Fuzzy Logic for Culture-aware Robotics

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Abstract. In the context of culture-aware robotics, we propose a method for the explicit, on-line mapping between cultural variables and robot behaviour parameters which relies on the linguistic variable formalism, fuzzy clustering and the principles of fuzzy controllers. As a case study, we consider the adaptation of the Human-Robot conversational distance to Hofstede's cultural dimension of Individualism.

Keywords: Human-Robot Interaction, Fuzzy Controllers.

1 Introduction

In 2013, in an experiment involving Arab and German participants, people were asked to place a Nao robot at a suitable distance to hold a conversation with them [1]. The participants placed the robot at a distance they deemed *appropriate* for a conversation among two persons, unconsciously assuming that a robot shouldn't be too far from a human. Anthropomorphism, albeit important in the interaction between humans and robots [2], is not the only key factor. In the study about appropriate distances, experimenters found a significant difference in the behaviour of the Arab and the German participants, with the latter placing the robot much farther (approx. 85 cm) than the former (approx. 65 cm), in accordance with the social norms of their respective *cultures* [3]. Culture comprises both nation-wide aspects and individual traits, measured with quantitative variables, such as net income, but also *nominal* variables, which only allow for differentiation, such as gender, and *ordinal* variables, which only allow for differentiation and ordering of values, such as the OCEAN factors describing personality traits [4] or Hofstede's dimensions for the cultural categorization of countries [5]. The influence of a person's culture on his attitude towards a robot is the subject of ongoing research [6, 7]. However, culture-dependent robot behaviours are often implicitly set by designers, which makes it hard to adapt robots to a different culture.

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We propose a method allowing for the automatic, on-line tuning of culture-dependent robot parameters in accordance with a cultural assessment which is explicitly expressed in terms of standard cultural variables. To this aim, we propose the *linguistic variable formalism* as a unifying representation of cultural variables, and *linguistic fuzzy controllers* for the definition of the mapping between cultural aspects and robot behaviours.

2 Method

The proposed method requires: i) the definition of the cultural variable domain and the acquisition of a training set of data points over the domain; ii) the definition of the robot behaviour parameter with the linguistic variable formalism; and iii) the description of the relation between the cultural variable and the parameter in the form of if-then rules for a fuzzy controller.

To illustrate the approach, let us consider a personal mobile robot, engaging an assisted person in a conversation. One of the parameters of such a behaviour is the conversational distance P. Literature specifies that suitable values lie within the range $\mathcal{P} = [0.45m, 1.2m]$ [8] and that this parameter is directly correlated with Hofstede's dimension of *Individualism* C [1, 9, 10].

The mapping between the two variables is only known in a qualitative form: *countries with a high individualism score tend to have larger values for the conversational distance than countries with a low individualism score.*

Literature provides the *Individualism* scores of 110 countries[3]. Our goal is to define a compact, complete and explicit mapping between C and P, induced by qualitative knowledge like the one above, which allows the robot to tune the conversational distance in accordance with the user's nationality.

3 Cultural Variables as Linguistic Variables

In Fuzzy Logic, a *linguistic variable* [11] can be expressed as the quadruple:

$$\langle C, \mathcal{C}, \mathcal{L}C, \mu_{LC} \rangle \tag{1}$$

where C is the name of the variable (e.g., *Age*), $\mathcal{C}$ is its domain (e.g., $[0, 117]$ years), $\mathcal{L}C$ is the set of linguistic values LC that C can take (e.g., $\{baby, teenager, adult, elderly\}$) and μ_{LC} is the membership function defining the relationship between a linguistic value and the domain values. In the case of nominal variables we can define a one-to-one mapping between $\mathcal{L}C$ and $\mathcal{C}$ (e.g., $\mathcal{L}C_{Gender} = \mathcal{C}_{Gender} = \{female, male\}$). In the case of ordinal variables, such as *Individualism* (for which $\mathcal{C} = [0, 100]$), the number of linguistic values LC to consider and their relation with the domain values is less obvious. Most studies arbitrarily impose $\mathcal{L}C = \{low, medium, high\}$ [9, 12], with a crisp mapping to the domain which only depends on its range. However, we argue that the introduced

[3] Publicly available at: `http://www.geerthofstede.com/dimension-data-matrix`

discontinuities may be unnatural since the range is arbitrary, and propose the extraction of the linguistic values from available data.

We denote with $C^T = \{c_1^T, \ldots, c_i^T, \ldots, c_I^T\}$ the set of data points to use for estimating $\mathcal{L}C$ and all corresponding μ_{LC}. The set can contain publicly available data, as well as user-specific information; moreover, it can be updated at any time, thus allowing for continuous learning and adaptation. We use as training dataset C^T for the *Individualism* variable the aforementioned publicly available scores of 110 countries. The x-axis of Figure 1 spans the domain $\mathcal{C}$ and the blue dots mark the 110 scores (e.g., $c_1^T = 6$ corresponds to the score of Guatemala and $c_2^T = 8$ corresponds to the score of Ecuador).

