Cognitive and Emotional Linguistic Interaction

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ABSTRACT

The MAPH project is an extension of the French therapeutic and robotics Emotirob project. Since Emotirob aims at conceiving and realizing a "reactive" companion robot, which can emotionnally interact with young weakened children, MAPH aims at implementing linguistic interaction between the soft toy robot and the child. The first step of this work aims at modelling the pragmatic and emotional world of a young child. From a set of 1500 words and the aid of questionnaires in a school, a taxonomy and a set of properties have been built which have made it possible to define a distance between two words and concepts of a higher level. Currently, our system is able to generate very simple sentences in the context of elementary linguistic games. As a perspective, we envisage making the robot able to enrich its vocabulary, and able to define a set of linguistic reaction patterns in accordance to a child's emotional state.

1. INTRODUCTION

Previous experiments have already shown the contribution of companion robots to bringing some confort to human beings weakened by disease [9]. Supported by the French ANR (National Research Agency), the therapeutic and robotics project Emotirob aims at conceiving and realizing a "reactive" soft toy, which can interact emotionally with weakened children, by using facial expressions and small simple sounds. The MAPH project (Active Media for the Handicap Project) is related to this project since it aims at extending the reaction capacities of the robot by providing it with some cognitive and linguistic capacities.

Currently, carrying on a "natural" conversation with a machine on a non-constraint subject seems unrealistic: operational man-machine dialogue systems are feasible, provided the interaction between the user and the system is restricted to a task-oriented dialogue with a restricted vocabulary [10]. In our project, we are dealing with vocabulary covering the child's entire surroundings and we envisage a non-restricted conversation domain. However, limiting the users of our system to young children makes the vocabulary in which we are interested quite restricted. Moreover, despite the fact that we have conceived different types of interactions, they are still well targeted. Under these conditions, producing a dialogue between the child and the robot is conceivable.

Child-machine interaction is currently a specific research domain with various topics and some specific difficulties. Current research includes educational or sociolinguistic topics [1], [6] and works which are related to the adaptation of man-machine dialogue modules for children: Automatic Speech Recognition (ASR), Spoken Language Understanding (SLU) [4]. The Emotirob project includes the implementation of an ASR and of a SLU adapted to young children and including an emotional component[1]. The work presented in this paper is based on the ouputs of these modules. It is focused on the modelisation of the linguistic and cognitive knowledge given to the companion robot. More precisely, it aims at providing this robot with the capacities to generate new "ideas" or to enrich its vocabulary, by implementing a part of the linguistic and cognitive knowledge of a young child. Here, we present the first step of this research. In the following section, the linguistic model, which we have built to have a plausible representation of the world of a young child, is presented. This model includes syntactic, pragmatic and emotional knowledge. In the following section (section 3), how we have made use of this model is presented, while the last section gives some applications and perspectives (section 4).

2. LINGUISTIC WORLD MODELLING

The set of words on which we are working was collected by D. Bassano [2] and is intended to evaluate language acquisition of young children (42 months). The first tool we have

[1]Emotirob SLU is an adaptation of the Logus system, based on a logical approach that we have previously implemented [8].

built is a taxonomy, in which words are classified according to syntactical, semantics or emotional criteria. At the first level, the nouns, the verbs, and the adjectives can be found. At the levels which follow, the criteria are mainly semantic and emotional. Figure 1 shows a little part of this work. In

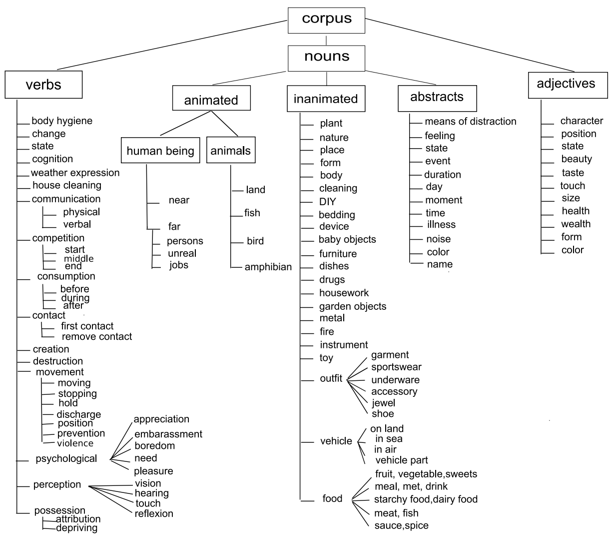

Figure 1: A part of the taxonomy.

some categories of the taxonomy, words are distinguished by a set of pragmatic or emotional properties. For example, in the animal set, there are properties of various types, such as *frightening* or *four_legs*. For the verbs, the properties make it possible to specify necessary knowledge: the type of subject and of complement they can have in a meaningful sentence.

