# Springer Handbook of Robotics

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fore it has 12 actuated DOF and four passive DOF. This robot can demonstrate remarkable walking performance in an outdoor environment, as well as can maintain its balance even when kicked by a human. This ability of dynamic balancing is helped by its design of high center of mass with the leg assignment with narrow lateral separation.

### Big Versus Small

Design concept is deeply affected by the robot size. Figure 17.6a shows one of the most famous hexapods, the adaptive suspension vehicle (ASV) developed by *Waldron* et al. [17.2, 12]. The ASV is a hydraulically driven hexapod robot which can carry a parson over rough terrain. Its length and height are 5.2 m and 3.0 m, respectively, and weighs 2700 kg. To walk around in 3-D space, each leg requires 3 DOFs, thus the robot has 18 DOF in total.

Figure 17.6b shows a small hexapod robot Genghis (35 cm length and 1 kg weight) developed by *Brooks* [17.13]. This robot could also demonstrate robust walking in 3-D space, but its weight is less than a thousandth of the ASV. As a result, Genghis does not need precise 3-D foot positioning for its walking control. Each leg has only two DOF and the robot has 12 DOF in total. Standing with three legs, the body position and orientation can be fully controlled as long as the feet is allowed to slip on the ground.

### Degree of Biomimesis

We can increase the degree of biomimesis by adding DOF; however, fewer DOF is preferable in terms of engineering. The first version of ASIMO has 26 DOF in total, 6 for each leg, 5 for each arm, one for each hand, and two for the head (Fig. 17.7a) [17.14]. As a biped walking humanoid robot, this is a reasonable configuration.

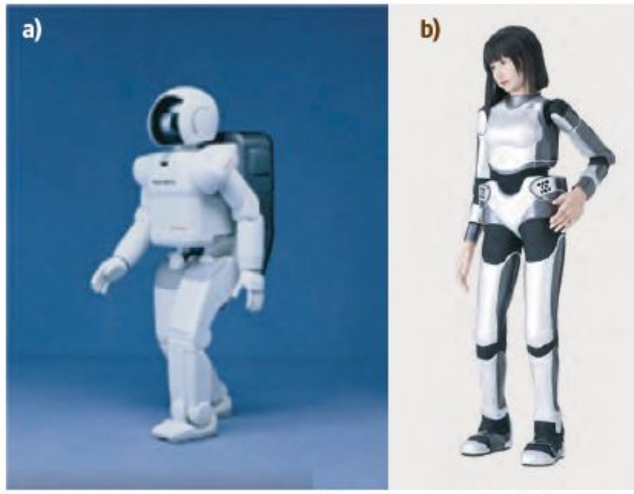


**Fig.17.7a,b** Humanoid designs. **(a)** ASIMO (2000); **(b)** HRP-4C (2009)

Cybernetic human HRP-4C (Fig. 17.7b) was designed to be as close as a human in consideration of applications in entertainment industry [17.15, 16]. It has 44 DOF in total, 7 for each leg, 6 for each arm, 2 for each hand and, three for its waist, 3 for its neck, and 8 for its face. Its design detail is discussed in the next section.

## 17.3 Whole Design Process Example

In this section, we explain the design process of a humanoid robot HRP-4C. We do this to give the readers an example of the whole development process of a limbed system. The readers are also recommended to see the comprehensive development report for the humanoid robot LOLA written by *Lohmeier* [17.3]. Also please watch another successful humanoid designs in VIDEO 522 and VIDEO 526. Note that a general mechanical design and construction process have already been discussed in this handbook (Chap. 4).

### 17.3.1 Conceptual Design of HRP-4C

At the beginning of our project, we defined *Cybernetic human* as a humanoid robot with the following features:

1. Have the appearance and shape of a human being.
2. Can walk and move like a human being.
3. Can interact with humans using speech recognition and so forth.

Such robots can be used in the entertainment industry, for example, exhibitions and fashion shows. It can also be used as a human simulator to evaluate devices for humans.

As the successor of our previous humanoid robots HRP-2 and HRP-3 [17.17, 18], we call our new humanoid robot HRP-4C, C stands for cybernetic human.

To determine the target shape and dimensions of HRP-4C, we used the anthropometric database for Japanese population, which was measured and compiled by *Kouchi* et al. [17.19]. The database provides

Some of the open questions for the future of robot learning include:

- How to choose appropriate representations automatically for model learning, value function learning, and policy learning? Perhaps, there is one particular choice that robustly works for many different robots, or maybe one could find a small set of possible approaches that can easily be compared.
- How to create useful reward functions? This topic connects to inverse RL, and on a higher level to how to understand the intentions of observed behavior.
- How much can prior knowledge help? How much is needed? How should it be provided?
- How to integrate more tightly with perception? Robot learning is largely *action-centric* and assumes that *perception* is provided. In reality, there is a perception-action-learning loop where the different components interact significantly, and need to be jointly developed.
- How to reduce parameter sensitivity? Manual tuning of hyperparameters such as gradient rates, forgetting rates, exploration rates, etc., are a common curse for the robot learning practitioner, and often, a small change in a parameter determines success or failure.
- How to robustly deal with modeling errors? Models are great when they work, but disastrous if they are not accurate enough. Probabilistic and robust control methods may help, but can also degrade performance due to very conservative learning results.

