# On the dynamics of active categorisation of different objects shape through tactile sensors

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**Abstract.** Active perception refers to a theoretical approach to the study of perception grounded on the idea that perceiving is a way of acting, rather than a process whereby the brain constructs an internal representation of the world. In this paper, we complement previous studies by illustrating the operational principles of an active categorisation process in which a neuro-controlled anthropomorphic robotic arm, equipped with coarse-grained tactile sensors, is required to perceptually categorise spherical and ellipsoid objects.

**Key words:** Active perception, categorisation, evolutionary robotics.

## 1 Introduction

Categorical perception is a fundamental cognitive capacity displayed by natural organisms, and it can be defined as the ability to divide continuous signals received by sense organs into discrete categories whose members resemble each other more than members of other categories [1]. Most of the work in literature focuses on categorization processes that are passive (i.e., the agents can not influence their sensory states through their actions) and instantaneous (i.e., the agents are demanded to categorise their current sensory state rather than a sequence of sensory states distributed over a certain time period). Active categorical perception can be studied by exploiting the properties of autonomous embodied and situated agents, in which categorical perception is strongly influenced by the agent action [see also 2, 3, on this issue].

The works described in [4, 5, 6, 7, 8, 9, 10] contributed to the study of active categorisation by showing that relatively complex categorisation tasks can be solved by autonomous agents equipped with simple sensory-motor and cognitive apparatus that lacks some of those elements previously assumed necessary to recognise and categorise various types of objects or environmental circumstances. By following this line of investigation, the work described in [11] focuses on the study of categorical perception in a task in which a simulated anthropomorphic robotic arm is demanded to actively categorize un-anchored spherical and ellipsoid objects placed in different positions and orientations over a planar surface. Populations of evolving robots are left free to determine the way in which they categorize the shape of the objects within the limits imposed by the experimental scenario and by the computational power of their neural controller. This implies that the robots are left free to determine (i) how to interact with the external environment (by eventually modifying the environment itself); (ii) how the experienced sensory stimuli are used to discriminate the two categories; and (iii) how to represent in the categorisation space each object category. The analysis of the obtained results indicates that the robots are indeed capable of developing an ability to effectively categorize the shape of the objects despite the high similarities between the two types of objects, the difficulty of effectively controlling a body with many degrees of freedoms (hereafter, DOFs), and the need to master the effects produced by gravity, inertia, collisions etc. More specifically, the best individuals display an optimal ability to correctly categorize the objects located in different positions and orientations already experienced during evolution, as well as an excellent ability to generalize their skill to objects positions and orientations never experienced during evolution.

This paper complements the results and analysis shown in [11] by describing interesting operational aspects of the categorisation ability of the best evolved agent. In particular, we look at (i) how the robot acts in order to bring fourth the sensory stimuli which provide the regularities necessary for categorizing the objects in spite of the fact that sensation itself may be extremely ambiguous, incomplete, partial, and noisy; (ii) the dynamical nature of sensory flow (i.e., how sensory stimulation varies over time and the time rate at which significant variations occur); (iii) the dynamical nature of the categorization process (i.e., whether the categorization process occur over time while the robot interacts with the environment).

## 2 Methods

In this Section, we provide only a minimal description of the methods employed to design successful controllers. More details on the methods of this study can be found in [11]. The simulated robot consists of an anthropomorphic robotic arm with 7 actuated DOFs and a hand with 20 actuated DOFs (see Fig. 1a). Proprioceptive and tactile sensors are distributed on the arm and the hand (see Fig. 1b and 1c). The robot and the robot/environmental interactions are simulated using Newton Game Dynamics (NGD), a library for accurately simulating rigid body dynamics and collisions (more details at `www.newtondynamics.com`). The active joints of the robotic arm are actuated by two simulated antagonist muscles implemented accordingly to the Hill's muscle model, as detailed in [12]. The agent controller consists of a continuous time recurrent non-linear network (CTRNN) with 22 sensory neurons, 8 internal neurons, and 18 motor neurons [see Fig. 1d and also 13]. $\tau_i \dot{y_i} = -y_i + gI_i$ for $i = 1, .., 22$ is the equation used to update the state of sensory neurons. $\tau_i \dot{y_i} = -y_i + \sum_{j=n}^{m} \omega_{ji} \sigma(y_j + \beta_j)$ for $i = 23, .., 30$; with $n = 1$, and $m = 30$ is the equation used to update the state of internal neurons, and for $i = 31, .., 48$; with $n = 23$, and $m = 30$ is used to update the state of motor neurons. $y_i$ represents the state of a neuron, $\tau_i$ the decay constant, $g$ is

