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Experimental validation of a proposed bio-inspired control algorithm for civil infrastructure

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ABSTRACT

Structural control of civil infrastructure in response to large external loads, such as earthquake or wind, is still not widely employed due to several key issues, such as latency in the system and challenges with information exchange. To promote information flow, wireless sensor networks have emerged as a potential solution that is also a low-cost alternative to the traditional wired sensing and actuation infrastructure. However, these systems also introduce additional challenges such as latency in the wireless communication channel and computational inundation at individual sensing nodes. Inspiration can be drawn from the real-time sensing and actuation capabilities of the biological central nervous system to overcome some of these challenges experienced by wireless sensor nodes. A novel bio-inspired wireless sensor node was developed that is capable of real-time time-frequency decomposition of a sensor signal, thus drawing inspiration from the frequency selectivity of certain neurons. Similar to the functionality of neurons, the node uses asynchronous sampling based on the content of the perceived signal, resulting in large power savings and compressed data communication. In this study, the bio-inspired wireless sensor node is utilized for a feedback control application in order to overcome the challenges currently seen in wireless control. The sensor node is able to transmit frequency-specific data in real-time to a controller node which constructs a control force using minimal computational resources. This study validates that performance of the bio-inspired wireless feedback control architecture on a one-story partial-scale shear structure that is seismically excited and controlled via active mass actuators.

Keywords: Bio-inspired control, structural control, wireless sensor networks

1. INTRODUCTION

Over the last several decades, structural control methods have been explored as a means for mitigating the undesired response of civil infrastructure (e.g., buildings, bridges) when subject to large external loads, such as earthquakes or high winds[1]. In particular, active control methods, which offer automatic adaptation and response to the excitation, have the capacity for enhanced control effectiveness and specific selectively to control objectives, making them an attractive option. These require extensive collaboration between sensors that measure the structure's response, such as displacement or velocity, and computational nodes that determine the appropriate reaction and command actuators. Traditionally, these systems used cables for communicating between such nodes, but these are cumbersome to install and also create delays in execution of control, thereby degrading the overall control effectiveness[2,3]. To alleviate this, researchers have explored using wireless telemetry as a means for communicating between sensing and actuating nodes, which increases data sharing capabilities and creates an improved system response.

Wireless telemetry allows nodes to become localized data acquisition centers that are 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. Each unit is amendable to serving in any role required by the control system, thus increasing the overall adaptability of the network. Numerous researchers have successfully demonstrated the flexibility of WSUs in global control architectures[4–6] while also highlighting the challenges, such as a higher probability of data loss during transmission and computational delays 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, this method typically increases computational requirements at the already resource-constrained node, as well as requires decision-making based on reduced information, which further degrades the control effectiveness.

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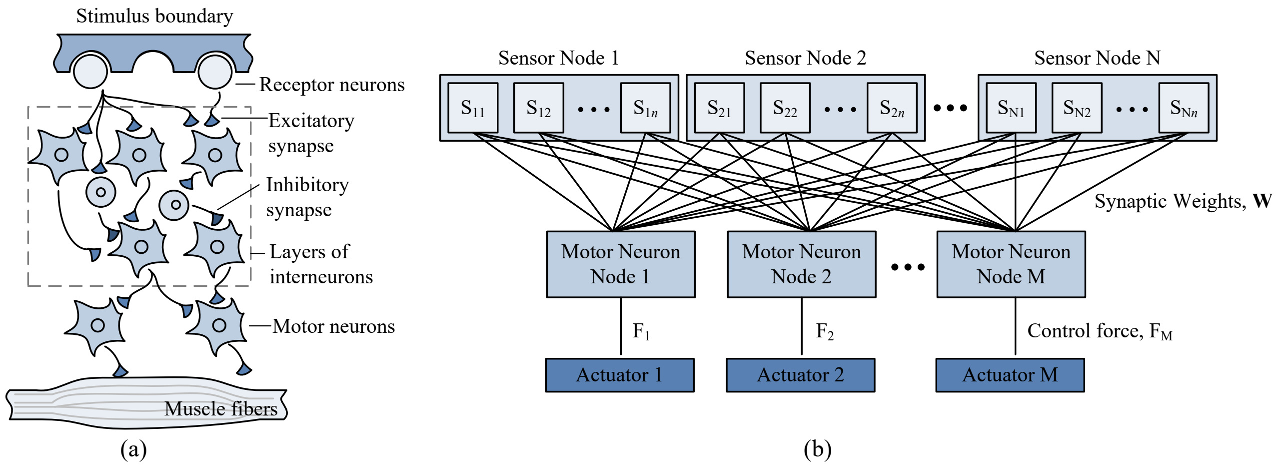

