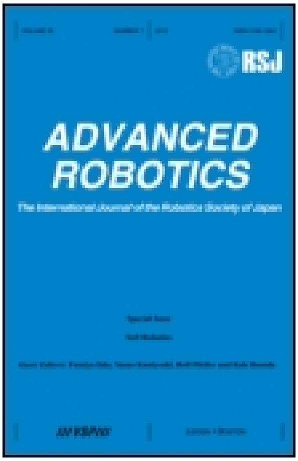


Advanced Robotics
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tadr20

Anthropomorphic Muscular-Skeletal Robotic Upper Limb for Understanding Embodied Intelligence

Koh Hosoda [a] , Shunsuke Sekimoto [b] , Yoichi Nishigori [c] , Shinya Takamuku [d] & Shuhei Ikemoto [e]

[a] Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan;, Email: koh.hosoda@ist.osaka-u.ac.jp

[b] Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan

[c] Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan

[d] Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan

[e] Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan

Published online: 13 Apr 2012.

///VSP/// Advanced Robotics 26 (2012) 729–744

ADVANCED ROBOTICS
brill.nl/ar

Full paper

Anthropomorphic Muscular–Skeletal Robotic Upper Limb for Understanding Embodied Intelligence

Koh Hosoda *, **Shunsuke Sekimoto**, **Yoichi Nishigori**, **Shinya Takamuku and Shuhei Ikemoto**

Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University, 1-5 Yamadaoka, Suita, Osaka 565-0871, Japan

Received 6 September 2011; accepted 13 October 2011

Abstract

In this paper, we describe an anthropomorphic muscular–skeletal robotic upper limb and focus on its soft interaction with the environment. Two experiments are conducted to demonstrate the ability of the system: object recognition by dynamic touch and adaptive door opening. The first experiment shows that the compliant robot is advantageous for categorizing an object by shaking and the second experiment shows that the human-comparable compliant robot can open a door without precise control. The robot is expected to have comparable anisotropic compliance to that of a human, which can be utilized for realization of human-like adaptive behavior.

Keywords

Upper limb, anthropomorphic, embodied intelligence, body compliance

1. Introduction

The distance between robots and humans is now becoming closer, not only in the sense of physical distance but also of structural similarity. Such robots should be soft in several meanings: they should have compliance to allow soft contact with humans, they should have similar structural compliance so that humans easily understand their motion and their behavior should be adaptive by ‘software’. A goal of soft robotics is to study the contribution of such softness to adaptive behavior by using robotics technology.

Recently, many humanoid robots have been developed targeting to share the daily environment with humans (e.g., HRP2-JSK from the University of Tokyo [1] and

* To whom correspondence should be addressed. E-mail: koh.hosoda@ist.osaka-u.ac.jp

 DOI:10.1163/156855312X625371

Robovie from ATR [2]). These robots are essentially hard because they consist of rigid metal/plastic parts driven by electric motors with gears. Although they can be soft when active compliance control is applied based on force/toque feedback, the motion will be limited by the bandwidth of the mechanical system [3] and will be computationally expensive. Pfeifer and Bongard [4] suggest that such expensive computation can be taken over by mechanical compliance, which is one of the original ideas of 'soft robotics'.

There are several levels for introducing mechanical compliance to the robot. Soft skin enables compliant contact with the environment. Using actuators with variable compliance is now gathering attention to realize natural human–robot interaction by introducing series elasticity [3, 5]. The tendon mechanism driven by artificial soft muscles is a solution to understand the role of the body's structural compliance for intelligence. There were several trials to realize anthropomorphic muscular–skeletal arm robots using electric motors [6, 7] and pneumatic muscles [8–11]. These studies mainly focused on motion control and less attention was paid to realization of interactive tasks with the environments using body compliance. Such compliant interaction is supposed to be a key for embodied intelligence [4].

In this paper, we develop an anthropomorphic muscular–skeletal robotic upper limb, and focus on the exploitation of body compliance for perception and action: we demonstrate its object recognition ability though dynamic touch and door-opening behavior utilizing the body compliance. First, to demonstrate how the structural compliance contributes to sensing, we conduct object recognition experiments by dynamic touch. Dynamic touch is a human's proprioceptive and tactile sensation during dynamic interaction with an object, such as touching, banging and shaking [12]. From the sensation, a human can obtain information about the object dynamics and utilize it for categorization. This aspect is gathering increasing attention and, recently, there have been several studies on the dynamic touch of robots. Suzuki *et al.* showed that a robot with joint torque sensors could discriminate cylinders of different length [13]. Bergquist *et al.* showed that a robot could discriminate several objects by lifting, shaking, dropping, crashing and pushing [14]. Takamuku *et al.* demonstrated that auditory information could be a key for categorization when a robot shakes an object [15]. Saal *et al.* showed that tactile sensors were effective for categorization by shaking [16]. Sinapov and Stoychev developed a robot system with joint torque and auditory sensors that could categorize objects based on a self-organizing map [17]. Suzuki *et al.* developed a system to select appropriate actions to categorize objects based on vision, force and auditory sensors [18]. In the existing work, however, they used non-compliant robots. If the robot is compliant, the mechanical eigenfrequency of the coupled system of the body and the object is relatively low. As a result, the resonance frequency can be observed by the proprioceptive sensors of the robot without additional sensors specialized for exploring the object. An even more interesting point is that the robot can modulate the sensitivity of the observation by changing the body compliance. From the sensation, the robot can obtain information on the object dynamics and utilize it for categorization.

