A comparison between human micro-affordances and computational classification

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Abstract

This study aimed to assess how specific components of an action could be selected by a simple computational system. We performed an experiment to test associations between grasps (precision or power grip) and several objects. We then ran simulations using a naive bayes classifier to study to what extent it could reproduce participants' choice. This classifier had two learning matrices containing objects' size associated with a grip by means of our experiment. When receiving a new object' size it computed the probability for each grip to be adapted. The highest probability was considered to represent which grip was associated with the object by the classifier. Results show that the classifier can reproduce participants' choice depending on the size of its learning matrices, and can quickly select the right type of grip for a majority of trials, showing that micro-affordances (Ellis & Tucker, 2000) can be reproduced through naive bayesian classification.

Keywords: affordance; grip; bayesian method; classifier

Introduction

As Leonard de Vinci said : "movement is principle of life". The way people interact with the world through body movements is indeed a corner stone of psychology, and especially of embodied psychology. As embodied psychology postulates that high-level cognitive processes are bodily rooted, or at least that their result depends on bodily states (Wilson, 2002), movements of the living body is a crucial point to attend. Yet how adapted body movements occur is not well determined and several propositions are made, one of them being particularly attractive for embodied cognitivists: theory of affordances (Gibson, 1979).

Affordance is a concept coined by Gibson (1979) that relies on direct perception. Although it has many interpretations, we will rely on the definition of Chemero (2003) in which affordances represent the relations between an animal's capacities and features of its environment. Abilities of an animal are functional properties, that depends on this animal's history.

This theory highlights the fact that voluntary actions are products of our perception of the situation, our abilities, and what we have learned. Moreover, this theory predicts that action is part of objects' memories and perception, as it is now established (Brouillet et al., 2015), which is of interest for psychology and for robotics as they permit to gain insight into the perception-action loop (Montesano et al., 2007, 2008).

Yet, the link between perception and affordances needs further investigation, as clues, or features, need to be extracted from, or constructed on the basis of the environment. Such clues would facilitate the link between a rich perception and an adapted movement, and permit on line adaptation.

Our purpose was to test how adapted voluntary movements could be selected, by a very simple computational system, on the basis of clues extracted from perception. To do this we chose to test some specific components of an action: grasping movements (Koester, Schack, & Westerholz, 2016). A lot of our interactions with the world depend on our ability to grasp things around us in a proper way, for example using a power or a precision grip (i.e. with all fingers of the hand or with the thumb and index, respectively, see Figure 1). These specific components of action (that doesn't include walking, reaching etc...) are termed micro-affordances by Ellis and Tucker (2000). These micro-affordances are supposed to emerge while looking at an object, and to facilitate a specific grasp. We selected object size to be the feature of the environment that could be associated to a specific grasp, in order to create a model that simulates a perceptually based motor activity.

The computational system we used to infer specific grasps rely on bayesian probability (Jones & Love, 2011; Pearl, 1985). The bayesian approach appears to be promising when studying how humans can interact with the world in presence of uncertainty (Perfors et al., 2011). It can apply to motor planning and control, estimation of context and motor learning (Wolpert & Ghahramani, 2000; Wolpert, Ghahramani, & Flanagan, 2001), and can be easily used in its simplest ways (Robert, 2000). This approach rely on conditional probability and allows to determine the probability of a certain event (for example a particular grasp) knowing some information :

past experiences (e.g. earlier grasp in presence of an object) or sensory inputs (e.g. object size) (Naïm et al., 2007).

The particular model we chose is a naive bayes classifier. This model has two learning matrices : one containing the size of objects graspable with a power grip, and one containing the size of objects graspable with a precision grip, size being represented by three parameters x, y, and z. Once it has computed these matrices, it receives the size of a novel object to be classified as graspable with a power grip or with a precision grip. In order to do so, it selects the most probable grasp, knowing the object size, to be the grasp to produce in presence of this particular object.

This approach of micro-affordances as naive bayesian classification can be of interest for psychologists and roboticians, as it can reduce the size of ontology, or databases, needed for an adapted system, and permits to infer micro-affordances in a very simple way.

In a first part we present the experiment to test micro-affordances with human beings and select objects that can be associated with a precision or a power grip. In a second part we explain how the model categorizes objects as being graspable with a precision or a power grip by means of naive bayesian classification, and show the results obtained with this model. We then compare human's and classifier's performances and discuss the possible developments of such applications.

