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Bio-inspired iterative learning technique for more effective control of civil infrastructure

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ABSTRACT

Civil structures, such as buildings and bridges, are constantly at risk of failure due to extensive environmental loads caused by earthquakes or strong winds. In order to minimize this risk, the application of control systems for civil infrastructure stabilization has been proposed. However, implementation challenges including communication latencies, computation inundation at the actuation node, and data loss have been impeding large-scale deployment. In order to overcome many of these challenges, inspiration can be drawn from the signal processing techniques employed by the biological central nervous system. This work uses a bio-inspired wireless sensor node, capable of real-time frequency decomposition, to simplify computations at an actuating node, thus alleviating both communication and computation inundation and enabling real-time control. The simplistic control law becomes $\mathbf{F} = \mathbf{wN}$, where $\mathbf{F}$ is the control force to be applied, $\mathbf{w}$ is a weighting matrix that is specific to the structure, and $\mathbf{N}$ is the displacement data from the wireless sensor node. There is no empirical solution for deriving the optimal weighting matrix, $\mathbf{w}$, and in this study the particle swarm optimization technique was used as a means for determining values for this matrix. Multiple parameters of this optimization method were explored in order to produce the most effective control. This bio-inspired approach was applied in simulation to a five story benchmark structure and using performance metrics it was concluded that this method performed similar to more traditional control method.

Keywords: wireless sensor networks, structural control, bio-inspired control, particle swarm optimization

1. INTRODUCTION

Active control methods offer an attractive method for mitigating the undesired response of civil infrastructure (e.g., buildings, bridges) when subject to large external loads, such as earthquakes or high winds. These integrated systems include sensors for measuring the structure's response, such as displacement or velocity, computational nodes for determining appropriate reactions, and actuators for applying this counteracting force. Traditionally, these systems have relied on numerous sensors that are distributed throughout the structure and a centralized computational node, thus requiring information from all sensors to be transmit back to a centralized location through cables prior to actuation occurring[1,2]. This inevitably leads to delays in the execution of the control action, which results in a degradation of the overall control effectiveness. As a result, researchers have explored using wireless telemetry as a means for communicating between sensors, controllers, and actuators, thus enabling increased data sharing and hence an improved system response.

Equipping nodes with wireless telemetry capabilities allows them to become localized data acquisition centers, commonly termed wireless sensor units (WSUs). Each node typically contains an on-board microcontroller, a transducer interface (i.e., analog-to-digital converter), an actuation interface (i.e., digital-to-analog converter), and a wireless transceiver. This allows the units to serve in any role required by the control system, thus increasing the overall adaptability of the network of nodes. While wireless telemetry has been shown to increase the overall flexibility of the network and was successfully integrated into global control architectures[3–5], the technology also presents other challenges, such as a higher probability of data loss during transmission. These studies also highlighted similar limitations as wired systems, such as delays in computations due to information bottleneck. To overcome these challenges, researchers leveraged the peer-to-peer communication capabilities of these nodes to enable decentralized control architectures and localized actuation[6–8]. While resulting in improved control effectiveness, it typically also increased computational requirements at the already resource-constrained node, as well as required decision-making based on reduced information, which further degraded the control effectiveness. Thus, in order to effectively implement structural control of civil infrastructure, it is imperative that the current challenges faced by the technology be addressed.

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One possible solution to this is to draw inspiration from the sensing and actuating techniques employed by the biological central nervous system (CNS), thus resulting in a new bio-inspired control paradigm. Due to the unique signal processing techniques employed by the CNS, biological systems are capable of integrating information the sensing layer to the actuating layer in a simplistic manner that is desirable for equivalent engineered systems. In particular, information is received at the receptor neurons where it is disseminated and aggregated across multiple layers of interneurons before being received at the motor neuron nodes. Due to the dissemination and aggregation of data at previous layers, the motor neuron node is able to perform a simplistic actuation action that requires no computational effort, which is a desirable consequence for engineered systems. In this paper a simplistic bio-inspired control algorithm is outlined and the details of the aggregation process are explored using an iterative optimization approach. The overall control effectiveness of this method is evaluated on a 5-story benchmark structure.

