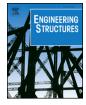
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# Input space dependent controller for civil structures exposed to multi-hazard excitations



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#### ABSTRACT

A challenge in the control of civil structures exposed to multiple types of hazards is in the tuning of control parameters to ensure a prescribed level of performance under substantially different excitation dynamics, which could be considered as largely uncertain. A solution is to leverage data driven control algorithms, which, in their adaptive formulation, can self-tune to uncertain environments. The authors have recently proposed a new type of data-driven controller, termed input space dependent controller (ISDC), that has the particularity to adapt its input space in real-time to identify key measurements that represent the essential dynamics of the system. Previous studies have focused on time delay formulations, where the adaptive control rule would use time delayed measurements as inputs. In this configuration, termed variable multi-delay controller (VMDC), the time delay itself was adaptive, which provided the input space dependence capabilities. However, the size, or embedding dimension, of the input space was kept constant. In this paper, the authors formulate and study a strategy to also have the embedding dimension vary, therefore providing full adaptive input space capabilities. This generalization of the ISDC algorithm will allow the controller to adapt to excitations with higher levels of chaos, such as a seismic event. The performance of ISDC under multi-hazard excitations is first investigated on a single-degree-of-freedom system and compared with the previously developed and demonstrated VMDC. Results show that the adaptive embedding dimension provides significantly enhanced mitigation performance. After, the ISDC performance is assessed on two benchmark buildings equipped with a semi-active friction device and subjected to non-simultaneous multi-hazard excitations (wind, blast and earthquake). Results are compared with a sliding mode controller, where the ISDC is shown to provide better mitigation capabilities.

### 1. Introduction

Motion-based design of civil structures is a design methodology that consists of sizing structural mass, stiffness, and damping in order to restrict structural motion within a prescribed level of performance, while ensuring that structural components meet safety requirements [1]. The utilization of passive supplemental damping strategies [2–5] to meet such motion requirements is now widely accepted by the field of structural engineering. However, a limitation of passive systems is in their restricted performance bandwidth, which typically makes them applicable to single types of hazard only. A solution is to employ highperformance control systems (HPCSs), which include semi-active [6–8], hybrid [9–11] and active damping systems [12–14], that offer significantly higher controllability due to their mechanical or chemical adaptive capability. HPCS can therefore be used to protect structures against multiple simultaneous or non-simultaneous types of hazards, termed multi-hazards. Nevertheless, the performance of HPCS depends heavily on the design of the controller, which itself relies on the availability of sensor information and capability of actuation. Challenges associated with designing controllers for multi-hazards include: (1) uncertainties and large variabilities in the external excitation dynamics; (b) uncertainties in the dynamic properties of controlled structures; and (c) limited available measurements with non-negligible probabilities of sensor failure.

To address these multi-hazard control challenges, one can utilize model driven controllers (MDCs) or data driven controllers (DDCs). Typical MDCs include linear quadratic regulator (LQR) [15,16] and nonlinear Lyapunov-based controllers [17,18]. They have shown great

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potential at providing robust mitigation capabilities, but they require some levels of knowledge about the system, such as the mass and stiffness parameters. It follows that MDCs may underperform when dynamic parameters are inaccurate or unknown [19,20]. Conversely, data-driven approaches rely on implicit information from measurements and do not require knowledge of system dynamics. These methods have been widely studied and applied in fault detection for example [21–23]. In the structural control field, typical DDCs include model-free adaptive controllers [24], fuzzy controllers [25], and neurocontrollers [26–28]. Generally, these controllers require some level of training through input-output examples, which is difficult to achieve when a wide range of excitation amplitudes, frequencies, and dynamics are considered.

Of interest to the authors are time delay controllers of the type

$$u(t) = \sum_{i=1}^{d} g_{i} y(t - (i - 1)\tau) = \mathbf{G}^{T} \nu$$
(1)

where *u* is the control force, *y* is an observation or input,  $\nu \in \mathbb{R}^{d \times 1}$  is the delay vector constructed from d observations delayed by  $\tau$ , and  $g_i$ and  $\mathbf{G} \in \mathbb{R}^{d \times 1}$  are the control gains and the control gain matrix, respectively, where  $g_i$  is not necessarily a constant and could be obtained through a function. In work on time delay controllers, Pyragas first proposed a time delay autosynchronization (TDAS) control for stabilizing periodic orbits of a chaotic system [29], which showed limited performance for highly unstable periodic orbits. Socolar et al. [30] overcame this issue by proposing an extended TDAS (ETDAS) for the stabilization of systems with high frequency chaotic oscillations. While successful, it was discussed that the ETDAS could be more effective, because  $\tau$  was constant and could not be selected appropriately for unknown systems. Ahlborn and Parlitz [31] proposed a multiple delay feedback control (MDFC) with two or more numbers of delays d. A good performance improvement was obtained, but the MDFC introduced a significant number of control parameters [32]. Instead of a constant time delay  $\tau$ , Gjurchinovski and Urumov [33] proposed a variable delay feedback control (VDFC) for stabilizing unstable steady states. The time delay  $\tau$  is varied using a periodic function that oscillates around a nominal value. A limitation of the VDFC is that the nominal delay value needs to be pre-selected appropriately. Pyragas et al. [34] proposed an adaptive delayed feedback control where the time delay can be adapted continuously by the descent gradient method. The advantage of this controller is that a knowledge of the system (e.g. period of controlled orbit) is not required. However, the adaptive time delay method requires an initial time delay that is close to the optimal value [35].

