Chaotic mimic robots

BY ARTURO BUSCARINO¹,², CRISTOFORO CAMERANO¹, LUIGI FORTUNA¹,² AND MATTIA FRASCA¹,²,*

¹Dipartimento di Ingegneria Elettrica Elettronica e dei Sistemi, Università degli Studi di Catania, Viale A. Doria, 6-95125 Catania, Italy
²Laboratorio sui Sistemi Complessi, Scuola Superiore di Catania, Via San Nullo 5/i, 95123 Catania, Italy

In this paper, chaos is applied to the control of moving robots in order to generate random-like trajectories needed in tasks such as exploration, scanning natural terrains or mapping of unknown environments. Synchronization between the robots of a team is achieved by exploiting the paradigm of mirror neurons, i.e. a neural structure playing a key role in the process of imitation and behaviour understanding. The experimental results discussed in the paper demonstrate that the introduced approach can be successfully applied to implement an efficient learning system for mobile robots.

Keywords: chaos; robotics; control systems; mirror neurons; learning

1. Introduction

In robotics tasks such as exploration, remote sensing, scanning natural terrains and mapping of unknown environments often require a random walk by the agent (or by the agents) devoted to the task itself. The range of applications of such types of robots is wide (Arkin 1998; Siegwart & Nourbakhsh 2004) and spans from space exploration to household applications. The recent technological advances in robot equipments (both sensing and telecommunication systems) make even more common the use of teams of robots for such applications, giving increasing importance to the need of coordinating such agents.

The idea explored in this paper is to use chaos to drive the trajectory of the robots in order to preserve the randomicity of classical algorithms based on random trajectory generators (Fortuna et al. 2008). At the same time, this allows the synchronization of the robot trajectories by applying chaotic synchronization techniques. The use of dynamical chaos instead of random processes to control robot trajectories thus offers the possibility of coordinating robots that move in a team and follow irregular trajectories as needed, for instance, for exploration purposes.

Moreover, the paper deals with a new idea in performing the synchronization between the robots by using a learning process realized through a bio-inspired control system based on mirror neurons. Mirror neurons are neural structures

*Author for correspondence (mfrasca@diees.unict.it).

One contribution of 10 to a Theme Issue ‘Experiments in complex and excitable dynamical systems’.
involved in the process of imitation and behaviour understanding. These are important topics of actual interest for several disciplines including neurophysiology and neuroscience (Iacoboni et al. 2007). Recently, they have also attracted the interest of engineers and researchers for applications in robotics (Oztop et al. 2006).

Mirror neurons are active cells initially found in the macaque brain and located in the ventral premotor area (Area F5): the study of these neurons revealed that they have motor and visual properties, and are cells emitting information either when the monkey performs a specific action or when it observes someone else performing similar actions.

The discovery of mirror neurons in monkeys has been defined as one of the most important discoveries in the last decade in all of neuroscience. Mirror neurons represent today the key element in the understanding of phenomena like imitation, evolution of language, autism and knowledge of the behaviour of others.

The studies on mirror neurons revealed that Area F5 of the macaque brain has a direct projection to the upper cervical segments of the spinal cord, and the stimulation of this area evokes in the motor cortex mouth and hand movements and also actions such as grasping, manipulating and holding (Urgesi et al. 2006). Unlike canonical visual neurons, mirror neurons are also activated when the monkey observes another one performing an action (Rizzolatti & Craighero 2004). This mechanism in the brain of the monkey is able to show the congruence between the observed and the executed action.

Mirror neurons have several applications in the modelling of auditory–motor integration and in applications of interaction and imitation between human and robots (Gallese et al. 1996; Gallese & Goldman 1998; Borenstein & Ruppin 2005; Spaak & Haselager 2008). In this paper, we take inspiration from mirror neurons to implement a learning system in robots driven by a chaotic law. In our experiment, a robot moves autonomously generating a chaotically driven trajectory. As a result of real-time learning on the observed behaviour, a second robot, identical to the first one, follows a trajectory which is synchronized to that of the first robot.