2. SENSING AND ACTUATION ARCHITECTURE IN BIOLOGICAL CENTRAL NERVOUS SYSTEM

Due to its up-front signal processing capabilities, as well as simplistic information integration capabilities, the biological CNS is able to sense and actuate using basic mechanisms which are desirable for equivalent engineered systems. CNSs are composed of basic processing units, termed neurons, which form simplistic networks in order to aggregate and integrate stimulus information, so that it can then be used for learning or actuation (Figure 1a). External information is received at the input layer, or receptor neurons, which typically perceive the stimulus based on their activation type, such as pressure, vibration, light, etc[9]. These neurons pass information in the form of electrical pulses, termed action potentials, to subsequent layers of neurons where additional information integration occurs[10]. Depending on the connection type (i.e., excitatory or inhibitory) and relationship strength between neurons, a decision is either further promoted or inhibited, thus allowing complex decision-making. This information integration can occur through several layers of neuron before reaching the motor neuron node, which commands the actuation by controlling muscle fibers[11].

Based on the information received from preceding layers of neurons, the motor neuron activates muscle fibers which provide the required force using both rate coding and size principle. Similar to the function of other neurons, the motor neuron node encodes the amplitude of the desired actuation into a series of electrical pulses, with each successive pulse increasing the intensity of the muscle activation, up to a limit[12]. The motor cortex uses feedback mechanisms to both ensure that the magnitude of response is large enough and if a larger response is required then more motor neurons are recruited by the motor cortex[13]. The neuronal network also uses feedback mechanisms to ensure that the overall desired response is achieved and to fine-tune the actuation based on this information[14]. This ensures that effective actuation is achieved while still maintaining real-time processing capabilities. To encapsulate the simplistic manner that biological organisms respond to external stimuli through muscle actuation, the overall network architecture will be mimicked in a

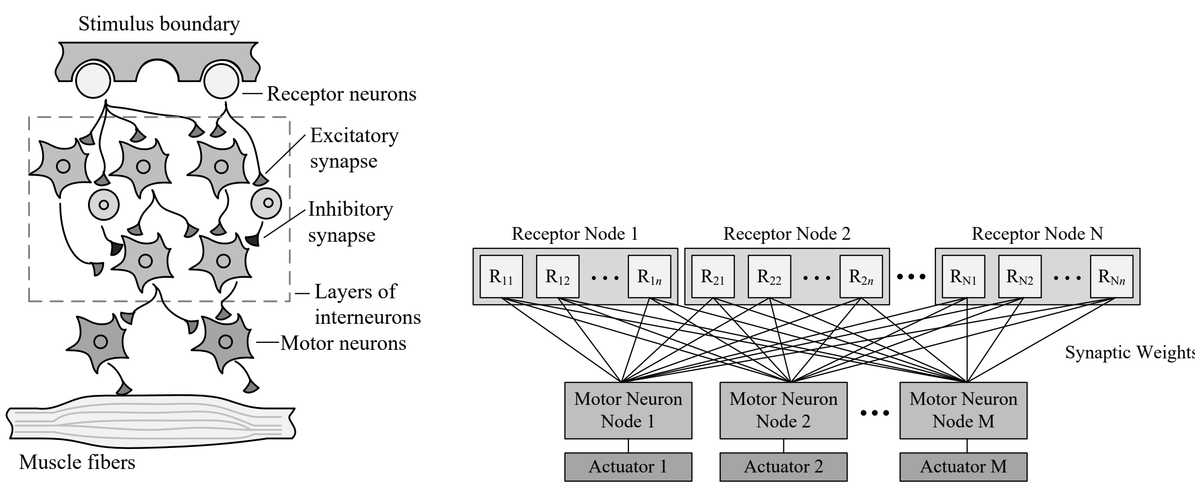

Figure 1. Sensing and actuating architecture in biological central nervous system (a) and propose bio-inspired sensing and actuating architecture (b).

bio-inspired control architecture (Figure 1b).

3. BIO-INSPIRED CONTROL ARCHITECTURE

The proposed bio-inspired control law mimics the simplistic architecture used in the biological CNS to achieve real-time control. In the biological system the sensing and actuating process is initiated at the receptor neurons, which conduct pre-processing of the input signal based on their activation type. In the bio-inspired engineered system a novel sensing node, termed the cochlea-inspired sensing node, inspired by the mammalian auditory system will be used as this input layer. This node, first proposed by Peckens et al.[15], uses a bank of parallel and analog bandpass filters to perform real-time spectral decomposition of a convoluted signal, thereby drawing inspiration from the mechanisms employed by the cochlea within the auditory system[16]. The sensing node is comprised of multiple "neuron" boards (represented as R_{ij} in Figure 1b), that each house a unique analog bandpass filter and microcontroller, thereby enabling parallel processing and data transmission[17]. The microcontroller on the board receives a filtered signal from its respective filter, performs a simple peak-picking algorithm, and instantaneously transmits a peak value, representative of a series of biological action potentials, once detected. This up-front signal processing allows the minimal computational requirements at the actuation node and also eliminates the need for scheduled data transmission schemes that are typically deployed at the sensing layer. Both of these result in an elimination of the inherent time delay that currently plagues control systems in civil infrastructure and allows real-time control to be realized.

