

# Experience Based Surface Discernment by a Quadruped Robot

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**Abstract**—The task of autonomous surface discernment by an AIBO robotic dog is addressed. Different surface textures (plywood board, thin foam, short carpet, shag carpet) as well as different inclines (0 and 10 degrees) are considered. Using a genetic algorithm, gaits are designed which allow the robot to traverse each of these surfaces in an (approximately) optimal fashion. Frequency domain analysis of actuator readings from individual leg joints is performed for data collected using each gait on each surface type. It is found that the spectral content of these signals is significantly dependent on the characteristics of both the gait in use and the surface being walked upon. Using tap-delay Adaline neural networks to integrate actuator readings from 15 independent joints into a set of models of different gait/surface *experiences*, an algorithm is designed which uses these experiences to yield high classification rates across surface transitions and with low latency.<sup>1</sup>

## I. INTRODUCTION

Biped and quadruped locomotion is a feat that has proven difficult to reproduce in a robotic medium. Even a seemingly simple task such as designing a four-legged robot that can walk efficiently across a flat, smooth surface is a daunting engineering challenge. At a first glance, this task may seem simple because we humans are so adept at it. Not only can we walk across a smooth surface, but we can run, skip, hop, or jump. We can modify each of these gaits to optimize certain qualities such as speed, energy expenditure, smoothness, or stability. Furthermore, we can do all of this in real-time on a surface that has continually changing qualities such as penetrability, friction, incline, and even obstacles.

When framing the task of robotic gait selection as a constrained optimization problem, one can consider both internal and external constraints. Internal constraints include the robot's mechanics, the range of available controls, and locomotion optimality criteria. External constraints include surface qualities and obstacles that must be accounted for in the optimization procedure. Together, these constraints define the problem *context*. Sometimes, certain aspects of the context must be *discerned* as part of the decision/control process. This is true of gait selection, where discernment of surface qualities is a key requirement for an autonomous robot intending to operate efficiently over a range of external environments.

From an engineering perspective, context discernment can be framed as a system identification problem, where the goal is to estimate selected model parameters that are relevant to the design or selection of a control policy for the system.

The Kalman Filter has famously been applied to the context discernment problem for systems whose dynamics can be described with a linear or linearizable state based model [1][2]. We propose, however, that context discernment can be addressed/enhanced by the accumulation of an intelligent agent's *experience* with its environment. Adaptive Critic Reinforcement Learning methods [3] have previously been applied to explore experience based context discernment in toy problems [4][5][6]. While this paper does not explore the learning phase of the autonomous accumulation of experience, it does show how experience can be leveraged in a real world robotic application for the task of context discernment.

This paper describes a surface discernment process for a quadruped robot. The range of surfaces considered includes four flat (zero inclination) surface types: plywood board, thin foam, short carpet, and shag carpet. In addition, a discernment task between a flat plywood board and inclined plywood board (inclined 10 degrees) is considered. A genetic algorithm (GA) was used to generate gaits (one per surface type and inclination) that allow the robot to traverse these surfaces in an (approximately) optimal fashion, as defined by our optimality criteria.

The robot used is a Sony AIBO ERS-7. This robotic platform was chosen primarily due to its ubiquity within the scientific community and the availability of open-source development tools. Due to the relatively small size of this robot, the performance of any individual gait differs substantially over the range of surface types considered in the experiments. In order to navigate across these surfaces in an (approximately) optimal fashion, it is necessary to reconfigure the walking behavior as new surfaces are encountered. Because of this, surface discernment by the AIBO is critical if it is to achieve (reasonably) optimal performance as it transitions from one surface type to another.

