7-15-2010

Classification and Identification of Environment Through Dynamic Coupling

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Keywords

legged robot, classification, dynamic behavior, tactile sensing

Disciplines

Controls and Control Theory | Electrical and Computer Engineering | Engineering | Robotics | Systems Engineering

Classification and Identification of Environment Through Dynamic Coupling

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I. Introduction

By definition all locomotors are inherently coupled to their environments. Whether a dog pushes against ground [1], or a fish undulates its body [2] or a bird flaps its wings [3], their actions cause reactive forces to be produced by their environment which in turn causes the displacement of the body. In essence, control of locomotion is the process of steering such reactive forces by proper application of actuation. Therefore, environment dynamics plays an important role in the locomotion process. Ability to identify environmental conditions can not only facilitate improvements in locomotion control but can also be employed in situational awareness supporting higher level tasks.

In this study our immediate interest is in terrestrial locomotion and we will limit our discussion to this area henceforth. However, the reader should note that arguments similar to the ones presented in this paper can be extended to other locomotive tasks.

A. Motivation

Typical terrestrial (natural) settings present significant variations in environmental conditions. Since we are concerned with locomotion in this discussion, we will be focusing on the mechanical properties, such as compliance, damping, roughness, penetrability and topology, that has strong impact on locomotive behaviors with respect to mobility and stability [4], [5].

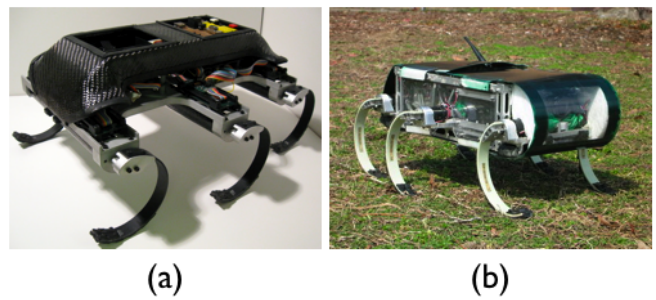

Fig. 1. EduBot (a) is a small form-factor and modular version of the RHex (b) robot.

Over the past decade a class of mobility platforms [6]–[10] has demonstrated [11] that hard locomotion tasks can be accomplished by the proper implementation of mechanical feedback [12] and well tuned task-level open-loop excitation schemes [13], [14]. Two examples of this class of robots are presented in Figure 1.

These machines in part owe their performance to their open-loop control strategy which requires a minimal sensory infrastructure that in turn leads to significantly simplified hardware and software implementations. The primary shortcoming in these systems is that gaits are built and tuned [13] for specific environment conditions and fail if these assumptions are not met. In earlier work [15] use of a specialized proprioceptive sensors in behavior adaptation was demonstrated. Recent studies [16], [17] offer further situational awareness but still capturing only a limited spectrum of environmental characteristics.

A robust characterization of mechanical properties of the environment can offer great advantages to behavior developers. Such information can be used to tune parameterization of the active gait to preserve energetic efficiency [13], improve behavioral stability [9] and extend addressable domain [15]. In fact studies on humans have demonstrated that people carefully monitor the mechanical properties of the ground and adjust their behavior accordingly [18]–[20].

Another potential use for the ability to identify environmental conditions can be found in the map building and path planning applications. Mechanical properties (compliance, damping, friction) of the surface, which is often hard or infeasible to measure, are distinct characteristic that can serve as a robust labels for map building algorithms. For instance, knowing whether the robot is on carpet or linoleum can render a situation, that is otherwise undistinguishable, a manageable localization task.

B. Related Work

The importance of the mechanical properties of ground in the context of terrestrial locomotion was recognized in earlier legged robotics research performing off-line lumped model fitting studies on certain ground scenarios [21]. More recent studies aim to develop phenomenological models for more complex granular media dynamics [22] has made strong connections to biology [23] and robotics [24], [25].

The literature on on-line locomotive procedures to measure ground conditions and adopt locomotive gaits also has a long history. In the earlier implementations [26], [27] robots performed a list of *exploratory procedures* intertwined with the actual locomotive actions to pseudo-simultaneously identify surface parameters and adapt the gait. While successfully demonstrating the multi-purpose utilization of legs [28] as a sensor and propeller, the iterative approach these systems employ severely limited their locomotive performance. In more recent work with a class of dynamic hexapods [15]–[17], [29] researchers demonstrated situational awareness and gait adaptation embedded within the gait without the use of specialized exploratory procedures and without specialized sensory hardware.

Remote sensing for surface characterization such as the use of vision [30] has also been investigated by robotic researchers. However, the complexity of natural environments coupled with the difficulty of assessing mechanical properties from appearance severely limits their efficacy.

