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Minimalistic Decentralized Control using Stochastic Resonance inspired from a Skeletal Muscle

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***Abstract*— Sarcomere is a functional unit constituting a skeletal muscle, which can only contract and relax in response to changes in Ca^+ concentration. In order from the simple to the most complex, it builds structures corresponding to myofibrils, muscle fibers, muscle fiber bundles and the skeletal muscle. This distinctive hierarchical structure of skeletal muscles has been intensively studied in interdisciplinary research fields. In engineering, how the system efficiently controls a large number of sarcomeres to express continuous output force, is a point that has been focused. In this research, we propose a new decentralized control which is very simple but can manage many binary functional units by exploiting environmental noise. The validity of method is confirmed in both numerical simulation and a developed biologically inspired actuator.**

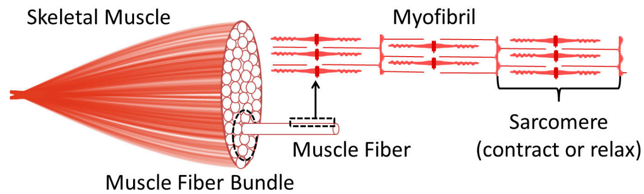

Fig. 1. A schematic illustration of hierarchical structure in a skeletal muscle. The sarcomere, which is a functional unit in the structure, can only contract or relax in response to changes in motor commands in the form of Ca^+ concentration

I. INTRODUCTION

A skeletal muscle consists of a large number of sarcomeres whose functional units can only contract and relax in response to motor commands in the form of changes in Ca^+ concentration. Sarcomeres constitute skeletal muscles. They sequentially build larger structures, corresponding to myofibrils, muscle fibers, and muscle fiber bundles as shown in Fig.1. This complicated hierarchical structure has been intensively studied and many researches have tried to model and clarify the structure and the mechanism by which the skeletal muscle can activate sarcomeres efficiently to realize given motor commands [1], [2], [3]. On the other hand, from the engineering point of view, clarifying the mechanism may lead to a highly sophisticated decentralized control method, because controlling each of a large number of sarcomeres is impossible and it must be done with a decentralized and distributed control manner.

A pioneering work on this point in engineering has been conducted by Ueda et al. They developed a cellular actuator which consists of many small ON-OFF piezoelectric elements [4] and proposed a stochastic decentralized control, which needs only one common scalar input signal for all ON-OFF elements, called broadcast feedback. In the method, each element state is stochastically determined by a Markov decision process and the number of activated elements determines the actuator output. The common scalar input signal is used to adjust the transition probability from one state to the other for all elements. Because it is not important whether or not a specific element is activated but how many elements are activated in the system, the proposed method exploits this feature and makes the control system simple. From the view point of biological plausibility, some analogies can be found in the broadcast control. For instance, the behavior of sarcomere is inherently stochastic because of the thermal noise [5]. However, despite they have mentioned that thermal noise plays an important role in the transmission of motor commands to each sarcomere, the broadcast control does not clearly separate the input signal and the noise. Because the existence of noise often gives merits for the system performance rather than demerits in biological systems, the noise may give not only stochasticity but also different advantage such as efficient transmission of motor commands.

In detail, Stochastic resonance(SR) is a phenomenon by which additional noise can enhance response of nonlinear systems, proposed by Benzi et al. to explain cyclic arrivals of ice ages [6]. Since then, SR has been found in wide variety of biological systems [7], [8], [9]. In a skeletal muscle, SR has been known to occur in an actin-myosin system, which is a micro model of a sarcomere, by thermal noise applied in Ca^+ transmission [10]. Because most of biological models of a skeletal muscle express the output force as the summation of constructional element outputs, they would also explain the effect of SR in the efficient control of vast number of sarcomeres.