Selection and association of objects with a precision or a power grip

Participants

Sixteen students were recruited for a pre-experiment in order to select the objects used in our experiment and simulation. Eighty students, different from the previous ones, were then recruited in order to select the appropriate grasp for each object (seven of them were not taken into account as they changed their grasping for the same objects between trials and differed drastically from the others). All participants freely signed a letter of consent, were right-handed, had normal or corrected to normal vision and over 18 years old, none had problems of motricity.

Materials

Forty-four pictures of objects were used. Each picture was modified to have the object being centered, vertically oriented, and a half of their real size when displayed on the computer screen.

These images were presented to sixteen students in a pre-experiment, with a hand near the object either making a power grip or a precision grip (see Figure 1). Participants had to indicate their level of agreement with the grip being displayed with the object. A high level of agreement with a grip meant that it was a reasonable grip to pick up and use the object.As a result, twenty objects were selected for the experiment, ten being graspable with a power grip and ten with a precision grip.

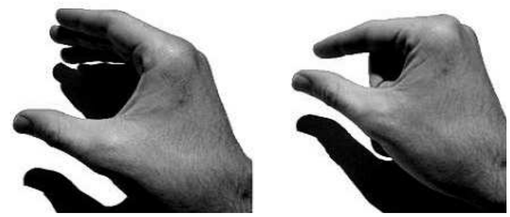

Figure 1: A hand making a power grip (left picture), and a precision grip (right picture).

Procedure

All of eighty participants were received one by one in an experimentation room, and sat in front of a computer Lenovo 17.3” with graphics card AMD radeon HD 8500M. They were asked to grab, with their right hand, a device that constrained them to make either a power or a precision grip. They were instructed to look at the computer screen and make the more appropriate grip on the device when seeing an object displayed on the screen. The twenty objects were then displayed randomly. When the twenty objects had been exposed, a second random presentation was made, in order to ensure the grip selected by participants for each object.

Results

Overall, the grips selected by means of the pre-experiment were respected, as shown in Table 1 and Table 2, and participants showed stable grip for each object. All of which allowed us to classify each object as associated with a precision or a power grip.

Table 1: Percentage of responses for objects associated with a precision grip, a number was attributed to each object for further comparison.

Objects	N	% power grip	%precision grip
grain of wheat	1	0.68	99.32
tweezers	2	3.42	96.58
nut	3	0.68	99.32
radish	4	10.96	89.04
smart card	5	1.37	98.63
screw	6	0.00	100.00
paper clip	7	0.00	100.00
strawberry	8	6.85	93.15
french beans	9	1.37	98.63
key	10	2.74	97.26

Simulation with a naive bayes classifier

The naive bayes classifier

The second step of this work was to put the naive bayes classifier to the test. To do so, we had to implement the size of objects used in our experiment. We chose to represent size in

Table 2: Percentage of responses for objects associated with a power grip, a number was attributed to each object for further comparison.

Objects	N	% power grip	%precision grip
glass	11	97.26	2.74
hair clipper	12	91.10	8.90
coconut	13	100.00	0.00
apple	14	99.32	0.68
corn	15	95.89	4.11
computer mouse	16	89.73	10.27
board wiper	17	92.47	7.53
universal pliers	18	95.21	4.79
pepper	19	95.21	4.79
deodorant	20	91.78	8.22

a three dimensional cartesian coordinate system, representing height, width, and depth.

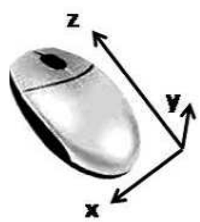

Figure 2: A computer mouse mesured on x, y and z.

Table 3: Mean and Variance for objects associated with a precision grip or a power grip.

Objects	Mean (Variance)		
	x	y	z
precision	1.265 (0.422)	0.62 (0.291)	4.87 (11.72)
power	6.76 (3.83)	5.27 (8.58)	13.92 (22.94)

We defined a rule to mesure our objects : z axis for the longest axis of the object, y axis for the shortest axis of the object, and x the last one, following the right hand rule (e.g. mesure of a computer mouse in centimeter: $x = 6$, $y = 1.65$, $z = 11.50$, see Figure 2).These rules were followed in order to satisfy the concept of axis for grasping proposed in Michel (2006), we simplified Michel's studies to reduce the natural axis of prehension of an object to its longest side. Mean and variance of objects associated with a precision grip and objects associated with a power grip are presented in Table 3.

Procedure

The model received an unknown object to be classified as graspable with a power grip or a precision grip. This object, represented by a vector (x_n, y_n, z_n), was associated by the model to probabilities $P(grip_i|x_n, y_n, z_n)$ for $i = 1$ the precision grip ($grip_1 = G_1$) and $i = 2$ the power grip ($grip_2 = G_2$).