C. Contribution

In contrast to some of the earlier work [26], [27] our focus in this study is not accurate measurement of surface parameterization. Nor we are interested in reactive adaptation of gait control [16], [17], [29]. Instead our work aims to 1) recover sufficiently expressive markers for encountered environmental conditions; 2) perform such measurements in real-time; 3) distinguish/classify different environments using such markers; and 4) perform all these services without requiring any change in the locomotive gait or hardware (sensor/actuator composition).

The ability to classify environmental conditions can serve as a key component in a wide range of applications. Coupled with external direct measurements for each known environment marker the classification can provide indirect measurements of hard to obtain mechanical properties. Another use for environmental classification can be found in map building and path planning applications where unique markers associated with each distinct environmental condition can server as a new and powerful set of labels.

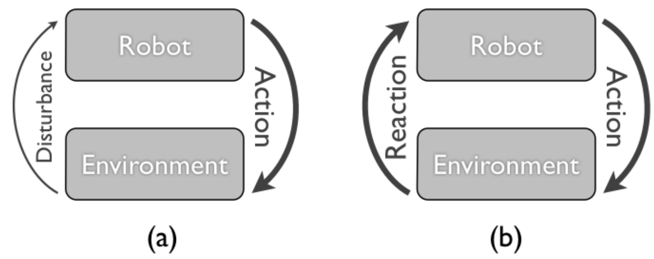

Fig. 2. (a) Classical control design treats environmental reactions as disturbance. (b) A physically relevant robotic behavior is the result of the interactions between the actuation actions of the robot and the reaction of its environment.

The organization of this paper is as follows. In Section II the basic idea behind the environment classification using the dynamic coupling between the robot and its environment will be introduced. The same section will outline a high level algorithm for the classification problem. Section III introduces Biped RHex model—a numerical model that captures a reduced sagittal dynamics of a class of hexapod robots [6]. In Section IV we present environment classification results from numerical experiments with the Biped RHex in the presence of a given match table. Section V extends the implementation into a dynamic setting where the match table is build simultaneously as the environment classification is performed. Section VI will conclude with final remarks on strengths and shortcomings of the presented method.

II. The Concept

A. Limit Behavior and Environment

In a classical setting, analysis of a control problem typically focuses on the mechanism of interest while ignoring most environmental conditions, considering them as disturbance that is to be suppressed and/or even ignored if sufficiently small. Although such an approach lends itself to convenient approximations for the engineering effort, it inherently locks the implementation into a constrained design space.

In contrast, we observe that the *physically unavoidable coupling* between a mechanism and its environment can in fact present unique control and sensing opportunities for a design. We note that the behavior of a controlled mechanism *emerges* from (active and passive) actuation actions interacting with the environment. In our formulation we emphasize this environmental dependency where the closed-loop system dynamics in Equation 1 is explicitly parameterized[1] by both robot, $\mathbf{r}$, and environment, $\mathbf{e}$, related parameters,

$$\dot{\mathbf{x}} = \mathbf{g}(\mathbf{x}, \mathbf{r}, \mathbf{e}). \tag{1}$$

Consequently, the evolution of the closed-loop system states[2], $\mathbf{g}^t(\mathbf{x}_0, \mathbf{r}, \mathbf{e})$, is a differentiable function of the parameterization of both the robot, $\mathbf{r}$, and the environment, $\mathbf{e}$, as well

[1] In this discussion we will assume that the parameterization is continuously differentiable. Physical systems will satisfy this condition.

[2] The solution to Equation 1.

as the initial condition, $\mathbf{x}_0$. It directly follows that for stable systems the positive limit set of Equation 1 (the *steady-state behavior*) is also characterized in part by the environmental conditions as captured by its parameterization, $\mathbf{e}$.

$$\mathcal{G}^*(\mathbf{r},\mathbf{e}) := \left\{\mathbf{x}_0 \in \mathcal{X} | \mathbf{g}^{t\rightarrow\infty}(\mathbf{x}_0,\mathbf{r},\mathbf{e})\right\} \tag{2}$$

This inherent intimate coupling between the steady-state behavior of the closed-loop system, $\mathcal{G}^*$, and the environmental conditions, $\mathbf{e}$, is the basis of the work presented in this paper. We posit that one can classify and identify environmental conditions by observing the steady-state behavior of the system as the task level control actions kept unchanged. In such a setup any variation in the steady state behavior, $\mathcal{G}^*$, would be attributed to a change in the environmental conditions, $\mathbf{e}$, since the controllable robot parameterization, $\mathbf{r}$, remains constant.