The rest of the paper is organized as follows. In §2, the mechanical structure of the robots used is presented. In §3, the control law of the robots is discussed. In §4, the experimental results are dealt with. In §5, the conclusions of the paper are drawn.

2. Mechanical and electronic architecture: the bubble robot

In this section, the structure of the robots is described. The two robots have the same mechanical structure, but differ in terms of the control law. While one is driven by a chaotic one, the second is controlled by a mirror neuron-like structure.

The particular mechanical structure used in this paper is referred to in the following as bubble robot. Each robot is in fact shaped as a hollow sphere containing three motors as shown in figure 1. Even if the mechanical structure of the robots is known (Halme et al. 1996), the sensors and the communication equipment have been conceived in order to implement the mirror neuron-based control. All of the shafts are radially mounted within the hollow sphere so
that an extension of them would intersect the sphere at its geometric centre. The centre of mass of the robot is also located on the axial direction of the geometric centre of the sphere. The robot has two motors fixed in the rear part of the chassis and one in front. The third motor guarantees a better control of steering. A low centre of gravity for increased stability is guaranteed by the positioning of the microcontroller, which is the heavier part of the robot.

This mechanical structure offers several advantages. The sphere in which the robot is located is realized in thick plexiglass, thus furnishing a protective structure for the robot itself. The robot can be designed to be holonomic and move in any direction. This increases its capabilities to avoid obstacles and prevents the robot from getting stuck in corners. Furthermore, a spherical robot cannot be overturned. A spherical robust robot can be ideal for homeland security, surveillance applications, autonomous exploration, pipe inspection and the entertainment industry.

The three motors are all 9 V/0.55 A DC motors. The robot inside the plastic sphere is able to maintain an always stable configuration with respect to the lower part of the sphere and to the floor where it moves. The core of the robot is the microcontroller ARM7/32 bit Atmel (AT91SAM7256) with 256 kB of FLASH memory and 64 kB of RAM memory; the chassis of the robot is realized with the mechanical parts of the Mindstorms Robotics Kit. The robot has the possibility to transmit data with a BlueTooth protocol.

The choice of the sensors equipped on each robot was dictated by the aim of our experiments. As discussed in the introduction, mirror neurons are essentially visual-motor neurons. In order to simplify the complexity of the learning experiment, we let the robot move in the absence of environment light and equip the first robot, i.e. the observed robot, with a series of 21 high-intensity light-emitting diodes (LEDs) so that its relative position can be easily identified by the second robot, i.e. the observer robot, without the need of sophisticated image processing algorithms. As shown in figure 2, this latter robot is equipped with four infrared sensors able to recognize the light emitted by the first bubble.
robot. Each infrared sensor (S1, S2, S3, S4) works at 9 V and is active on an area of approximately 90°. The sensor displacements and the trajectory control are conceived in such a way that the relative motion of the observed robot is easily detected. In practice, starting from its sensor inputs, the observer robot is able to understand the behaviour of the other robot in terms of its left/right or forward movements. The sensor outputs constitute four different inputs for the control system of the observer robot.

3. The control system

As introduced above, one of the two robots, called the observed robot, autonomously moves, driven by a chaotic law, while the second one, referred to as the observer robot, through a mirror neuron-like system, learns how to synchronize its trajectory to the first one. The control law is described taking into account the different behaviour of the two robots.