The Bayes' theorem permits to decompose these probabilities :

$$P(grip_i|x_n, y_n, z_n) = \frac{P(grip_i, x_n, y_n, z_n)}{P(x_n, y_n, z_n)} \tag{1}$$

The probability $P(grip_i, x_n, y_n, z_n)$ can be written as :

$$\begin{aligned} P(grip_i, x_n, y_n, z_n) &= P(x_n, y_n, z_n, grip_i) \\ &= P(x_n|y_n, z_n, grip_i) \times P(y_n, z_n, grip_i) \\ &= P(x_n|y_n, z_n, grip_i) \times P(y_n|z_n, grip_i) \times P(z_n, grip_i) \\ &= P(x_n|y_n, z_n, grip_i) \times P(y_n|z_n, grip_i) \times P(z_n|grip_i) \times P(grip_i) \end{aligned} \tag{2}$$

Here, the naive assumption of conditional independence assumes that given the category $grip_i$, x_n, y_n and z_n are independent, so that :

$$P(x_n|y_n, z_n, grip_i) = P(x_n|grip_i) \tag{3}$$

and

$$P(y_n|z_n, grip_i) = P(y_n|grip_i) \tag{4}$$

Thus, using equations (1) (2) (3) and (4)

$$P(grip_i|x_n, y_n, z_n) = \frac{P(x_n|grip_i) \times P(y_n|grip_i) \times P(z_n|grip_i) \times P(grip_i)}{P(x_n, y_n, z_n)} \tag{5}$$

The model then selected the adapted grip for the object (x_n, y_n, z_n) using :

$$argmax[P(G_1|x_n, y_n, z_n); P(G_2|x_n, y_n, z_n)] \tag{6}$$

In concrete terms the naive bayes classifier had two learning matrices of size $(j, 3)$, j being the number of objects in the learning matrices, represented by their three coordinates (x_j, y_j, z_j). One matrix included the objects classified as graspable with a precision grip (G_1), the other included the objects classified as graspable with a power grip (G_2).

The following calculations were applied similarly for G_1 and G_2, we will only present the calculations for parameter x in G_1 for the sake of clarity. The classifier computed the probability for an object to be graspable with a precision grip ($P(G_1) = \frac{j}{2j} = \frac{1}{2}$).

And the mean and variance of each parameter x, y, and z for a precision grip : $\mu_{G_1}(x)$, $\mu_{G_1}(y)$, $\mu_{G_1}(z)$ and $\sigma^2_{G_1}(x)$, $\sigma^2_{G_1}(y)$, $\sigma^2_{G_1}(z)$; and for a power grip, resulting in $\mu_{G_2}(x)$, $\mu_{G_2}(y)$, $\mu_{G_2}(z)$ and $\sigma^2_{G_2}(x)$, $\sigma^2_{G_2}(y)$, $\sigma^2_{G_2}(z)$.

When a novel object with parameters (x_n, y_n, z_n) was presented to the model, the classifier had to compute the probabilities $P(G_1|x_n, y_n, z_n)$ and $P(G_2|x_n, y_n, z_n)$, using (5).

As measurements were on continuous variables, the new parameters were computed given the known parameters of the model using a gaussian probability density function, in order to calculate $P(x_n|G_1), P(y_n|G_1), P(z_n|G_1)$ and $P(x_n|G_2), P(y_n|G_2), P(z_n|G_2)$ with:

$$P(x_n|G_1) = \frac{1}{\sqrt{2\pi\sigma^2_{G_1}(x)}} e^{-\frac{[x_n - \mu_{G_1}(x)]^2}{2\sigma^2_{G_1}(x)}}$$

Then the model selected the highest probability (the appropriate grip), using (6).

As gaussian probability density function could return 0 for the probability of a parameter given a class $grip_i$, we distinguished two cases. In the first case only one parameter of the novel object had a probability equal to zero, in this case we did not change anything (we show in discussion why this case is a limit for this type of classification). In the second case two parameters of the novel object, one for each class, had a probability equal to zero (for example $P(y_n|G_1) = 0$ and $P(z_n|G_2) = 0$), we changed these probabilities to ε close to zero , this changed $P(G_1|x_n, y_n, z_n)$ and $P(G_2|x_n, y_n, z_n)$ to

$$P(G_1|x_n, y_n, z_n) = \lim_{\varepsilon \to 0} \frac{P(x_n|G_1) \times \varepsilon \times P(z_n|G_1) \times P(G_1)}{P(x_n, y_n, z_n)} \tag{7}$$

and

$$P(G_2|x_n, y_n, z_n) = \lim_{\varepsilon \to 0} \frac{P(x_n|G_2) \times P(y_n|G_2) \times \varepsilon \times P(G_2)}{P(x_n, y_n, z_n)}$$