The founding principle of the biological CNS architecture is the information integration from multiple sources between layers of neurons using synaptic strengths (i.e., amplification or attenuation factors). This structure is mimicked in the bio-inspired control law with motor neuron nodes aggregating information from the neuron boards on multiple receptor nodes using weighting values which can be both positive for amplification and negative for attenuation. This results in a simple control law in which the control force output, F_k, from each actuator is a weighted aggregation of the received information

$$F_k = \sum_{i=1}^{n} \sum_{j=1}^{b} W_{ijk} R_{ij} \tag{1}$$

where W_{ijk} is the synaptic strength between the j^{th} neural unit for b units on the i^{th} receptor node for n nodes and the k^{th} motor neuron node for M nodes. R_{ij} is the output of the j^{th} neural unit on the i^{th} receptor node. In this architecture, as shown in Figure 1b, N represents the number of sensing nodes and M is the number of actuating nodes in the system. Developing the weighting matrix, $\boldsymbol{W}$, is imperative to the success of the bio-inspired control algorithm and there is no empirical method for this derivation. As a result, the particle swarm optimization (PSO) method will be used in order to derive these values. In this study, various parameters for this optimization method are considered so as to ensure the best resulting weighting matrix using this technique.

Particle swarm optimization (PSO) is an iterative learning technique that draws inspiration from biology and is capable of optimizing continuous nonlinear functions. In PSO, a number of solutions, or particles, are dispersed randomly in a search space and each particle location is evaluated according to a specified objective function. With each iteration of the algorithm, each particles moved to a new location in the search space that is dependent on its own history, as well as the behavior of other nearby particles, with the goal of moving closer to the optimum of the objective function[18]. Each particle in the swarm tracks three vectors: $\boldsymbol{x}$ which is the particle's current position, $\boldsymbol{v}$ which is its current velocity, and $\boldsymbol{x_b}$ which is its previous best position. Each particle also interacts with neighboring particles and stores the best solution found from all neighbors, $\boldsymbol{g}$, in order to leverage the benefits of the swarm. Each particle updates its three vectors every iteration through the equations:

$$\boldsymbol{v_i}(k+1) = \omega \boldsymbol{v_i}(k) + \rho_1 \gamma_1 \left(\boldsymbol{x_{b,i}}(k) - \boldsymbol{x_i}(k)\right) + \rho_2 \gamma_2 \left(\boldsymbol{g}(k) - \boldsymbol{x_i}(k)\right) \tag{2}$$

$$\boldsymbol{x_i}(k+1) = \boldsymbol{x_i}(k) + \boldsymbol{v_i}(k+1) \tag{3}$$

$$\lambda = \lambda \times \tau \tag{4}$$

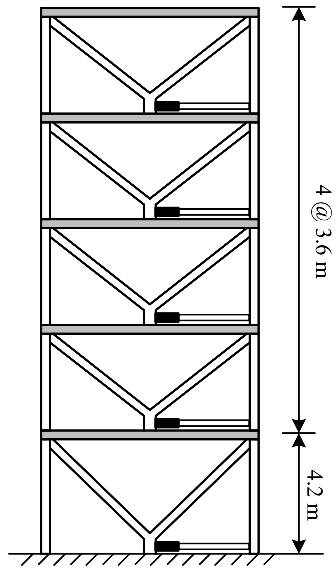

Figure 2. 5-story benchmark structure.

where i is the particle number, k is the iteration number, ρ_1 and ρ_2 are random numbers between 0 and 1, and γ_1 and γ_2 are the acceleration coefficients which are both assigned to be 2 as recommended in[18]. Equation 4 also includes an inertia weight, λ, which affects the convergence and plays a role in balancing local versus global search of the particles[19], as well an inertia damping constant, τ, which gradually modifies this balance. The inertia coefficient, λ, is initially assigned to be 1, and is decreased using a damping constant, τ, of 0.99[20], which results in a global search that gradually becomes more localized. Each particle represents a potential weighting matrix, $\boldsymbol{W}$, between the receptor nodes and the motor neuron nodes in the bio-inspired control theory. After completing the optimization, the particle that most closely matched the objective function was chosen as the resulting weighting matrix.

