	grass	solid	gravel	pebbles	sand
st	1.0	0.0	0.0	0.0	0.0	0.0
gs	0.1	0.9	0.0	0.0	0.0	0.0
sd	0.0	0.0	1.0	0.0	0.0	0.0
gl	0.0	0.0	0.0	0.2	0.5	0.3
ps	0.0	0.0	0.0	0.1	0.8	0.1
snd	0.0	0.0	0.0	0.3	0.0	0.7

tion of the foot contact torque/force responses for the different types of terrain.

The experimental validation proved that the on-line terrain classification for the walking robot is feasible. Robot does not have to stop to identify the terrain. It could be done while walking.

Moreover conducted research allowed to find the components of the 6-DOF foot contact generalized force vector which gives the best classification results. Namely, it is F_z signal and T_z. This information is useful while constructing classifiers as well as designing the robot foot contact sensors.

As a future work the research on combining three or more signals for the classifier is foreseen. Some boosting methods could be applied or the longer vectors of features could be employed to make the classification process more reliable. The test of other classification methods will also be done. Furthermore the research on the influence of the direction and speed of the movement on the classification process has to be done. Additionally the information from other sensing modalities such as 2-D and 3-D visual sensors could be used to support ground identification process.

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