Second, to demonstrate the contribution of compliance to adaptive behavior, we conducted door-opening experiments by the anthropomorphic robot arm. Normally, the door-opening task is very hard for a 'hard' robot: it should generate a trajectory to open the door and track it while it is precisely force-controlled (e.g., Ref. [19]). However, opening a door seems an easy task for humans since they can utilize body compliance. If the robot has a similar structure as a human, the task is expected to be easy for it. As stated above, existing muscular–skeletal robots [8–11] did not perform interactive tasks with the environment, although compliant robots are beneficial for such tasks.

This paper is organized as follows. We first describe the design of the anthropomorphic robotic upper limb consisting of bones, artificial muscles and soft skin. Then, we demonstrate object recognition ability by shaking the target object. Finally, we demonstrate that the robot can open a door very smoothly utilizing its compliance without precise control. We suppose that these two results on perception and action demonstrate the role of human-like embodiment in the human environment, and that these will be key to understand the human intelligence.

2. Design and Features of an Anthropomorphic Robotic Upper Limb

To investigate the contribution of the body compliance to intelligent behavior, we develop an anthropomorphic robotic upper limb (Fig. 1). The limb consists of a shoulder, an upper arm, an elbow, a forearm, a wrist and a hand. The shoulder has a ball joint driven by nine artificial muscles (Fig. 2a). The elbow has one rotational joint driven by a pair of muscles (Fig. 2b). The forearm consists of two bones — a radius and an ulna — and is driven by two twisted muscles (pronation and spination). The wrist has an oval sphere joint driven by four muscles. Since the joint is an oval sphere, the hand cannot rotate along the longitudinal direction of the arm; therefore, the wrist has 2 d.o.f. In total, the arm part of the upper limb has 7 d.o.f.

Since the contraction rate of the artificial muscle was up to 30% and the space to put the artificial muscles was limited, we had to design the arm slightly bigger than

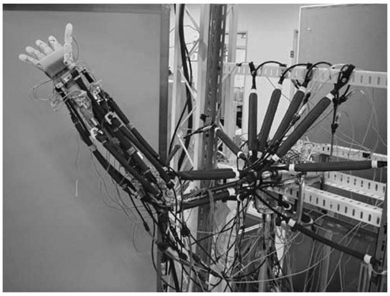


Figure 1. Anthropomorphic upper limb. It has a human-like muscular–skeleton structure. The shoulder is a ball joint driven by nine muscles. The elbow is a joint driven by agonistic and antagonistic muscles. The fore arm consists of two bones — a radius and an ulna. The wrist is an oval sphere driven by four muscles. The hand consists of bones and silicon skin, which is driven by four muscles.

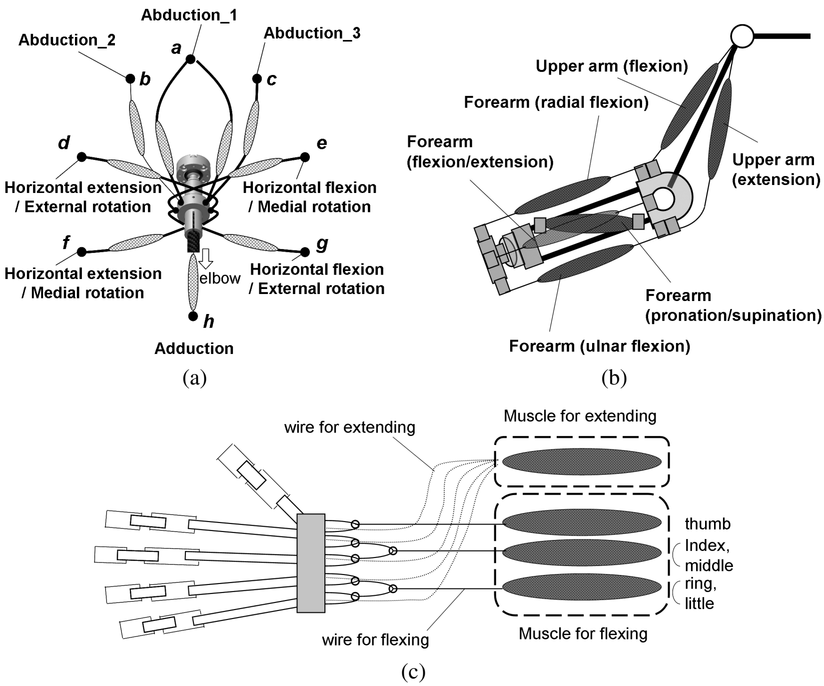


Figure 2. Muscular–skeleton system of the upper limb: (a) shoulder, (b) arm and (c) hand. (a) The shoulder functionally 3 d.o.f. driven by nine muscles. (b) The arm. The elbow has a rotational joint driven by two antagonistic muscles. The forearm consists of two bones and is driven by six muscles: pronation/spination, ulna and radial flexion, and wrist flexion/extension. In total, the arm has 4 d.o.f. (c) The hand is driven by four muscles. For extension, it has one muscle for all the joints. Three muscles are used for flexion of the groups of fingers.

Table 1.
Range of motion (upper/lower; deg) of the anthropomorphic upper arm compared with that of a human [22] (since the range of the shoulder joint depends on the payload, it is not shown in the table)

	Robot	Healthy human [22]
Elbow	−3.6/63.2	0/145
Pronation/spination	−78.3/78.6	−85/85
Radial/ulnar flexion	−37.0/39.6	−45/45
Wrist flexion/estention	−37.8/22.3	−85/85

a human's so that it could cover a comparable range of motion to that of a human. As a result, the total length and weight of the arm are approximately 0.85 m and 3.5 kg, respectively — 1.5 times as big as a human's. It can lift up around 2 kg weight, but it depends on the arm configuration. In Table 1, we show the realized range of motion compared with that of a human.