Researchers have explored various forms of surface classification for mobile robots. For example, in the case of an autonomous wheeled vehicle, stereo visual imaging and single-axis ladar imaging has been used for long and short distance obstacle detection (respectively) and terrain classification [7]. For legged robots, the legs themselves have been used as probes for sensing material properties like penetrability, friction, and surface roughness while walking; these attributes have been measured using specialized sensors in a robotic leg-ankle-foot system [8]. Surface classification for the Sony AIBO has been addressed by statistical classification of read-

<sup>1</sup>This work was partially supported by NSF Grant ECS-0301022

ings gathered from the AIBO's internal accelerometers [9] and through the use of acoustic cues [10]. In one of Sony's bipedal robots, the QRIO, surface conditions and slope are determined using four pressure sensors in the sole of each foot to gather data on the amount of force being received from the walking surface. This allows the QRIO to adjust to disparities in elevation up to 1 cm, and slopes up to 10 degrees.

It is compelling to pursue the idea put forth in [8] that information about surface characteristics can be gathered by the very legs providing the locomotion. While visual and other contextual information (weather, time of year, past experiences) may provide valuable data for the classification task, physical contact with the surface itself provides the final word. In general, it would not be desirable to require a special gait for the purpose of probing the surface; it would be significantly better if the necessary information could be gathered through the normal walking behavior of the robot (gaits optimized for locomotion, not for surface discernment). This complicates the classification task, since surface discernment becomes dependent on the current gait in use. The approach used for the QRIO is not possible with the AIBO because the AIBO has only one pressure sensor on each foot and this sensor only records binary data (on/off). On the other hand, for the AIBO, continuous readings can be gathered from the 15 joint sensors within the dog (3 for each leg and 3 for the head).

Through spectral analysis of measurements from these sensors, it is shown that there is statistically significant information buried within these signals relevant to the surface discernment task. Because of non-stationarities in these signals due to surface irregularities (carpet pile directions, seams, etc.) and the dynamics of locomotion (swaying, jerking, etc.), it is necessary to incorporate considerable periodogram smoothing and lengthy periods of data collection (~60s) to perform the surface discernment task using features derived from spectral estimation alone. Since the goal is to be able to quickly (~3-5s) identify new surfaces as they are encountered, this approach is unacceptable.

To overcome this complication, tap-delay Adaline neural networks were used to model the dynamic *experience* of each joint for each gait/surface combination, resulting in an integrated model of the gait/surface experience. Surface classification is then performed by seeing which gait/surface model provides the best fit. With this novel approach, high classification rates (92-100%) are possible in a much shorter period of time (~1-4s).

## II. METHODOLOGY

### A. The Development Environment

The interface to the AIBO was implemented using the Tekkotsu framework; an open-source AIBO software development platform designed at Carnegie Mellon University [11]. The default Tekkotsu gait has the AIBO walking on its forearms with its hind legs fully extended. This gait is popular because it is stable, relatively fast, and works on different surface types. Furthermore, the showcase for autonomous AIBO development is the Robocup, where teams of AIBOs

compete in a soccer-like game. This gait is tailored to this competition, where being low to the ground is useful for trapping the ball. This gait was used as a starting point in the experiments reported here for developing more optimal (as defined through our criterion function) surface-specific gaits. Tekkotsu provides a set of Java classes which allow wireless communication with the AIBO from a remote computer. Additional Java classes and Matlab scripts were written to initiate the desired gait, collect the joint sensor readings, and perform the surface discernment task.

### B. Gait Generation

The primary focus of this paper is surface discernment using a range of gaits optimized for locomotion on specific surfaces - not the generation of the gaits themselves. In brief, the goal was to generate one gait for each surface type which is (approximately) optimal with respect to locomotion (the criteria function considered both gait speed and smoothness). We used a genetic algorithm (GA) to search the highly non-linear and multi-dimensional space defined by the gait parameters available in the Tekkotsu framework [12][13]. The process involved 30 individuals per generation and 6 generations, with Generation 0 representing the AIBO default walking parameters plus a normally distributed random number. This method found gait parameter values for each surface resulting in a significant improvement over the performance of the default Tekkotsu gait.

