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# An Inertia-Based Surface Identification System

Jens Windau, Wei-Min Shen

*Abstract*—**In many robotics applications, knowing the material properties around a robot is often critical for the robot's successful performance. For example, in mobility, knowledge about the ground surface may determine the success of a robot's gait. In manipulation, the physical properties of an object may dictate the results of a grasping strategy. Thus, a reliable surface identification system would be invaluable for these applications. This paper presents an Inertia-Based Surface Identification System (ISIS) based on accelerometer sensor data. Using this system, a robot actively "knocks" on a surface with an accelerometer-equipped device (e.g., hand or leg), collects the accelerometer data in real-time, and then analyzes and extracts three critical physical properties, the hardness, the elasticity, and the stiffness, of the surface. A lookup table and k-nearest neighbors techniques are used to classify the surface material based on a database of previously known materials. This technique is low-cost and efficient in computation. It has been implemented on the modular and self-reconfigurable SuperBot and has achieved high accuracy (95% and 85%) in several identification experiments with real-world material.**

## I. Introduction

Knowing the material properties around a robot is often critical for the robot's performance. For example, in manipulation, the physical properties of an object may dictate the results of a grasping strategy. In mobility, mobile robots need to adapt their gaits to the current environmental surface in order to achieve maximum performance. In order to adapt moving behaviors and related parameter settings (e.g., tire pressure or suspension) to the current environment, autonomous robots must continuously analyze the local surface conditions during run-time and use that information to guide its decisions.

Many robotic applications are related to exploration, navigation, error-correction, error-prevention, and/or learning to use feedback from the environment. In particular, robots for exploration and navigation need environmental information for calibration. One example is motion applications such as ground moving robots which simply choose the gait that fits best to their local surface material. For example, a set of combinable and self-configurable robot modules could reconfigure themselves to different shapes by reconnecting its modules to different configurations [10]. Such robots can choose between different motion types such as rolling [11], snail moving, or humanoid walking (see http://www.isi.edu/robots/superbot). In addition, certain parameters (such as wheel pressure or stiffness of the robot body) could be automatically adjusted based on the surface information. Finding the optimal gait that best fits the given surface and adapting the gait properties accordingly would improve the speed, accuracy, reliability, and efficiency of the robot. This is particularly important for autonomous mobile robots, which often have to be recalibrated during run-time to adapt to the changing environment conditions. However, it is very challenging for robots to gain reliable information about material properties in real time. In fact, it is still an open problem how to optimally recognize and classify surface materials in order to improve the overall performance of a robot. The key difficulties include how to choose measurable properties of the surface, how to find an adequate sensor for measuring those, how to extract important surface information from the raw sensor data, and how to evaluate and classify any given surface correctly. The goal of this paper is to develop a reliable sensor measurement approach based on accelerometers to characterize and classify the physical properties of a given material or surface. Such knowledge will enable future robots to achieve high performances in motion speed, navigation accuracy, moving efficiency, or grasping success. Surface identification is a classification problem and there are different approaches to achieve the desired results. For example, different sensors have been tested to discover the most valuable information for a measurement: Vision-based surface identification systems have been developed with good performance [4][5], however, tradeoffs such as high sensor costs, expensive processing power and remaining failure classification are still unavoidable. In 1992, a research team from University of Pennsylvania recommended using legs to characterize surface materials [6]. Four years later, a research team from McGill University developed a microphone-based surface recognition system attached to a robot leg. The acoustic signal from tapping different floor materials was used for classifying surface materials with good results. However, ambient/motor noise may cause some real difficulties [3]. A recent significant development is the MEMS-accelerometer sensor technology that made it possible to use an accelerometer for surface classification. Low cost, less computational expenses, and very small size are the strengths of this sensor technology for surface recognition purposes. The ongoing collaborative research project "SandBots" (by Georgia Tech and University of Pennsylvania) tries to measures the knocking forces between a robot foot and the surface with an accelerometer while walking. Their approach distinguishes between high- and low-volume-fraction materials in order to adjust the robot's gait [2]. A recent project from Carnegie Mellon University gathered accelerometer data from a moving robot and attempted to classify the surface by