In this research, we propose a minimalistic decentralized control for a biologically inspired actuator consisting of many binary elements. The output of the actuator is determined by the summation of the number of contracted binary elements as happens for the biological models of a skeletal muscle. As for the assumption on the actuator required to apply the proposed control, each element, instead of having a explicit probabilistic model as in [4], is only required to have single threshold and contract when the input exceeds the threshold. This indicates that the proposed control can simplify the required assumptions more than the

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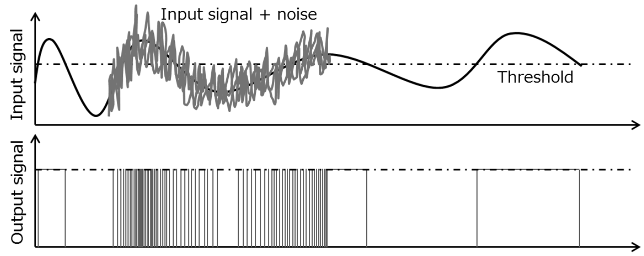

Fig. 2. The simplest example of SR in a threshold element. In contrast with the element can originally express only whether or not the input is larger than the threshold, the magnitude information of input signal rises as the activation density in the region where noise is applied. An adequate level of noise intensity is required to maximize the information transfer.

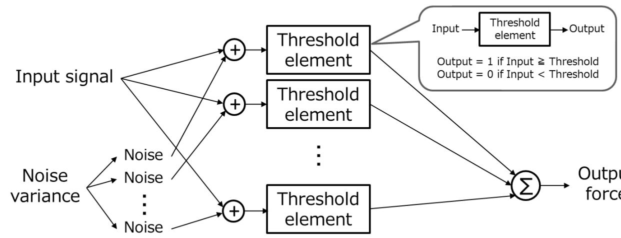

Fig. 3. The schematic figure of out biologically inspired actuator consisting of many binary state functional units. Because SR occurs by adding an adequate level of noise, each element will stochastically express the magnitude information of input signal and the output force is determined by the statistics of all the elements.

existing method [4]. The main idea is to exploit SR effect which enables threshold elements to stochastically express a magnitude information of an input signal by adding a noise. In this paper, we demonstrate the validity of the minimalistic decentralized control by conducting both numerical simulation and experiments using a prototype actuator developed by mimicking the features of a skeletal muscle.

II. STOCHASTIC RESONANCE

The theoretical aspects of SR have been intensively studied in parallel with research aimed at proving its existence in a wide variety of biological and engineering systems [11]. The simplest example of SR, which often focused to investigate its theoretical aspect and quantitative evaluation, can be seen in a threshold element. Fig.2 illustrates the mechanism of simplest example. The single threshold element can output only whether or not the input signal exceeds the threshold at that moment. More specifically, the output of element cannot express the magnitude information of the input signal. However, when an additional noise is added to the input signal, the input can exceed the threshold stochastically thanks to the noise. Consequently, the probability relates not only the noise variance but also the difference between the input signal and the threshold. In other words, the output of element can stochastically express the magnitude information of the input signal. If the noise is white Gaussian noise with the variance σ, the probability that the element is activated $y(t) = 1$ by the current input $u(t)$ is written by the following equation:

$$\mathrm{P}(y(t) = 1) = \frac{1}{2}\left\{1 + \mathrm{erf}\left(\frac{\mathrm{u(t)} - \theta}{\sigma\sqrt{2}}\right)\right\}. \tag{1}$$

Where θ is the threshold value and erf indicates the error function defined as:

$$\mathrm{erf}(\xi) = \frac{2}{\sqrt{\pi}}\int_0^v e^{-v^2}\, dv. \tag{2}$$

From these equations, it is clear that the probability becomes independent to the changes in the input $u(t)$ when $\sigma = 0$ or $\sigma = \infty$. Therefore, the emergence of SR effect requires a proper value of noise variance. In fact, one of most distinguishing features of SR is that its effect is maximized by a specific level of noise and that the performance takes a shape of a monomodal curve in response to changes in the noise variance.

In this research, we exploit the simplest example of SR as a model of functional unit constructing a biologically inspired actuator. In [4], the functional unit was modeled as a binary state unit which determines the state according to a Markov decision process. In contrast with this model, it is clearly simpler to model a functional unit as a single threshold element. This simplicity is thought of as an advantage to construct an actuator consisting of many binary state functional units.