Figure 1. Biological central nervous system's sensing and actuating architecture (a) and proposed bio-inspired sensing and actuating structure (b).

One possible mechanism for addressing these limitations is to simplify the computational complexity of the process by drawing from the sensing and actuating techniques employed by the biological central nervous system (CNS), thus resulting in a new bio-inspired control paradigm. Biological systems are capable of disseminating and integrating information from a sensing layer to an actuating layer in a simplistic manner that is desirable for equivalent engineered systems. In this paper, a bio-inspired control algorithm is outlined and then experimentally validated on a partial-scale, single-story shear structure.

2. BIO-INSPIRED CONTROL ARCHITECTURE

The biological CNS is able to sense and actuate using basic mechanisms due to its up-front signal processing capabilities and its ability to complete simplistic information integration (Figure 1a). The CNS receives information at the receptor neurons via the stimulus boundary. Receptor neurons are typically activated based on a specific excitation, such as pressure, vibration, light, etc., and a specific magnitude, thus enabling pre-processing of incoming information[9]. These neurons pass information as electrical pulses to subsequent layers of neurons, termed interneurons, where additional information integration occurs[10]. Depending on the connection type (i.e., excitatory or inhibitory) and the relationship strength between two neurons, a decision can be easily promoted or inhibited, which allows for quick and complex decision-making. This information integration occurs through several layers of neurons before reaching the motor neuron node, which commands the actuation through muscle fibers[11].

The proposed bio-inspired control algorithm follows the same structure as the biological CNS (Figure 1b). The algorithm relies on a novel bio-inspired sensor unit, proposed by Peckens and Lynch[12], that is based off of the signal processing mechanisms employed by the mammalian cochlea. As such, a bank of neural units, housed on a single sensing node and shown as S_{ij} blocks in Figure 1b, act as the biological receptor nodes and decompose the incoming excitation into narrow-band frequency signals using a bank of bandpass filters[13]. These decomposed signals are passed to unique microcontrollers, which perform a simple peak-picking algorithm to detect and transmit peak values. This leverages parallel processing, as well as utilizes up-front signal processing to minimize computations at the actuation node. Both of these strategies eliminate time delays in the control system and allow the realization of real-time control.

To make a control decision, the bio-inspired control law mimics the biological motor neuron nodes that aggregate information from multiple sources through amplification and attenuation factors. This results in a simple control law in which the output control force, F_k, from each k^{th} actuator is a weighted aggregation of the received information, where

$$F_k = \sum_{i=1}^{N} \sum_{j=1}^{n} W_{ijk} S_{ij} \quad (1)$$

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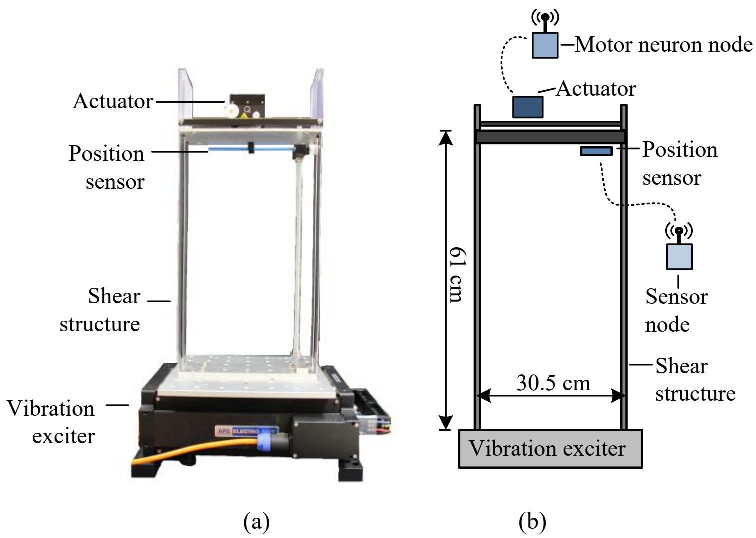