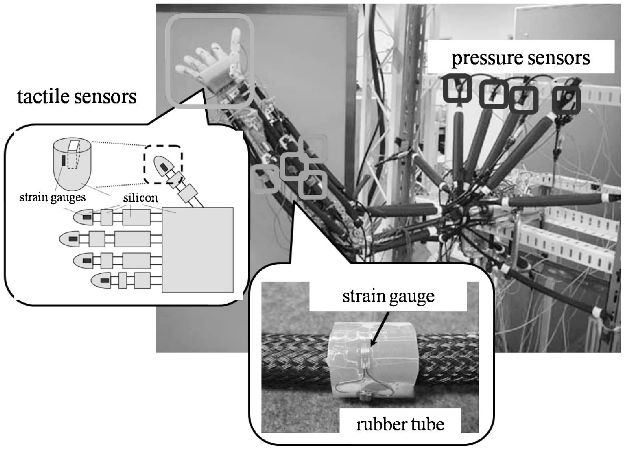


Figure 3. Tactile and proprioceptive sensors. Strain gauges are embedded inside silicon skin of the robotic hand. Each fingertip has one strain gauge. Two kinds of proprioceptive sensors are embedded: pressure sensors and strain gauges mounted on rubber tubes around the muscles.

The hand has five fingers, each of which is driven by wires. It is a simplified version of the Bionic Hand [20, 21]. We reduced the number of actuators since we do not have enough space in the arm to put many artificial muscles. The hand is driven by four muscles — one for extension and three for flexion of fingers (Fig. 2c).

The robot has several sensing modalities. We embed proprioceptive and tactile sensors to the limb (Fig. 3). As proprioceptive sensors, we normally use joint sensors such as optical encoders. However, since the limb has anthropomorphic ball-like joints, we cannot adopt conventional joint angle sensors. As proprioceptive sensors, therefore, we adopt two types of sensors: pressure sensors and stain gauges. They have pros and cons: a pressure sensor is easy to put on the muscle, but does not have a strong correlation with the length of the muscle. A strain gauge can sense muscle expansion that has a certain correlation with muscle length (measured relation between strain gauge output and displacement of the muscle is shown in Fig. 4), but it is hard to put it on the muscle stably. Since the state of a muscle is observed by two out of three measurements — pressure, length and force [23] — we have to put pressure and strain sensors on each muscle to observe all the states of the arm. In this experiment, however, we reduce the number of sensors since our aim is not to estimate all the states of the arm, but to realize categorization tasks with it.

3. Object Recognition Base by Dynamic Touch

3.1. Dynamic Touch

To demonstrate how the structural compliance contributes to sensing, we conducted object recognition experiments by dynamic touch. We prepared plastic bottles filled with different materials: water, oil, powder (flour), sand (grain size: 1 mm) and

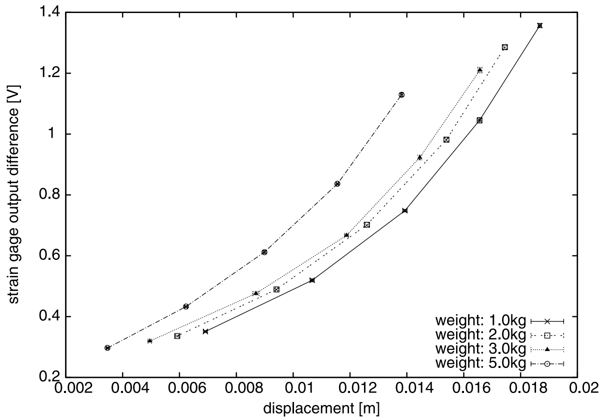


Figure 4. Preliminary experimental result on a proprioceptive sensor. The relation between strain gauge output and displacement of the muscle is investigated. It is robust against changes of load.

object	weight(including bottle weight)
vacant	50g
water	100g, 125g 150g
oil	100g, 125g, 150g
powder(flour)	100g, 125g, 150g
sand(grain size: 1mm)	100g, 125g, 150g
stone(grain size: 10mm)	100g, 125g, 150g

Figure 5. Bottle used for the experiments. Water, oil, powder, sand and stone are put inside the bottle.

stone (grain size: 10 mm). We also had weight varieties — 100, 125 and 150 g, for each material (i.e., 15 variations of shaken objects).

Since the limb has many d.o.f., the robot can shake the object in many different ways. In this paper, we do not explore the varieties of shaking patterns, but focus on simple patterns: shaking the object vertically and horizontally. The shaking frequencies are 0.75, 1 and 1.25 Hz. The limb shakes the object in six patterns in total. We conducted five experimental trials for each object for each shaking pattern (i.e., 480 trials in total).

3.2. Raw Measurement from Sensors

In Fig. 6, we show the raw measurements from sensors when the limb shakes the bottle containing 100 g water horizontally at 1 Hz. From Fig. 6, we can see that the robot is able to sense resonance including harmonic oscillation through both pressure sensors and strain gauges. Note that the phase of the sensation from one muscle is completely opposite to that of the antagonistic muscle.