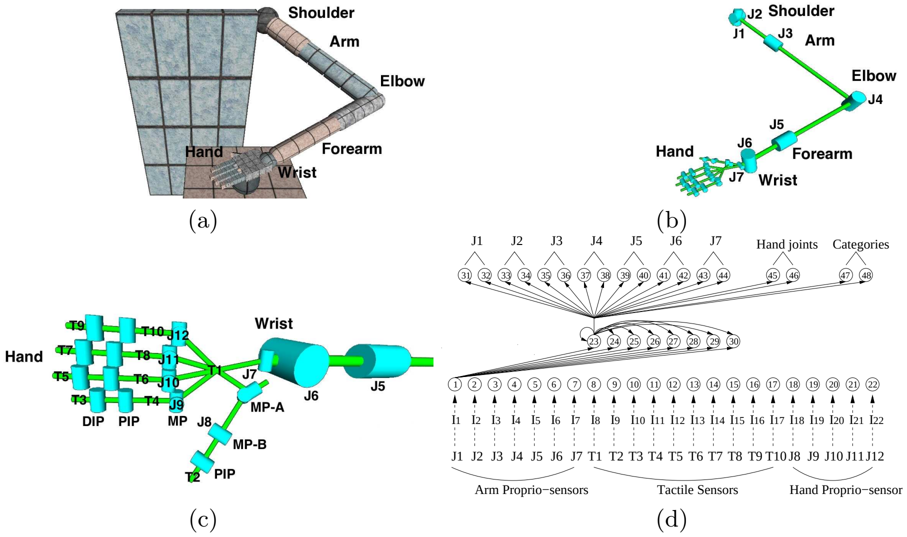



**Fig. 1.** (a) The simulated robotic arm. The kinematic chain (b) of the arm, and (c) of the hand. In (b) and (c), cylinders represent rotational DOFs; the axes of cylinders indicate the corresponding axis of rotation; the links among cylinders represents the rigid connections that make up the arm structure. $J_i$ with $i = 1, .., 12$ refer to the joints whose state is both sensed and set by the arm's controller. $T_i$ with $i = 1, .., 10$ indicate the tactile sensors. (d) The architecture of the arm controller. The circles refer to the artificial neurons. Continuous line arrows indicate the efferent connections for the first neuron of each layer. Dashed line arrows indicate the correspondences between joints and tactile sensors and input neurons. The labels on the dashed line arrows refer to the mathematical notation used to indicate the readings of the corresponding sensors.

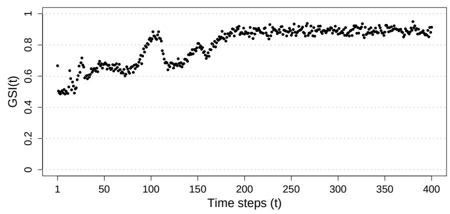
a gain factor, $I_i$ the intensity of the perturbation on sensory neuron $i$, $\omega_{ji}$ the strength of the synaptic connection from neuron $j$ to neuron $i$, $\beta_j$ the bias term, $\sigma(y_j + \beta_j)$ the firing rate. $\tau_i$ with $i = 23, .., 30$, $\beta_i$ with $i = 1, .., 48$, all the network connection weights $\omega_{ij}$, and $g$ are genetically specified networks' parameters. $\tau_i$ with $i = 1, .., 22$ and $i = 31, .., 48$ is equal to $\Delta T$. There is one single bias for all the sensory neurons. The activation values $y_i$ of motor neurons determine the state of the simulated muscles of the arm [see 12, for a detailed description of the functional properties of the arm]. The activation values $y_i$ of output neurons $i = 47, 48$ are used to categorize the shape of the objects. In particular, in each trial $k$, the agent represents the experienced object (i.e., the sphere $S$ or the ellipsoid $E$) by associating to it a rectangle $R_k^S$ or $R_k^E$ whose vertices are: $(\min_{0.95T<t<T} \sigma(y_{47}(t) + \beta_{47}), \min_{0.95T<t<T} \sigma(y_{48}(t) + \beta_{48}))$ for the bottom left vertex, and $(\max_{0.95T<t<T} \sigma(y_{47}(t) + \beta_{47}), \max_{0.95T<t<T} \sigma(y_{48}(t) + \beta_{48}))$ for the top right vertex, with $T = 400$ time steps (i.e., 4 simulated seconds) corresponding to the length of a trial. The sphere category, referred to as $C^S$, corresponds to the minimum bounding box of all $R_k^S$; the ellipsoid category, referred to as $C^E$, corresponds to the minimum bounding box of all $R_k^E$.