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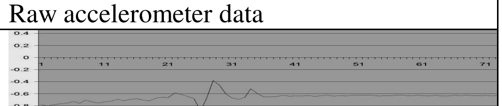
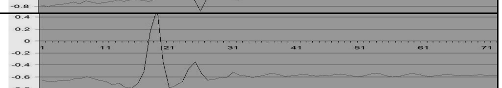
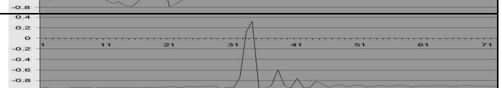
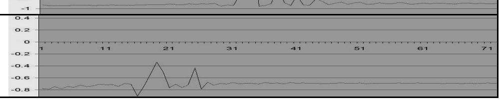
generating features and using a decision tree learning algorithm [1]. The ISIS approach presented in this paper is also based on accelerometers, but it has a set of unique contributions: (1) an effective definition for an active "knocking" procedure to produce critical accelerometer data; (2) a set of analytical techniques to divide the raw data into segmentations of raw sequences (characteristic phases); (3) the identification of physical properties (or meanings) that are closely related to the phases in the data; (4) an extendable database of previously identified physical properties, and (5) a classification technique to use the above ideas to classify and learn future materials in real time.

## II. THE ISIS APPROACH

### *(1) Producing raw data by actively knocking on the surface*

Most accelerometer based approaches use passive observation techniques. No acceleration data is actively produced, but natural acceleration forces are recorded which occur e.g. in robot legs while walking [1][2]. However, ISIS classifies surfaces by analyzing measurement data from knocking an accelerometer against a surface in purpose. The knocking is a controlled movement independent from the situation such that time, speed and force are predefined. Depending on the type of surface, material characteristic acceleration data can be measured. The challenge is to classify the surface material based only on this actively produced raw accelerometer data [Table 1].

Table 1: Acceleration data recorded during knocking

| Material | Raw accelerometer data |
|---|---|
| rock |  |
| grass |  |
| mulch |  |
| **material X** |  |

### *(2) Dividing raw data into characteristic phases*

The key step of the ISIS algorithm is to identify five phases automatically from the raw data [Fig. 1]. Each of the five phases represent a segment of the knocking procedure, which contains independent measurement recordings and simplify further processing, particularly the extraction of material data.

### *(3) Discovery of the physical meanings of the phases*

The idea behind ISIS is to pay attention to physical properties which can be extracted from the five phases. Phase 2, 3 and 4 contain information of material properties; Phase 1 and 5 act as time buffer zones and do not contain any valuable information. Based on extensive experimental data, it appears that three indicators for the following material properties can be measured with reliable results: Hardness (in phase 2), elasticity (in phase 3), and stiffness (in phase 4). However, these material properties represent qualitative labels rather than canonical definitions. All indicators were shown to be valuable and sufficient key properties to distinguish between surface materials.

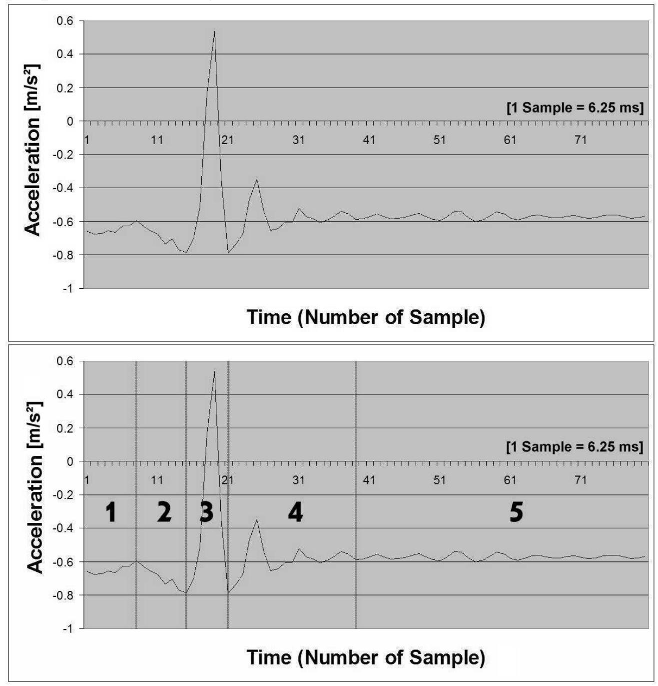



Fig. 1: Dividing the acceleration data in five phases

### *(4) Creating an extendable database*

ISIS must have information about the properties of the surface in advance to classify it. Therefore, sample data from each surface material is required for the ISIS algorithm. The following sample data was measured in previous experiments and stored in a simple lookup table [Fig. 2].