### C. The Data

Sensor data was gathered from each of the 15 joint sensors on the AIBO (3 for each leg and 3 for the head) while traversing each surface using each gait. Four surface types were chosen for the experiment: plywood board, thin foam, short carpet, and shag carpet. Four gaits (the ones generated through the GA) were also considered. Due to physical space constraints, each data collection run could span only 15 seconds. In order to balance the need for data and the cost (time) of collection, 10 data realizations were collected for each gait/surface combination.

The maximum sample rate for sensor data collection using Tekkotsu is 31.25 Hz (the actual sample rate for the AIBO is 125 Hz). To complicate our task at hand, it was found that there is a significant amount of jitter present in this sample rate (up to 1/5 the inter-sample interval). Furthermore, due to limitations in the wireless communication between the workstation and the AIBO, samples are occasionally dropped. Because of these irregularities in the data stream, each sample received from the dog is time stamped before it is sent. Piecewise cubic Hermite interpolation was performed to resample the signal at a constant 31.25 Hz. The mean was then removed from each signal for further processing.

### D. Spectral Analysis

A periodogram of the joint actuator signal was calculated for each realization of each gait/surface/joint combination. Each periodogram was calculated using a Hamming window (note:

the use of a non-rectangular window technically makes this a *modified* periodogram).

The Welch method for periodogram smoothing was applied to the joint actuator signal for each gait/surface/joint combination of each of the  $N$  data realizations recorded. In the Welch method, each realization is divided into  $K$  segments of length  $L$  and overlap  $M$ . The segment overlap was fixed to be  $L/2$ . The Welch-Bartlett method was then applied by averaging the  $N$  Welch smoothed periodograms.

The upper and lower estimated confidence intervals for the Welch-Bartlett method are given by

$$\left[ \frac{\hat{R}_x^{(WB)} D}{\chi_D^2(1 - \alpha/2)}, \frac{\hat{R}_x^{(WB)} D}{\chi_D^2(\alpha/2)} \right] \quad (1)$$

where  $\hat{R}_x^{(WB)}$  is the Welch-Bartlett smoothed periodogram and  $D$  is the degrees of freedom of a  $\chi^2$  distribution [14]. For the Welch-Bartlett method,  $D$  is given by  $2KN$ , where  $N$  is the number of realizations,  $K$  is the number of segments per realization used for the calculation of the smoothed Welch periodograms, and the product  $KN$  is simply the total number of segments whose modified periodograms are being averaged.

The segment length  $L$  used for the periodogram calculation was adjusted with the goal of maximizing the confidence in these estimates. Because of this, more smoothing was performed than if the goal had been to minimize, for example, the mean squared error of the spectral estimation.

#### E. Actuator Signal Modeling

To model the signal generated by a joint actuator for a particular gait/surface/joint combination, a tap-delay Adaline neural network was used resulting in a linear forward prediction model:

$$\hat{x}(n) = \sum_{k=1}^M a(k)x(n-k) \quad (2)$$

where  $\hat{x}(n)$  is single step-ahead prediction,  $[x(n-1), x(n-2), \dots, x(n-M)]$  are past values of the signal,  $a$  is the weighting sequence for the model, and  $M$  is the length of the weighting sequence (the model order or number of tap delays). This simple, linear model was chosen to model the actuator signals because there is a unique analytical solution which minimizes the mean squared error (MSE) of the model over the training set, where MSE is defined as

$$\text{MSE} = \frac{1}{N} \sum_N (x(n) - \hat{x}(n))^2 \quad (3)$$

The  $a$  which minimizes the MSE is given by the solution to the normal equations

$$Ra = d \quad (4)$$

In the case of the forward linear predictor,  $R$  and  $d$  are found in the following manner:

- 1) Remove the estimated mean of the signal.
- 2) Extract each  $M+1$  length sequence out of the length  $l$  signal being modeled and collect them in a  $(l-M) \times (M+1)$  matrix,  $P$ .