III. PROPOSED SYSTEM AND CONTROL

Fig.3 shows the schematic of a biologically inspired actuator taken into consideration in this work. The actuator consists of a large number of functional units, which contract if the input signal, effected by noise, exceeds a unit-specific threshold. In addition, all functional units have the same threshold value and receive the same input signal but independent noise with the same variance. As explained in the last section, since SR occurs in each element, the output pattern of each element stochastically expresses the magnitude information of the input signal. Because all elements are identical and the output force depends on how many functional units are activating, the probability of activation rises as the output force normalized to the range between zero to one.

In this actuator, the parameters regarding to the performance are the noise variance and the common threshold value. Historically, the noise variance is adjusted to investigate SR effect in a system in both experimental and theoretical research. However, in engineering terms, the noise variance is not a tunable parameter. Therefore, it is necessary to optimize SR effect by adjusting other naturally tunable parameters. In this paper, we propose to optimize the intensity of the input signal instead of adjusting the noise variance because it is relatively similar operation in the system shown in Fig.3. If the input signal $u(t)$ was transformed by a linear mapping $f(x) = Ax + B$, the probability shown in Eq.1 can be changed as following equation:

$$\mathrm{P}(y(t) = 1) = \frac{1}{2}\left\{1 + \mathrm{erf}\left(\frac{\mathrm{u(t)} - \frac{\theta - \mathrm{B}}{\mathrm{A}}}{\frac{\sigma}{\mathrm{A}}\sqrt{2}}\right)\right\}. \tag{3}$$

From this equation, if the parameter B is configured as $B = (1-A)\theta$ to make the threshold θ invariant to changes in the parameter A, varying A indicates similar operation as changes in the noise variance σ.

To summarize the point, three assumptions are made for the actuator:

1) A collection of binary state functional units which can only contract and relax and the entire output is determined by the number of activated units.
2) All units have a common threshold and contract when the input signal exceeds the threshold.
3) All units receive a common input signal and independent noises with a common variance.

Then the proposed minimalistic decentralized control is applied according to following procedures:

1) Identifying a noise variance (for each input level if it depends on).
2) Optimizing the parameter A and θ in Eq.3 to make SR emerge efficiently by evaluating the mutual information between the input and the output signals which is computed by using Eq.3 or Monte Carlo simulations.
3) Sending the input signal with the optimized parameters A and $B = (1-A)\theta$ to all units with the optimized common threshold θ.

Mutual information between the input and output signals is one of general measures to evaluate how strongly SR effects [12]. The definition is following:

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \quad (4)$$

where $p(x,y)$, $p(x)$, and $p(y)$ are the joint probability of the input and output signal, the occurrence probabilities of the input and output, respectively. The mutual information is the non-negative metric that quantifies the amount of information shared between the two stochastic variables. As explained in last section, it is well known that the mutual information between the input and output signals shapes the monomodal curve in response to changes in the noise variance.

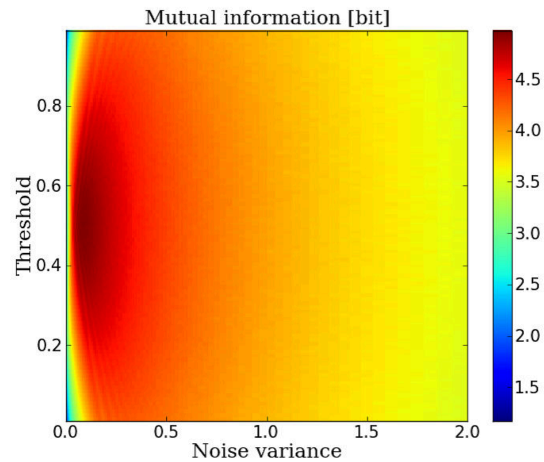

Fig. 4. Mutual information between the input and output signals. The horizontal and vertical axes indicate the noise variance and the threshold value, respectively. The input signal is a sinusoidal wave with the amplitude 0.5, the period 2π, and the offset 0.5. The output signal indicates the ratio of activated units in 10,000 units.

