Toward an implementation of a Biologically Inspired Expected Perception Mechanism

Roberto Prevete, Matteo Santoro, Ezio Catanzariti, Giovanni Tessitore

Department of Physical Sciences, Compl.Univ. Monte Sant'Angelo Naples, NA 80126 Italy
{Roberto.Prevete, Matteo.Santoro, Ezio.Catanzariti, Giovanni.Tessitore}@na.infn.it

Abstract. In a previous paper, we have proposed a visuo-motor control architecture, which we called MEP, oriented to the execution of Goal Oriented actions (GO-action). Here the expression "Goal Oriented action" is used to denote a series of prehension movements that relate body parts of the subject to a three-dimensional object. MEP architecture is based on a biologically inspired expected perception mechanism. In this paper we discuss some issues concerning the implementation of the proposed architecture. In particular, we focus our attention on the implementation of the expected perception mechanism. To this end, we argue some basic hypothesis regarding the semantic segmentation of GO-action and their observer independence representation. We give a preliminary account of how the plausibility of such hypothesis can be fulfilled and tested in experimental settings.

1 Introduction

It has been shown the existence of a population of neurons in the macaque's F5 motor area which are "active" during both the execution of a Goal Oriented action (GO-action) and the observation of the same action executed by another individual. Because of their characteristic activation, these neurons have been called mirror neurons [1–3]. The expression "Goal Oriented action" is used to denote a series of prehension movements that relate body parts (effectors like a hand or a foot) of the subject to a three-dimensional object (target), such as to grasp a piece of food by a precision grip. We have found in the literature several functional interpretations of mirror neurons: i) Action understanding and representation [4, 1], ii) language evolution [5], iii) evolution of mind-reading abilities [6].

In our work we focus on action understanding and representation. Moreover, we suppose that action understanding can be subdivided into two subsequent stages: i) a *structural description* of the observed behavior and ii) an interpretation stage.

We suppose that mirror activity is involved in both recognizing the structural features of an action and associating these features to motor abilities. In our supposition, understanding of an observed GO-action is the capability to associate

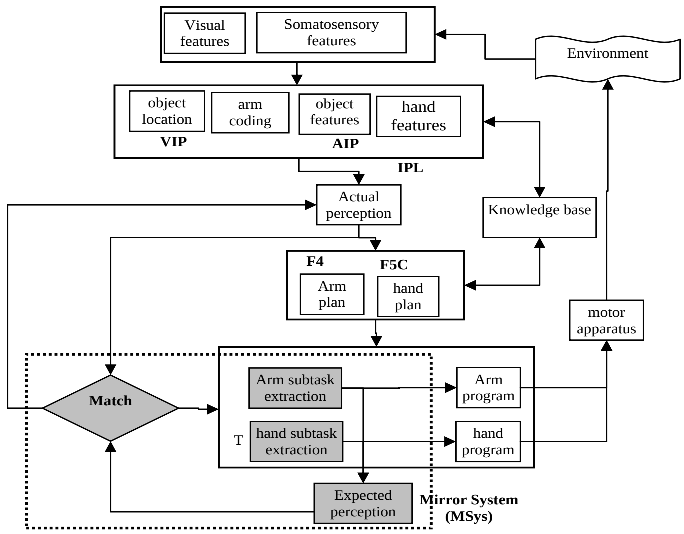


Fig. 1. Architecture of the MEP model

the correspondent visual sequence with a sequence of motor commands such that if the motor command sequence is carried out then the same GO-Action is performed. To achieve this functionality, we suppose that mirror neurons take part in an anticipatory mechanism which verifies whether the actual visual input matches a predicted visual input computed on the basis of a motor command sequence. The proposed mirror neuron functionalities can be achieved through a hypotized mechanism of expected perception [7, 8]. As explained in [7], an expected perception mechanism mainly involves comparison processes between incoming actual sensory perception and Expected Perception (EP). In a sensory - motor control model based on EP mechanisms an action is not construed as the result of continuous sensory-motor coordination, as in typical reactive architecture; it is basically viewed as a pre-planned execution, continuously monitored by comparisons between actual and expected perceptions. Sensory data are more extensively processed for the purpose of action re-planning only when actual sensory perception conflicts with the current EP.