This list is by no means exhaustive, but captures some of the key issues. In the end, there is strong need for researchers and scientists who are willing to tackle a complex mixture of theoretical problems and experimental problems. Often, just setting up an experimental robot environment with accurate and efficient debugging and visualization tools is a formidable effort. Then, finding the right experiment and the right data trace that allows for error diagnosis in robot learning is still a bit of an art and requires fairly deep insights into physics, algorithms, software architectures, and technology.

## Video-References

VIDEO 352 Inverted helicopter hovering
available from http://handbookofrobotics.org/view-chapter/15/videodetails/352

VIDEO 353 Inverse reinforcement
available from http://handbookofrobotics.org/view-chapter/15/videodetails/353

VIDEO 354 Machine learning table tennis
available from http://handbookofrobotics.org/view-chapter/15/videodetails/354

VIDEO 355 Learning motor primitives
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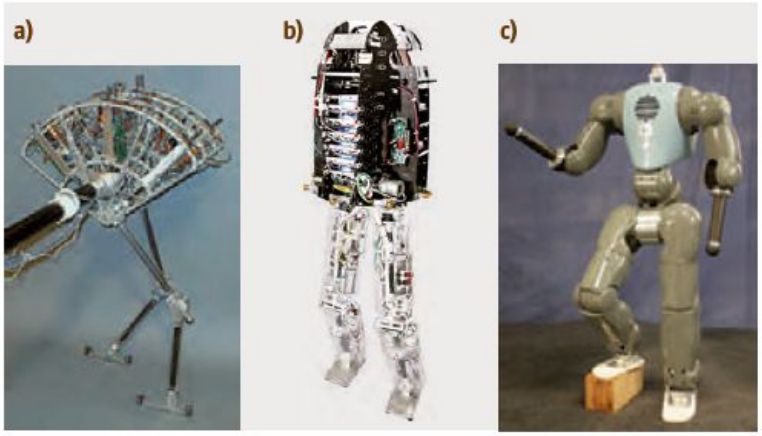


**Fig. 17.29a–c** Bipedal robots using serial elastic actuators: **(a)** Spring Flamingo (1996) (after [17.50]); **(b)** M2V2 (2008) (after [17.51]); **(c)** COMAN (2011) developed at IIT utilizing SEA in selected joints (hip, knee, ankle)

veloped at DLR, including the light-weight robot in Fig. 17.26b [17.52] and the upper body robot Justin as shown in Fig. 17.28a [17.53]. Recently, the same drive technology has been integrated in the design of the torque-controlled humanoid robot TORO (Fig. 17.27a) [17.54] (VIDEO 531). Torque sensing and control have also been employed in the hydraulic humanoid CB developed by Sarcos (Fig. 17.27b).

In series elastic actuators (SEAs), the joint torque sensing is implemented indirectly by measuring the deflection of an elastic element which is introduced into the drive train [17.55]. Early robots with compliant actuators were the two armed systems COG [17.56] from MIT and Wendy [17.57] from Waseda university, which even allowed the adaptation of the compliance. More recently, series elastic actuators are used in the compliant arm A2 from Mekka (Fig. 17.26c) and the humanoid upper body robot Twendy-one from Waseda university (Fig. 17.28). They have been also applied to bipedal systems in the robots as shown in Fig. 17.29 (also watch VIDEO 529 and VIDEO 530).

While the mathematical models of torque controlled robots and robots with SEA have the same structure it should be mentioned that the source of elasticity is different in these approaches. In SEA, the deflective element for the torque sensing represents the main source of elasticity and its role is to decouple the motor and link side dynamics for high frequency disturbances like impacts. A well-designed torque sensor instead should not introduce a big effect on the overall joint stiffness (in this case usually the gear introduces the main source of elasticity). Despite their conceptual similarity, the literature of SEA and elastic joint robots also differs in the way that in the context of SEA usually the linear dynamics of a single compliant actuator is considered for the controller design, while in the context of elastic joint robots the full nonlinear multibody dynamics is considered.