Although the generic argument above considers the full states of the closed-loop system, $\mathbf{x} \in \mathcal{X}$, in many cases *partial* observations, $\tilde{\mathbf{x}} := P(\mathbf{x}) \in \tilde{\mathcal{X}} \subset \mathcal{X}$, can be used to determine changes in steady-state behavior, $\mathcal{G}^*$. This feature of our approach is the key enabler in most practical implementations where only partial observational affordance is available.

B. Classification Process

In this section we will provide a high level algorithmic overview of environment classification based on observed behavior.

We consider a locomotor system that has a unique asymptotically stable period-1 limit cycle. We assume that the system maintains its asymptotic stability (although the actual limit set will change) across all environmental conditions it will be presented to. Finally, we also assume that the environmental conditions vary in a piece-wise constant manner.

The classification process associates each environmental setting, $\mathbf{e}_i$, with a particular limit behavior, $\mathcal{G}_i^*$, preconditioned to system being in steady-state operation. The process is an repetitive application of two steps: 1) identify steady-state condition explained in Section II-B1; and 2) environment lookup covered in Section II-B2.

1) Stability Condition: Since the environment classification employs limit behaviors as markers it can only operate when the system is in steady-state. The first step uses the Cauchy condition over the Poincare sample sequence, $\{\mathbf{p}_i\}_{i=0}^N$, of the system flow, $\mathbf{g}^t(\mathbf{r},\mathbf{e})$, to determine 1) if the system behavior has reached a limit; or 2) if environmental conditions has changed.

Poincare sequence, $\{\mathbf{p}_i\}_{i=0}^N$ is a series of projected[3] discrete samples, $\{\mathbf{x}_i\}_{i=0}^N$, of the system state flow, $\mathbf{g}^t(\mathbf{x}_0,\mathbf{r},\mathbf{e})$, taken when the flow intersects (in a certain direction) with a chosen manifold, $\mathcal{X}_\mathcal{P} \subset \mathcal{X}$. As a direct consequence of uniqueness of solutions to differential equations[4] a limit cycle in the continuous state space, $\mathcal{G}^* \subset \mathcal{X}$, corresponds to a fixed point in the Poincare space, $\mathbf{p}^* \in \mathcal{P}$.

Hence, to test if the continuous time system has reach its limit behavior, $\mathcal{G}^*$, we simply need to check if the Poincare sequence, $\{\mathbf{p}_i\}_{i=0}^N$, has reach its corresponding fixed point, $\mathbf{p}^*$. However, neither the limit cycle nor the corresponding Poincare fixed point can be known/computed a priory in typical scenarios. Instead, we compute the pair-wise Euclidian distance of consecutive Poincare samples,

$$d_i := ||\mathbf{p}_i - \mathbf{p}_{i-1}||_2\,, \tag{3}$$

and check if $\{d_i\}_{i=0}^N$ is monotonically decreasing and reaching to a close neighborhood of zero, $d_{i\rightarrow\infty} \in B_\epsilon(0)$, which signals that the system has reached to its steady-state behavior.

Conversely, any abrupt increase in the distance sequence, $\{d_i\}_{i=0}^N$, signals a disturbance. In the absence of any change in the task level control or any other robot parameterization, $\mathbf{r}$, such a change implies that there has been a change in the environmental conditions, $\mathbf{e}$.

2) Matching: In steady-state regime state flow, $\mathbf{g}^t(\mathbf{x}_i,\mathbf{r},\mathbf{e})$, of a system with a period-1 orbit traces its entire limit cycle, $\mathcal{G}^*$, between two consecutive Poincare samples, $\{\mathbf{x}_i,\mathbf{x}_{i+1}\}$. Therefore, during steady-state operation the state flow recorded between consecutive Poincare sample events, $\left\{\mathbf{g}^t(\mathbf{x}_{i-1},\mathbf{r},\mathbf{e})\,|\,t \in \left[t_{\mathbf{x}=\mathbf{x}_{i-1}}, t_{\mathbf{x}=\mathbf{x}_i}\right)\right\}$, can serve as a perfect (time parameterized) surrogate for the limit cycle, $\mathcal{G}^*(\mathbf{r},\mathbf{e})$,

$$d_i = 0 \Rightarrow \mathbf{g}^t(\mathbf{x}_{i-1},\mathbf{r},\mathbf{e}) \in \mathcal{G}^*(\mathbf{r},\mathbf{e}),\ \forall t \in \left[t_{\mathbf{x}=\mathbf{x}_{i-1}}, t_{\mathbf{x}=\mathbf{x}_i}\right) \tag{4}$$

which will be referred as the "marker,"

$$\mathbf{m}_i^t := \mathbf{g}^t(\mathbf{x}_{i-1},\mathbf{r},\mathbf{e}) \text{ where } t \in \left[t_{\mathbf{x}=\mathbf{x}_{i-1}}, t_{\mathbf{x}=\mathbf{x}_i}\right) \tag{5}$$

for the particular environmental condition, $\mathbf{e}$, that gave rise to it.

