ABSTRACT
The US Army designed Experimental Unmanned Vehicle (XUV) [1], shown in Figure 1, is a semi-autonomous unmanned ground vehicle (UGV) that uses high fidelity sensors for reconnaissance, surveillance, and target acquisition. One of the goals of XUV research is to develop autonomous mobility that enables the vehicle to maneuver over rugged terrain as part of a mixed manned and unmanned vehicle group. As part of this goal, the XUV must be able to autonomously navigate over different terrains at high speeds. The performance of autonomous navigation improves when the vehicle’s control system takes into account the type of terrain on which the vehicle is traveling. For example, if the ground is covered with snow a reduction of acceleration is necessary to avoid wheel slip. Previous researchers have developed algorithms based on vision and digital signal processing to categorize the traversability of the terrain. Others have used classical terramechanics equations to identify key terrain parameters. This paper presents a novel algorithm1 that uses the vehicle’s internal sensors to qualitatively categorize the terrain type in real-time. The algorithm was successful in identifying gravel, packed dirt, and grass.

KEY WORDS
Mobile robot, terrain identification, neural network, pattern classification, pattern recognition, and XUV.

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2. Existing Methodologies
Howard, Seraji, and Tunstel of Jet Propulsion Laboratory (Caltech) [2-5] created a vision based algorithm for assessing the traversability of the terrain for robotic vehicles. Their four traversability characteristics, roughness, slope, discontinuity, and hardness are determined by digitally processing extracted images of the approaching terrain. Then the traversability characteristics are combined to form a fuzzy traversability index that quantifies the ease of travel over the terrain by the mobile robot.

Karl Iagnemma and Steven Dubowsky of MIT developed a terrain parameter identification algorithm based on an analysis of wheel-terrain interaction [6, 7]. The authors state that wheel-terrain interaction plays a decisive role in rough-terrain mobility. In their algorithm the key terrain parameters are calculated in real time using on board sensors. The algorithm relies on a simplified form of classical terramechanics equations and uses a least squares estimator to efficiently compute the terrain parameters in real time.
The algorithm from the Jet Propulsion Lab is best described as an obstacle avoidance algorithm because its results are used to pick the most easily passable path. Furthermore, the algorithm uses vision sensors, which can be problematic in low light conditions and where the scene is rather homogenous. The algorithm by Iagnemma and Dubowsky does focus more on the character of the terrain, but the means, measuring the amount that a wheel sinks into a laboratory soil bed, is unlikely to transfer to real-time implementations on mobile robotics. Unlike these algorithms, the goal of our research is to qualitatively determine the type of terrain.

3. Algorithm Development

To find out what humans detect when traveling over different terrains, a consumer sports utility vehicle (SUV) was driven over different terrains at low to moderate speed. We found that wheel slip and vehicle vibration are key characteristics for discriminating between terrains such as gravel, packed dirt, asphalt, and grass. At the time, we did not have the ability to measure wheel slip on our robotic platform, so we decided to further investigate the applicability of vibration alone to classify terrain.

Using ADAMS dynamic simulation software [8] we simulated terrain-induced vibrations on a mobile ground robot. We modeled the surface as a flat plane with bumps spaced at regular intervals. Our goal was to determine how to characterize the simulated terrain based on the model’s induced z-axis acceleration.

The model robot was made to travel at speeds of 1250, 2500, and 3750 mm/sec over terrains made up of triangular shaped bumps 20mm tall with 10,000mm between them. The acceleration data in the Z direction was collected and the FFT of this data was taken.

We discovered that the FFT of the z-axis acceleration, while speed dependent, was unique to the terrain type. We experimentally verified the uniqueness of z-axis acceleration based FFT’s by driving an ATRV-Jr mobile robot over a terrain test track made up of grass, dirt, and gravel (Figure 2). Our next step was to develop a classification strategy for the FFT signals.

4. Terrain Identification as Pattern Classification

Identifying a particular terrain from an FFT signal is a pattern classification problem. Generally, in pattern classification, predefined pattern classes are presented to a computer algorithm, and future patterns are classified into one of the classes. The classification process is sometimes referred to as supervised pattern recognition and can be accomplished using a neural network [9, 10]. There are several types of network architectures that can be used for pattern identification. One, called the probabilistic neural network or PNN (Figure 3), is gaining in popularity because it learns quickly in one pass without the need for traditional training [11-13].

A PNN asymptotically achieves the Bayes-optimal decision boundary. It is based on the Bayes classifier method where the conditional probability density functions of the type \( P(c_j | x) \) are estimated using the Parzen windows approach. Parzen showed that a class of probability density function estimators asymptotically approaches the underlying density provided that the density is smooth and continuous.

Parzen’s estimation amounts to approximating the pdf’s as a weighted sum of Gaussian pdf’s centered at the class training points provided,

\[
P(c_j | x) = \frac{1}{(2\pi)^{d/2} \sigma^d} \frac{1}{n_j} \sum_{i=1}^{n_j} \exp \left( -\frac{(x-x_{ij})^T (x-x_{ij})}{2\sigma^2} \right)
\]
where $M$ is the dimensionality of input patterns $n_j$ is the number of training patterns belonging to class $c_j$, $x_{ij}$ represents the $i$-th training pattern from class $c_j$ and $\sigma$ is the smoothing parameter.