- 3) Calculate  $\bar{R}$ , the  $(M+1) \times (M+1)$  time averaged correlation matrix of  $P$ :

$$\bar{R} = \frac{1}{l-M} P^T P \quad (5)$$

- 4) Let  $R$  equal the matrix formed by collecting the first  $M$  columns of  $\bar{R}$ . This is the correlation matrix for the model inputs. Let  $d$  equal the  $(M+1)$ th column of  $\bar{R}$ . This is the correlation vector between the model inputs and the model outputs.
- 5) Solve for  $a$  in (4), where  $a = R^{-1}d$ .

Where  $r$  multiple data realizations of length  $l_r$  are used for the calculation, the  $P_r$  matrices formed from each realization in step 1) above are stacked on top of each other, resulting in a composite  $\bar{P}$  matrix with  $\sum_{i=1}^r (l_i - M)$  rows and  $M+1$  columns. Steps 2-4 are then applied to  $\bar{P}$  to solve for  $a$ .

#### F. Surface Classification

As the AIBO walks on one of the four specified surfaces using one of the four specified gaits, we can calculate the normalized mean squared error (NMSE) of each of the gait/surface/joint models for each sample period using

$$\begin{aligned} \text{NMSE}_{g,s,j}(n) &= \frac{1}{\sigma_{X_{g,s,j}}^2} (x_{g,s,j}(n) - \hat{x}_{g,s,j}(n))^2 \\ &= \frac{1}{\sigma_{X_{g,s,j}}^2} (x_{g,s,j}(n) - \sum_{k=1}^M a_{g,s,j}(k) \tilde{x}_{g,s,j}(n-k))^2 \end{aligned}$$

where  $g$  is the gait index,  $s$  is the surface index,  $j$  is the joint index,  $a_{g,s,j}$  are the model coefficients for the  $\{a, j, k\}^{\text{th}}$  model,  $M$  is the order of the models,  $\sigma_{X_{g,s,j}}^2$  is the variance of the  $j^{\text{th}}$  actuator signal using gait  $g$  on surface  $s$ , and

$$\tilde{x}_{g,s,j} = x_{g,s,j} - \bar{x}_{g,s,j} \quad (6)$$

where  $\bar{x}_{g,s,j}$  is the mean of  $x_{g,s,j}$  estimated over the model training data.

By finding the average NMSE over all of the actuator models for each gait/surface combination, we can get a measure of the instantaneous NMSE for each gait/surface model using

$$\text{NMSE}_{g,s}(n) = \frac{1}{J} \sum_{j=1}^J \text{NMSE}_{g,s,j}(n) \quad (7)$$

where  $J$  is the total number of joint actuator signals being modeled.

To smooth the instantaneous  $\text{NMSE}_{g,s}(n)$  signals, a moving average was performed in the temporal domain using

$$\overline{\text{NMSE}}_{g,s}(n) = \frac{1}{N} \sum_{k=0}^{N-1} \text{NMSE}_{g,s}(n-k) \quad (8)$$

For this experiment,  $\overline{\text{NMSE}}_{g,s}(n)$  forms a set of 16 signals (one for each gait/surface combination). Since this set of signals indicate levels of fit between the current actuator recordings of the AIBO and models of actuator recordings for

the 16 gait/surface combinations, we call this set of signals the *kinesthetic experience*,  $\hat{K}(n)$ , of the AIBO:

$$\hat{K}(n) \equiv \overline{\text{NMSE}}_{g,s}(n) \quad (9)$$

The hypothesis driving the classification task is that, for each given point in time, the gait/surface signal out of the kinesthetic experience which has the smallest magnitude (the best fit between current experience and all modeled experiences) will correspond to the gait/surface currently being experienced. To simplify the classification task further, the current gait being performed is known, meaning that we only need to consider the signals from  $\hat{K}(n)$  for the gait currently being employed. The surface classification signal,  $\hat{s}(n)$ , is discretely valued, with possible values corresponding to each of the surfaces used in the experiment.