From a modeling and control point of view, the use of torque sensors in the joints leads to a robot model with elastic joints. For actuators with a high transmission ratio, a common modeling assumption is that the kinetic energy of each rotor depends only on its own spinning motion and not on the rigid body motion of the other joints [17.58]. Let the motor and link side joint angles be denoted by $\theta \in \mathbb{R}^n$ and $q \in \mathbb{R}^n$, then the *reduced flexible joint model* (Chap 11 for a detailed derivation) is given by

$$\mathbf{M}(q)\ddot{q} + \mathbf{C}(q,\dot{q})\dot{q} + \boldsymbol{g}(q) = \boldsymbol{\tau} + \tau_{f,q} , \qquad (17.5)$$

$$\mathbf{B}\ddot{\theta} + \boldsymbol{\tau} = \tau_{m} + \tau_{f,\theta} , \qquad (17.6)$$

where $\mathbf{M}(q)$, $\mathbf{C}(q,\dot{q})\dot{q}$, and $\boldsymbol{g}(q)$ represent the link side inertia matrix, the centrifugal and Coriolis forces, and the gravity term of the rigid body dynamics. The motor inertia is given by the diagonal matrix $\mathbf{B}$. The vector $\boldsymbol{\tau}$ represents the joint torques. In the case of an elastic joint with linear joint stiffness $k_i$ the torque is given by $\tau_i = k_i(\theta_i - q_i)$. The terms $\tau_{f,q}$ and $\tau_{f,\theta}$ represent friction terms at the link side and the motor side, respectively.

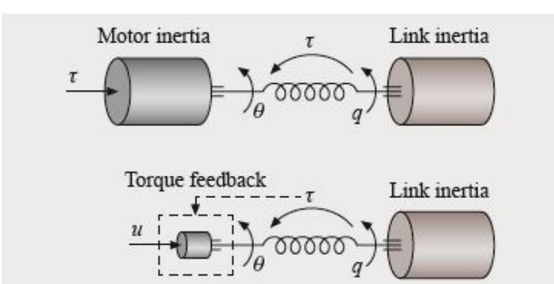


**Fig. 17.30** Conceptual model of an elastic joint: A proportional feedback of the joint torque reduces the effective motor inertia and motor friction

specialized operations but not suitable for other tasks. At the moment, dexterous multifingered hands have not really been applied to any major application, mainly because of problems of reliability, complexity, cost.

On the other hand, more and more operations are currently envisaged for robots working in environments designed for, and utilized by, human operators. Entertainment, maintenance, space/underwater applications, help to disable persons are just a few examples of use of robotic systems in which interaction with tools and objects designed for human beings (or directly with them) is implied. In all these circumstances, the robot must be able to grasp and manipulate objects (different in dimension, shape, weight, ...) similarly to humans, and therefore a robot hand, with a proper number of fingers and joints and also with an anthropomorphic appearance, seems to be the most adequate solution.

There are several projects aiming at developing anthropomorphic robots. Among others, one can mention the NASA/JPL Robonaut [19.24], Fig. 19.22, the devices developed at the DLR, the several projects on humanoid robots currently under development.


**Fig. 19.22** The NASA/JPL Robonaut



## 19.6 Conclusions and Further Reading

The design of multifingered robot hands has attracted the interest of the research community since the early days of robotics, not only as a challenging technical problem itself but, probably, also because of anthropomorphic motivations and the intrinsic interest for a better knowledge of the human beings. In the last decades, has previously discussed, several important projects have been launched, and important examples of robot hands developed. Nevertheless, the current situation is that reliable, flexible, dexterous hands are still not available for real applications. For these motivations, it is easy to foresee also for the future a consistent research activity in this fascinating field, with developments at the technological (sensor, actuator, material, ...) and methodological (control, planning, ...) level. Important connections with other scientific fields are also expected, as for example with cognitive science.

Being this research area so wide, it is not simple to suggest to interest readers further readings, except for quite classical books such as [19.43–45]. As a matter of fact, depending on the specific research area, many publications are available, although often not organized as reference books, but mainly as technical papers published in journals or presented at international conferences. Moreover, since hundreds of new papers are published every year covering the different aspects of this robotic field, it is really quite difficult, and also not fair, to give at the moment specific suggestions for further readings. We can only refer to the citations already provided in the references.

### Video-References

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| VIDEO 749 | The PISA-IIT SoftHand<br>available from http://handbookofrobotics.org/view-chapter/19/videodetails/749 |
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| VIDEO 751 | The Salisbury Hand<br>available from http://handbookofrobotics.org/view-chapter/19/videodetails/751 |
| VIDEO 752 | The Barrett Hand<br>available from http://handbookofrobotics.org/view-chapter/19/videodetails/752 |
| VIDEO 753 | The Shadow Hand<br>available from http://handbookofrobotics.org/view-chapter/19/videodetails/753 |