Given a database of markers for all environmental conditions of interest is available the classification process simply boils down to a multiple hypothesis testing problem where the marker of the current Poincare period, $\mathbf{m}_i$, is compared against markers of all potential environmental conditions, $\overline{\mathbf{m}}_j^t,\ j \in \{0,...,M\}$, by ranking the known environments in accordance to the L2-norm of their difference from the current marker[5],

$$s_j^i := \int \left|\left|\mathbf{m}_i^t - \overline{\mathbf{m}}_j^t\right|\right|_2 dt,\ j \in \{0,...,M\}\,, \tag{6}$$

and picking the environment with the smallest associated L2-norm, $j_i := \arg\min_j \left[s_j^i\right]$.

[3]Since all Poincare samples are constrained to be on the Poincare sampling manifold, $\mathcal{X}_\mathcal{P} \subset \mathcal{X}$, their dimensionality is one less than that of the state space, $\mathcal{X}$.

[4]Provided that the Lipschitz condition is satisfied by the system function, $\mathbf{g}(\mathbf{x},\mathbf{r},\mathbf{e})$.

[5]The reader should assume that the time time parameterizations of the markers in Equation 6 are normalized such that they all span the same time interval. In certain settings the Poincare sampling can guarantee that all markers span the same length time interval independent of the environmental conditions where the time normalization will boil down to a simple offset subtraction.

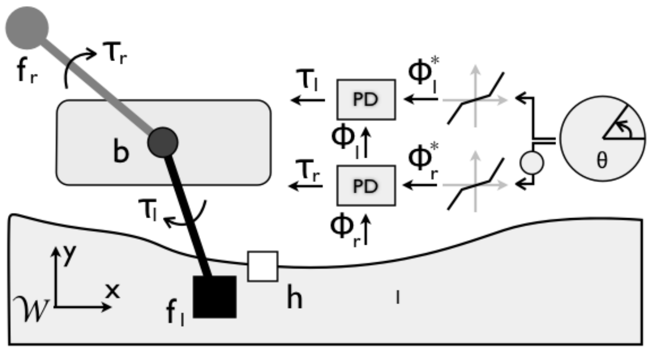

Fig. 3. Biped RHex is a reduced order numerical model for the saggital plane dynamics of RHex class [6] robots operating in a tripod gait. Each tripod is captured by one virtual leg. The body is constrained to maintain zero pitch. A CPG generated target angular hip positions are tracked by a proportional/derivative controller acting on a DC motor model. The legs are modeled as prismatic linear springs with viscous damping. The contact dynamics for the ground is specified in two parts: 1) a ground reaction model defining the forces acting on the foot as a function of the foot's displacement with respect to its first contact point, the foot hold; and 2) surface topology defining the geometry of the surface boundary.

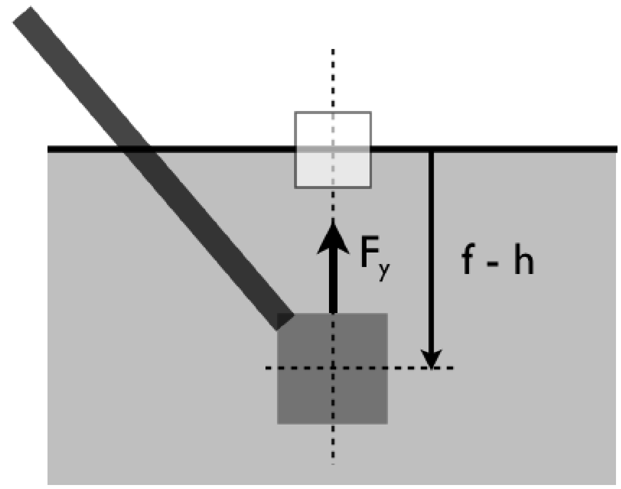

Fig. 4. Compliant ground model. The foot in contact is permitted to move along the vertical but fixed in the horizontal direction. Ground applies a force that is proportional to the penetration of the foot into the ground and penetration speed.