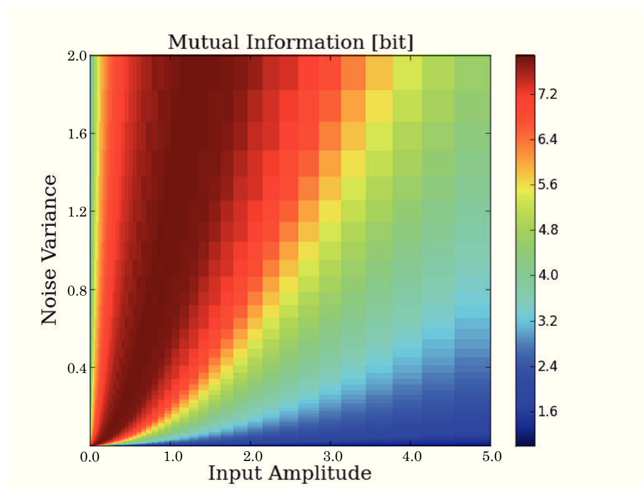

Fig. 5. Relationships among the input amplitude and noise variance, and mutual information between the input signal and the output signals. The threshold value is fixed to the average of input signal.

IV. SIMULATION

In this section, we confirm that the proposed system exhibits SR and that it can be exploited by tuning the input signal intensity relative to the environmental noise. In all simulations, the white Gaussian noise with the average 0 is employed as an environmental noise. Fig.4 depicts relationships among the noise variance, threshold, and mutual information between the input and output signals. The input signal is a sinusoidal wave with the amplitude 0.5, the period 2π, and the offset 0.5. From this figure, it is confirmed that the system can undergo SR because monomodal curves can be seen in the relationship between the noise variance and mutual information which is the distinctive feature of SR emergence. In addition, it can be observed that SR effect is enhanced when the threshold value locates on the average of input signal 0.5. Therefore, for simplicity, we always use 0.5 as the threshold value in following simulations and experiments.

The main concern of simulations is to confirm that changing in the input amplitude can be used instead of tuning the noise variance. Fig.5 depicts relationships among the noise variance, the input amplitude and mutual information with the same setup used in Fig.4. In this simulation, the sinusoidal input is modulated by using a linear mapping $f(x) = Ax + B$ and the input amplitude is corresponding to the parameter A. At that time, the parameter B is automatically tuned to maintain the threshold at the average of the sinusoidal input signal. In this figure, it is shown that there is an optimal combination of the input amplitude and the noise variance which can lead to the maximum mutual information between the input and the output signals. From this result,

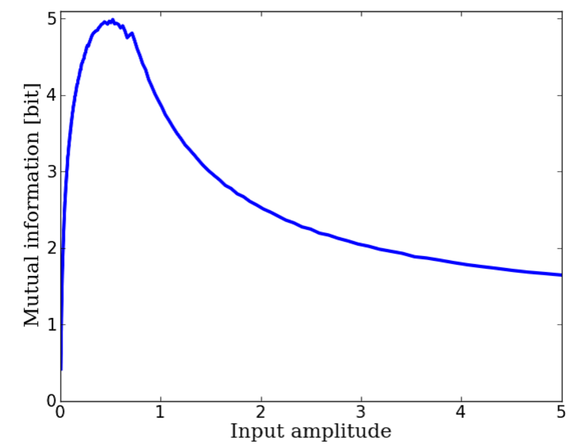

Fig. 6. The changes in mutual information between the input and output signals in response to changes in the input amplitude. The curve exhibits monomodality which is the distinctive feature of SR.

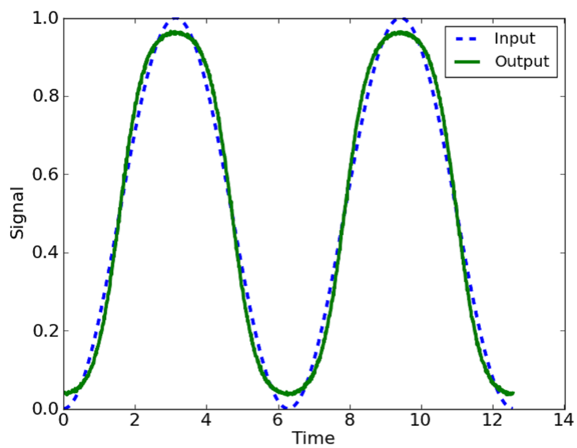

Fig. 7. The response of system with optimal parameters $(\sigma, A) = (0.085, 0.5)$ obtained in the simulation shown in Fig.5.

we pick up the setting $(\sigma, A) = (0.085, 0.5)$ as the instance of the optimal combination.