Figure 2. Single-story shear structure (a) and schematic (b).

W_{ijk} is the synaptic strength between the j^{th} neural unit for n units on the i^{th} sensor node for N nodes and the k^{th} motor neuron node for M actuation nodes. S_{ij} is the output of the j^{th} neural unit on the i^{th} sensor node. In this architecture, as shown in Figure 1b, N represents the number of sensor nodes and M is the number of actuator nodes in the system. There is no empirical method for deriving the synaptic weighting matrix, $\boldsymbol{W}$, but it can be developed through various optimization techniques, as discussed by Peckens et al.[14]

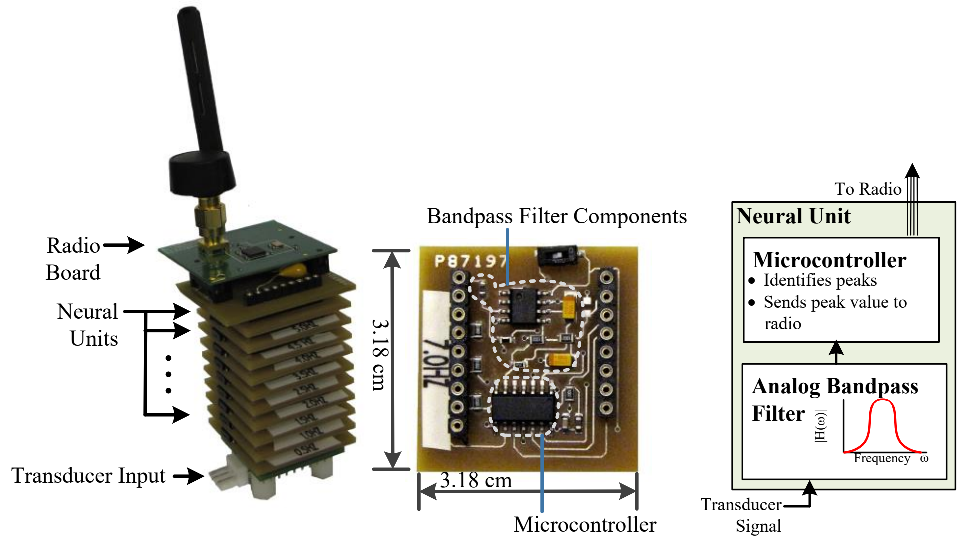
3. EXPERIMENTAL VALIDATION

3.1 Experimental Test Bed

In this study, the bio-inspired control algorithm is experimentally validated on a small-scale, single story shear structure (Figure 2). The shear structure is comprised of a 10.8 cm x 30.5 cm x 2.54 cm aluminum plate that is connected to a ground floor by four T6061 aluminum columns of size 61 cm x 3.8 cm x 0.016 cm. The structure is attached to a vibration exciter (APS Dynamics Electro-seis) that induces seismic base excitation. An active mass damper (AMD) is placed on the top aluminum plate and serves as the actuator that mitigates the displacement of the structure resulting from this ground motion. The AMD is an aluminum cart that is manufactured by Quanser[15] and is equipped with a high quality DC motor and a quadrature encoder, thus enabling high precision control. The structure is outfitted with a magnetostrictive linear-position sensor (MTS sensors, C-series core sensor) that is used to measure the displacement of the floor. The floor and the cart apparatus weigh 1.93 kilograms, giving a modal frequency of 1.81 hertz. This frequency is calculated by assuming shear structure behavior but then is also verified experimentally through the frequency response function using an input sine sweep of ground motion. The damping of the structure was estimated based on Rayleigh damping that is both mass-proportional and stiffness-proportional, using a 3% damping ratio[16].