III. Biped RHex Model

Our ultimate goal in this research project is to provide environmental classification and identification capabilities based on the concept outlined in Section II in EduBot [31] and SandBot [25] platforms—small form-factor RHex class [6] mobile robots—to assist behavioral adaptation and map building tasks. To evaluate the classification methodology in a controlled environment we developed the *Biped RHex*—a numerical model depicted in Figure 3 that captures a reduced saggital dynamics of RHex class robots. Section III-A outlines the specifications of this model. Section III-B describes a particular implementation and Section III-C defines a particular partial marker that are employed in result Sections IV and V.

A. Specification

The Biped RHex model in Figure 3 is made up of two parts: 1) the robot model; and 2) the contact model.

The robot consists of a large point body mass, M_b, and two small feet point masses, M_f, that are attached to the body via prismatic legs governed by Hook's law spring parameterized by stiffness, k, rest length, l_0, and viscous damping, μ. Legs are attached to the body at its center of mass (COM) by rotary hip joints. Each hip is driven by a DC motor which can apply torques to its associated leg. The controller, which was defined in [6] in detail, consists of a central clock (CPG) producing two out-of-phase hip target position profiles which are enforced by separate proportional/derivative controllers.

The contact model characterizes the interactions of the feet with the ground. It determines how the ground reaction force (GRF) will affect the feet that are in stance. The contact model is specified in two parts: 1) GRF model; and 2) topology model. The GRF model gives the forces that the ground will apply to a foot in contact. We define the point of first contact with the ground as the *foot hold*. The GRF is defined as a function of the position of the foot with respect to its hold. For instance, a compliant ground applies forces on the foot proportional to the foots displacement away from its foot hold. The surface topology defines the geometry of the surface boundary in the World Coordinates System, $\mathcal{W}$.

B. Biped RHex with Compliant Ground

One of the surface properties that often varies in natural settings is the surface compliance. This environmental condition has strong impact on behavioral performance. Several biological studies [18], [20] demonstrated that a wide number of biological systems actively detect surface compliance and adjust their gait accordingly. Previous work [32] addressed the same issue in legged robotic implementations. Given its variability we also suggest that when measured reliably surface compliance can also serve as a new label for map building and localization applications.

Driven by the above mentioned previous work, biological relevance and potential new applications we implemented a particular compliant contact model for our numerical studies presented in Sections IV and V.

This model adopts a simple flat topology. That is, the surface boundary height is at 0 for all horizontal positions.

The GRF model fixes the horizontal position of the foot in contact while permitting it to move along the vertical in the World Coordinates, $\mathcal{W}$. During ground contact the foot experiences a normal force, F_y that is proportional to its penetration into the ground, $\mathbf{f}_y - \mathbf{h}_y$, and damped by viscous damping, μ_g,

$$\mathrm{F}_y := -k_g(\mathbf{f}_y - \mathbf{h}_y) - \mu_g \dot{\mathbf{f}}_y, \tag{7}$$

where k_g is the surface compliance and μ_g is the surface damping.

C. Stride Marker

For our numerical studies we employ a partial state marker,

$$\mathbf{m} = \left[\phi_e, \dot{\phi}_e\right]^T, \tag{8}$$

consisting of the hip angular position error, $\phi_e := \phi - \phi^*$ and the hip angular speed error, $\dot{\phi}_e = \dot{\phi} - \dot{\phi}^*$ recorded between consecutive Poincare samples defined by the zero crossings of the clock phase, $t_i = t_{\theta=0}$.

The use of the clock reset, $\theta = 0$, to trigger Poincare sampling results in constant duration Poincare periods, $\forall i,\ t_i - t_{i-1} = $ const, independent of the environmental conditions, $\mathbf{e}$. Taking advantage of the constant Poincare period feature we normalize the time offset of markers and compute the similarity, s, using uniformly discretized position and speed error functions,

$$s^i_j := \sum_{k=0}^{K} \left|\left|\mathbf{m}_i^{t_k} - \mathbf{m}_j^{t_k}\right|\right|_2. \tag{9}$$

Note that the particular choice of the Poincare sampling event gives rise to a Poincare period that is identical to the locomotion stride. Therefore, the marker computed in this process will be referred as the *stride marker*.

IV. Static Identification

In the static surface classification implementation we assume there is a collection of markers, $\overline{\mathbf{m}}_j,\ j \in \{0, ..., M\}$, evaluated at environmental conditions that are expected to be encountered. We will call this marker collection *marker lookup table* for our discussion below. In Section IV-A we describe how the marker lookup table is produced. Section IV-B discusses the results of the static identification.