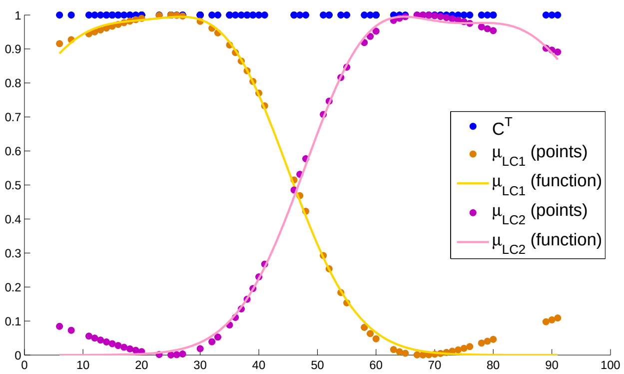

Fig. 1. Clustering & Fuzzification of the training set C^T of a cultural variable C.

We propose a three-step procedure for the automatic estimation of $\mathcal{L}C$ and all corresponding μ_{LC} on the basis of C^T, based on the intuition that we can define the linguistic values LC as clusters on C^T. We use Subtractive Clustering [13] for the estimation of the number of clusters to use and Fuzzy C-means Clustering [14] for the association of the points to the clusters. More specifically, the algorithm computes for each point c_i^T its membership value $\mu_{i,LC}$ to each cluster LC. In our case: i) the Subtractive Clustering algorithm identifies 2 as the optimal number of clusters; ii) Fuzzy C-means Clustering computes the membership values $\mu_{i,LC1}$ to cluster $LC1$ (orange dots) and the membership values $\mu_{i,LC2}$ to cluster $LC2$ (purple dots). Finally, we approximate each membership function μ_{LC} with a two-terms Gaussian function defined as:

$$\mu_{LC} = \alpha_1 e^{-\frac{(c-\beta_1)^2}{\gamma_1^2}} + \alpha_2 e^{-\frac{(c-\beta_2)^2}{\gamma_2^2}} \tag{2}$$

where c spans the domain $\mathcal{C}$ and the parameters $\alpha_1, \beta_1, \gamma_1, \alpha_2, \beta_2, \gamma_2$ are estimated to best fit the distribution of the values $\mu_{i,LC}$. In Figure 1, the yellow line corresponds to the two-terms Gaussian function μ_{LC1}, while the pink line corresponds to the two-terms Gaussian function μ_{LC2}.

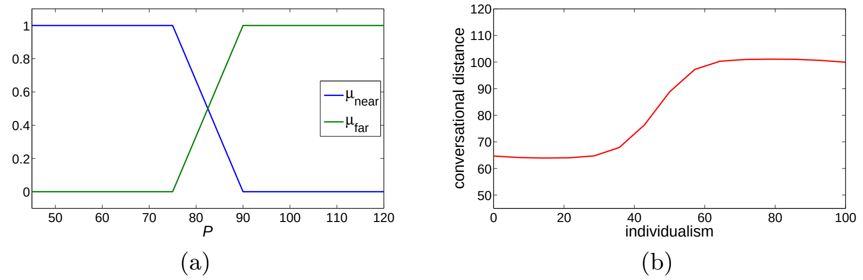

Fig. 2. (a) Description of the *conversational distance* as a linguistic variable. (b) Mapping between the *Individualism* and *conversational distance* given by (3).

4 Parameters setting with Fuzzy Controllers

Linguistic fuzzy controllers allow for describing relations between linguistic variables in natural language, by means of *if-then* rules specified over the respective linguistic values [15]. Let us assume that we describe parameter P with the linguistic variable $\langle P, \mathcal{P}, \mathcal{L}P, \mu_{LP} \rangle$, with $\mathcal{L}P = \{near, far\}$ as shown in Figure 2(a); then we might define the rules as:

$$\begin{cases} \texttt{if } C \texttt{ is } LC1 \texttt{ then } P \texttt{ is } near \\ \texttt{if } C \texttt{ is } LC2 \texttt{ then } P \texttt{ is } far \end{cases} \tag{3}$$

Fuzzy controllers require the specification of: i) the fuzzification method, which takes a value $c^* \in \mathcal{C}$ in input and computes the linguistic value LC^* it corresponds to; ii) the inference method, which solves the set of if-then rules, and iii) the defuzzification method, which finally computes the value $p^* \in \mathcal{P}$ on the basis of the linguistic values LP^* activated by the rules. We use a fuzzy controller relying on Mamdani implication and composition-based inference, and on the Center-of-Area defuzzification method. Then, the set of rules specified in (3) generates the continuous mapping $\mathcal{C} \to \mathcal{P}$ shown in Figure 2(b). As an example, $c^* = 38$ (Arab countries) is mapped to $p^* = 69.9cm$, while $c^* = 67$ (Germany) is mapped to $p^* = 100.7cm$.

A mock-up system has been implemented in MATLAB (R2014a), making use of the Fuzzy Logic Toolbox (2.2.19) and the Curve Fitting Toolbox (3.4.1).

5 Conclusions

Cultural adaptation of robots is an important but under-addressed problem. We have presented an approach to dynamic, on-line cultural adaptation based on the mapping of cultural variables to parameters of robots behaviours. We have illustrated our approach on a simple case involving one variable and one parameter, but work is under way to generalize this approach to consider several cultural variables and several behavioural traits.

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