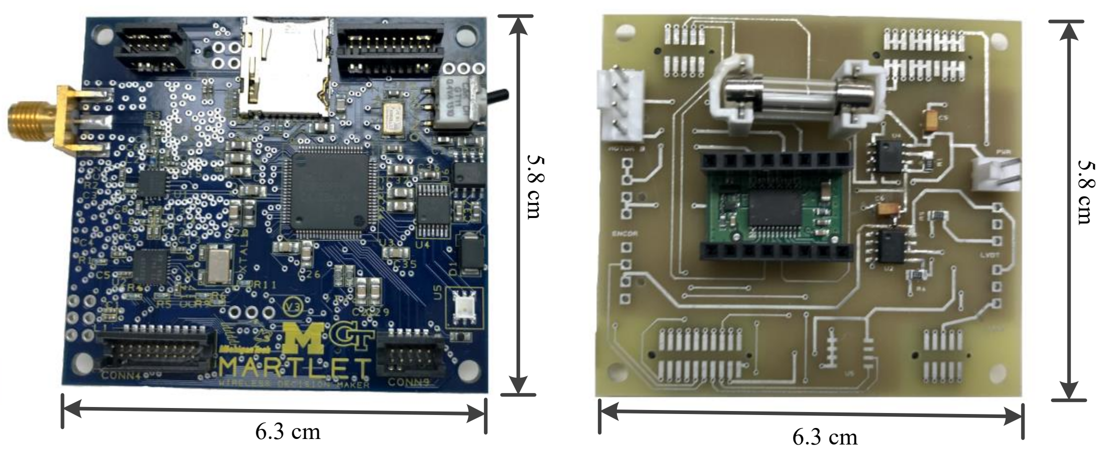
To fully exploit the real-time benefits of bio-inspired control, the test bed transducers (*i.e.,* position sensors) interface with the bio-inspired sensor node. The bio-inspired sensor node (Fig. 3a) reads the linear-position sensor output and then transmits its information to an actuation node that serves as the motor neuron. The bio-inspired sensor node consists of neural units that bandpass filter the sensor signal through overlapping passbands (Fig. 3b, Fig. 3c). A simple peak-picking algorithm is applied to the sinusoidal output of each analog filter and detected peaks are instantaneously communicated as a single packet, using wireless telemetry. The bio-inspired sensor node can be optimized according to its application and for the purposes of control, previous analysis has found that 12 neural units, each with a bandwidth of 0.5Hz and a frequency spacing of 0.7Hz is optimal[13].

The *Martlet*[17] (Fig. 4a), developed at the University of Michigan in collaboration with Georgia Institute of Technology and Michigan Technological University, is chosen as the motor neuron node due to its fast processing capabilities, which eliminates any further delays within the system. The *Martlet* receives information from all of the neuron boards and



(a) (b) (c)

Figure 3. Bio-inspired sensing unit (a), with neural unit board (b) and neural unit function schematic (c).

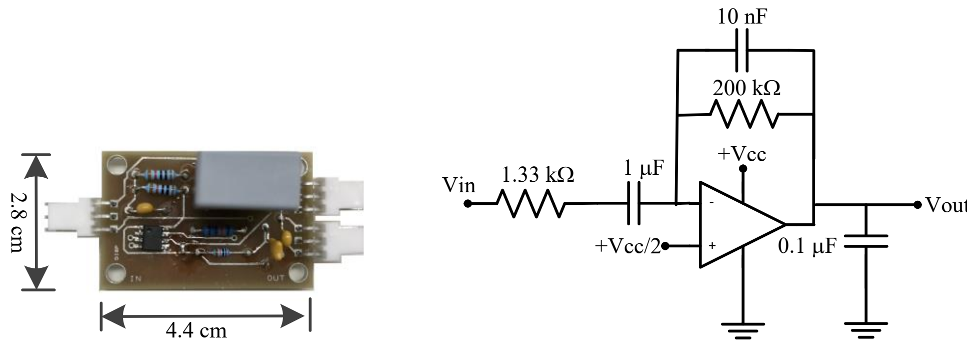


(a) (b)