A. Marker Lookup

To compute the marker, $\mathbf{m}_j$ for a given surface compliance, k_g^j, we run a simulation of the system starting from a favorable initial condition on a rigid surface. The model is allowed to bring itself to steady-state on the rigid surface and then the surface compliance is switched over to the the target compliance, k_g^j. Letting the model run until the system comes to steady-state we stop the simulation after a number of steady-state strides on the target compliance are captured. Next, the position and speed error variables for each stride are extracted and resampled uniformly to construct their respective markers. Finally, these markers are averaged to construct the marker, $\mathbf{m}_j$, for the target surface compliance, k_g^j.

Figure 5 exhibits a collection of markers, $\mathbf{m}_j$, evaluated for various surface compliance values. You can notice the changes in the marker as the surface compliance changes. Over a certain range of surface compliance the corresponding markers are clearly distinguishable. However, as the surface gets stiffer the difference between markers diminish. Therefore, in this setup the environmental classification resolution is not uniform but reduces at higher stiffnesses.

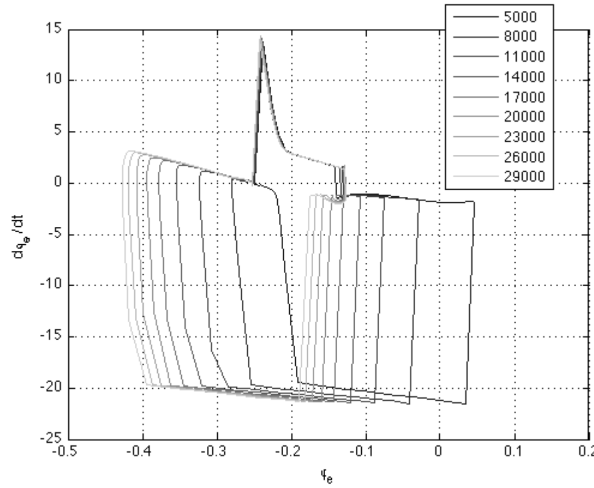

Fig. 5. Marker lookup table consisting of position and speed error flows, $\mathbf{m}_j = \left[\phi_e(k_g^j), \dot{\phi}_e(k_g^j)\right]$ evaluated at the limit behaviors of the Biped RHex running over surfaces with different stiffness, k_g^j.

Horizontal Range (m)	0-10	10-20	20-30	30-40	40-50
Vertical Stiffness (N/m)	30000	15000	10000	8000	5000

TABLE I
SURFACE VERTICAL STIFFNESS DISTRIBUTION OVER THE HORIZONTAL DIMENSION IN THE WORLD COORDINATES, $\mathcal{W}$.

B. Classification Process

For this experiment we setup a contact model that is partitioned into five sections along the horizontal direction. In each partition the surface adopts a different surface compliance the compliance settings are given in Table I. Starting at beginning of the track the Biped RHex model runs across the entire runway crossing all partitions.

The classification process sweeps through the simulation data and for each stride computes the similarities, $s^i_j,\ j \in \{0, ..., K\}$, using Equation 6 and finds the minimum which identifies the most similar marker to current stride marker. The index of this best match entry is assigned to the current stride labeling its environment. Figure 6(top) show the resulting classification of the environment at each stride.

Simultaneously, the stability state of the system is evaluated at each stride by evaluating the consecutive Poincare sample distance, d, using Equation 3 to determine if the state flow in the current stride is similar to that of the previous. If so, it is concluded that the system is in steady-state. The classification described in the previous paragraph is only considered viable if the the consecutive Poincare sample distance is less than a threshold[6], $d < 0.01$. Otherwise, the system is considered to be in a transient behavior and since our methodology requires the system to be in the steady-state the classification is marked invalid.

[6]The threshold is selected experimentally such that the small variations caused by various numerical disturbances do not affect the identification of stable stride while filtering out the transient strides