In addition, ISIS can easily extend the database. Each new material requires only a few measurements in order to determine appropriate ranges for the three physical properties (hardness, elasticity, stiffness) (see Fig. 2). Once these ranges have been selected, the data can be stored in the lookup table.

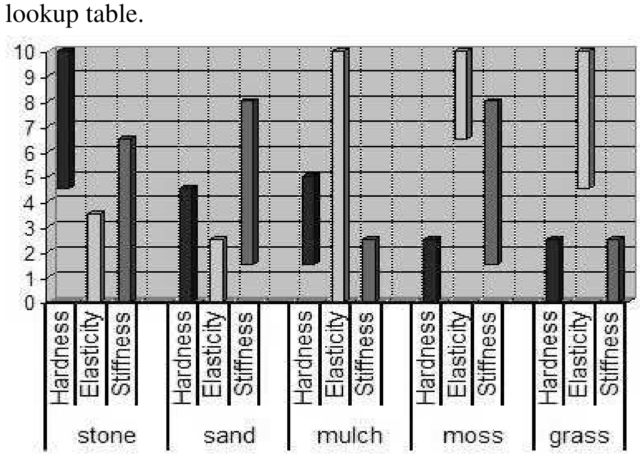



Fig. 2: Lookup table for surface materials on a scale from 0 to 10
Hardness&Elasticity: 0 (min) -10 (max), Stiffness: 0 (max) – 10 (min)

*(5) Classification technique for surface materials*

Once hardness, elasticity, and stiffness of a given knocking are calculated, ISIS compares them with the data from the lookup table and outputs the matching materials.

## III. MEASUREMENT PROCEDURE

### A. *Overview*

The measurement procedure of ISIS is a simple knocking movement [Fig. 3] between an accelerometer equipped knocking device (2) and the surface material (3) - both attached to a platform (1). The device (2) is simply moving towards the surface, knocks a single time on the surface (3) and returns to its initial position. The surface (3) can represent any surface material, even the platform material (1) itself. All experiments were performed with the SuperBot module [9] as a knocking device, equipped with a KXP74-1050 accelerometer sensor (±2g range, 2KHz sampling rate, 1.22 mg resolution). ISIS records the acceleration data while the knocking movement takes place.

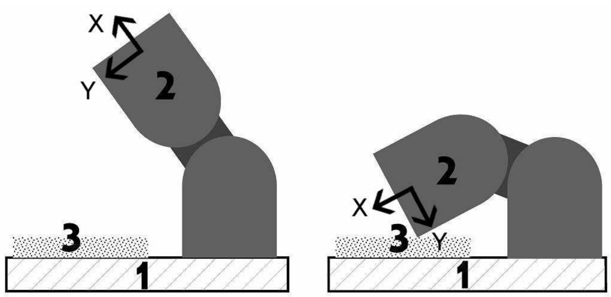



Fig. 3: Knocking movement (with accelerometer axis X and Y)

The SuperBot module (2) was fixed to the platform (1) during the test series. Accordingly, by applying ISIS to a real robot application, the body weight of the robot must be heavy enough to avoid getting lifted by the knocking forces, which could otherwise damp the raw acceleration data.

The height of the surface material does not need to be determined prior to the measurement. However, if memory is limited for acceleration recordings, an optional detection measurement can be performed in advance to detect the height of the surface – also by accelerometer data. Memory can be saved by starting the accelerometer recording only a short time before the knocking device hits the surface.

Acceleration data must be recorded with a high signal-to-noise ratio and low influence of damping effects for a good measurement result. Two construction techniques improve the quality of ISIS: First, the accelerometer sensor should be mounted on the robot at a location close to the knocking edge. Second, a high stiffness of the robot body (arm or leg) should be maintained during the entire knocking measurement.

Two orthogonal accelerometer axes (X,Y) are located in the robot motion plane that runs vertical to the platform (1) [Fig. 3]. The sum of the vertical acceleration component of both axes results in the output graph [Fig 1]. The third accelerometer axis runs parallel to the platform plane without measuring any valuable data for ISIS.

The actual surface measurement of the whole knocking movement procedure lasts only for 0.5 seconds. During this time window, the acceleration of the knocking device is measured 80 times (~160 Hz). The time window is then divided into five phases for further processing of the recorded knocking data [Table 2].