### G. Model Calibration

In order to generate the kinesthetic experience  $\hat{K}(n)$  resulting from a stream of actuator data collected from the AIBO, the values of two meta-parameters had to be determined. These parameters are the number of delay taps  $M$  given in (2), and the number of samples  $N$  used in (8) to smooth  $\text{NMSE}_{g,s}(n)$ .

Values for these parameters were found empirically using a holdout cross-validation technique. For each gait/surface combination, 8 of the 10 data realizations were used in the calculation of the model parameters. These models were then used to calculate  $\hat{K}(n)$  for the remaining 2 data realizations. From  $\hat{K}(n)$ , the time dependent surface classification,  $\hat{s}(n)$ , was calculated.  $\hat{s}(n)$  was then compared to  $s(n)$ , the actual surface signal, in order to calculate the classification rate. Since the classification algorithm requires  $M + N + 1$  samples of the joint actuator data to make a decision, a data realization of length  $l$  from the dog will result in  $l - M - N$  individual classifications.

For the model parameter search, values of  $M$  ranged from 1 to 40, in steps of 1, and values of  $N$  ranged from 5 to 300 in steps of 5. A balance was sought which had a high classification rate (our primary performance criteria) yet small values of  $M$  and  $N$ , since not as many consecutive samples are required for each sample of  $\hat{s}(n)$ , which would provide for faster classification during surface transitions.

## III. RESULTS

### A. Spectral Analysis of Joint Actuator Data

Fig. 1 shows the results of the spectral analysis of the left hip joint actuator data while walking on the four flat surface types considered in this experiment. Only the gait optimized for use on the thin foam surface was considered for this figure. The top panel shows the periodogram estimates along with their 95% confidence intervals after 6 seconds of data collection. As can be seen, there is substantial overlap of the confidence intervals over the full frequency range considered. The bottom panel shows the same calculation after 60 seconds of data collection. In this case, there is little or no overlap of the 95% confidence intervals at the third harmonic peak (at  $\sim 4.5$  Hz). This gait/joint combination was chosen because the

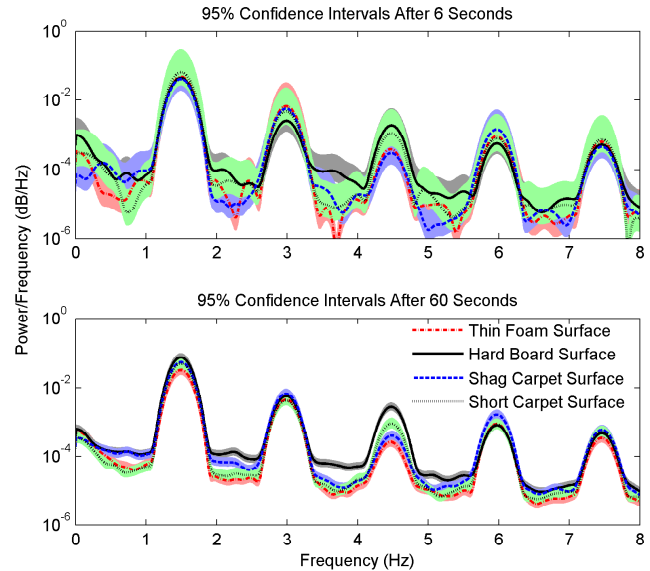


Fig. 1. Welch-Bartlett smoothed periodogram of the left hip joint actuator while walking on each of the four surface types. Note:  $\sim 60$  seconds of actuator data is required to reduce the 95% confidence intervals of the estimations to the point of little or no overlap.

spectral analysis indicated the least amount of overlap of the calculated confidence intervals, indicating that it may provide useful information for surface classification.