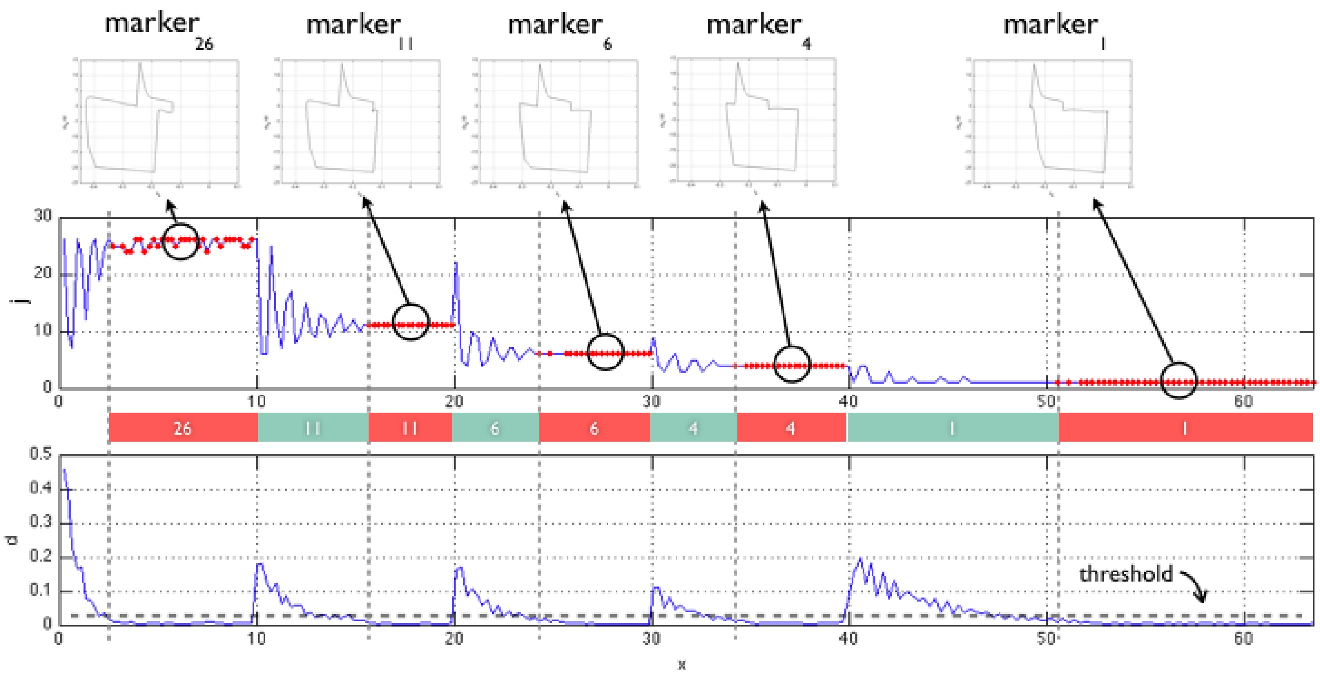

Fig. 6. Classification of environmental conditions at each stride using the marker lookup table. The middle plot is the identified environment index, j, based on the best matches found among the entries of the marker lookup table. The red dots indicate stable strides. The very top plots are the marker lookup tables entries that present the best matches to each stable operating region. The bottom plot is the consecutive Poincare sample distance, d, with the threshold (dashed line) distinguishing stable strides from unstable ones. Larger the distance farther the system from steady state. The x-axis of the plots is the horizontal position of the left foot during each stride. The middle color coded stripe summarizes the classification decision: red blocks are what is decided based on the stride markers from stable strides; blue blocks are the stride classification based on the assumption that the surface properties vary in a piece-wise constant manner.

Figure 6 exhibits the results of this numerical study. It can be immediately seen that upon an environmental change occurs the system undergoes a transient behavior during which the environmental classification process is inoperable. However, one can employ the fact that the surface stiffness is changing in a piece-wise constant manner to fill the gaps in the straightforward classification. The Poincare sample distance, d, can be employed to detect changes in the environment. Although one cannot pass any judgement about the environmental conditions until the transients die out, timely realization of the environmental change can be helpful. Once the transient period is over, we assign stride in this period to the dominant classification found in the steady-state period that follows it.

V. Dynamic Identification

The static environment classification process described in Section IV is a straightforward process. However, the availability of a marker lookup table is not satisfied in most physically relevant unstructured scenarios. Instead a more appropriate engagement would need to construct the marker lookup table during run-time.

The run-time construction of the marker lookup table is a direct extension to the off-line construction process described in Section III-C and the static classification algorithm in Section IV. A simplified outline of the algorithm is given in Figure 7.

The primary modification in the dynamic environment classification process in comparison to that of the static process in Section IV is that when we encounter a sequence of stable strides with markers that do not resemble any of the known markers, we accumulate these stride markers until the system goes into a transient operation. The onset of the transient signals the boundary of the tracked environment. Using all collected stride markers and the computational process from the off-line approach in Section IV-A we evaluate the new marker and insert it into the marker lookup table. Note that this process inherently assumes that the changes in the environment occurs in a piece-wise constant manner.

This approach gradually builds the marker lookup table with the markers evaluated for each distinct environmental condition. The environment classification process remains the same as in Section IV.

VI. Conclusion

This paper introduces an environment classification methodology for mobile platforms. While our discussion focuses on legged terrestrial platforms, presented arguments are applicable to a wider application domain.