To confirm some categories of the taxonomy and of the word properties, especially when they are related to animated beings and to emotional criteria, we used questionnaires submitted to young children (5-7) of an elementary school. These children were a little older than those concerned by our study, but according to Piaget [5] the children of lower ages tend to say anything and everything when they don't know the answers to the questions. We used various types of questions to try to minimize the risks of falsifying child spirit orientations. In the great majority of cases, the results were in accordance with our expectations, but nethertheless some of them led to modifications of some parts of our representation. For example, we had surprising results related to the real existence of some characters.

Characters	Children's percentage believing that he exists only in the tales
Father Christmas	50%
Prince	90%
King	92%

The results related to animal classifications or to the impressions aroused by insects were not very surprising but very mixed, as it is shown in the following table: the elementary knowledge related to scientific classifications are vague and not fully relevant for young children.

Animal classification			
Proposition	Yes	No	I don't know
The ostrich is a bird	35%	45%	20%
The penguin is a bird	30%	40%	30%
The fish spawns	60%	30%	10%
The shark is a fish	45%	40%	15%
The whale is a fish	20%	70%	10%

How insects are seen			
Proposition	Yes	No	I don't know
An insect falls	65%	25%	10%
An insect frightens	5%	95%	0%
An insect flies	70%	20%	10%
An insect is kind	70%	15%	15%
An insect is attractive	40%	40%	20%

3. WORD DISTANCES AND CLASSIFICATIONS

We try to measure the semantic and emotional links which exist between the words of the corpus, according to this taxonomy. Two methods are used: the first one is based on a distance calculus, and the second one uses classification algorithms.

3.1 Word Distances

The calculation of the distance between two words is related to their syntactics categories. The distance between two nouns is a weighted average between the distance separating the words in the taxonomy and a coefficient calculated from the number of their common properties.

More precisely, it is a weighted average between two coefficients, the first of which, *R1(N1,N2)*, calculates the rapprochement between both words in the taxonomy, whereas the second evaluates their rapprochement regarding their common properties number.

$$Rapproch(N1, N2) = \frac{C1 * R1(N1, N2) + C2 * R2(N1, N2)}{C1 + C2} \quad (1)$$

We distinguished two types of properties: affective properties and objective ones. Each property was balanced with a weight measuring its importance in defining a certain set of words. R2 is then the weighted average of an affective rapprochement *Ra(N1,N2)* weighted by an affective coefficient *Qa*, and an objective rapprochement *Ro(N1,N2)* weighted by an objective coefficient *Qo*.

$$Ra(N1, N2) = \frac{nb\_prop\_aff\_com(N1, N2)}{max(nb\_prop\_aff(N1), nb\_prop\_aff(N2))} \quad (2)$$

$$Ro(N1, N2) = \frac{nb\_prop\_obj\_com(N1, N2)}{max(nb\_prop\_obj(N1), nb\_prop\_obj(N2))} \quad (3)$$

$$R2(N1,N2) = \frac{Qa * Ra(N1,N2) + Qo * Ro(N1,N2)}{Qa + Qo} \quad (4)$$

The rapprochement coefficients we obtained depend on the Qa and Qo that we chose. For instance, *"ladybird"* and *"louse"* will be semantically close if Qo is bigger than Qa. Otherwise, they will be distant.

In the same way, the distance between two verbs or two adjectives takes into account their distance in the taxonomy. The distance between two adjectives takes into account the types of subjects on which they can be applied. For the verbs, the other criteria are their syntactics type: intransitive, transitive and double transitive and the ontological distance between their subjects and their complements.

These distances make it possible to "generate" very simple new sentences "close to" a simple input sentence, in the sense given by our child word knowledge: it is a first small step toward our objective.