Figure 4. Motor neuron board, *Martlet* (a), and motor controller peripheral (b)

integrates that information together using equation 1. In this scenario, the weighting matrix, ***W***, is a 1x12 vector (= 12 neural units on 1 sensing node x 1 actuator) whose values are determined offline using the output-only linear quadratic regulator (LQR) optimal control theory[18], as outlined in Peckens et al.[14] The *Martlet* passes the resulting control force to a mounted motor controller peripheral board (Fig. 4b). The motor controller peripheral board is equipped with the Pololu TB6612FNG Dual Motor driver, which converts commands from the *Martlet* to voltage signals that drive the motor on Quanser's AMD.

As a comparative baseline, a traditional control method is also implemented. In this scenario, a second *Martlet* replaces the bio-inspired sensor node and transmits information about the structure's motion to the actuating *Martlet*. The actuating *Martlet* implements full-state feedback control using the full-state linear quadratic regulator optimal control theory. In full-state feedback control, the control algorithm requires both displacement and velocity measurements. For control purposes, velocity can be approximated from displacement using a Kalman filter but this has been shown to impede the overall control sampling frequency[8,19]. Therefore, a differentiating circuit (Fig. 5) converts the displacement signal directly into a velocity signal. The sensing *Martlet* then transmits both displacement and velocity to the actuating *Martlet* and uses these to calculate the corresponding control force.



(a) (b)

Figure 5. Differentiating circuit board (a) and circuit schematic (b). Note: Vcc is the power supply, Vin is the displacement measure and Vout is the resulting velocity.

3.2 Quantification of Control Effectiveness

The effectiveness of the bio-inspired control algorithm is compared to the centralized LQR method using four cost functions, adapted from Ohtori et al.[20] 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

$$\boldsymbol{J_1} = \frac{\max\left(|\boldsymbol{d}(t)_{controlled}|\right)}{\max\left(|\boldsymbol{d}(t)_{(uncontrolled}|\right)} \tag{2}$$

where $\boldsymbol{d}$ is the time history of the displacement for the single story structure, and

$$\boldsymbol{J_2} = \frac{\|\boldsymbol{d}(t)_{controlled}\|}{\|\boldsymbol{d}(t)_{uncontrolled}\|} \tag{3}$$

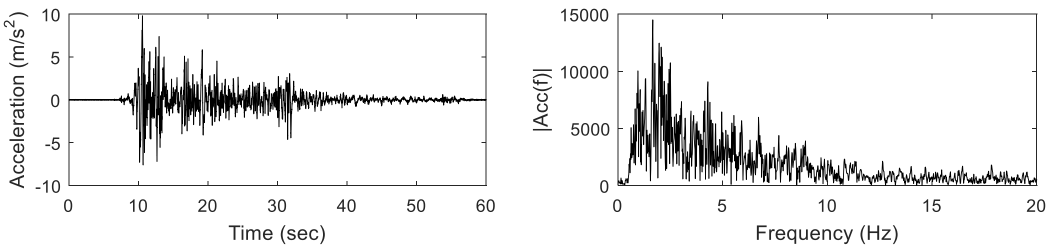
where $\|\cdot\|$ denotes the l_2-norm function. For quantification of acceleration, $\boldsymbol{a}$, the cost functions are

$$\boldsymbol{J_3} = \frac{\max\left(|\boldsymbol{a}(t)_{controlled}|\right)}{\max\left(|\boldsymbol{a}(t)_{uncontrolled}|\right)} \tag{4}$$

and

$$\boldsymbol{J_4} = \frac{\|\boldsymbol{a}(t)_{controlled}\|}{\|\boldsymbol{a}(t)_{uncontrolled}\|}. \tag{5}$$

Equations 2-5 are quantified for the single story structure using the bio-inspired control algorithm and the baseline LQR method.