4. BENCHMARK STRUCTURE

In order to validate the proposed bio-inspired control algorithm and further study the impacts of varying parameters in the PSO optimization technique, a model of the 5-Story Kajima-Shizuoka building was developed (Figure 2). The model is similar to the lumped mass system used by Wang [21], which is based on the actual structure used in the study conducted by Kurata et al.[22]. The model assumes seismic mass values of 215.2 x 10^3, 209.2 x 10^3, 207.0 x 10^3, 204.8 x 10^3, and 266.1 x10^3 kg on floors 1 through 5 respectively, and corresponding interstory stiffness of 147 x 10^3, 113 x 10^3, 99 x 10^3, 89 x 10^3, and 84 x 10^3 kN/m. This results in five natural frequencies of 1.00, 2.82, 4.49, 5.80, and 6.77 Hz. Additionally, the damping was modeled using Rayleigh damping that is both mass-proportional and stiffness-proportional, using a 5% damping ratio[23]. It is assumed that only the horizontal degrees-of-freedom are measurable and controllable. Each floor is assumed to include an installed transducer that measures interstory displacement, which is input into the cochlea-inspired sensing node, as well as an ideal actuator. It is also assumed that each sensing node is capable of directly communicating with the motor neuron nodes, which command their respective actuators.

A state-space model was developed that encompasses the dynamics of the 5-story benchmark structure, as well as the dynamics introduced by the cochlea-inspired sensing node. These equations are given as

$$\dot{\boldsymbol{z}} = \boldsymbol{A}\boldsymbol{z} + \boldsymbol{B}\boldsymbol{u} + \boldsymbol{G}\ddot{x}_g \tag{5}$$

$$\boldsymbol{y} = \boldsymbol{C}\boldsymbol{z} + \boldsymbol{D}\boldsymbol{u} + \boldsymbol{H}\ddot{x}_g \tag{6}$$

where $\boldsymbol{A}$ is the state transition matrix, $\boldsymbol{B}$ is the control matrix, $\boldsymbol{G}$ is the ground input matrix, $\boldsymbol{C}$ is the measurement output matrix, $\boldsymbol{D}$ is the control feedforward matrix, and $\boldsymbol{H}$ is the ground feedforward matrices. The states of the system are represented by the vector $\boldsymbol{z}$ which includes the structure's displacement and velocity terms, as well as the displacement and velocity terms of the cochlea-inspired sensing nodes. The vector input of control forces (equivalent to $\boldsymbol{F}$ in Equation 1) is represented by $\boldsymbol{u}$, $\boldsymbol{y}$ is the output vector, and $\ddot{x}_g$ is the ground acceleration.

As a comparative baseline to the bio-inspired control algorithm, traditional optimal control theory was also used to develop a centralized linear quadratic regulator (LQR). The LQR uses the algebraic Riccati equation to minimize the cost function

$$\mathrm{J} = \int_0^{\infty} (\boldsymbol{z}^{\mathrm{T}} \boldsymbol{Q} \boldsymbol{z} + \boldsymbol{u}^{\mathrm{T}} \boldsymbol{R} \boldsymbol{u})\, dt \tag{7}$$

subject to the full state feedback control law, $\boldsymbol{u} = -\boldsymbol{K}\boldsymbol{z}$, where $\boldsymbol{K}$ is the resulting constant feedback gain matrix. This minimization is subject to two parameters: $\boldsymbol{Q}$ which applies a weight to the cost of the structural response and $\boldsymbol{R}$ which applies a weight to the cost of control effort. In the algorithm, $\boldsymbol{Q}$ and $\boldsymbol{R}$ are chosen using the commonly accepted Bryson's Rule[24] that establishes these values as proportional to the inverse of the square of the maximum acceptable displacement and control force, respectively. As such, $\boldsymbol{Q}$ is chosen as $10^{10} \times \boldsymbol{C}^{\mathrm{T}}\boldsymbol{C}$, and $\boldsymbol{R}$ is set to be $10^{-5.4} \times \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix. As it is often difficult to measure all of the states of the system in civil infrastructure (i.e., displacement and velocity), it was also assumed that a Kalman filter was implemented to approximate any unknown states. Based on the physical challenges presented by Spencer et al.[25] and Wang et al.[3] that impede the overall control sampling frequency, it was assumed that this baseline system could operate at a maximum of 40 Hz.