We have proposed a biologically inspired visuo-motor control model, which we called MEP (Mirror Expected Perception model, see Figure 1), based on the above mentioned interpretation of mirror neurons [9]. MEP model enables us to explain the following biological data: i) mirror neurons are equally active during both executed-GO-actions and observed-GO-actions [10, 1, 2, 11], ii) inactivation of mirror neurons causes a motor slowing but the correct action is still performed [12]. On the basis of MEP model, when an agent A observes another agent B to carry out a GO-action the understanding of the observed action is the A's capability to associate the incoming visual sequence $v_1v_2...v_{k+1}$with a sequence of motor commands $cs = c_1c_2...c_k$ such that if cs is carried out by A then A

should be able to perform the same GO-action of B. Thus, according to MEP, the role of F5 Mirror neurons is to control whether the sequence cs is correct on the basis of the EP mechanism.

2 MEP Basic Hypothesis

In order to make our model work, the EP mechanism has to be implemented. In the rest of this section we will focus our attention on the basic hypothesis underlying the proposed model.

2.1 Observer Independence

From neurophysiologic data it appears that the activity of several cortical areas (e.g. AIP, F5 canonical) involved in recognizing and executing a particular GO-action is independent/tolerant of the location of the observed target relative to the observer [3]. This independence/tolerance begins from the very first steps of the processing of visual information [13, 14]. These findings seem to support the hypothesis, implicitly assumed in MEP, that:

Hyp. 1 *An agent A observing himself to perform a GO-action or observing an agent B to carry out the GO-action computes a sequence $s = v_1, v_2, , v_n$ of N-dimensional visual feature vectors in an observer independent/tolerant internal representation.*

This assumption allows us to refer to the GO-action through its internal representation s. It implies that the same sequence $s = v_1, v_2, , v_n$ is computed when an agent A observes himself to perform a GO-action or when he observes an agent B to carry out the same GO-action.

2.2 Observed GO-Action Structural Description

The aim of this Subsection is to refine the notion of GO-action structural description. Let's consider the set of all GO-actions and let's call V the set of all instances of their visual feature vectors. We suppose that:

Hyp. 2 *V is composed of a collection of equivalence classes $VC_1, VC_2, ..., VC_M$.*

Let us now call S the set composed of all instances of s, i.e., the set of the internal representations of all observed GO-actions. Under the hypothesis 2 it exists a unique partition $s_1, s_2, ..., s_k$ of s into subsequences such that $(\forall i \exists! k_i : x \in s_i \Rightarrow x \in VC_{k_i})$ and $(\forall i (\forall x \in s_i, \forall y \in s_{i+1} \nexists k : x, y \in VC_k))$. Consequently, under the hypothesis 2, it is possible to segment each GO-action s in one and only one sequence of V's equivalence classes. This corresponds to assuming that it exists a dictionary of tokens (VC_i) such that every observed GO-Action is composed of tokens belonging to the dictionary.
Let us define the following equivalence relation:

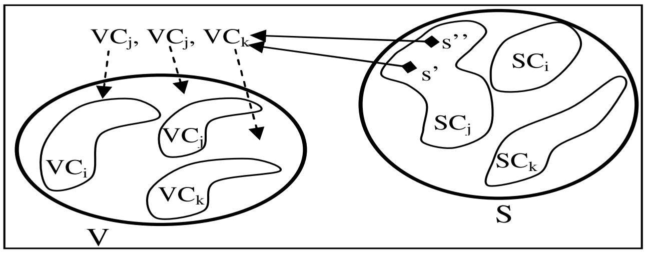


Fig. 2. V is the set of all instances of the visual feature vector. S is the set composed of the instances of the internal representations of all observed GO-actions. Both V and S are subdivided in equivalence classes. Each S's class is associated with one and only one sequence of V's equivalence classes