Table 2: Information contained in each phase

| | |
|---|---|
| Phase 1 | Time buffer zone; no information |
| Phase 2 | Moment of knocking |
| Phase 3 | Moment of rebound |
| Phase 4 | Post-knocking oscillations |
| Phase 5 | Time buffer zone; no information |

### B. *Three physical characteristics of the surface*

During the knocking movement [Table 2], ISIS measures and subsequently calculates three physical indicators of the surface: **Hardness** (from phase 2), **elasticity** (from phase 3), and **stiffness** (from phase 4). ISIS characterizes and recognizes materials only based on these three physical characteristics. Accelerometer experiments have shown that these three material properties can be independently measured and are sufficient for distinguishing between most surfaces.

**Hardness indicator**

The hardness of the surface is measured in phase 2 when the accelerometer touches the surface. The more the knocking device decelerates, the sharper the graph declines in this phase [Fig. 4]. The graph represents the speed in which the surface can be compressed.

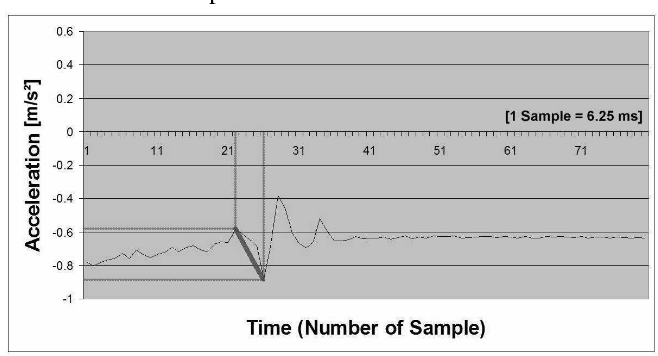



Fig. 4: Hardness is measured by the steepness of the deceleration

**Elasticity indicator**

Phase 3 contains information about the elasticity of the surface. The higher the acceleration peak, the more the surface material decompresses [Fig. 5]. This rebound is caused by the tension force of the deformed surface from phase 2. The elasticity is calculated through using the height difference between the maximal value of the acceleration peak in phase 3 and the reference point which is located between phase 1 and 2.

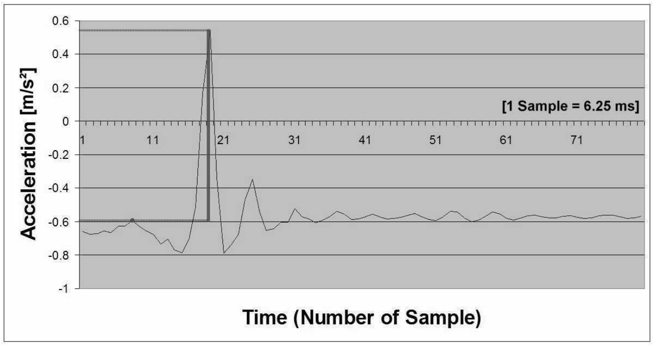



Fig. 5: Elasticity is related to the relative height of the acceleration peak of the bounce-back

**Stiffness indicator**

In phase 4, the number of post-oscillations represents the stiffness of the surface material. A post-oscillation is defined as a full oscillation through the reference point height. The more post-oscillations occur, the lower the stiffness of the surface material is [Fig. 6].

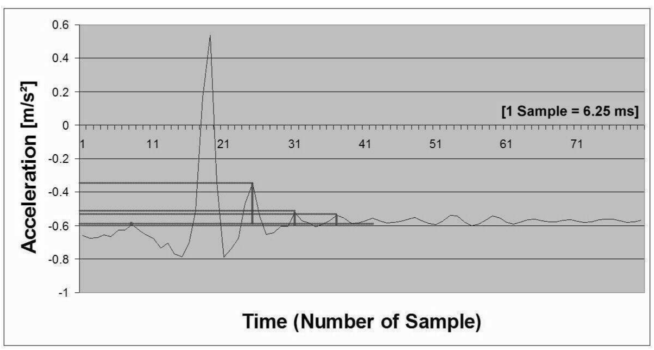



Fig. 6: Post-knocking oscillations act as an indicator for stiffness

## C. *Measurement details*

**Measurement process**

ISIS only extracts information from the surface measurement (five-phase time window) and not from the entire knocking movement [Fig. 7]. Furthermore, the time window is not divided into five phases during run-time, but in a subsequent calculation which identifies the phases.