4.1 Quantification of Control Effectiveness

The effectiveness of the bio-inspired control theory using the PSO method is compared to the centralized LQR using four cost functions, adapted from Ohtori et al.[26] These cost functions focus on quantifying the minimization of interstory displacement, which directly affects the damage to nonstructural elements, and the minimization of acceleration, which relates to occupational comfort during a seismic event. Each of these variables are minimized through two cost functions; one cost function compares the absolute maximum value of the variable of the uncontrolled response to the controlled response and the other compares the vector norm of the uncontrolled versus controlled over the entire event. The cost functions are given as

$$\boldsymbol{J_1} = \frac{\max(|\boldsymbol{d}(t)_{controlled}|)}{\max(|\boldsymbol{d}(t)_{(uncontrolled}|)} \tag{8}$$

where $\boldsymbol{d}$ is the time history of the interstory displacement for all floors, and

$$\boldsymbol{J_2} = \frac{\|\boldsymbol{d}(t)_{controlled}\|}{\|\boldsymbol{d}(t)_{uncontrolled}\|} \tag{9}$$

where $\|\cdot\|$ denotes the l_2-norm function. For quantification of acceleration, $\boldsymbol{a}$, the cost functions are

$$\boldsymbol{J_3} = \frac{\max(|\boldsymbol{a}(t)_{controlled}|)}{\max(|\boldsymbol{a}(t)_{uncontrolled}|)} \tag{10}$$

and

$$\boldsymbol{J_4} = \frac{\|\boldsymbol{a}(t)_{controlled}\|}{\|\boldsymbol{a}(t)_{uncontrolled}\|} \tag{11}$$

Equations 8-11 result in vectors of cost functions, where each indexed entry is associated with a floor. Additionally, the control force demand is also quantified through a cost function provided in Ohtori et al., which is subsequently defined as

$$\boldsymbol{J_5} = \frac{\max(|\boldsymbol{F}(t)|)}{W_s} \tag{12}$$

where $\boldsymbol{F}(t)$ is the time history of the control force for each floor and W_s is the seismic weight of the building based on the above ground mass of the structure.

4.2 Particle Swarm Optimization Parameters

There are several parameters within the PSO algorithm that can be modified to affect the overall speed of convergence, distribution across the search space, and the appropriateness of the solution. In particular, these include the number of particles, the number of iterations of the optimization and the objective function. The objective function dictates the appropriateness of the solution and in this study several different functions were explored that all focused on minimizing the cost functions defined in Equations 8-11. One objective function, C_1, is the cumulative sum of each cost function over all floors,

$$C_1(x_{ij}) = \sum_{m=1}^{4}\left(\sum_{l=1}^{n} J_{m,l}\right) \tag{13}$$

where n is the number of floors and equals 5 for the benchmark structure and m is the associated cost function. In this objective function, each cost function is equally weighted so as to minimize both inter-story drift and acceleration. A second objective function, C_2, is the cumulative sum of the cost functions associated with displacement ($\boldsymbol{J_1}$ and $\boldsymbol{J_2}$) over all floors and a third objective function, C_3, is the cumulative sum of the cost functions associated with acceleration ($\boldsymbol{J_3}$ and $\boldsymbol{J_4}$) over all floors,

$$C_2(x_{ij}) = \sum_{m=1}^{2}\left(\sum_{l=1}^{n} J_{m,l}\right) \tag{14}$$

$$C_3(x_{ij}) = \sum_{m=3}^{4}\left(\sum_{l=1}^{n} J_{m,l}\right) \tag{15}$$

Each particle position, x_{ij}, represents a potential weighting matrix solution for the bio-inspired control theory and each objective function is evaluated on each position using the controlled structure's response subject to the 1940 El Centro (SE) earthquake (Figure 3).