A simple generational genetic algorithm is employed to set the parameters of the networks [see 14]. The initial population contains 100 genotypes. Generations following the first one are produced by a combination of selection with elitism, and mutation [see also 11, for details]. Cell potentials are set to 0 when the network is initialised or reset (i.e., at the beginning of each trial), and circuits are integrated using the forward Euler method with an integration step-size $\Delta T = 0.01$ [see 15]. During evolution, agents have been rewarded by an evaluation function which seeks to assess their ability to recognise and distinguish the ellipsoid from the sphere. Note that, rather than imposing a representation scheme in which different categories are associated with *a priori* determined state/s of the categorization neurons (i.e., neurons 47 and 48), we left the robots free to determine how to communicate the result of their decision. That is, the agents can develop whatever representation scheme as long as each object category is clearly identified by a unique state/s of the categorisation neurons. More precisely, we scored agents on the basis of the extent to which the categorization outputs produced for objects of different categories are located in non-overlapping regions of a two dimensional categorization space $C \in [0, 1] \times [0, 1]$.

## 3 Results

Results of post-evaluation tests illustrated in [11] shows that the best evolved agent (hereafter, $A_1$) possesses a close to optimal ability to discriminate the shape of the objects as well as an excellent ability to generalize their skill in new circumstances. Moreover, in [11] it is shown that $A_1$, for one of the two positions experienced during evolution (i.e., position A, angle of joints $J_1, ..., J_7$ are $\{-50°, -20°, -20°, -100°, -30°, 0°, -10°\}$), exploits only tactile sensation to categorise the objects. In this Section, we take advantage of this latest result by running tests that further explore the dynamics of the decision of $A_1$ in position A, beyond the qualitative description illustrated in [11]. In particular, our interest is in finding out whether there are distinctive and functionally different temporal phases during the categorisation process. How long does the agent need to interact with the object before been able to tell whether is touching a sphere or an ellipsoid? Does the discrimination process occur at a specific moment, as a response to a sensory pattern that encode the regularities which are necessary for discriminating, or does it occur over time by integrating the information contained in several successive sensory states? Note that movies of the best evolved strategies can be found at `http://laral.istc.cnr.it/esm/active_perception`.

To answer these questions we begin by using a slightly modified version of the Geometric Separability Index (hereafter, referred to as *GSI*) originally proposed in [16]. GSI represents an estimate of the degree to which tactile sensor readings experienced during the interactions with the sphere or with the ellipsoid are separated in sensory space. We built four hundred data sets, one for each time step with the ellipsoid (i.e., $\{\tilde{I}_k^E\}_{k=1}^{180}$), and four hundred data sets, one for each time step with the sphere (i.e., $\{\tilde{I}_k^S\}_{k=1}^{180}$). Where, $\tilde{I}_k^E$ is the tactile sensor readings