**Phase details**

Phase 1 and 5 are time buffers without useful data for further processing. The moment of knocking covers phase 2-4. It lasts for at least 120 ms, depending on the surface material.

**Phase 1:** *Before phase 1 starts, the knocking device moves towards the surface.* Once it is in close distance proximity to the surface (50 ms before knocking), ISIS starts phase 1 and records accelerometer sensor data. Phase 1 terminates as soon as the reference point is reached. The reference point is defined as the moment when the knocking device collides with the surface. Since the knocking device moves towards the surface with a slightly increasing acceleration, it reaches its maximum value at the time of the reference point (knocking moment). In view of the whole time window, it is the local acceleration maximum prior to the global acceleration peak.

**Phase 2:** Phase 2 starts immediately following the reference point. The knocking with the surface causes high deceleration values for a short time. The stronger the knocking, the more the acceleration graph will decline. A graph for hard materials declines much faster than a graph for soft materials. ISIS characterizes the material hardness based on the steepness of the graph.

**Phase 3:** The knocking of phase 2 is followed by a rebound in phase 3 which lets the knocking device bounce back from the surface again. Specifically, the knocking device starts accelerating in the opposite direction. The acceleration peak size provides information about the elasticity of the surface. The larger this peak, the more elastic the surface is. ISIS mathematically defines the elasticity indicator as the height difference between the global acceleration peak and the reference point. Phase 3 terminates at the next local acceleration minimum.

**Phase 4:** The task of phase 4 is to count the number of post-oscillations. The knocking and rebound process of phase 2 and 3 causes the knocking device to post-oscillate with decreasing amplitude. Depending on the damping characteristics of the surface material, the number of post-oscillations varies. Only oscillations around the reference point (equal to the equilibrium point of the knocking device) are valid counts. The more post-oscillations occur, the less stiff the surface is considered. Phase 4 terminates as soon as the first non-valid post-oscillation is detected.

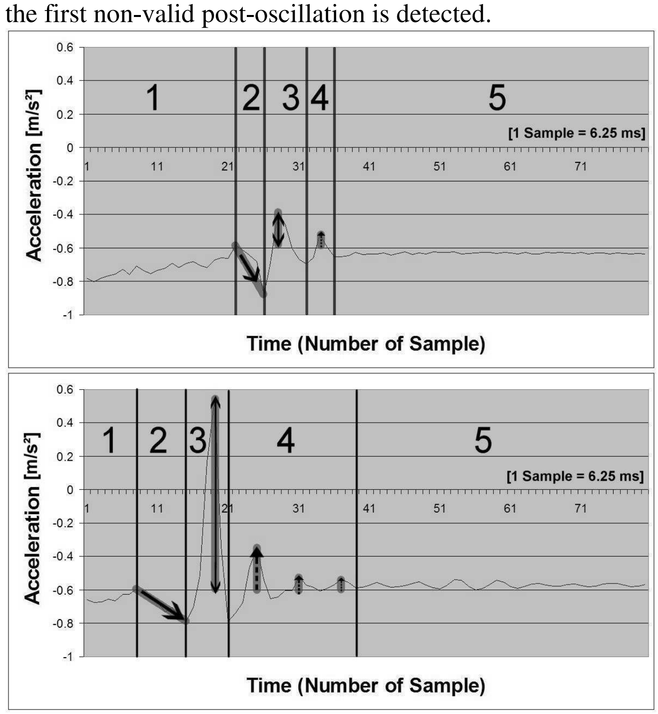



Fig. 7: Data recordings for metal (above) and soft paper (below)
**Phase 2**: Strength of graph decline (indicator for hardness)
**Phase 3**: Size of peak (indicator for elasticity)
**Phase 4**:Number of post-oscillations (indicator for stiffness)

**Phase 5:** Phase 5 acts as a time buffer. In case surface materials have a very low stiffness, many post-oscillations occur. If phase 4 requires more time to record further post-oscillations, phase 5 simply provides buffer time for extension. The remaining buffer time between the last valid post-oscillation and the end of the measurement process is defined as phase 5. No valuable information (only non-valid post-oscillations) is left in this phase.