As $P(x_n, y_x, z_n) = P(x_n, y_n, z_n, G_1) + P(x_n, y_n, z_n, G_2)$

$$\begin{aligned} P(x_n, y_n, z_n) = & \\ & P(x_n|G_1) \times \varepsilon \times P(z_n|G_1) \times P(G_1) + \\ & P(x_n|G_2) \times P(y_n|G_2) \times \varepsilon \times P(G_2) \\ = & \ \varepsilon \times [P(x_n, z_n, G_1) + P(x_n, y_n, G_2)] \end{aligned} \tag{8}$$

So that, using (7) and (8):

$$P(G_1|x_n, y_n, z_n) = \frac{P(x_n|G_1) \times P(z_n|G_1) \times P(G_1)}{P(x_n, z_n, G_1) + P(x_n, y_n, G_2)}$$

Thus the probability of a grip given the three parameters of the novel object became the probability of a grip given the two parameters of the novel object for which probability was not changed by ε, as the changes operated cancelled each other out.

Simulation

Simulation was performed using Matlab R2015a with a computer running on Windows 7 with a CPU Intel Core i5-4258U 2.10GHz.

We aimed at assessing naive bayes classification by analysing classifier's performance with different learning matrices (different learned objects and number of objects learned). In addition we compared the results of the classifier to the results obtained with human participants.

Simulation ran using $j = 1$ to 7 learned objects for each category (we always used the same number of learned objects in the two categories : objects associated with a precision grip and objects associated with a power grip).

Objects that were not used in learning matrices were categorized using the method described earlier.

As learning order did not have any impact on classification, number of trials was defined using the binomial coefficient $\binom{N}{j}$ with $N = 10$ the total number of objects in each category and j the number of objects learned in each category. This binomial coefficient gives the number of combination of learned objects without taking into account possibilities of permutation (learning order). The classifier was tested for every possible combination of learning: for each combination of precision grip's learning, we tested all combinations of power grip's learning. This way the results presented in Table 4 and Table 5 show the proportion of correct classification for every object over all possible learnings of our material.

For each object and each j we verified the grip selected by the classifier within each trial. For objects associated with a precision grip by means of our experiment (see Table 1), classification was recorded as right when the classifier calculates a higher probability for precision grip than for power grip. The reverse was made for objects previously associated with a power grip (see Table 2). If probabilities for a precision grip and for a power grip were equal, we considered that classification was incorrect.

Results

Overall it took 1397.71 seconds (23 minutes and 29 seconds) for the program to select learning matrices and make 1837440 classification. The classification of one object took in average 7.61×10^{-1} ms.

When more than one parameter for one class was equal to zero (33 cases), or when $P(x_n, y_n, z_n)$ was considered equal to zero due to very small probabilities (82 cases), classification was impossible. These particular numeric cases happened rarely (115 objects impossible to classify over 1837440 classified objects).

We computed the percentage of right classification for each object and each j (number of learned objects before classification). The percentages of right classification are shown in Table 4 (the percentage of right classification for objects considered as associated with a precision grip), and Table 5 (the percentage of right classification for objects considered as associated with a power grip).

A few things are to be discussed here. First, we can see that overall the classifier returned the right grip most of the time, in all the conditions (92.86% of right classification).

Secondly we can see that classification was better for objects that were considered associated with a power grip than for the others.

Thirdly, we see that classification performance increased as number of learned objects increased. This is because pa-

Table 4: Percentage of right classification for objects associated with a precision grip and for k objects learned.

Objects	Number of learned objects					
	2	3	4	5	6	7
1	85.22	95.95	99.60	100	100	100
2	76.62	86.97	95.57	99.21	100	100
3	88.39	96.83	99.90	100	100	100
4	43.34	47.52	46.28	45.85	42.15	30.36
5	82.93	93.91	98.81	99.73	100	100
6	84.07	95.37	99.43	100	100	100
7	87.49	98.33	100	100	100	100
8	63.03	80.10	91.42	96.49	98.76	100
9	52.78	56.54	63.03	67.64	73.39	80.37
10	86.63	94.98	99.26	100	100	100
Mean	75.05	84.65	89.33	90.89	91.43	91.07

Table 5: Percentage of right classification for objects associated with a power grip and for k objects learned.