Definition 1. *$\forall s', s'' \in S$ $s' = s''$ if and only if it is possible to associate to both s' and s'' the same sequence of V's equivalence classes.*

From definition 1 the set S is divided into K equivalence classes SC_1, SC_2, ... , SC_K such that each class is associated with one and only one sequence of V's equivalence classes, i.e., $SC_i \equiv VC_1^i\ VC_2^i ... VC_r^i$ (see Figure 2). We now make this basic assumption:

Hyp. 3 *Each SC_i class corresponds to a set of semantically related GO-actions.*

Hypothesis 2 and 3 enables us to define how an EP (Expected Perception) can be computed and how the matching between the EP and the actual perception can be implemented. The computation of an EP becomes indeed the selection of a sequence of V's equivalence classes. In fact, when an agent A observes an agent B carrying out a GO-action, he, on the basis of an initial actual visual vector v_1 incoming at the time t_1, pick up the equivalence class VC_k to which v_1 belongs. An equivalence class $SC_i \equiv VC_k VC_2^i$ ... VC_r^i is then selected from VC_k, i.e., the agent A supposes that the achievement of the GO-action will produce, at selected times $t_2 < ... < t_r$, a sequence of visual vectors v_2, ..., v_r belonging to $VC_2^i, VC_3^i, ..., VC_r^i$, respectively. Let's call the classes VC_2^i, .., VC_r^i Expected Visual Classes (EVCs). Hence the matching between the EP and the following actual perception becomes a classification problem, i.e., verifying if at each time t_i the actual perception v_i belongs to the EVC VC_i. Therefore, the behavior of the MEP model illustrated in the Introduction can be formally defined by the algorithm in Table 1.

Note that according MEP-algorithm if the visual feature vectors are extracted in an observer independent manner we have the same sequence of commands $cs \equiv c_1 c_2 ... c_{r-1}$ when either the agent A carries out a GO-Action or the agent A observes an agent B carrying out the same GO-action.

In the remaining part of the paper we will give a preliminary account of how the plausibility of the hypothesis 1, 2 and 3 can be fulfilled and tested in an

MEP algotithm

- REPEAT
  - $t_1 \leftarrow 0$
  - Compute the visual feature vector v_1 at the time t_1 and Select k : $v_1 \in VC_k$
  - Choose both a sequence of EVCs $SC_h = VC_1^h VC_2^h \ ... \ VC_r^h$ such that $VC_1^h = VC_k$ and a time-sequence $t_2 < ... < t_r$. A sequence of commands $cs = c_1 c_2 ... c_{r-1}$ is computed on the basis of SC_h. {*The execution of c_i is equivalent to hypothesizing an environment modification so that the agent A computes a visual feature vector belonging to VC_{i+1}^h at the time t_{i+1}*}
  - $i \leftarrow 1$, $success \leftarrow FALSE$, $match \leftarrow TRUE$
  - WHILE ($success = FALSE$) AND ($match = TRUE$)
    * Command c_i is sent to a controller which transforms c_i in an arm motor program and a hand motor program controlling the motor apparatus {*note that this step is absent when an agent A observes another agent B*}
    * $i \leftarrow i + 1$
    * At the time t_i compute the new feature vector v_i {get next percept}
    * $match \leftarrow (v_i \in VC_i^h)$
    * IF ($cs = VOID$) AND ($match$ = TRUE) THEN $success \leftarrow$ TRUE
- UNTIL $success$ = TRUE

Table 1. Behavior of the MEP model is formally defined by the MEP algorithm

experimental setting. In the next Section we show how a set of scale and position independent/tolerant features of a GO-action can be computed.