Prior to exploring these cost function, however, the number of particles in the algorithm was also considered. Each particle represents a potential weighting matrix that can be used in the bio-inspired control algorithm. As there are no physical bounds on this weighting matrix, the search space is infinitely large. As such, a larger number of potential solutions (i.e., particles) allows the system to span an adequate search space while also converging to a local minimum during a reasonable number of iterations. The algorithm was executed using Equation 13 as an objective function with the stopping condition that the solution either performed better than the centralized LQR solution or else the best particle did not change for 100 iterations. This criterion was explored for 10, 25, 50, and 100 particles (Table 1), with each particle solution initialized as a vector of random numbers. For every iteration each particle has to be evaluated, which results in a significant number of calculations as the number of particles increases. All of these trials were stopped after the best particle did not change for 100 iterations, indicating that the PSO did not find a solution that was better than the centralized LQR. The search path of this algorithm is stochastic in nature, however, as it is dictated by the initial positional of all of the particles, which is randomly assigned. As such, if these trials were repeated again they would require a different number of iterations and would presumably end with a different solution. While 50 particles do require more computations than 25 or 10, it was chosen as the number of particles going forward as it allowed an adequate coverage of the search space.

Table 1. Convergence of PSO when varying number of particles

No. of Particles, N_p	No. of Iterations, It	No. of Calculations (= N_p x It)
10	407	4070
25	443	11075
50	334	16700
100	285	28500

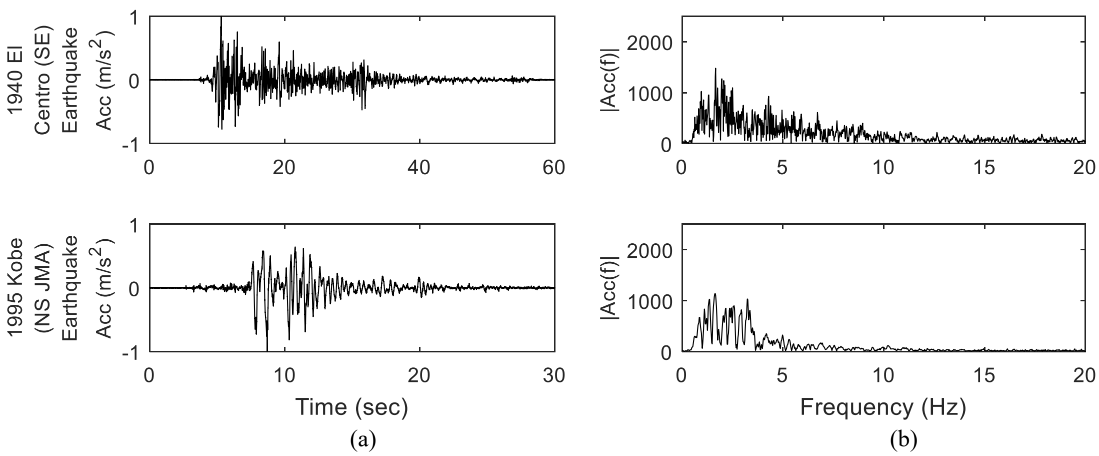

Figure 3. Seismic signals used as base excitation in simulation in time (a) and frequency (b) domains. SE: Southeast, JMA: Japan Meteorological Agency.

4.3 Simulation Results

To evaluate the effectiveness of the different objective functions, the PSO training was again executed using 50 particles and the El Centro earthquake. Once a solution was found then the 5-story structure was also excited and assessed using the 1995 Kobe (JMA NS) earthquake (Figure 3) to ensure that the solution was not being overtrained to the El Centro earthquake. The response of the structure was also compared against the idealized scenario using the centralized LQR method. The resulting cost functions for the different training methods and the two earthquakes are shown in Figure 4.

From these results, several interesting observations can be made. First, in general, C_2 performs poorly when considering $\boldsymbol{J}_3$ and $\boldsymbol{J}_4$. This is expected as this objective function focuses on minimizing the cost functions associated with displacement, $\boldsymbol{J}_1$ and $\boldsymbol{J}_2$, which often results in a larger acceleration of the structure. This is not true, however, when considering the Kobe earthquake which may indicate that the function was overtraining to the El Centro earthquake. Conversely, it can be observed that C_3 typically performs better than the other two objective function scenarios when considering the cost functions associated with acceleration, $\boldsymbol{J}_3$ and $\boldsymbol{J}_4$, but does still perform moderately well for $\boldsymbol{J}_1$ and $\boldsymbol{J}_2$. In order to assess the overall performance of the various methods, the average value for the three methods across both earthquakes and all cost functions was determined (Table 2). It is observed that optimizing using C_3 results in a slightly improved performance over using C_1. Additionally, C_2 can be deemed inadequate as any benefits gained in $\boldsymbol{J}_1$ and $\boldsymbol{J}_2$ are offset by the poor performance for $\boldsymbol{J}_3$ and $\boldsymbol{J}_4$. As a result, it can be concluded that using Objective Function 3 for training the PSO algorithm results in an acceptable performance.