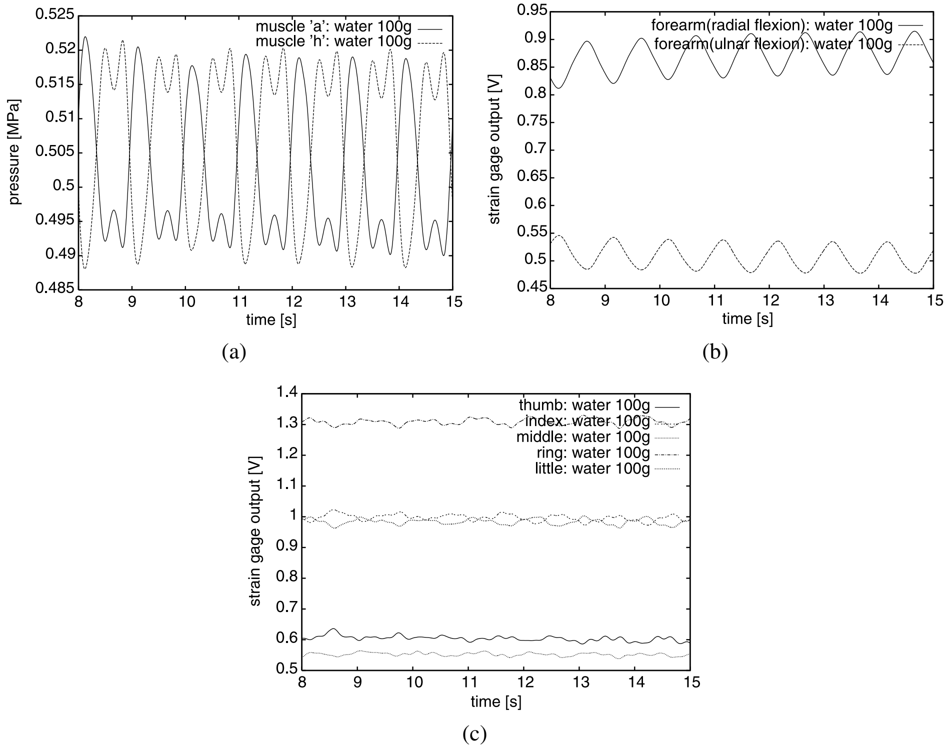


Figure 6. Raw data from sensors when the robot shakes a bottle with 100 g of water horizontally. We can observe resonance and harmonic oscillation. (a) Measurement of pressure sensors of muscles in the shoulder. (b) Measurement of strain gauges sensing muscle expansion of the forearm. (c) Measurement of strain gauges in the fingers of the hand.

We adopt fast Fourier transform (FFT) to analyze the raw data. The sampling rate is 2 ms and we use 2048 data points (i.e., data through approximately 4 s). A result is shown in Fig. 7. In Fig. 7, the first peak comes from forced oscillation of the limb: 1 Hz. We also can observe integral multiples of harmonic oscillation in Fig. 7. To characterize the sensor response, we pick first two peaks of the FFT results. We can get 22 values — two peaks of resonance frequencies out of 11 sensors (five tactile sensors in the hand, two strain gauges and four pressure sensors in the muscles). Since the dimension of the raw data is too high, we adopt principal component analysis (PCA) for categorization. In this paper, we use two components.

3.3. Categorization Result

First, we focus on weight. In Fig. 8, we show PCA results of vertical shaking at different frequencies. Figure 8 shows that when the robot shakes the bottle vertically at 1 Hz it can beautifully categorize the weight of the bottle no matter what it contains (all the plots are results of five contents). Investigating the contribution ratio, we can find that data from the pressure sensor largely contribute to the first component.

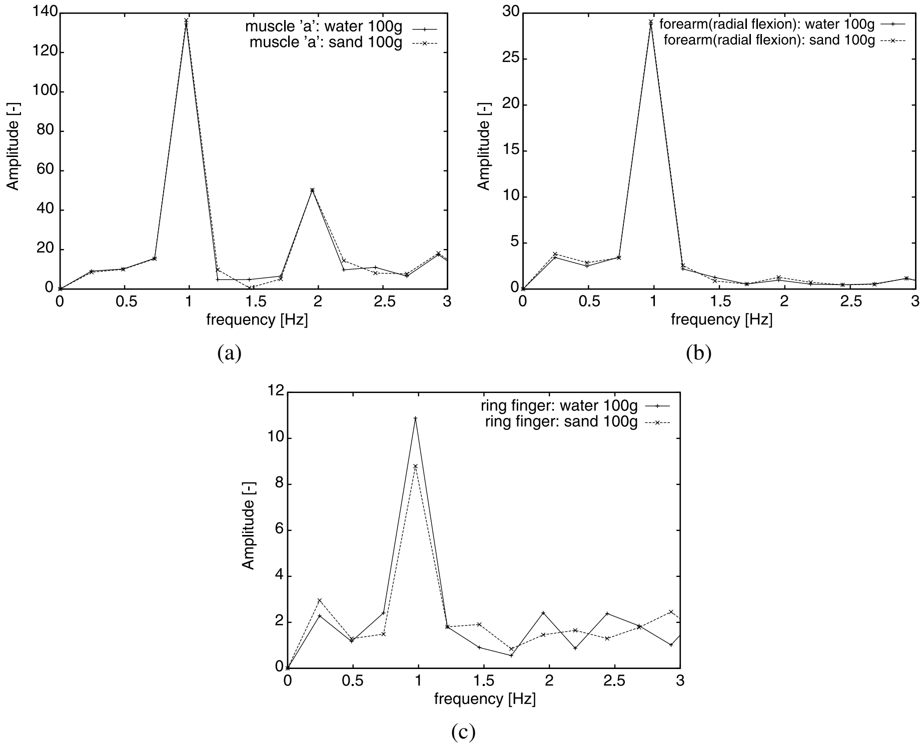


Figure 7. FFT result through shaking a bottle with 100 g of water horizontally. (a) FFT results of pressure sensors of muscles in the shoulder. (b) FFT results of strain gauges sensing muscle expansion of the forearm. (c) FFT results of strain gauges in the fingers of the hand.

Second, we focus on material. In Fig. 9, we show PCA results of horizontal shaking at different frequencies. Figure 9 shows that when the robot shakes the bottle horizontally at 1.25 Hz, it can detect whether the contained material is solid (powder, sand or stone), liquid (water or oil) or empty. Although the category of oil is partly overlapping that of water, and that of powder, sand and stone are also overlapping, we can find each category in Fig. 9c. This means that the robot can to some extent categorize material contained in the bottle by dynamic touch.