3 The computation of GO-action's invariant features

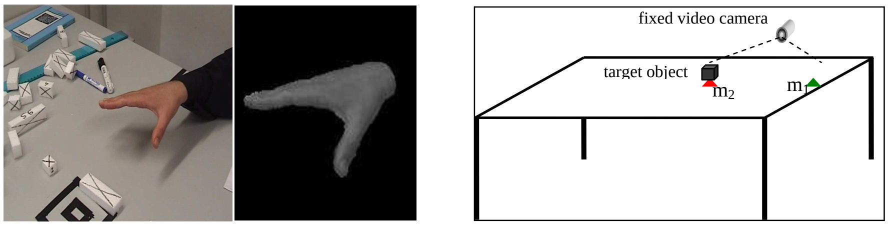
In [13, 14] a quantitative theory is described to account for the computation performed by the feedforward path of the ventral stream of visual cortex. The theory is shown to be consistent with several properties of neurons in areas V1, V2, V4, IT. According to the model, computation of visual features which are invariant to scale and position is performed in a feedforward fashion by a hierarchy of cells of increasingly receptive fields and responding to increasingly complex preferred stimuli. The computation is sequentially performed in two main phases, the view-tuned phase and the object-tuned phase [14]. According to the model, simple S cells take their inputs from units that "look" at the same local neighborhood of the visual field but are tuned to different preferred stimuli, while complex C cells pool over inputs from S units tuned to the same preferred stimuli but at a slightly different positions and scales. In the overall architecture, layers of simple S cells with Gaussian-like tuning to provide data-selectivity (generalization) are interleaved with layers of complex C cells which perform a soft-max operation on their inputs in order to provide invariance to position and scale. We implemented a version of the view-tuned module using four layers of cells: S1, C1, S2 and C2 for the extraction of position and scale tolerant features of observed GO-actions. The different responses of both S and C cells having varying receptive fields and responding to different preferred stimuli were obtained by hierarchical convolution of the input image with a bank of Gabor functions with varying spatial extent and which were tuned to different spatial frequencies. Our implementation does not use learning. The scale and position independent features as computed by the architecture thus implemented appear in the form of 256 features maps which constitute the input to the clustering program which will be described later on.

4 Experiment 1

In order to test the validity of the hypothesis 2 and 3 we have chosen two semantically different classes of GO-actions: Precision Grip (PG) and Whole-Hand prehension (WH). Two GO-actions belonging to PG and two GO-actions belonging to WH have been selected, viz., "paperclip gripping" and "bottle-tap gripping" for PG, and "tennis-ball gripping" and "piece-of-wood gripping" for WH. Twenty subjects from faculty, staff and graduate students were selected. Each subject was asked to perform all four mentioned GO-actions. The actions were executed with the subjects seated at a table with two marks (m_1 and m_2) at a distance of roughly 40cm from each other: each GO-action starts at m_1 and ends at m_2. For each target-object, each subject was asked to position the hand on starting position m_1 and to reach and grasp the target object located on mark m_2. Each action was recorded using a fixed video camera (see Figure 3-b).

Each GO-action is therefore represented as a sequence of frames (160X160 pixels). For each frame, a N-dimensional visual feature vector F is extracted. F is composed of the C2 layer output values. Although the general scheme requires that F be composed of the features relative to both the target and the agent performing the action, only features relative to hand shape and target location relative to the hand were considered in this experiment. The feature extraction phase consists of two steps: the skin detection module and the view tuned module. For each GO-action, a skin model is computed from an histogram color model in RGB color space. A simple non-parametric model is therefore used to transform each frame in a gray-level image where each pixel value represents the probability of that pixel to be skin. The image thus obtained is further post-processed by morphological filtering to eliminate the effect of image noise on the segmented image. The final result is a gray-level image in which the hand is shown as a gray region on a black background (Figure 3).

This image is given as input to the view-tuned module described previously for the subsequent feature extraction step. The process of feature extraction is performed for all recorded GO-actions. Each GO-action is therefore represented as a sequence of the F vectors thus extracted. In the limited setting of this exper-



(a) Skin detection. (b) Experimental environment.