The other parameter that should be considered for control is the control effort exerted for each method, which is quantified using the cost function defined in Equation 12 or $\boldsymbol{J}_5$ (Figure 5). During simulation, no constraint was applied to the actuators and it was assumed that they had unlimited actuation capabilities. As a result, each method could demand as much actuation force as desired. When considering the four methods, C_2 placed the greatest demand on the

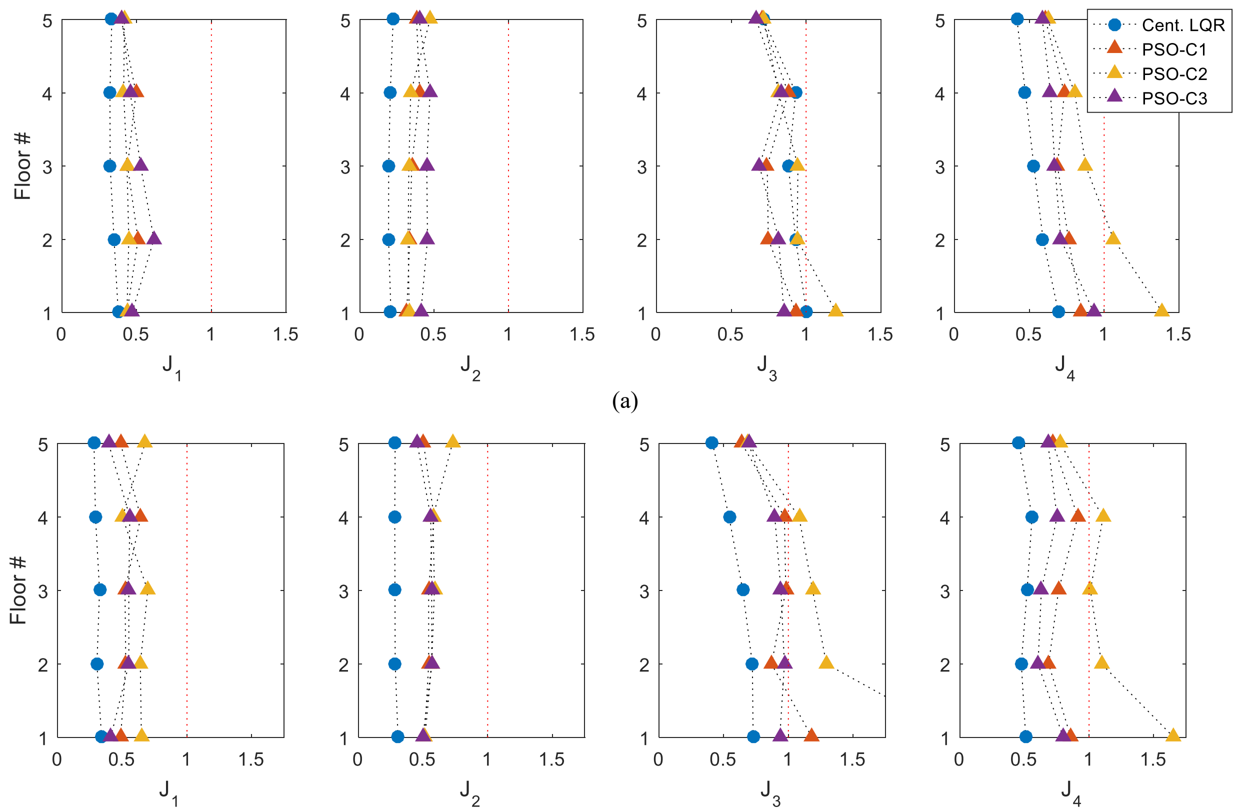

Figure 4. Cost functions for benchmark structure subject to El Centro earthquake (a) and Kobe earthquake (b). PSO-C*i* is the PSO algorithm executed using objective function *i*, as defined by Equations 13-15.

Table 2. Average cost functions for various control methods and earthquakes

Method	**El Centro earthquake**	**Kobe earthquake**	**Avg. all earthquakes**
Cent. LQR	0.6185	0.5348	0.5767
PSO-C_1	0.7314	0.8748	0.8031
PSO-C_2	0.8328	1.1477	0.9902
PSO-C_3	0.7532	0.8133	0.7833

controllers, approximately 48% more effort than the case that placed the least demand on the controllers (centralized LQR). C_3 placed the least amount of demand on the controllers of the three PSO cases, approximately 12% more effort than the centralized LQR case. In the future, an objective function that considers the control force should also be considered in order to better apply this realistic constraint.