3.4. Summary and Discussion of the Shaking Experiment

By the experiment, we can show that the dynamic interaction between the object and the robot body can be utilized for object categorization. Since the robot body is compliant, proprioceptive sensors can be used for the categorization and the robot does not have to have additional external sensors. This shows that the body compliance can enhance the sensing ability of the robot.

The difference in categorization ability in shaking directions shows that the anisotropic nature of the body compliance can be used for getting rich information on the object. The robot can change the shaking direction during the shaking sequence to explore the object, but it is not investigated in this paper.

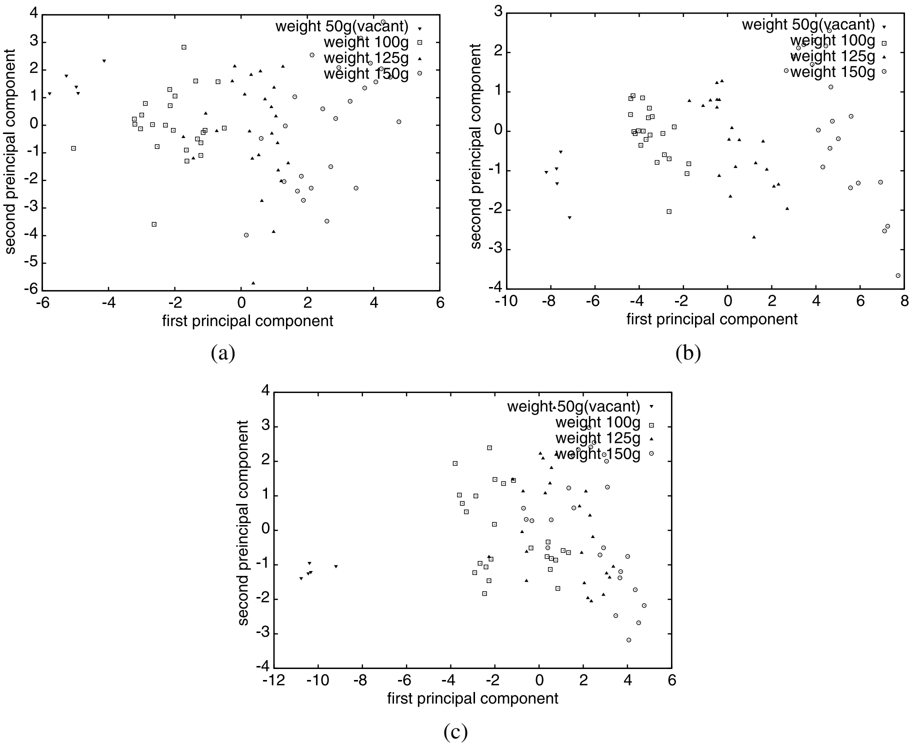


Figure 8. PCA results. When the robot limb shakes the bottles at 1 Hz vertically, it can categorize the weight of the bottle no matter what it contains. (a) PCA result in vertical shaking at 0.75 Hz. (b) PCA result in vertical shaking at 1 Hz. (c) PCA result in vertical shaking at 1.25 Hz.

We also asked human subjects to detect the material inside by shaking the bottle and they found it difficult if they did not use their ears. Object recognition only by dynamic touch is, we must say, a relatively difficult task even for humans. To increase the ability, the robot should have additional external sensors such as auditory sensors [15].

Using proprioceptive sensors for categorizing is really interesting from the perspective of body image. If the robot uses end-effector sensors such as force sensors, it only estimates the dynamics of the object. However, if the robot uses proprioceptive sensors, then the robot senses combined dynamics of the limb and the object [24]. This fact suggests that the body image of the robot changes when it grasps an object, which is demonstrated by Iriki [25]. This kind of work can be a probe to study how body image can be constructed.

4. Adaptive Behavior Utilizing Body Compliance

In this section, we conduct a door-opening experiment to demonstrate how the human-like structure contributes to realization of adaptive behavior in the human environment.

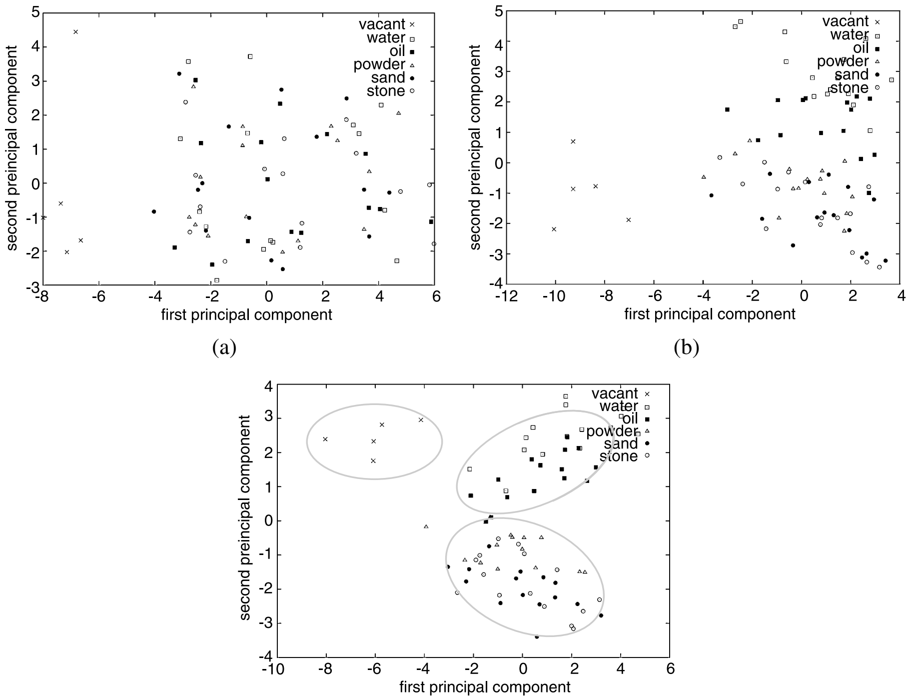


Figure 9. PCA results. When the robot limb shakes the bottles at 1.2 Hz horizontally, it can categorize the contained material to some extent: whether it is liquid, solid or empty. (a) PCA result in horizontal shaking at 0.75 Hz. (b) PCA result in horizontal shaking at 1 Hz. (c) PCA result in horizontal shaking at 1.25 Hz.