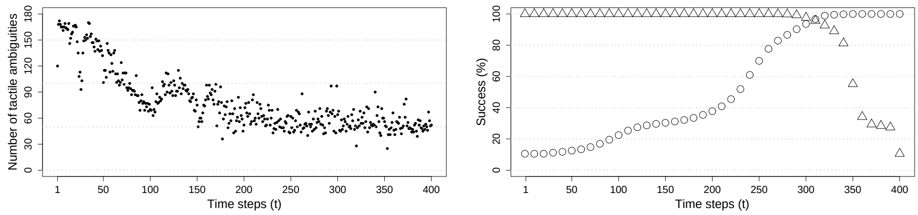

(a)

$$GSI(t) = \frac{1}{K}\sum_{k=1}^{K} z_i, \text{ with } K = 180;$$

$$z_k = \begin{cases} 1 & if m^{EE} < m^{ES}; \\ 0 & if m^{EE} > m^{ES}; \\ \frac{u}{u+v} & otherwise; \end{cases}$$

$$m^{EE} = min(H(\tilde{I}^E_k, \tilde{I}^E_j))$$
$$m^{ES} = min(H(\tilde{I}^E_k, \tilde{I}^S_j))$$
$$u = |\{\tilde{I}^E_j : H(\tilde{I}^E_k, \tilde{I}^E_j) = m^{EE}\}^K_{j=1}|$$
$$v = |\{\tilde{I}^S_j : H(\tilde{I}^E_k, \tilde{I}^S_j) = m^{ES}\}^K_{j=1}|$$

(b)




(c) (d)

**Fig. 2.** (a) The Geometric Separability Index (GSI); (b) the formal definition of GSI; (c) the number of tactile ambiguities; (d) the percentage of success in *pre-substitution tests* (see triangles) and *post-substitution tests* (see empty circles).

experienced by $A_1$ while interacting with the ellipsoid at time step t of trial $k$; and $\tilde{I}^S_k$ is the tactile sensor readings experienced by $A_1$ while interacting with the sphere at time step t of trial $k$. Trial after trial, the initial rotation of the ellipsoid around the z-axis changes of 1°, from 0° in the first trial to 179° in the last trial. Each trial is differently seeded to guaranteed random variations in the noise added to sensors readings. At each time step t, the *GSI* is computed as shown in Fig. 2b, where H(x, y) is the Hamming distance between tactile sensor readings. $|x|$ means the cardinality of the set x. *GSI*=1 means that at time step t the closest neighbourhood of each $\tilde{I}^E_k$ is one or more $\tilde{I}^E_k$. *GSI*=0 means that at time step t the closest neighbourhood of each $\tilde{I}^E_k$ is one or more $\tilde{I}^S_k$.

As shown in Fig. 2a, the *GSI(t)* tends to increase from about 0.5 at time step 1 to about 0.9 at time step 200, and to remain around 0.9 until time step 400. This trend suggests that during the first 200 time steps, the agent acts in a way to bring forth those tactile sensor readings which facilitate the object identification and classification task. In other words, the behaviour exhibited by the agent allows it to experience two classes of sensory states, rather well separated in the sensory space, which correspond to objects belonging to two different categories. However, the fact that the *GSI* does not reach the value of 1.0 indicates that the two groups of sensory patterns belonging to the two objects are not fully separated in the sensory space. In other words, some of the sensory patterns experienced during the interactions with an ellipsoid are very similar or identical to sensory patterns experienced during interactions with the sphere and vice versa. This is confirmed by the graph shown in Fig. 2c, which refers to the number of tactile ambiguities at each time step. A tactile ambiguity is defined as the condition in which $m^{ES} = 0$. This means that some of the patterns are experienced during interactions with both an ellipsoid and a sphere. This implies that $A_1$ can not determine the category of the current object solely on the basis of the current sensory stimuli. Thus, it follows that the most plausible hypothesis about the categorization process is that it involves an ability to integrate sequences of experienced sensory states over time. To test this hypothesis we employ *substitution tests*.