5. CONCLUSIONS

While feedback control systems integrated into civil infrastructure is not a new area of research, several challenges of the technology, such as computational delays and communication constraints, have prevented their widespread adoption. This study proposed a bio-inspired control algorithm that leverages front-end signal processing to enable streamlined control at the actuating node, thus overcoming many of these challenges. The control algorithm is reduced down to a simplistic weighted combination of the inputs, similar to mechanisms employed by the central nervous system. The

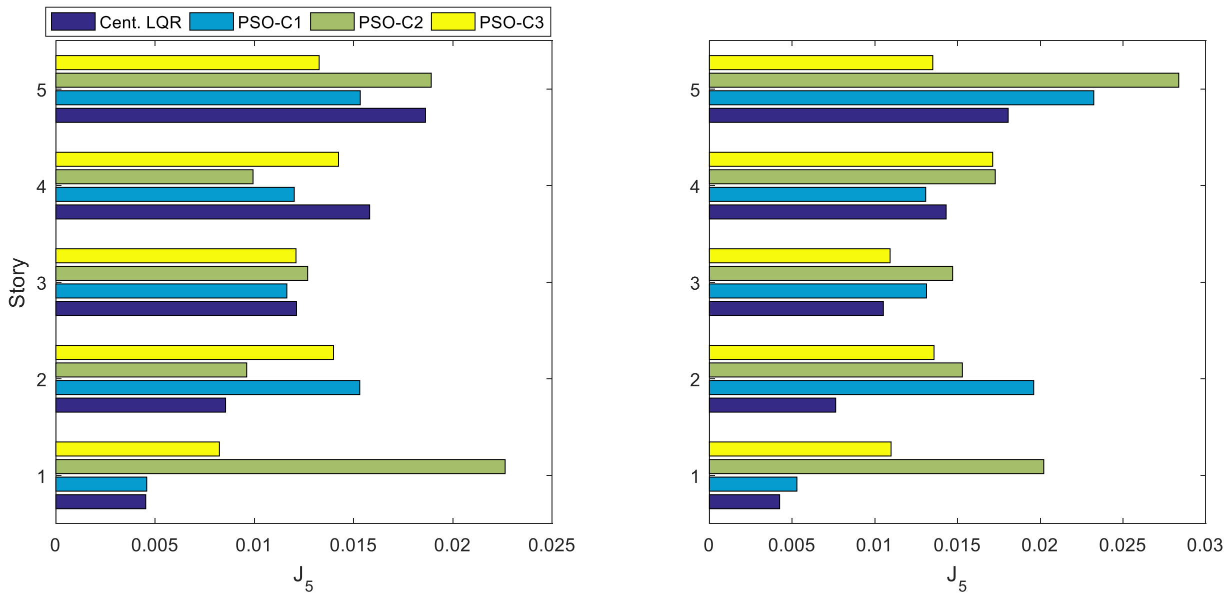

Figure 5. Control effort cost function for benchmark structure subject to El Centro earthquake (a) and Kobe earthquake (b). PSO-C*i* is the PSO algorithm executed using objective function *i*, as defined by equations 13-15.

weights of this algorithm were developed using the particle swarm optimization method based on various objective functions. The effectiveness of this method was assessed in simulation on a five-story benchmark structure. While the traditional full-state optimal control theory does outperform the bio-inspired control algorithm, the PSO technique in particular offers a competitive alternative in overall control effectiveness. The drawback of the PSO technique, however, it is that it does place a higher demand on the actuators, as compared to the full-state LQR method and this must be considered when completing an experimental validation of these techniques.

Future work will include experimental validation of the bio-inspired algorithm using the PSO technique, as well as the full-state feedback control system. This experimental validation will use WSNs for communicating information about the structural response, as well as commanding the actuator. To implement the full-state feedback method, a Kalman filter will be implemented which will inhibit the real-time capabilities of the full-state feedback method, due to communication sequencing and computational delays. The PSO methods, however, will leverage the real-time front-end signal processing capabilities of the cochlea-inspired sensing node which will alleviate computations at the actuating node and prevent delays in the overall control system.

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