### B. Flat Surface Classification

The first classification task is to discern which of the 4 flat surface types is being traversed when using any of the 4 gaits designed for these surfaces. Classification rates of 100% on the holdout set are possible for appropriate choices of  $M$  and  $N$ , but this level of performance requires at least 10 seconds of data collection. A combination where  $M = 21$  and  $N = 100$  was chosen which resulted in a 92% classification rate on the holdout set and required just under 4 seconds of data collection.

Using the  $M = 21$ ,  $N = 104$  configuration, Fig. 2 shows  $\hat{K}(n)$  using the gait designed for the thin foam surface while traversing across each of the four surface types. Similar plots can be generated for each of the other gaits. The error signal corresponding to the thin foam gait and the particular surface being traversed is indicated by the weighted black line. In each of these cases, this error signal is also the minimum at each time step, indicating perfect classification. The data used in this example belonged to the holdout set (was not used in training the models used in the calculation of  $\hat{K}(n)$ ).

$\hat{K}(n)$  was also calculated for experiments where the AIBO traversed across surface type transitions while remaining in a fixed gait. Fig. 3 shows the results of a typical test where the gait designed for the short carpet was used as the AIBO transitioned from the short carpet to the shag carpet. The top pane of the figure shows  $\hat{K}(n)$ , comprised of the NMSE signals generated by models of each gait/surface combination.

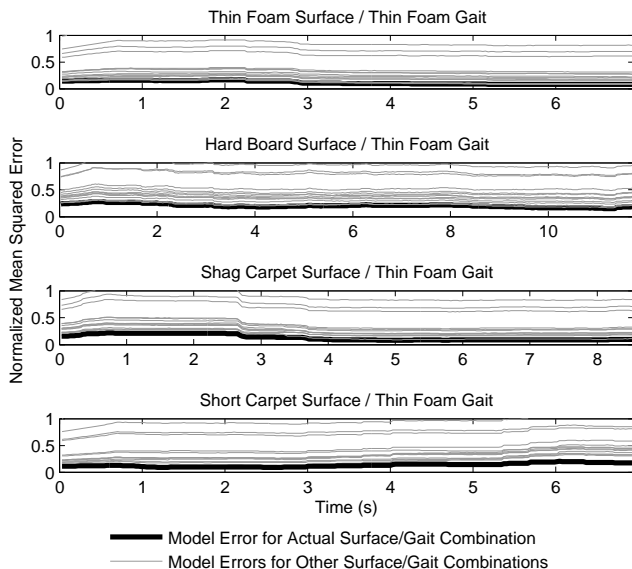


Fig. 2.  $\hat{K}(n)$  while traversing across each of the four surface types using the gait designed for the thin foam surface. Note: the error signal corresponding to the actual gait being used and surface being traversed is the minimum in each of these cases, indicating perfect classification.

The middle pane shows a rescaled version of the same data to make it easier to see the details of the two signals of interest (one corresponding to the initial gait/surface combination and one corresponding to the gait/surface combination after the surface transition). The lower pane of the figure shows  $\hat{s}(n)$ , the surface classification signal. As can be seen, correct classification of the transition occurs within 2 seconds of the time of transition. Here, the time of transition is the point at which all 4 legs of the AIBO are in contact with the second surface type.

### C. Incline Surface Classification

The second classification task is to discern whether the AIBO is traversing across a flat or inclined surface, while using either the flat surface or inclined surface gait. A combination where  $M = 2$  and  $N = 30$  was chosen which resulted in a 99% classification rate on the holdout set and required just 1 second of data collection.

Using the  $M = 2, N = 30$  configuration, Fig. 4 shows  $\hat{K}(n)$  for the AIBO using each of the two gaits (flat and incline) on each of the two surfaces. The error signal corresponding to the particular gait being used and surface being traversed is indicated by the weighted black line. In each of these cases, this error signal is also the minimum at each time step, indicating perfect classification. The data used in this example belonged to the holdout set.