Objects	Number of learned objects					
	2	3	4	5	6	7
11	96.22	99.93	100	100	100	100
12	86.66	96.26	99.52	100	100	100
13	96.82	99.79	100	100	100	100
14	95.54	99.56	100	100	100	100
15	94.21	98.77	99.82	100	100	100
16	92.29	98.75	99.96	100	100	100
17	95.09	99.73	100	100	100	100
18	86.63	94.82	98.82	99.84	100	100
19	96.97	99.76	100	100	100	100
20	94.04	99.30	100	100	100	100
Mean	93.45	98.67	99.81	99.98	100	100

rameters μ and σ were more representative of a class (power or precision grip) as number of learned objects increased.

What is counterintuitive is that classification of object number 4 got worse and worse, it is because we put more objects different from object 4 in the precision grip's learning matrice as the simulation went on. Object 4 had its three parameters close to boundaries of the precision grip space (represented by its mean and variance for each parameter x, y and z). Thus, depending on the objects learned, increasing the number of learned objects put object 4 out of the boundaries: the more learned objects associated with a precision grip had parameters close to the parameters of object 4, the more object 4 was classified as part of precision grip's objects. Conversely the more learned objects associated with a precision grip had parameters distant from object 4, the more it was classified as part of power grip's object. Compared to object 4, other precision grip's objects had one of their parameter close to the boundaries of precision grip's space, but not all of their parameters, which made them easier to classify correctly.

The fact that object 4 was hardly well classified, instead of being a real issue for naive bayesian classification, could be an advantage when comparing the classifier's performance and human classification: in our experiment object 4 reveals the higher percentage of selection for the competing grip (see Table 1).

Comparison of human and classifier's performance

To compare human's and classifier's performance we used a χ^2 test of independence between variable object (object 1 to object 20) and variable responding entity (human participants or naive bayes classifier).

When three, four, five and six objects of each category were put in the classifier's learning matrices, we found that the two variables were independent ($\chi^2(19) = 25.22,\ p = 0.15$; $\chi^2(19) = 23.06,\ p = 0.23$; $\chi^2(19) = 21.69,\ p = 0.30$; $\chi^2(19) = 22.71,\ p = 0.25$, respectively), this meaning that classifier's performance and human grip's choice were not significantly different.

When two objects of each category were put in the classifier's learning matrices, we found that variables object and responding entity were independent, but with a greater difference between human's and classifier's performance ($\chi^2(19) = 29.26,\ p = 0.06$).

Finally, when seven objects of each category were put in the classifier's learning matrices, it appeared that the two variables were not independent anymore ($\chi^2(19) = 33.01,\ p < 0.05$), human's and classifier's performance became significantly different.

Discussion

The results we obtained reveal that naive bayesian classification can reproduce the grip's choice made by human participants.

A good association of a novel object and its adapted grip can be accomplished with a reduced database and few parameters. This may permit to determine quickly a subclass of grips belonging to the precision or power grip classes when looking at an object, in other words to detect the possible nested micro-affordances associated with the object (for example a precision grip could comprise several nested micro-affordances: a grip with the thumb and the index, a grip with the thumb, the index and the middle finger, with more or less strenght etc...). Quickness of the categorisation in precision or power grip classes could then be an advantage for real-time adaptation.

But some limitations are to be exposed. The calculation of conditional probabilities through gaussian probability density function implies that a parameter could have a zero probability given a certain grip class. This pulled the probability of this grip to zero, while the probability of the competing grip automatically became one, biasing the classification of the object. A second limitation is the ad hoc hypothesis that parameters are independent, which could induce errors for other parameters than the ones we used.

When seven objects of each category were learned by the classifier, the selection made by the classifier and human choice became significantly different probably because classifier's selection only account for a calculation made on the basis of mean and variance of the three parameters representing the objects. This calculation is always the same and as long as enough objects are learned the mean and variance of each class' parameter began to show little variability no matter the learning matrices. This shows that the algorithm used with this classifier produces a rigid classification, and cannot, at some point, reproduce the diversity created both by the complexity of our cerebral structures and the variations of embodiment between different human beings.

Yet this classifier can reproduce, in the majority of cases, human grip's choice in a small amount of time, and with few parameters needed to be taken into account. This shows that micro-affordances could be reproduced in some way with a simple computational system using naive bayesian classification, suggesting that some early stages of the processes linked to human micro-affordance could be performed by some simple probabilistic mechanisms.

Future studies should take more parameters for an object by cutting up the objects in three parts in order to determine the type of grip and the position of the grip on the object (Faria et al., 2014), and introduce action's consequences (Hommel, 2015; Shin, Proctor, & Capaldi, 2010) through tactilo-kinesthetic parameters (Pfister et al., 2014), like pressure induced by the weight of the object, or muscle tension, in order to permit an efficient grip with a simple classification algorithm. We should also investigate the classifier's performance when an increased number of objects are learned and classified.

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