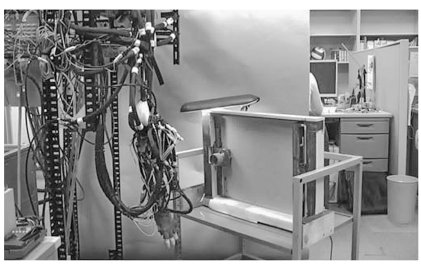


Figure 10. Experimental setup for door-opening task. The position and orientation of the door can be changed to demonstrate the robustness provided by the body compliance.

4.1. Experimental Setup

An experimental setup for the door opening task is shown in Fig. 10. The position and orientation of the door with respect to the robot are not carefully calibrated. The robot first moves its hand near to the knob utilizing equipped visual sensors or just performing the pre-programmed motion and grabs it. Therefore, the robot cannot precisely move its hand toward the knob, but if it can move the hand near

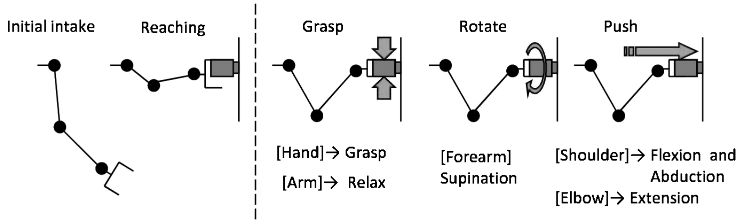


Figure 11. Control strategy based on our experience to open the door.

to the knob, it can grasp the knob at a certain probability since the hand is soft and underactuated [20, 21]. After it succeeds in grasping the knob, the robot moves according to a fixed sequence of movements (Fig. 11), which is realized by a fixed valve operation without sensory feedback. In the rotating phase, the robot twists the forearm utilizing pronation/spination muscles. In the pushing phase, the robot pushes the door by using its shoulder and elbow. The pre-programmed trajectory of the hand is almost straight when it does not hold the knob. However, if it firmly grasps the knob, it can follow the movement of the door because the limb is compliant. Just after it opens the door, it stops grasping the knob since it cannot avoid collision with the door frame.

4.2. Experimental Results

We conducted 110 experimental trials by changing the position of the door relative to the robot to investigate how the size of the area of successful door opening. A successful opening sequence is shown in Fig. 12. The robot reaches the knob from 3 to 6 s, grasps the knob until 9 s, rotates the forearm until 12 s, and opens the door by stretching the shoulder and the elbow. We determine the trial is successful when the arm moves the knob more than 2 cm after opening it. Since the position and orientation of the door are randomly selected (shown in Fig. 13), it is difficult for the robot to locate its hand near to the knob automatically. In these experiments, therefore, the hand is guided by the human operator to the knob and he/she lets the robot grasp it for simplicity. The robot does not change the control strategy; it uses the same valve operation in every trial.

In Fig. 13, successful movement of the hand is shown by a dashed arrow and failure by a solid arrow. We can see that the robot can open the door when the door is within a certain area, even if the relative position and orientation are not the same. In Table 2, we show the success rate in each area in distance from the shoulder. When the hand is within 0.45 m, the robot can open the door around 50% of the time. In Table 3, the area is divided by the angle in the same set of experiments. In the range of $65 < \theta < 115$, the robot can successfully open the door around 50% of the time.

4.3. Summary and Discussion of the Door-Opening Task

From the experiments, we can show that the developed human-like muscular–skeletal upper limb can open the door with a high probability when the door is

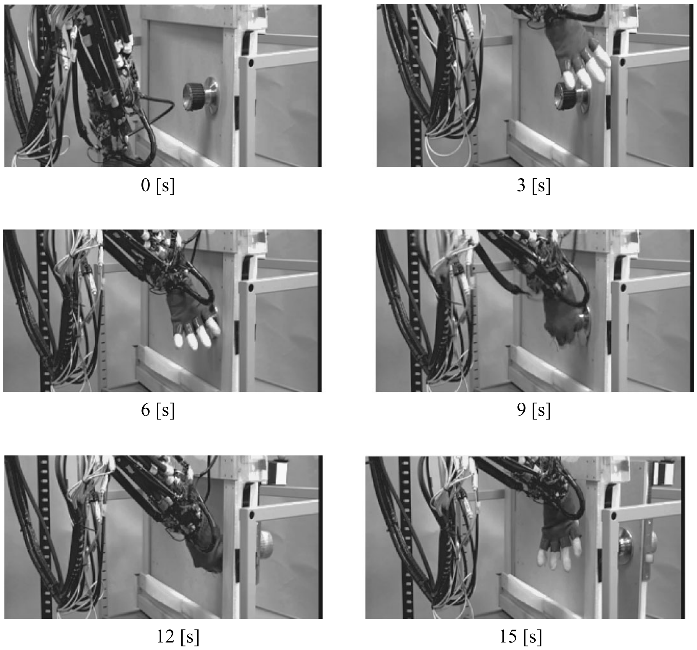


Figure 12. Successful sequence of door opening. The robot reaches the knob from 0 to 6 s, grasps the knob until 9 s, rotates the forearm until 12 s, and opens the door by stretching the shoulder and the elbow.