Fig.6 shows the relationship between the input amplitude and mutual information with the fixed noise variance $\sigma = 0.085$. This graph clearly exhibits the monomodal curve where the peak is located at $A = 0.5$ and indicates that the input amplitude can be used to optimize the SR effect instead of the noise variance.

Fig.7 shows the time-series response of system shown in Fig.3 when a sinusoidal signal is applied as input. Although the output is just the summation of binary units holding a common threshold value, it continuously responds to changes in the input signal. Because the error function is nonlinear, the relationship between the probability of the unit activation and the input signal is also nonlinear, as shown in Eq.3. Therefore, the output will not be the same to the input signal, but the response successfully expresses the shape of input

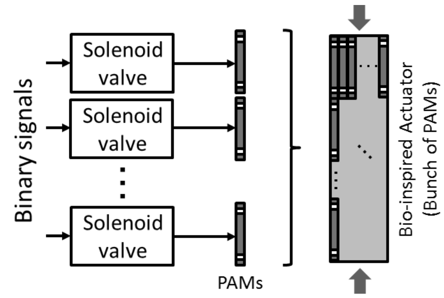

Fig. 8. The design overview of the developed biologically inspired actuator. The actuator consists of many pneumatic artificial muscles (PAMs) which are not only serially but also connected in parallel. Each PAM is controlled by an ON-OFF solenoid valves.

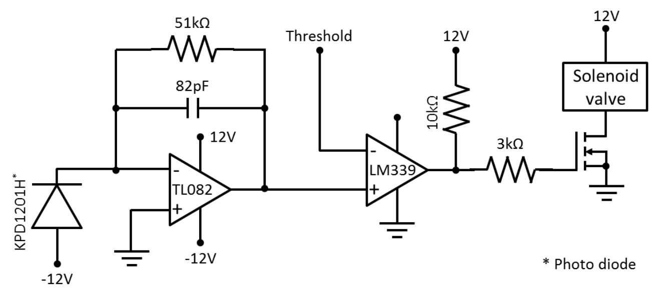

Fig. 9. The control circuit of each functional unit. The current of the photo diode is converted into voltage. The value is compared to the threshold voltage and the solenoid valve is opened if it exceeds the threshold. The common input signal and independent environmental noises are transmitted in a form of light intensity.

signal time-series thanks to optimal parameters maximizing the mutual information. From these simulations, the proposed system and control are validated.

V. DEVELOPED HARDWARE

To confirm the proposed system and control also in a real system, we developed a biologically inspired actuator schematically shown in Fig.8. This actuator consists of many pneumatic artificial muscles (PAMs), which are not only serially but also connected in parallel. Although a PAM is suitable for realizing a functional unit which can exert contracting force but not extending force, like for a sarcomere, the control property is strongly nonlinear. However, because each PAM is controlled by an ON-OFF solenoid valves to mimic the behavior of sarcomeres, which can only contract and relax, it can be assumed that the control is not influenced much by the nonlinearity.

Fig.9 shows a schematic of the control circuit, designed to drive one solenoid valve by meeting the last two assumptions given in section III. Focusing on the design, its simplicity can be easily observed, as it consists of only one photo diode, one op-amp, one comparator, one capacitor, and few resistors. Therefore, to control the binary state of the solenoid valve, no computer is required in the system.