A common feature of those time delay controllers is the reliance on an offline selection of  $\tau$  and d. The ability to, instead, select these parameters online and in real-time would improve the performance of these controllers by tailoring their input-space to the excitation. In fact, the architecture of the input-space of DDC is often overlooked [36,37]. For instance, it was demonstrated by Hong et al. [38] that the optimal values of  $\tau$  and d merely remains constant throughout a high-rate dynamic event. A solution is to allow the input-space of a given DDC to vary with time. This idea, termed Input Space Dependent Controllers (ISDCs), was first proposed by Laflamme et al. [39]. The authors presented a sequential adaptive neurocontroller for which a time-varying delay vector was used as the input space. Later work in Ref. [40] studied a multi-delay controller based on a time-varying  $\tau$  selected online, while d was kept constant. This specialized type of ISDC was termed Variable Multi-Delay Controller (VMDC). Work included boundaries on the selection rule to ensure stability. In both cases, the online selection of parameters was based on the Embedding Theorem [41-43]. The theorem states that the essential dynamics of a stationary system can be represented by an optimal delay vector  $v^*(\tau^*, d^*)$ , where the asterisk denotes an optimal value. The theorem has been initially developed for autonomous systems [41], and applied in many fields such as system identification and model prediction. See Refs. [44-46] for instance.

In this paper, we present a general formulation of the ISDC, which includes an online selection strategy for both  $\tau$  and d. Unlike prior work from the authors in Ref. [39], the controller is based on a simple time delay formulation as shown in Eq. (1) where  $g_i$  are constants, in order for the focus to be on the selection of the input space itself. Unlike the work in Ref. [40], the embedding dimension *d* in this paper is also allowed to vary. It follows that, by varying both  $\tau$  and d, the ISDC identifies in real time the essential dynamics found in the input space (from measurements) produced by different or combined hazards, and adapt its architecture accordingly for enhanced mitigation capabilities. Therefore, the ISDC can adapt to unknown excitation dynamics, including nonstationary systems, using local and limited measurements only enabling implementations through either wired or wireless communication protocols [47,48]. Note that due to its simple time delay formulation and limited dimensionality, the ISDC is computational efficient and can be used in real time, as demonstrated in prior work [39,40].

The upcoming section provides the background on the Embedding Theorem. The subsequent section presents the ISDC algorithm, which includes the adaptive rules for the control gains, and the time delay and embedding dimension selection rules. This is followed by studies of ISDC in a single-degree-of-freedom (SDOF) system to evaluate its performance under non-simultaneous multi-hazards excitations. The performance of the ISDC is compared with the previously developed VMDC. After, the ISDC is further evaluated on two benchmark buildings equipped with semi-active damping devices subjected to multi-hazard excitations. The results are summarized in the last section.

#### 2. Background

This section introduces the Embedding Theorem that constitutes the basis of the ISDC, and presents the online adaptation rules for  $\tau$  and *d*.

#### 2.1. Embedding Theorem

Consider a SDOF system of the type

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = u(t) + f(t) - ma_g(t)$$
<sup>(2)</sup>

where *m*,*c*, and *k* are the system's mass, damping, and stiffness, respectively, x(t) is the displacement state, the dots represent time derivatives, u(t) is the control force from Eq. (1), f(t) is an external loading, and  $a_g(t)$  is ground acceleration, as illustrated in Fig. 1. For simplicity, the observation feedback y(t) (Eq. (1)) is taken as the displacement state (y(t) = x(t)). Assuming stationary inputs  $u_s f$ , and  $a_g$ , the Embedding Theorem states that the unknown system (Eq. (2)) can be topologically reconstructed from a properly formulated delay vector  $v^*(t)$ 

$$v^{*}(t) = [y(t) \ y(t-\tau^{*}) \ \dots \ y(t-(d^{*}-1)\tau^{*})]$$
(3)

where  $\nu^*(t)$  preserves all of the system's essential dynamics or topology. In other words, there exists a one-to-one (diffeomorphic) map between

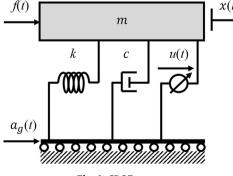


Fig. 1. SDOF system.

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