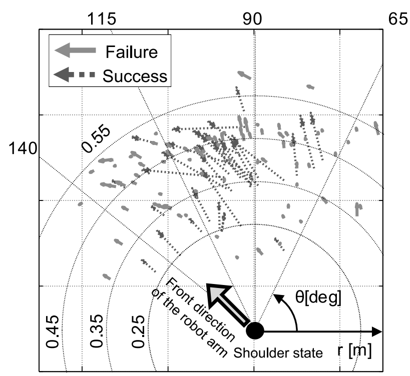


Figure 13. Movement of the hand in the trials. Successful movement is shown by a dashed arrow whereas failure is shown by a solid arrow. We can see the area where the robot can open the door.

within a certain range. However, door opening is a very precise task for rigid robots (e.g., Ref. [19]). Therefore, we can conclude that the robustness of door opening comes from the structural compliance of the muscular–skeletal robot. In particular, to open the door, pronation/spination rotation works pretty well. This means that the human-like structure is advantageous to open the door knob.

Table 2.
Success rate in distance from the shoulder

r (m)	Success rate (%)	No. of trials
$r < 0.25$	60.0	10
$0.25 < r < 0.35$	57.1	21
$0.35 < r < 0.45$	43.2	44
$0.45 < r < 0.55$	24.2	33
$0.55 < r$	0.0	2

Table 3.
Success rate in angle with respect to the shoulder

θ (deg)	Success rate (%)	No. of trials
$\theta < 65$	14.3	7
$65 < \theta < 90$	42.9	28
$90 < \theta < 115$	52.4	42
$115 < \theta < 140$	27.6	29
$140 < \theta$	50.0	4

In this experiment, we only used a cylindrical knob, but we can expect that almost the same strategy can be applied for other types of knobs — once the robot grasps the knob, the compliance of the limb allows the robot to track the movement of the door. Generally speaking, useful tools are designed so that we can utilize our body constraints [4]. In this sense, we may be able to find many tasks in our daily life utilizing our muscular–skeleton structure. Having the same structure as a human would, therefore, be advantageous for realizing such tasks without formally describing them — common sense is programmed implicitly within the 'soft' body.

We have not yet implemented any feedback from the proprioceptive sensors to control the muscles. It is, to some extent, obvious that the robot becomes robust when it utilizes sensors and this will be investigated in the near future. Related to this point, we can also take the local reflexes found in a human into account, such as the stretch reflex. We may be able to investigate their role. In any case, having an anthropomorphic structure is advantageous for studying a human's embodied intelligence.

5. Conclusions

In this paper, we propose to use an anthropomorphic muscular–skeletal robotic upper limb as a tool for studying embodied intelligence of humans. We introduce the design of the upper limb driven by artificial pneumatic muscles and describe the equipped sensors. Two experiments are conducted: object recognition by dynamic touch to demonstrate the sensing ability and door opening to demonstrate adaptive maneuverability.

If the robot body is compliant, the behavior emerges from the interaction between the body and the environment. The interaction deeply depends on the structure of the compliance. Therefore, to determine the human's adaptive behavior, it is crucial to have a similar body structure. This might be a unique view of soft robotics which was not dealt with in rigid robots, in which they only imitated the human's kinematics. More interestingly, compliance of the human body is not isotropic because of the muscular–skeleton structure. Since the human environment is supposed to be designed for a human's anisotropic compliance, a robot with a similar structure is expected to be advantageous to realize human-like adaptive behavior.

Having a similar muscular–skeletal structure is also important for human–robot communication. The emergent behavior from such a structure has a tendency to be similar to that of humans. It would be intuitive for us to predict the behavior of the robot. By having similar bodies, it will be easier for us to share common sense existing in our body, without analyzing it very carefully.

References

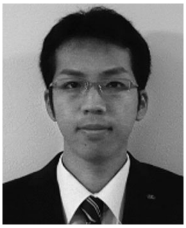
1. K. Okada, T. Ogura, A. Haneda, J. Fujimoto, F. Gravot and M. Inaba, Humanoid motion generation system on HRP2-JSK for daily life environment, in: *Proc. IEEE Int. Conf. on Mechatronics and Automation*, Niagara Falls, ON, pp. 1772–1777 (2005).
2. H. Ishiguro, T. Ono, M. Imai, T. Maeda, T. Kanda and R. Nakatsu, Robovie: an interactive humanoid robot, *Int. J. Ind. Robotics* **28**, 498–504 (2001).
3. A. Albu-Schaeffer, O. Eiberger, M. Grebenstein, S. Haddadin, C. Ott, T. Wimbock, S. Wolf and G. Hirzinger, Soft robotics — from torque feedback-controlled lightweight robots to intrinsically compliant systems, *IEEE Robotics Automat. Mag.* **15**, 20–30 (2008).
4. R. Pfeifer and J. Bongard, *How the Body Shapes the Way You Think*. MIT Press, Cambridge, MA (2007).
5. R. Filippini, S. Sen and A. Bicchi, A study of antagonistic actuation, *IEEE Robotics Automat. Mag.* **15**, 31–41 (2008).
6. O. Holland and R. Knight, The anthropomimetic principle, in: *Proc. AISB06 Symp. on Biologically Inspired Robotics*, Bristol (2006).
7. Y. Sodeyama, T. Nishino, Y. Namiki, Y. Nakanishi, I. Mizuuchi and M. Inaba, The designs and motions of a shoulder structure with a spherical thorax, scapulas and collarbones for humanoid kojiro, in: *Proc. Int. Conf. on Intelligent Robots and Systems*, Nice, pp. 1465–1470 (2008).
8. D. G. Caldwell, N. Tsagarakis, D. Badhihi and G. Medrano-Cerda, Pneumatic muscle actuator technology a light weight power system for a humanoid robot, in: *Proc. Int. Conf. on Robotics and Automation*, Leuven, pp. 3053–3058 (1998).
9. B. Tondu, S. Ippolito, J. Guiochet and A. Daidie, A seven-degrees-of freedom robot-arm driven by pneumatic artificial muscles for humanoid robots, *Int. J. Robotics Res.* **24**, 257–274 (2005).
10. M. Van Damme, B. Vanderborght, B. Verrelst, R. Van Ham, F. Daerden and D. Lefeber, Proxy-based sliding mode control of a planar pneumatic manipulation, *Int. J. Robotics Res.* **28**, 266–284 (2009).