(a) The observed robot

The observed robot is driven by a control law that specifies the velocities of each of the three motors of the robot: \( v_{M1} \), \( v_{M2} \) and \( v_{M3} \). In particular, a logistic map described by the following equation:

\[
z_{k+1} = az_k(1 - z_k) \quad (3.1)
\]

with \( a = 4 \) is used. When the robot goes in the forward direction, all the three motors are switched on, while, when it turns, one of the two rear motors (M1 or M2) is switched off. The velocity of the motors is directly connected to the value

---

*Phil. Trans. R. Soc. A* (2010)
of the logistic map at time $t$ through a proportionality constant labelled as $K$, according to the following rule:

$$v_{M1}(k) = \begin{cases} K \cdot z_k & \text{if } z_k > 0.4, \\ 0 & \text{if } z_k < 0.4 \end{cases} \quad (3.2)$$

and

$$v_{M2}(k) = \begin{cases} 0 & \text{if } z_k > 0.65, \\ K \cdot z_k & \text{if } z_k < 0.65. \end{cases} \quad (3.3)$$

The value of the constant $K$ was experimentally determined and fixed to $K = 1000$. With this simple rule, the chaoticity of the time series $z_k$ generated by the logistic map is reflected in two characteristics of the robot trajectory: the sequence of left and right turns of the observed robot is unpredictable, and the steering angle is irregular.

(b) The observer robot

The observer robot is equipped with an artificial neural network able to learn the behaviour observed in the other robot. A Hebbian rule is implemented in order to adjust the weights of the network.

The architecture of the neural network is reported in figure 3 showing how each input neuron receives a sensory input and how the output of the network is directly connected to the motor system. In particular, the implemented neural
network has four input neurons (each one controlled by one of the robot sensors),
one hidden layer with seven neurons and three output neurons to control
robot motors.
The observer robot determines the relative motion between itself and the
observed robot. The objective of the control is such that, if the observed robot
makes a right turn, the observer robot must perform the same rotation, and
vice versa. In particular, the neural network in figure 3 enables the robot to
perform the actions in order to follow the motion of the observed robot. The
training of the network is performed by using the motion information of the
observer robot itself and the detected measurements from the observed robot
in order to establish, while the two robots are moving, a set of reinforcements
for those motor signals (in the observer robot) that make the motion of both
robots similar. In the real-time performance of the observer–observed robots,
the network allows the establishment of motor controls in order to achieve
the correct movement like that of the observed robot. Thus, it works like a
mirror neurons network, in the sense that the observer robot looks at the
observed robot and mimics its behaviour performing the action driven by
the network.

The neurons of the network have sigmoidal activation function. The correlation
between the presynaptic and postsynaptic activity is controlled by a typical
Hebbian learning rule. Each synapse of the network $i, j$ that connects the neuron $j$
to neuron $i$ is governed by three parameters: $w_{i,j}^0$ that represents the initial weight
of the input at time $t = 0$ (the real value is in the range $[0,1]$); $s_{i,j}$ that represents
the sign of the connection ($1$ or $-1$); and $\eta_{i,j}$ that represents the learning rate
and varies in the range $[0,1]$.

The update of the synaptic weights is performed at each time step
(a sensory–motor cycle). The updating rule for the weights of the network is
given by

$$w_{i,j}^t = w_{i,j}^{t-1} + \eta_{i,j} \cdot \Delta w_{i,j},$$

(3.4)

where $\Delta w_{i,j}$ is defined as follows:

$$\Delta w_{i,j} = (1 - w_{i,j}^{t-1}) \cdot o_j \cdot o_i.$$  

(3.5)

In the learning rule, $o_j$ represents the activity of the presynaptic neuron
and $o_i$ the activity of the postsynaptic neuron. The learning rate $\eta$ modulates
the variations of $\Delta w$. The sensors placed on the observer robot activate the
corresponding input neurons set to 0 if the sensor does not see the other robot
and set to 1 if the sensor sees the robot. This architecture is suitable for online
learning of sensory–motor associations.

The next section describes the obtained results and in particular shows how
some of the hidden neurons of the networks behave like mirror neurons, i.e.
the same specific hidden neurons being active in two separate cases—when
the second robot sees the first robot and starts to imitate it, and when it does
not see the observed robot but ‘unconsciously’ activates the same pattern of hidden
neuron activities.