Fig.10 shows the implementation of the proposed system. In this system, the input signal takes the form of light

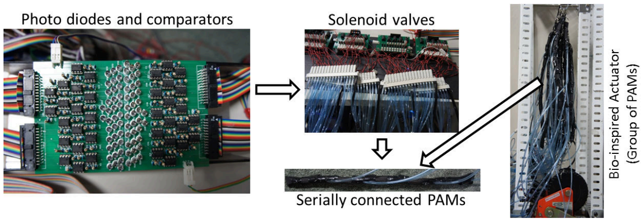

Fig. 10. The parallel parts are connected by using pulleys to distribute the load. 70 sets of the control circuit, solenoid valves and PAMs are used to build the biologically inspired actuator.

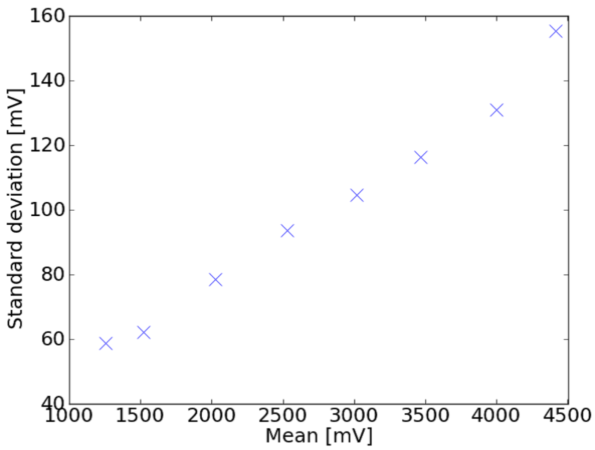

Fig. 11. Relationship between the input intensity and noise standard deviation. The true input intensity is decided by the time average of photo diode output voltage. To measure one point in the graph, the distance between the light source and photo diode plane is fixed.

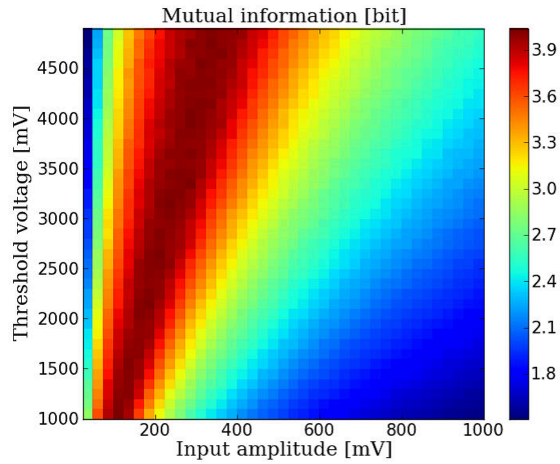

Fig. 12. Relationships among the input amplitude, threshold, and mutual information between the input and output signals computed in a Monte Carlo simulation. The noise variance is configured according to the result obtained in Fig.

intensity and 70 densely placed photo diodes receive the input with environmental noises assumed independent among them. Because each photo diode is connected to the circuit shown in Fig.9, there are 70 sets of solenoid valves and PAMs to build the biologically inspired actuator. In addition, all parallel parts are connected by using pulleys to distribute the load.

In this setting, we have confirmed that the actuator output force is linearly determined by the number of contracting PAMs. Therefore, the first assumption described in section III is satisfied. In the previous section, we confirmed that the system appropriately works if three assumptions described in section III are satisfied. However, it is difficult to ideally satisfy the last assumption, where all units receive a common input signal and independent noises with a common variance, in real world systems. In next section, we confirm the validity of the proposed system by conducting an experiment using the developed hardware.

VI. EXPERIMENT

We conducted an experiment in which a filament lamp is moved vertically against the plane containing the photo diodes to provide a variable input signals. At first, to determine the optimal input amplitude parameter A corresponding to the environmental noise, noise variances at each input intensities are measured as shown in Fig.11. In this result, the distance between the light source and photo diode plane is fixed during the measuring. Because the true input signal is not measurable, we decide to use the time average of photo diode output voltage as the value. Therefore, in Fig.11, the horizontal and vertical axes indicate the mean and standard deviation of output voltages in different locations of the light bulb. From this figure, we linearly approximated the relationship and got $y = 0.029x + 18.853$.