11. A. Sugahara, Y. Nakamura, I. Fukuyori, Y. Matsumoto and H. Ishiguro, Generating circular motion of a human-like robotic arm using attractor selection model, *J. Robotics Mechatron.* **22**, 315–321 (2010).
12. M. T. Turvey, Dynamic touch, *Am. Psychol.* **51**, 1134–1152 (1996).
13. M. Suzuki, K. Noda, Y. Suga, T. Ogata and S. Sugano, Dynamic perception after visually guided grasping by a human-like autonomous robot, *Adv. Robotics* **20**, 233–254 (2006).
14. T. Bergquist, C. Schenck, U. Ohiri, J. Sinapov, S. Griffith and A. Stoytchev, Interactive object recognition using proprioceptive feedback, in: *Proc. IROS 2009 Workshop Semantic Perception for Mobile Manipulation*, St. Louis, MO (2009).
15. S. Takamuku, K. Hosoda and M. Asada, Object category acquisition by dynamic touch, *Adv. Robotics* **22**, 1143–1154 (2008).
16. H. P. Saal, J. Ting and S. Vijayakumar, Active estimation of object dynamics parameters with tactile sensors, in: *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Taipei, pp. 916–921 (2010).
17. J. Sinapov and A. Stoychev, The odd one out task: toward an intelligence test for robots, in: *Proc. IEEE Int. Conf. on Development and Learning*, Ann Arbor, MI, pp. 126–131 (2010).
18. T. Suzuki, S. Yano, and K. Suzuki, Motivation oriented action selection for understanding dynamics of objects, in: *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Nice, pp. 846–851 (2008).
19. S. Chitta, B. Cohen and M. Likhachev, Planning for autonomous door opening with a mobile manipulator, in: *Proc. IEEE Int. Conf. on Robotics and Automation*, Anchorage, AK, pp. 1799–1806 (2010).
20. S. Takamuku, A. Fukuda and K. Hosoda, Repetitive grasping with anthropomorphic skin-covered hand enables robust haptic recognition, in: *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Nice, pp. 3212–3217 (2008).
21. K. Hosoda and T. Iwase, Robust haptic recognition by anthropomorphic Bionic Hand through dynamic interaction, in: *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Taipei, pp. 1236–1241 (2010).
22. I. A. Kapandji, *The Physiology of the Joints: Vol. 1. Upper Limb*, 2nd edn. Churchill Livingstone, Edinburgh (1982).
23. S. Sugimoto, K. Naniwa and K. Osuka, Stability analysis of robot motions driven by McKibben pneumatic actuator, in: *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, Taipei, pp. 3049–3054 (2010).
24. C. Nabeshima, Y. Kuniyoshi and M. Lungarella, Towards a model for tool-body assimilation and adaptive tool-use, in: *Proc. IEEE Int. Conf. on Development and Learning*, London (CD-ROM) (2007).
25. A. Iriki, M. Tanaka, S. Obayashi and Y. Iwamura, Self-images in the video monitor coded by monkey intraparietal neurons, *Neurosci. Res.* **40**, 163–173 (2001).

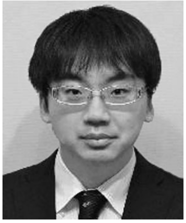
About the Authors

Koh Hosoda received his PhD degree in Mechanical Engineering from Kyoto University, Japan, in 1993. From 1993 to 1997, he was a Research Associate of the Mechanical Engineering Department, Osaka University. From 1997 to 2010, he was an Associate Professor of the Graduate School of Engineering, Osaka University. Since 2010, he has been a Professor of the Graduate School of Information Science and Technology, Osaka University. In the meantime, from 1998 to 1999, he was a Guest Professor in the Artificial Intelligence Laboratory, University of Zurich. From 2005 to 2010, he participated in the JST Asada ERATO Project as a Group Leader.

Shunsuke Sekimoto received the BS and MS degrees in Engineering from Osaka University, in 2008 and 2010, respectively. Since 2010, he has been working for Shimadzu Corp.



Yoichi Nishigori received a BE degree from Kansai University and a ME degree from Osaka University. Since 2011, he has been working for Kubota Corp.



Shinya Takamuku recieved the BE, ME and PhD degrees from Osaka University, in 2003, 2005 and 2008, respectively. He worked as a Researcher in JST Asada ERATO project, in 2008. Since 2009, he has been working as a Researcher in NTT Communication Science Laboratories. His research interests cover the broad field of embodied cognitive science and he is currently working on pseudo-haptic sensations generated by delayed visual feedback.

Shuhei Ikemoto received his PhD degree in Engineering from Osaka University, in 2010. He had been a JSPS Research Fellow, from 2009 to 2010. He is now an Assistant Professor in the Department of Multimedia Engineering, Graduate School of Information Science and Technology, Osaka University. His research interests include biologically inspired robots and machine learning.