Fig. 5 shows the results of a typical test where the gait designed for the flat surface was used as the AIBO transitioned from the flat to the inclined surface. The top pane of the figure shows  $\hat{K}(n)$ , comprised of the NMSE signals generated by models of each gait/surface combination. The lower pane of

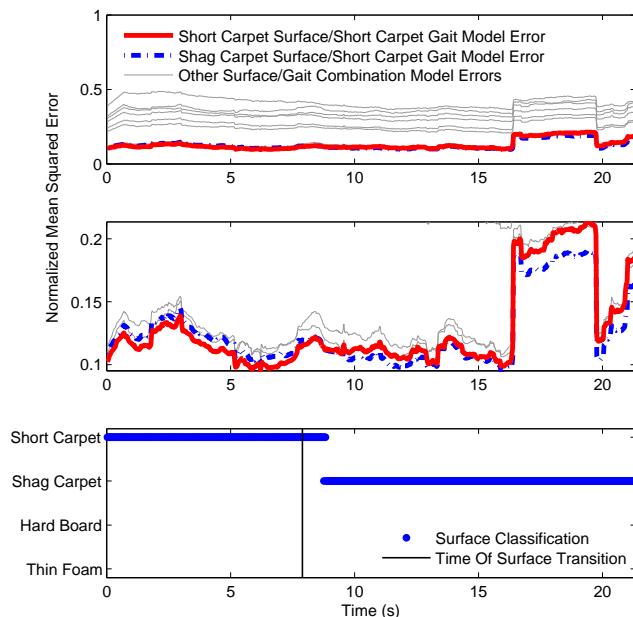


Fig. 3. Top Pane:  $\hat{K}(n)$  for the transition from short carpet to shag carpet using the gait designed for the short carpet. Middle Pane: magnified view of  $\hat{K}(n)$  to make visible the crossover of the two signals used to make the classification. Bottom Pane: the classification signal,  $\hat{s}(n)$ . Note: the new surface is correctly classified about 2 seconds after the transition.

the figure shows  $\hat{s}(n)$ , the surface classification signal. As can be seen, correct classification of the transition occurs within 1 second of the time of transition. Again, the time of transition is the point at which all 4 legs of the AIBO are in contact with the second surface type.

## IV. DISCUSSION

Several things were learned from the spectral analysis phase of this experiment. First, as exemplified in Fig. 1, there is statistically significant information present in the estimated spectrum of the joint sensors relevant to the task of surface discernment. A number of approaches were attempted which made use of the peak estimated power spectral densities (PSDs) of these signals directly. The most promising and successful attempts were based on clustering algorithms, such as Learning Vector Quantization (LVQ). Using LVQ and spectral estimates of the harmonic peaks from all 15 joints, it was possible to achieve classification rates approaching 80% on the holdout data. These classification rates were only achievable after 20 or more seconds of data collection - an unacceptable period of time for the classification task.

Some of this can be blamed on hardware and software constraints. The slow on-robot sampling speed (31.25 Hz) was exacerbated by the presence of significant jitter (deviations from a constant sampling rate) in the joint sensor readings and occasional missed samples. These obstacles may have been surmountable if not for the presence of non-stationarities in these signals due to surface irregularities (carpet pile directions, seams, etc.) and the dynamics of locomotion (swaying,