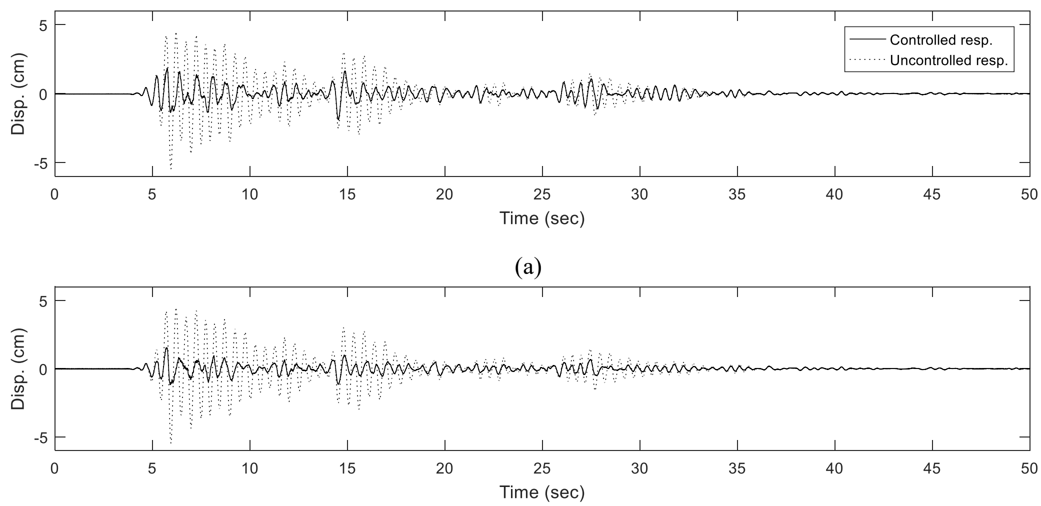


(a) (b)

Figure 6. 1940 El Centro (Southeast) Earthquake in the time (a) and frequency (b) domains.

Table 1. Cost functions for single story structure subject to El Centro earthquake.

	J_1	J_2	J_3	J_4
Bio-inspired control method	0.35	0.37	1.60	1.16
Traditional LQR method	0.28	0.25	1.21	0.79



(b)

Figure 7. Measured structure displacement when subject to the El Centro earthquake using the bio-inspired control algorithm (a) and the traditional LQR algorithm (b).

3.3 Preliminary Experimental Results

The single-story structure is excited using the 1940 El Centro earthquake record (Fig. 6) and subject to the bio-inspired control algorithm and then the baseline LQR method. The resulting cost functions are shown in Table 1. Both methods are able to reduce the maximum displacement (J_1) and the averaged displacement (J_2) (Fig. 7). The baseline LQR method is slightly more effective than the bio-inspired method and additional improvement of the weighting matrix should be considered in order to match or exceed the baseline method. This will include exploring the Particle Swarm Optimization method and various algorithm adaptions, as discussed by Peckens and Fogg[21]. When considering the acceleration metrics, however, neither method is very effective and in some cases the acceleration is increased. It is hypothesized that this occurs because of the small scale of the structure, as well as the jitter that the AMD's motor introduces into the system.