Fig.12 depicts the result of Monte Carlo simulation using the linearly approximated relationship. Because the noise variance is varying in response to changes in input signals, computing the average of the input signals to use as the threshold is not very easy. Thus, in Fig.12, we investigated about not only the input amplitude but also the threshold value by using 1,000 simulated units. From Fig.12, it can be seen that the optimal parameters lie in a ridge in the parameter space. Considering the ease of experimental configurations, we chose the threshold value $\theta = 4400$ [mV] and the input amplitude $A = 300$ [mV] from the result.

Fig.13 shows the relationship between the input signal and the exerted tension of the actuator. As shown in this figure, the relationship can be linearly approximated by the equation $y = 0.046x - 189.723$ with the small residual mean squared error $R^2 = 2.069$, despite it is theoretically nonlinear due to the nonlinearity of the error function included in Eq.1 and 3. Because the same property can be seen in the simulation result shown in Fig.7, this does not depend on the property of the developed hardware. The linear response indicates that the magnitude information of given input signals is maintained in the output force, which is a desirable property for an actuator. As a consequence, we successfully confirmed that the proposed decentralized system and control is valid in both a numerical simulation and a real world application.

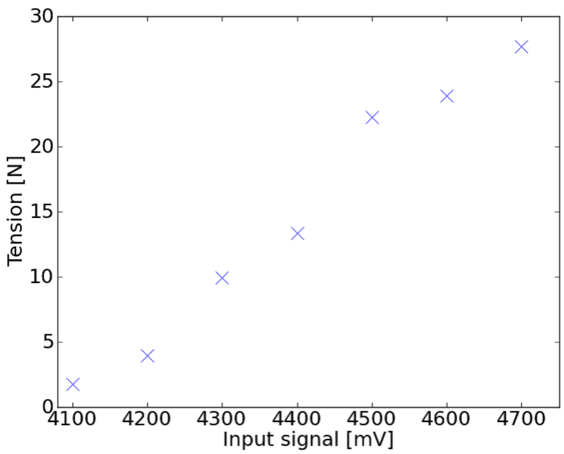

Fig. 13. Relationship between the input signal and the exerted tension of the actuator. The input signal is obtained by the time average of photo diode output voltage. The tension of the actuator is measured by using a load cell (KYOWA, LUX-B-500N-ID).

VII. DISCUSSION

In this paper, we did not strongly focus on the biological plausibility of the proposed system and control. Some similarities however can be found such as the existence of noise and the uncontrollability of such noise. In the proposed system and control, the most suggestive point is that enhancing the input signal intensity, which is generally beneficial to increase the input signal information contained in the output signal, is not always beneficial in our settings. This point would be suggestive for biological research fields because the Ca^{+} transmission, which is the input signal for the assembly of sarcomeres, is also not intense enough to permit ignoring the environmental noise [5], [10]. Therefore, tuning the input intensity is also thought as beneficial for exploiting SR effect in the biological muscle. On the other hand, the biological muscle has the distinctive hierarchical structure which is not fully mentioned in the proposed system. In future work, we will try to figure out the concrete similarity between the proposed system and its biological counterpart by focusing on the hierarchical structure.

In addition, because the output force of the biological muscle is nonlinearly transformed into the torque of the articulation, it is possible to imagine that linearizing the changes in the output force in regard to the increase in the motor command does not always provide benefits in the motions. In other words, it is more desirable that the biologically inspired actuator is evaluated by focusing on not only the characteristics of its output force but also how the actuator is suitable for developing a biologically inspired robots. To cope with this important and complex point, developing a biologically inspired robot driven by this biologically inspired actuators would be one reasonable approach. Therefore, we will try to redesign the biologically inspired actuator to enable the development of a musculokeletal robot arm in the future. In addition, in this paper, we had not investigated whether or not the control property and the mechanical feature of PAMs influence the possibility of applying the proposed decentralized control. The challenge in the redesign will require to investigate this point and contribute to clearly show the engineering advantage of the proposed decentralized control.

Because the proposed system and control are very simple, it will be possible to apply the method to other problems requiring a decentralized control scheme. For instance, it gives new perspective to transmit a control signal to a number of robots. In the future, we will investigate the applicability of the proposed method and aim to generalize the method as a decentralized system and control using SR.

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