Our approach is founded on the observation that the behavior of a locomotor is tightly coupled to its environmental dynamics. Therefore, while keeping the gait constant, any variation in the environment will cause a change in the behavior

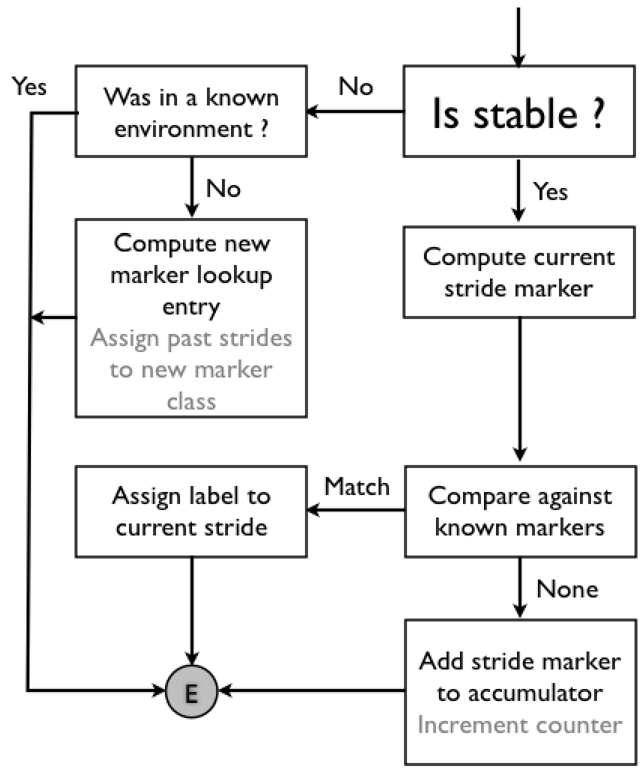

Fig. 7. Simplified outline of the algorithm for dynamic environment classification. This flow diagram is design with the assumption that environment conditions vary in a piece-wise constant manner. Upon encountering a marker for a stable stride that is not in the current marker lookup table, a data collection process starts. When the system loses it stability it is treated as the end of the new environmental condition initiating the computation of the new marker.

(as captured by the state flow). It directly follows that for stable cyclic locomotive behaviors the time parameterized state flow of the system within a gait period can serve as a unique marker for the particular environmental conditions. Furthermore, full state observation is not a must in this architecture. Conditional to the design specifications the use of partial state information can potentially facilitate effective environment classification as well.

Environment classification based on inherent dynamic coupling offers various advantages over previously reported techniques. The most noteworthy aspect of this approach is that it employs preexisting proprioceptive sensory hardware and does not require any specialized system to gather situational information. In physical implementations this means reduced cost and increased robustness while acquiring a new capability. Another important aspect of our approach is that it does not require a specialized gait for exploratory purposes but instead uses the default gait of the machine. Moreover, those environmental conditions that are ”trackable” are not limited to just topological changes but can include hard to measure parameters such as compliance, penetrability, damping and more. Finally, presented algorithm operates in real-time and temporal resolution determined by the periodicity of the active gait.

However, it should be noted that there are various practical considerations the designer must be aware of in using dynamic coupling for environmental classification. First, since the methodology is based on the steady-state behavior of the system, during transients no classification will be possible. For this reason in situations where environmental parameters are constantly changing this approach will not be applicable. However, provided that the environmental conditions take a piece-wise constant form, periods of transients can be classified by the use of environmental continuity. Another issue a physical implementation must address is the unavoidable effects of wear and tare which also will impact the behavior. In general these changes occur slowly and can be ignored. However, if a part fails catastrophically the algorithm will not be able to distinguish it from changes in the environment. Finally, in a partial state based implementation which states to employ in markers is a choice that needs to be made carefully and on a case by case basis. It is important to pick a marker that offers high signal-to-noise-ratio (SNR) for the purposes of environmental classification.

Situational awareness provided through the ability to classify and identify environmental conditions coupled with other information sources can facilitate several applications. Foremost use of such an information will be in gait adaptation. A second and equally exciting application domain can be map building, localization and path planning area. A new label that can distinguish the environment based on its mechanical properties can provide a major advantage in otherwise topologically undistinguishable situations.

In our follow up work we are planning on implementing the presented algorithm in a dynamic hexapod robot to demonstrate a physical situational awareness capability.

Acknowledgment

We gratefully acknowledge the support of NSF grants IIS-0427313 and IIP-0742304, ARO Grant W911NF-05-1-0219, ONR Grants N00014-07-1-0829, N00014-08-1-0696 and N00014-09-1-1051, and ARL Grant W911NF-08-2-0004.

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