Unsupervised effect clusterization

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Learning affordances is a critical step in a developmental robotics approach. The data required for such learning can be provided by a babbling approach consisting in applying random action and observing the corresponding effects, but this approach raises specific challenges. Defining a priori a limited set of possible actions and corresponding effects is a strong limitation to what the robot can achieve. On the contrary, applying completely random actions results in a large set of possible effects that may be hard to exploit, in particular if the affordance is represented by discrete structures such as Bayesian networks (Montesano et al. (2008)).

In this work, a clustering method is proposed to automatically build a limited set of effects on the basis of data generated by a babbling method relying on random actions and on a given task.

Several methods can be used to perform the aforementioned effect clustering. In the related literature the most popular method is *X-means* (Pelleg and Moore, 2000) that relies on the *k-means* algorithm to define the clustering. Its main feature is to determine an optimal value *k*, i.e., an optimal number of clusters, based on the dataset used as input. This method has been used multiple times in developmental robotics to clusterize features and effects of objects (Montesano et al., 2008) or to distinguish categories of effects (Ugur et al., 2012). There is a tension between the precision of the representation, that may push towards a large number of effects in order to precisely act and understand what happens, and its simplicity, to reduce the memory and computational cost. The number of clusters therefore depends on a context that cannot be inferred by such an algorithm. It is proposed here to take the context into account to automatically tune the clustering algorithm in order to discover clusters of effects that make sense for the robot given this context.

The task given to the robot provides a mean to evaluate the relevance of a particular discretization. The main hypothesis made in this work is thus that the discretization depends on the context defined by the task to be achieved. The task is defined as a particular position to reach in the effect space associated to an object, for instance moving an object to a particular position. The data generated by the babbling tells

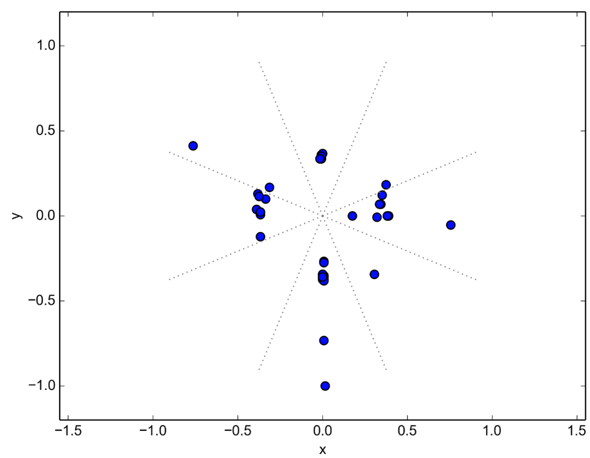

Figure 1: An example of dataset where effects in blue need to be grouped into clusters.

the possible movements in this space. The proposed method consists in an iterative algorithm in which a clustering algorithm is tuned in order to satisfy three different objectives: (1) the number of moves to reach the goal, to be minimized to make the robot as fast as possible, (2) the number of clusters, to be minimized in order to simplify computations and (3) the final distance to the goal, to be minimized for the accuracy of the control.

NSGA-II, a multi-objective evolutionary algorithm (Deb et al., 2002), was used to generate the set of non-dominated parameters of the clustering algorithm optimizing these objectives. The algorithm used to compute the fitness function is described thereafter (Algorithm 1).

An experimental validation of our method was performed using the *Mean Shift* clustering algorithm (Fukunaga and Hostetler, 1975), which empirically revealed to generate more diverse clusters than X-means when their parameters were changed. The genotype was constituted by the value of the single float parameter associated with this algorithm. Ini-

Algorithm 1 Evaluation algorithm for fitness function

$E = \{C_{e1}, \ldots, C_{en}\}$ ▷ Set of clusters containing effects
$F = \{f_1, \ldots, f_n\}$ ▷ Set of final points
$I = (0;0)$ ▷ Initial point
$t = 0$ ▷ Number of tries
Compute the set of effects E from genotype
for all final point f_i in F **do**
  for $j = 1$ to *nb_repeat* **do**
    while $dist(I,\ f_i) > \varepsilon$ **and** $t < t_{max}$ **do**
      $M = \{m_i \mid m_i = rand(C_{ei})\ \forall\, C_{ei} \in E\}$
      $m = \underset{m_i \in M}{\mathrm{argmin}}(dist(I + m_i,\ f_i))$
      Apply movement m to I
      $t = t + 1$
    end while
  end for
end for
return ($\overline{\text{nb movements}}$, nb clusters, $\overline{\text{final distance}}$)

tial population was made of 32 individuals, evaluated during 25 generations. Crossover and mutation rates for NSGA-II were respectively set to 0.8 and 0.1. We used a movement dataset generated by a simulated object-oriented babbling (Figure 1). One final point was randomly generated at the beginning of the experiment. The fitness was evaluated 30 times for each individual, the average objective values being reported.

The results were compared to discretizations obtained by a simple grid search over the parameter space.

Figure 2 shows some of the non-dominated points that have been generated. It contains the clustering results and the trajectories generated in the fitness function. The two clusterings optimize different objectives: speed and accuracy versus computational cost. The parameters shown on the left contain more clusters and allow a fast and accurate control. The other solution found relies on less clusters.

In that paper, we have proposed an approach to allow a robot learn from its own experiments and exploit babbling data in order to identify sets of reachable effects that define actions relevant to a task-dependant context. In the future, we will extend that approach by using more clustering algorithms and parameters, and investigate its application to more complex and varied tasks.

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[1] http://www.robotsthatdream.eu/

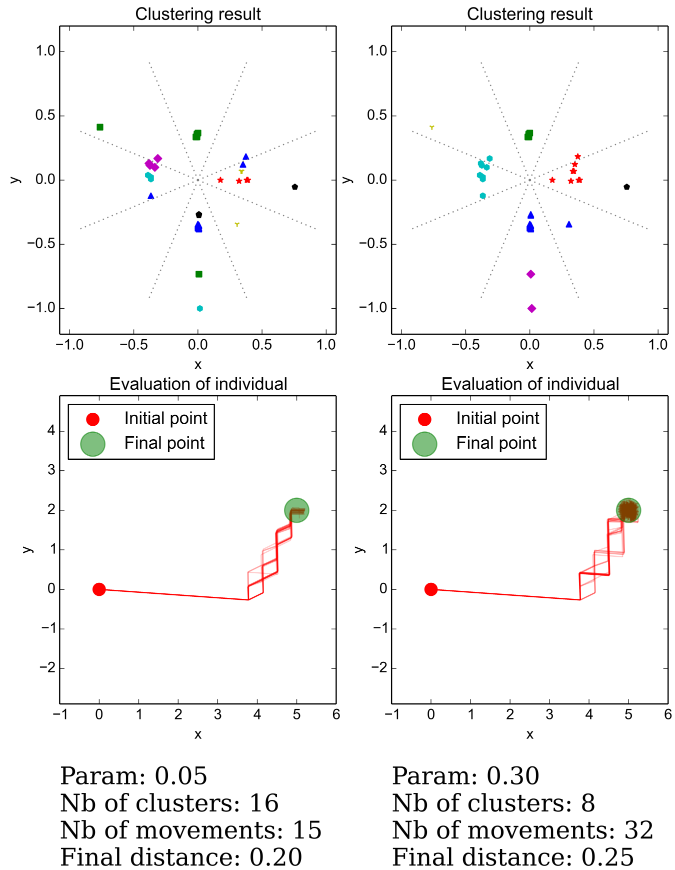

Figure 2: The two columns show different clustering results and evaluation trajectories based on parameter values belonging to indivuals on Pareto Front.

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