*Phil. Trans. R. Soc. A* (2010)
The experimental set-up consists of an arena where the two robots move and a videocamera recording the trajectories of the robots. The analysis of the robot trajectories is then performed through EXPOSURE software (Nimisis 2009). We carried out several experiments on different environments and initial conditions. Each test lasts for about 200 s (each second corresponds to a sample for the network training).

At the beginning of the experiment, the observed robot turns on the LED system and moves following a trajectory driven by the logistic map control. During this first phase of the experiment, learning takes place. The observer robot receives inputs from its sensors on the basis of the movements performed by the observed robot (i.e., it is able to identify the changes of position of this robot calculated on the basis of the light emitted by its LED system). The phase of learning takes about 100 s, after which the two robots are synchronized and the observer robot follows the trajectory of the observed robot, in the sense that it mimics the actions (such as a right turn, for instance) performed by the other robot. Since the sensors perceive relative motion, to establish if the observer robot is properly working, it may be necessary to rotate/translate its trajectory before comparing it with that of the observed robot. Figure 4 shows two different frames of an experiment demonstrating the synchronized behaviour of the two robot trajectories.

The experiments previously discussed clearly demonstrate the capability of the robot equipped with the neural network controller to mimic the behaviour of the observed robot. In order to demonstrate that some of the neurons of such a network behave as mirror neurons, we now show how the same pattern of neuron activation is observed under two different conditions: either when the observer robot sees and mimics the action performed by the observed robot or when the observer robot performs the same action. In the last condition, in order to simulate an autonomous behaviour of the observer robot, the experiment was carried out by giving random signals to the sensor inputs. During this autonomous navigation of the observer robot, sequences of actions similar to those registered for the observed robot can be found. We have found that such sequences of actions (or pieces of trajectories) in the absence of the observed robot are generated by the same pattern of activation generated as a result of the imitation of the observed robot in the opposite case that the observed robot is indeed operating in the arena. This behaviour was found for three of the seven neurons of the networks, thus demonstrating they have mirror neuron-like properties, since they activate either when the action is performed or is observed in another agent.

An example of such experiments is reported in figures 5 and 6. In figure 5, the trajectory followed by the observer robot in the absence of the observed robot (figure 5b) is compared with a part of a trajectory followed while imitating the behaviour of the observed robot. The two trajectories are similar (obviously, the similarity starts from a given time instant, since in the absence of the observed robot, the observer robot moves in an autonomous way). Corresponding to this, the activation patterns of the three mirror neurons of the network are similar. Figure 6 shows an example for one of the three mirror neurons. Starting from \( t > 105 \) s, the activation pattern of this neuron is similar to that which would
Figure 4. Synchronization between robot trajectories. Each frame represents a trajectory lasting about 8 s.

Figure 5. (a) Trajectory of the observer robot in the presence of the observed robot. (b) Trajectory of the observer robot in the absence of the observed robot.

Figure 6. Activation of neuron 1 when the observed robot is visible (a) and when it is not (b).

Happen in the presence of an observed robot performing an action similar to that autonomously performed by the observer robot. The other two behave in an analogous way.

Phil. Trans. R. Soc. A (2010)
5. Conclusions

Mirror neurons are one of the most important and fascinating discoveries in recent trends in neuroscience. Initially found in the macaque brain, they are visual-motor neurons that activate either when the monkey performs a given action or when it sees the same action performed by another monkey. In this paper, the paradigm of mirror neurons is applied to a moving robot in order to make it able to learn the behaviour of another identical robot driven by a chaotic law and thus following unpredictable trajectories. Synchronization through classical approaches has been studied in Fortuna et al. (2008).

The experimental results discussed in the paper show how, after learning, the observer robot is able to synchronize its trajectory to that of the observed robot and how mirror neuron-like properties can be found in the neurons of the trained network. The paradigm of mirror neurons can be thus successfully applied to robotics and, in particular, to the problem of learning how to synchronize the behaviour of chaotically driven robots. This type of chaos-based trajectory control substantiates the possibility of generating random trajectories needed for tasks such as exploration with easy distributed coordination strategies needed to control groups of robots instead of single units.

References