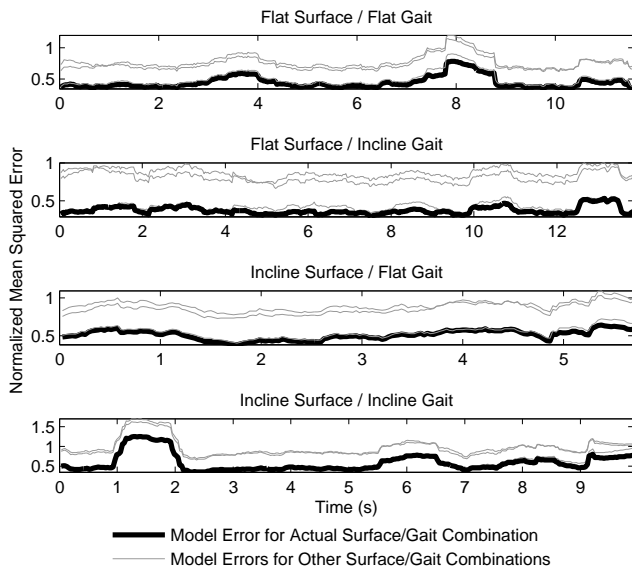


Fig. 4.  $\hat{K}(n)$  calculated for each of the two gaits (flat/incline) on each of the two surfaces (flat/incline). Note: the error signal corresponding to the actual gait being used and surface being traversed is the minimum in each of these cases, indicating perfect classification.

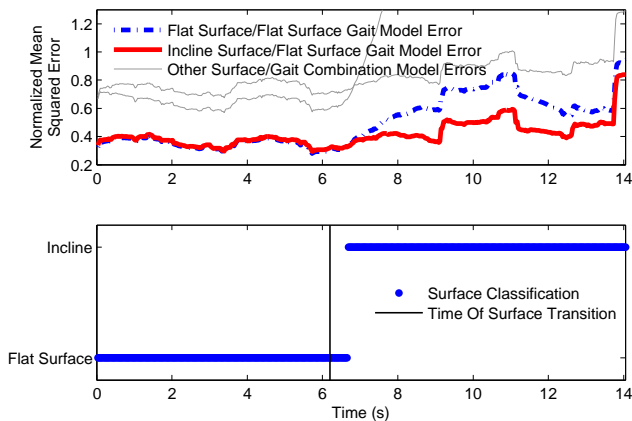


Fig. 5. Top Pane:  $\hat{K}(n)$  for the transition from a flat surface to an inclined surface using the gait designed for the flat surface. Bottom Pane: the classification signal,  $\hat{s}(n)$ . Note: the new surface is correctly classified within 1 second of the transition.

jerking, etc.). This created a large amount of variance in the PSD estimates (bad for clustering algorithms) that only excessive periodogram smoothing could address (requiring long periods of data measurement). Similar problems were encountered when using parametric approaches for spectral estimation (e.g. using a Kalman filter to estimate time varying parameters of an autoregressive signal model).

To overcome the problems inherent in parametric or non-parametric estimation, we opted to avoid the on-line estimation task completely, and instead chose to leverage the past *experiences* of the AIBO. Tap-delay Adaline neural networks were used to model the dynamic experience of each joint for each

gait/surface combination, resulting in an integrated model of the gait/surface experience. With this approach, given a short history of signal data, we don't need to estimate the spectrum of the signal or estimate the signal model parameters. Instead, we determine which modeled experience is the best fit, on (moving) average. This has the benefit that when unpredictable "events" occur, such as stepping on a seam in the shag carpet, nearly all of the gait/surface models are affected similarly. For example, the middle pane of Fig. 3 shows such an event at  $\sim 17$  seconds. Even though the prediction errors for all of the models changed drastically at this point, the classification (shown in the bottom pane) was steady throughout. Using this approach, classification rates higher than 92% (for the 4 gait / 4 surface task) were achievable in as little as 4 seconds.

This paper suggests an obvious research direction - to explore the real-time selection of optimal gaits as new surfaces are encountered and discerned by the robot. Initial experiments have been performed using the discrete gait/surface combinations outlined in this paper with promising results. Furthermore, we are exploring extensions to the methods used here to enable our robot to classify previously un-encountered surfaces and to generate an (approximately) optimal gait for this new surface by generalizing among previous gait/surface experiences and dynamically adding to the experience repository. We believe that efficient accumulation and exploitation of experience is central to these efforts.

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