Fig. 3.

iment, the set of all sequences thus obtained constitutes S, while the complete set of feature vectors constitutes V (Figure 2). Let's recall that the main goal of this experiment is to verify the plausibility of hypothesis 2 and 3 as previously stated. In our case, this correspond to verifying that S can be "naturally" segmented in two classes, which we will call SC_{PG} and SC_{WH}, such that elements belonging to class SC_{PG} are coded sequences of PG GO-actions and elements belonging to class SC_{WH} are coded sequences of WH GO-actions. To this end, a clustering algorithm is applied to the elements of V to obtain k clusters VC_1,VC_2,..., VC_k. As a consequence, as pointed out in a previous section, each sequence belonging to S can be coded as a unique sequence of V clusters. Therefore, each of such sequences can be treated as a string defined over the alphabet VC_1, VC_2, ... , VC_k. Under a suitable measure of string similarity a clustering algorithm should be able to group the whole set of strings in the classes SC_{PG} and SC_{WH} .

4.1 Preliminary results

We have implemented the module for the extraction of features (skin-detection followed by the view-tuned module). We applied the well known k-means algorithm for the initial segmentation of V, setting different values for the number k of clusters. Evaluation of the results thus obtained show that the algorithm performs the best for k=6. Results are dependent from the initial setting of cluster centers. Presently, we are experimenting with a better performing clustering algorithm - Fuzzy-C-means algorithm [15]. In order to test the correctness of our results, we manually created the two SC_{PG} and SC_{WH} string classes corresponding to the PG and WH GO-actions. We computed the intra-class distances, $IaC(SC_{PG})$ and $IaC(SC_{WH})$, and the inter-class distance, $IrC(SC_{PG}, SC_{WH})$, for the two classes. Under our assumption, the inter-class distance has to be consistently greater than the intra-class distances. In order to compute the above distances we have to define a string distance measure. A commonly used technique for measuring string similarity is to look for the longest common subsequence (LCS) of characters in two strings. The length of the LCS is usually divided by the length of the longer string of the two original tokens in order to obtain a normalized value. This score is called the longest common subsequence ratio (LCSR) [16]. We have defined $d(x, y) = 1 - LCSR(x, y) \in [0, 1]$ as measure of distance between strings x and y. Results from our data show the encouraging values of $IrC(SC_{PG}, SC_{WH}) = 0.7$ for the inter-class distance and $IaC(SC_{PG}) = 0.4$ and $IaC(SC_{WH}) = 0.5$ for the the intra-class distances.

4.2 Discussion

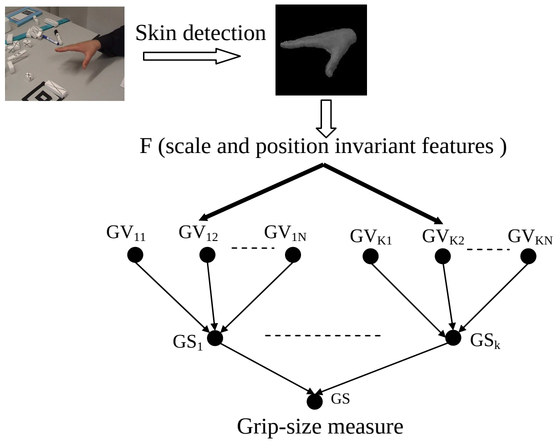
In the previous sections we have presented a preliminary experiment to test the validity of hypothesis 2 and 3. As already said, the results proved encouraging. However, in this experiment the hypothesis 1, observer independence (view independence), is not fulfilled. Let's not forget that the feature vector F is composed of scale and position indipendent/tolerant values, but this vector is not invariant under view changes. In order for the conditions stated on hypothesis 1 to be fulfilled an observer independent/tolerant measure of object features needs to be given. In [14] the classical task of observer independent object recognition takes place in the object-tuned stage of the recognition process, but the problem of how to extract observer independent features is not been explicitly tackled. How can the observer independent features be extracted? For example, how can features such as grip-size (measured by the index-thumb distance [17]), or hand-target distance be extracted in an observer independent way? In the next Section we propose a neuronal architecture for performing an observer independent/tolerant measure of some relevant hand-target features which is based on the very same Poggio's recognition system.