**Post-calculation processing**

The surface measurement is followed by a subsequent calculation process, in which the recorded accelerometer data is split in the five phases as previously described. Furthermore, ISIS extracts the necessary data to evaluate the surface in terms of hardness, elasticity, and stiffness on a scale of 0 to 10 [Fig. 8]. Eventually, ISIS uses a lookup table containing previous training material to classify the surface material [Fig 2]. If measurement data cannot be assigned to any material of the lookup table, the closest matching surface material will be selected by the k-nearest neighbors algorithm.

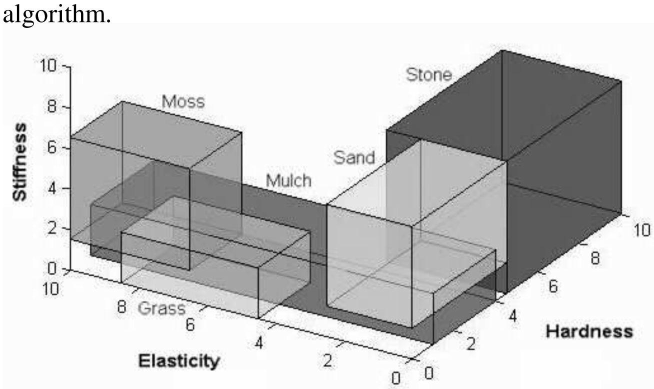



Fig. 8: Sample 3D-Visualization of a material database

Hardness & Elasticity: 0 (min) - 10 (max), Stiffness 0 (max) - 10 (min)

## IV. TEST RESULTS

**Basic recognition test**

In an initial series of experiments, the recognition performance of ISIS was tested with three clearly distinguishable materials: a block of iron, multiple layer of soft paper, and a spring. Physical peak characteristics were expected [Table 3][Table 4].

Table 3: Peak characteristics in the basic recognition test

| Material | Hardness | Elasticity | Stiffness |
|---|---|---|---|
| Iron | High (6-10) | | |
| Soft Paper | | High (6-10) | High (0-4) |
| Spring | | High (6-10) | Low (6-10) |

Table 4: Results of the basic recognition test (performed 3 times in total)

| Overall Performance (between Samples)<br>Total of 100 readings (33 Iron, 33 Spring, 34 Soft Paper) | |
|---|---|
| Correct | 95 % |
| Incorrect | 5 % |
| *Comparing to random guess* | 33 % |

**Advanced recognition test**

In order to apply ISIS to the real world, the ability to recognize natural surface materials is required. For this reason, five natural materials were chosen: stone, sand, grass, moss, and mulch. Some of these materials have significant physical differences (stone vs. grass), but some also have similar physical characteristics (grass vs. moss). Based on the lookup table [Fig. 2] that was recorded in a previous learning run, a total of 100 readings (20 for each material) resulted in the following classification performance.

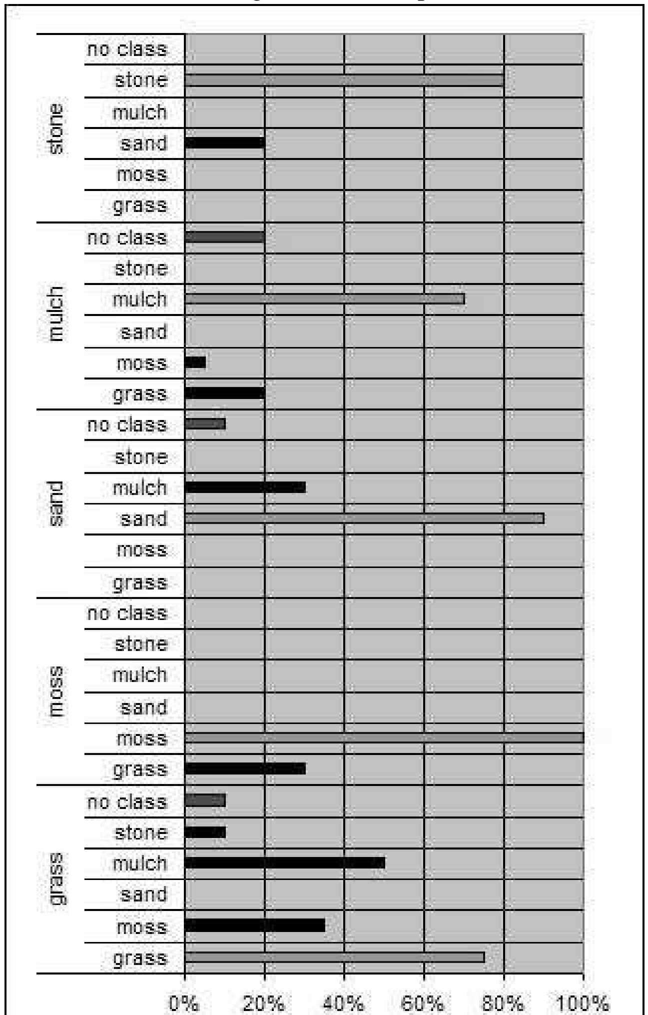



Fig. 9: Classification result using a lookup-table.
Correct classification (green)
Incorrect/multiple classification (black)
No classification (red)