Important with a PNN is the selection of the correct value for the smoothing operator. The method of cross-validation [11] is generally used for proper selection of this operator. In practice the first smoothing value is picked randomly. If the resulting pattern classification does not produce the desired results the smoothing value is modified slightly and the neural network is re-tested. This procedure is continued until the PNN produces the desired results.

One advantage of the PNN is that training is instantaneous making it preferable for real time applications. When a pattern representing each category has been observed, the network can begin to categorize all future input patterns. Another practical advantage is that a PNN operates without the need for feedback from the output neurons. The shape of the decision boundaries can be made simple or complex by varying the smoothing parameter, and since the decision surfaces approach the Bayes optimal, which is optimal with respect to the miscalculation rate, the PNN is more able to tolerate erroneous samples and work from sparse samples.

5. Algorithm Overview and Experimental Results

Our algorithm is composed as follows. z-axis acceleration data is read from the INS at the rate of 100 Hertz and a Fast Fourier Transform (FFT) of the data is performed to determine the frequency content of the signal. This frequency information is the terrain signature, and it is fed to the probabilistic neural network (PNN). To date the network can recognize three terrains: grass, packed dirt, and gravel.

To present the PNN with data representing the three terrains, a test bed (Figure 2) was built at our college of engineering. It is 1.5 m wide and comprised of four sections 10.0 m long of gravel, packed dirt, sand, and grass. At that length, we can collect 10 sec of data in each section from our test vehicle traveling at its top speed. Our test vehicle is an ATRV-Jr from iRobot a photo of which on the test bed is shown in Figure 4.

To generate data classes for the PNN, the ATRV-Jr traveled over gravel, packed dirt and grass at speeds of 0.2 m/sec, 0.4 m/sec, 0.6 m/sec, and 0.8 m/sec. Acceleration data was recorded for 10 seconds at 100 Hz. A FFT was taken of the acceleration data. The resulting acceleration vectors had 1000 elements. The frequency data was then presented to the PNN for classification.

The acceleration data had to be classified as gravel, packed dirt, or grass using a trained probabilistic neural network (PNN). There was a minimum of twelve training vectors for each surface since the network needed to classify three terrains at four different speeds. We found that using two vectors per surface per speed (i.e. 24 vectors) provided good results. It was noted earlier that the smoothing parameter is adjusted to improve the classification results in the case of the PNN. We found that a smoothing factor of 0.1 produced the best results.

The resulting z-axis acceleration data for gravel is shown in Figure 5 below. While these plots differ somewhat in magnitude for the three surfaces, they otherwise appear identical. When the FFT’s are taken, significant differences are apparent in the frequency range of 10-20 Hz. Since it is also desirable to reduce the length of the pattern vectors presented to the PNN, only the FFT data in the 10-20 Hz range was used for terrain identification. The FFT’s in this range for the three terrains at four different speeds are shown in Figure 6 - Figure 8.

The FFT for gravel-induced acceleration is plotted in Figure 6. The shape of the signal can be treated as the terrain signature for gravel. Note that the maximum magnitude occurs in the frequency range 10-12 Hz, and the frequency data is generally distributed in three lumps. These characteristics were specific to gravel.
The terrain is classified offline in Matlab and the result is presented in the form of bar charts. After the PNN had been “trained” by the presentation of the FFT signals above it was presented with a new yet unseen signal representing gravel. The PNN correctly identified the data set as gravel. The probabilities of this classification were 71.21% gravel, 3.47% packed dirt and 25.32% grass.

Next the PNN was presented with a set of ten vectors for gravel, grass, and packed dirt. The results are shown in Figure 9. From these results we observe that classification accuracy is better when the ATRV-Jr is traveling at higher speeds. This result is understandable considering that the algorithm is a function of the z-axis vehicle acceleration that is more pronounced at higher speeds.

Our terrain identification algorithm has several noteworthy features. It is capable of real-time terrain identification on a mobile robot using only the internal sensors that would be part of any basic sensor suite; in our case we use the inertial navigation sensor (INS), and in the future, we plan to use the wheel encoders to include wheel slip measurements. Because perception sensors are not used, the drawbacks of vision-based schemes including a large computational expense are avoided.

6. Conclusions and Future Work

From the experimental results shown we believe that vehicle vibration analysis can be utilized for terrain estimation. The PNN based classification learns in one pass and is not computationally expensive. Our immediate goal is the addition of wheel slip readings into the PNN data classes. We believe that measuring wheel slip along with vehicle vibration will increase the robustness of our algorithm and enable us to differentiate between a larger set of terrain types. We are also interested in developing an autonomous drive controller that can safely maintain
higher speeds and accelerations when provided with knowledge of the terrain.

**Disclaimer**

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**References:**

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