A *substitution test* is a post-evaluation test in which one type of sensory information experienced by the agent during the interactions with an ellipsoid is replaced with the corresponding type of sensory information previously recorded in trials in which the agent was interacting with a sphere. In this case, we replace tactile sensation at specific interval of time during each trial. In a first series of tests, referred to as *pre-substitution tests*, substitutions have been applied from the beginning of each trial up to time step t where t = 1,..,400. In a second series of tests, referred to as *post-substitution tests*, substitutions have been applied from time step t, where t = 1,..,400, to the end of a trial t=400. Each test has been repeated at intervals of 20 time steps. The test is repeated for 180 trials in which the orientation of the ellipsoid object around the z-axis varies from 0°, in the first trial, to 179°, in the last trial. In a *substitution test*, a 400 time steps trial $k$ can: (i) successfully terminate if the $R_k^E$, built as illustrated in Sec. 2, completely falls within the bounding box $C^E$, previously built by running specific post-evaluation tests, and corresponding to the ellipsoid category for agent $A_1$; (ii) unsuccessfully terminate with a sphere response if the $R_k^E$ completely falls within the two-dimensional space delimited by the bounding box $C^S$ previously built by running specific post-evaluation tests, and corresponding to the sphere category for agent $A_1$; (iii) unsuccessfully terminate with a none response, if the $R_k^E$, completely falls outside the two-dimensional space delimited by the bounding boxes $C_i^S \cap C_i^E$. The results of *pre-substitution tests* and *post-substitution tests* are illustrated in Fig. 2d, which shows that, regardless of the rotation of the ellipsoid, pre-substitutions which do not affect the last 100 time steps do not cause any drop in performance. For *pre-substitution tests* that involve more than 300 time steps the amount of performance drop is higher for longer substitution periods (see triangles in Fig. 2d). Similarly, the agent does not incur in any performance drop if post-substitutions affect less than 100 time steps. For *post-substitution tests* that affect more than the last 100 time steps the amount of performance drop is higher for longer substitution periods (see empty circles in Fig. 2d). Overall, the results shown in Fig. 2 as well as the trajectories of the average decision outputs shown in [11] indicate that, for what concerns position A, the interactions between the agent and the objects can be divided into three temporal phases that are qualitatively different from the point of view of the categorization process: (i) an initial phase whose upper bound can be approximately fixed at time step 250, in which the categorization process begins but in which the categorization answer produced by the agent is still reversible; (ii) an intermediate phase whose upper bound can be approximately fixed at time step 350, in which very often a categorization decision is taken on the basis of all previously experienced evidences; and (iii) a final phase in which the previous decision (which is now irreversible) is maintained. As also noticed by looking at the trajectories of the average decision outputs shown in [11], during the initial phase the robot starts to differentiate the categorization output produced for different type of objects by accumulating the evidences provided by the experienced sensory states. The fact the sensory states provide sufficient information for discriminating the two categories is demonstrated by the fact that the *GSI* increases from the chance level (0.5) up to a value of about 0.9 at the end of the initial phase (see Fig. 2a). The fact that the categorization decision formed by the agent during the initial phase is not definitive yet is demonstrated by the fact that substitutions of the critical sensory stimuli performed during this phase do not cause any drop in performance (see Fig. 2d, triangles). The fact that the intermediate phase corresponds to a critical period is demonstrated by the fact that pre-substitutions and post-substitutions affecting this phase produce a significant drop in performance (see Fig. 2d). The fact that the robot take an ultimate decision during the intermediate phase is demonstrated by the fact that post-substitutions affecting the last 80 time steps, approximately, do not produce any drop in performance (see Fig. 2d, empty circles).

## 4 Conclusion

This paper illustrates post-evaluation tests that complement the results shown in [11] concerning the perceptual categorisation ability of a simulated autonomous agent. The analysis indicates that one fundamental skill that allows the best evolved agent to distinguish sphere from ellipsoid objects consists in the ability to interact with the external environment and to modify the environment itself so to experience sensory states which are as differentiated as possible for different categorical contexts. On the one hand, this result represents a confirmation of the importance of sensory-motor coordination, and more specifically of the active nature of situated categorization, already highlighted in previous studies [e.g., 7, 8]. On the other hand, the results demonstrate that, in this specific scenario, sensory-motor coordination needs to be complemented by other additional mechanisms. In fact, the best evolved robot does not succeed in acting in a way to experience at any time step separated sensory states for different object categories. The categorization process displayed by this agent is realized dynamically by integrating the evidences provided by the experienced sensory stimuli over time.

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