The results show that certain materials were not uniquely classified [Fig. 9]; instead the measurement outcome was assigned to multiple materials in the lookup-table at the same time. This is because the characteristics of certain materials coincide [Fig 8]. However, this is not surprising, because these materials are very similar. Sometimes, measurement outcomes were not able to be assigned to any of the materials in the lookup table. In this case, the k-nearest neighbors algorithm assigned it to the material with the closest characteristics. After applying this algorithm, ISIS showed the following overall performance:

Table 5: Results of the advanced recognition test (including k-NN) (performed 3 times in total)

| Overall Performance (between Sample and N/A) | |
|---|---|
| Correct<br>(Correct material found,<br>multiple classifications possible) | 85 % |
| Incorrect<br>(Incorrect material(s) only found) | 15 % |
| *Comparing to random guess* | 20 % |

Table 6: Performance details

| Percentage of correct classified materials | | | | |
|---|---|---|---|---|
| Grass | Moss | Sand | Mulch | Stone |
| 75% | 100% | 100% | 70% | 80% |

ISIS shows valuable results for applications that do not require distinguishing between materials of similar physical characteristics [Table 5][Table 6]. For example a certain gait of a robot might perform on grass as well as on mulch and just needs to distinguish between stone and grass/mulch. However, if it is required to distinguish between similar materials (e.g. mulch/grass), further improvements are needed to raise the overall performance into the 90% zone.

In comparison to the surface recognition approach of Carnegie Mellon University (84.9%, total of three surfaces), ISIS distinguished between a total of five surface materials and scored a similar overall performance (85%).

## V. FIELDS OF APPLICATIONS

The project idea was initially developed to let autonomous robots optimally adjust their gait to the given surface. ISIS provides required surface information to a robot by analyzing knocking data continuously. However, navigation with adjusted gait (mobility) and grasping strategy (manipulation) are only two of several fields of applications. ISIS can also be used for:

**Exploration:** ISIS can simply be used for getting feedback about the physical characteristics of the surface material, without classifying it: Hardness, elasticity and stiffness can be shown on a scale from 1 to 10, without classifying the surface material with a lookup table. This information might be a useful feedback for an exploration robot, if its primary goal is not necessarily to adapt its gait to the surface.

**Error-Correction:** ISIS can be used to tackle the positional error inherent in odometry [3]. Knowledge about the surface material provides information about how high the rate of error accumulation for dead-reckoning might be. It is possible to determine how often localization and sensor data acquisition must be performed to navigate a robot.

**Learning by accident:** A robot falls over because its gait parameters are not sufficiently adjusted to the given surface. ISIS provides feedback to a learning algorithm which let the robot change certain gait parameters when moving on this surface.

**Quality control:** Knocking on materials while achieving continuously equally physical characteristics each time.

## FUTURE IMPROVEMENTS AND CONCLUSION

The reliability of ISIS to correctly recognize one out of five different real-world surface materials is 85%. In order to provide helpful surface information to a robot application, it might be advantageous to achieve an even higher rate of correctly classified surfaces. There are many additional adjustments which could improve the classification process of ISIS. A possible way might be to extract more useful information from the measurement graph, e.g. to evaluate the speed of incline in phase 3. Increasing the sampling rate and resolution of the accelerometer might also improve the accuracy of measurement values. In addition, if the application allows ISIS to perform multiple knocking measurements and simply averaging them instead of evaluating only a single measurement, ISIS might be able to distinguish between materials with a higher certainty.

With an increasing number of electronic devices being equipped with accelerometer sensors, the fields of application for accelerometer sensors are also increasing. Focusing on robotics, accelerometers could more and more be used for control and monitoring tasks to provide feedback information to robot applications in future. By performing valuable surface recognition, we hope that ISIS made a contribution to this development.

## ACKNOWLEDGMENT

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