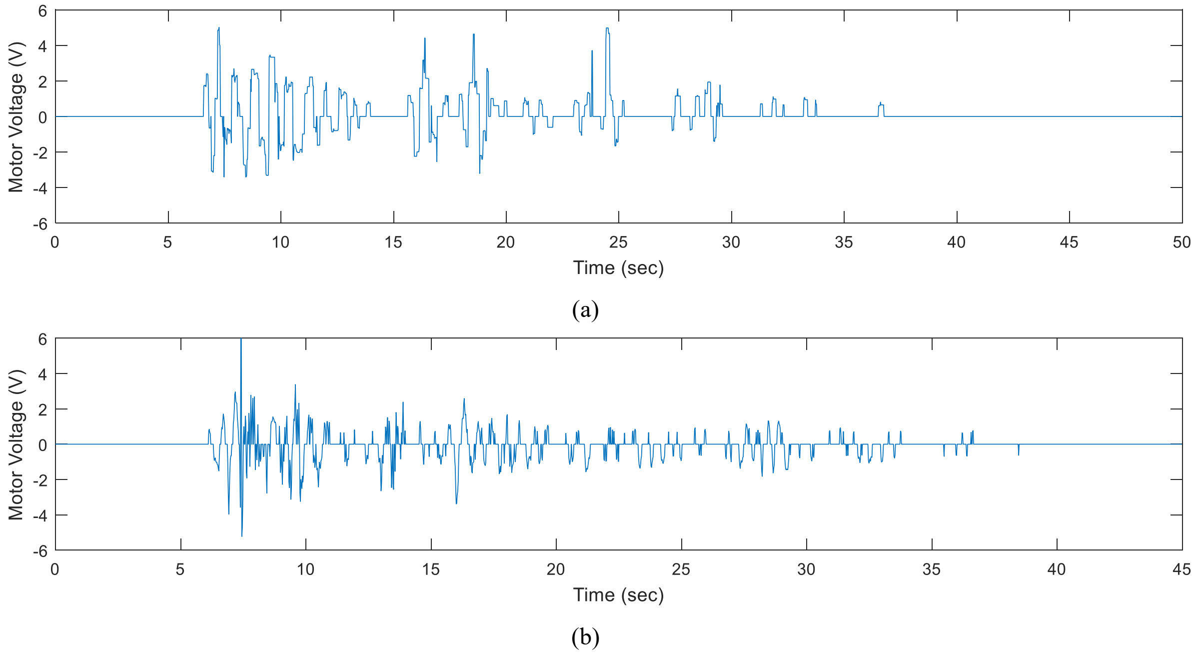


Figure 8. Output control force, or motor voltage, when the single story structure is subject to the El Centro earthquake using the bio-inspired control algorithm (a) and the traditional LQR algorithm (b).

The control output is also considered as a metric for quantifying the overall performance of the two control scenarios. The recommended motor voltage for the Quanser AMD is 6V so in its calculations, the *Martlet* caps the control force at this value. Additionally, to prevent significant wear on the motor, if the desired motor voltage is less than 0.6V then it is set to zero. This eliminates small and erratic changes to the motor, which naturally occurs due to the stochastic behavior of the seismic excitation. The resulting control force, or motor voltage, is shown in Figure 8. While the bio-inspired method does have a smaller peak control force than the traditional control method (5.0V versus 6.0V), it does expend more energy over the entire time history. Using the l_2-norm function, the traditional method demands 30.9V, while the bio-inspired method demands 45.6V, or 47.6% more control force.

4. 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 uses 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 effectiveness of this method was experimentally validated on a single-story shear structure and compared against a traditional control scheme that uses full-state LQR. Both methods are able to reduce the overall displacement of the structure but the traditional method does outperform the bio-inspired method when considering both reduction of displacement and minimization of control demand. Both methods did little to reduce the overall acceleration of the structure, in part due to the effects of the motor of the AMD. In summary, while the traditional full-state optimal control theory does outperform the bio-inspired control algorithm, the bio-inspired control algorithm offers promising results.

Future work will include further refinement of the weighting matrix, using other optimization methods in order to improve the bio-inspired control algorithm's control efficacy. In particular, the PSO algorithm has shown to be more effective than the LQR method in simulation[14]. Additionally, pruning methods will be applied to the weighting matrix, $\boldsymbol{W}$, with the goal of eliminating extraneous information, thereby further minimizing communication and improving control effectiveness. Finally, future work will include extending this control set-up to a four-story structure with increased complexity which will further validate the findings.

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