5 Observer independent measure of hand features

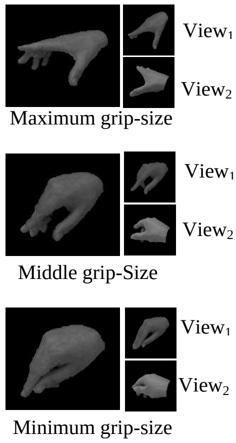
As we have said before, although our general schema requires that during grasp actions the visual feature vector F be composed of the features relative to both the target and the agent performing the action, in the following paragraphs we will consider only features relative to hand shape. Santello [18, 19] argued that: i) hand shape evolves gradually, ii) hand shape depends on object shape and iii) hand shape can be completely individuated from very few features.
Based on the above mentioned considerations, we think that to focus on one hand feature only could be appropriate as a first approach. In the next paragraph a feed-forward Neural network architecture representing a Grip-size Observer Independent measure (NeGOI) is defined. According to Jeannerod [17] we define the hand grip-size measure as the distance between thumb and index tip.

5.1 NeGOI architecture

We assume that for a given observer point of view the hand grip-size can be computed as the superposition of K basic hand postures corresponding to predefined grip-size such as "maximum grip size", "middle grip size" and "minimum grip size". Once a hand grip-size measure is obtained from N selected points of view, the observer independence can be achieved by an integration of the N measures.



(a) NeGOI architecture.



(b) Basic grip-size.

Fig. 4.

NeGOI architecture is composed of three layers (Figure 4). The first layer consists of neurons selective to both basic grip-size and point of view. The layer is composed of K ordered groups of neurons. Each group is composed of N ordered neurons. Let be GV_{ij} the j-th neuron belonging to i-th group, with $i = 1, 2, ..., K$ and $j = 1, 2, ...N$. Each GV_{ij} neuron is selective to the basic grip-size i and the point of view j. The input of each GV_{ij} is the vector F (output of C2 layer). The second layer is composed of K observer independent neurons selective to basic grip-sizes . Let be GS_i the i-th neuron of the second layer, with $i = 1, 2, ..., K$. The neuron GS_i receives only connections from neurons belonging to i-th group of the first layer. The third layer is composed of just one neuron. Let us call it GS. GS neuron receives connections from all GS_i. GS output is scale, position and observer independent.

6 Experiment 2

In order to test the observer independence property of the architecture just described we have recorded 8 grasp actions with 8 targets (cubes) of different dimensions (cm 2,3, ...,9). Each grasp action is recorded from two different point of view, $view_1$ and $view_2$ (see Figure 4-b). The first point of view, $view_1$, can be taken as the point of view of an agent A observing a grasp action, while $view_2$ can be taken as the point of view of an agent A carrying out a grasp action. It is known [17] that during a grasp action the hand grip-size profile has a typical form (see Figure 5-a). Moreover, the value of the maximum grip size occurs at roughly $70 - 80\%$ of the action duration and it has a linear relation with the dimension of the target.
The correctness of NeGOI approach to measure grip-size can be proved if the values thus obtained exhibit the above mentioned properties.

6.1 NeGOI implementation

The first layer neurons are the output neurons of a Radial Basis Function neural network (RBF) [20] receiving the F vector as input. In this experiment we have only six neuron, i.e., two neurons for each selected basic grip-size: GV_{1j} selective to both maximum grip-size and $view_j$, GV_{2j} selective to both middle grip-size and $view_j$, GV_{3j} selective to both minimum grip size and $view_j$, with $j = 1, 2$. In the second layer the GS_i neurons ($i = 1, 2, 3$) compute the maximum of the outputs of GV_{ij}, with j=1,2. Therefore, the GS_1,GS_2 and GS_3 neurons are selective to maximum, middle and minimum grip-size, respectively (Figure 4-b). In the last layer, the neuron GS is obtained as output node of a RBF network.

6.2 Training phase

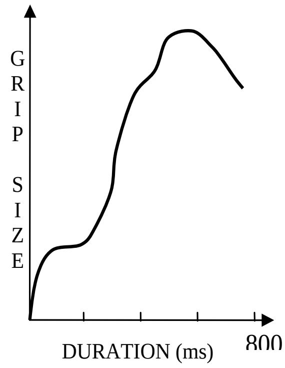
We have trained the GV_{ij} neurons using two different sets. The first set is composed of 600 frames of hand postures recorded from the point of view $view_1$, of which 200 frames of hand postures representing maximum grip-size, 200 frames representing middle grip-size and 200 frames representing minimum grip-size. The second set is composed as well of 600 frames of hand postures recorded from the point of view $view_2$ subdivided as the first set. The GS neuron has been trained under the hypothesis that the output of the GS_1, GS_2 and GS_3 neurons are Gaussians centered on maximum grip-size, middle grip-size and minimum grip-size, respectively.

6.3 Preliminary Results

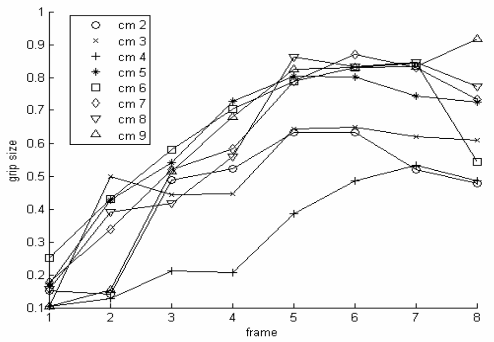
For all eight grasp actions the profile of grip-size as measured by NeGOI (Figure 5-b) has the same form as the one predicted by Jeannerod [17] (Figure 5-a). The maximum grip size value presents a clear linear relation with the dimension of the target, see Figure 5-c. By performing a linear regression between maximum grip size value and the target dimensions we obtain a determination index $r_2 = 0.98$.

7 Conclusions

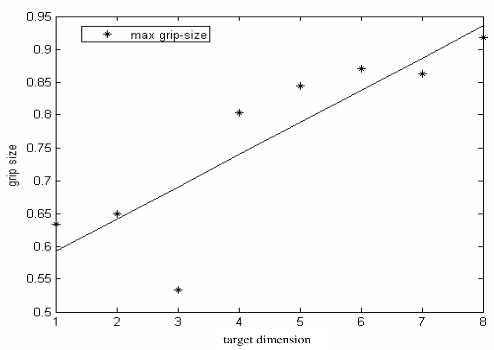
In a previous paper [9], we have proposed a visuo-motor control model, which we called MEP, based on a specific functional interpretation of mirror neurons. This functional interpretation can be explained through a mechanism of expected perception. In this paper we have focused our attention on some issues concerning the implementation of the expected perception mechanism. To this end, we have discussed some basic hypothesis regarding the semantic segmentation of GO-actions, and we have given a preliminary account of how the plausibility of such hypothesis can be fulfilled and tested in an experimental setting. Preliminary results are encouraging. More thorough experimentation is in progress. Be aware that we have not yet addressed some central questions, such as, how is the



(a) Standard grip-size profile.



(b) Grip-size profile as measured by NeGOI.



(c) Linear regression between maximum grip-size and target dimension.

Fig. 5.

command sequence computed? How is the sequence of expected classes selected? We have merely supposed that it is possible to perform these subtasks. We want to stress again that our chief concern here has been to expose some basic issues regarding the implementation of the expected perception mechanism.

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