3.2 Classifications

Classification is an important part of this work and its purpose is double. First, we want to establish that the ontology is a relevant child world modelisation: if the properties that we have defined lead to a consistent classification, we can suppose that our choices are relevant. Then, we want to try to obtain concepts of higher levels according to the achieved classes of words: it is a significant step to implement the emergence of new "ideas" and the enrichment of the world knowledge.

The first classification algorithm we tried is inspired by the Hyperlex algorithm used for automatic discrimination of words in a textual database [7]. This very simple algorithm gives word classes built from a head element and its neighbours. We used it with various definitions of "neighbour" by giving different values for the acceptable distance.

Figure 3 shows the results related to a value of proximity of 60%, with two different values given to **Qo** and **Qa**. The results are noticeably different. In the first table, *"louse"* and *"ladybird"* are in the same class: it is relevant since their physical aspects are very similar. Nevertheless, when an affective coefficient is taken into account, *"louse"* is rejected from this class and becomes an isolated word.

Although we have generally obtained relevant results according to our subjective world perception, complementary information is needed to improve and refine our classification. The hyperlex algorithm is not a good tool for such a purpose, because it is based only on the previously defined word distance with no direct relation to the concerned properties. Currently, we are working to apply classical classification algorithms as hierarchical ascending classification with chi-two distance. We give a part of the results obtained by applying this methods to the 50 animals of the corpus, using nine qualitative variables: three of which are related to physical properties, two to the way of life, and one to eating habits. Two other variables are subjective: they estimate how the children perceive the animals. These data are given as a full

Qo=1, Qa=0	
Class	Animals
1: squirrel	: squirrel, elephant, giraffe, hedgehog, kangaroo, marmot, panda, monkey
2: pigeon	: great duck, rooster, swan, owl, sparrow, pigeon, penguin, green woodpecker, hen, chick
3: ladybird	: spider, ladybird, ant, dragonfly, fly, butterfly, louse, earthworm
4: rabbit	: lamb, donkey, camel, cat, horse, pig, dog, hamster, rabbit, sheep, pony, bull, cow, calf, rat, mouse
5: whale	: whale, shark
6: crocodile	: crocodile, frog
7: wolf	: leopard, lion, lioness, wolf, bear, fox, tiger, zebra
Isolated words	: doe, toad, dragon, snail, goldfish, snake, tortoise

Qo=1, Qa=1	
1: horse	: cat, horse, goat, pig, dog, hamster, rabbit, pony, calf
2: squirrel	: doe, squirrel, giraffe, kangaroo, marmot, panda, monkey, mouse, zebra
3: sparrow	: great duck, swan, owl, sparrow, pigeon, penguin, green woodpecker
4: leopard	: leopard, lion, lioness, wolf, fox, tiger
5: duck	: duck, rooster, hen, chick
6: dragonfly	: ladybird, ant, dragonfly, fly, butterfly
7: lamb	: lamb, sheep, cow
8: whale	: whale, elephant
Isolated words	: donkey, spider, camel, toad, crocodile, dragon, snail, frog, hedgehog, bear, goldfish, louse, rat, shark snake, bull, tortoise, earthworm

Figure 3: Animal classification resulting from Hyperlex, with different values given to *Qo* and *Qa*.

disjunctive table as shown in Figure 4: each variable is split into several modalities. For each variable and for each word, value 1 is for one and only one modality, 0 for the others.

In that approach, the distances are calculated by weighting each modality with the inverse of its frequence: the weight of an uncommon modality is larger than that of a common one. To group the words together and build the classes, we have chosen the Ward criterion, which minimizes the inertia within the classes and maximizes the inertia between the classes. The resulting classes are homogenous with the greatest distance from each other as possible.

Figure 2 shows part of the resulting dendrogramme, with some comments (in italics). A possible classification resulting from this dendrogramme (shown in the rounded boxes of Figure 2) splits the set of animals into the six following classes:

1. Bare skin and disgust: *frog, toad, earthworm, snail...*
2. Aquatic animals: *whale, shark, goldfish.*
3. Insects or similar animals: *spider, louse, ant, fly, ladybird, butterfly* and *dragonfly.*
4. Poultry: *duck, chick, etc.*
5. Harmless mammals which are split into two sub-classes:

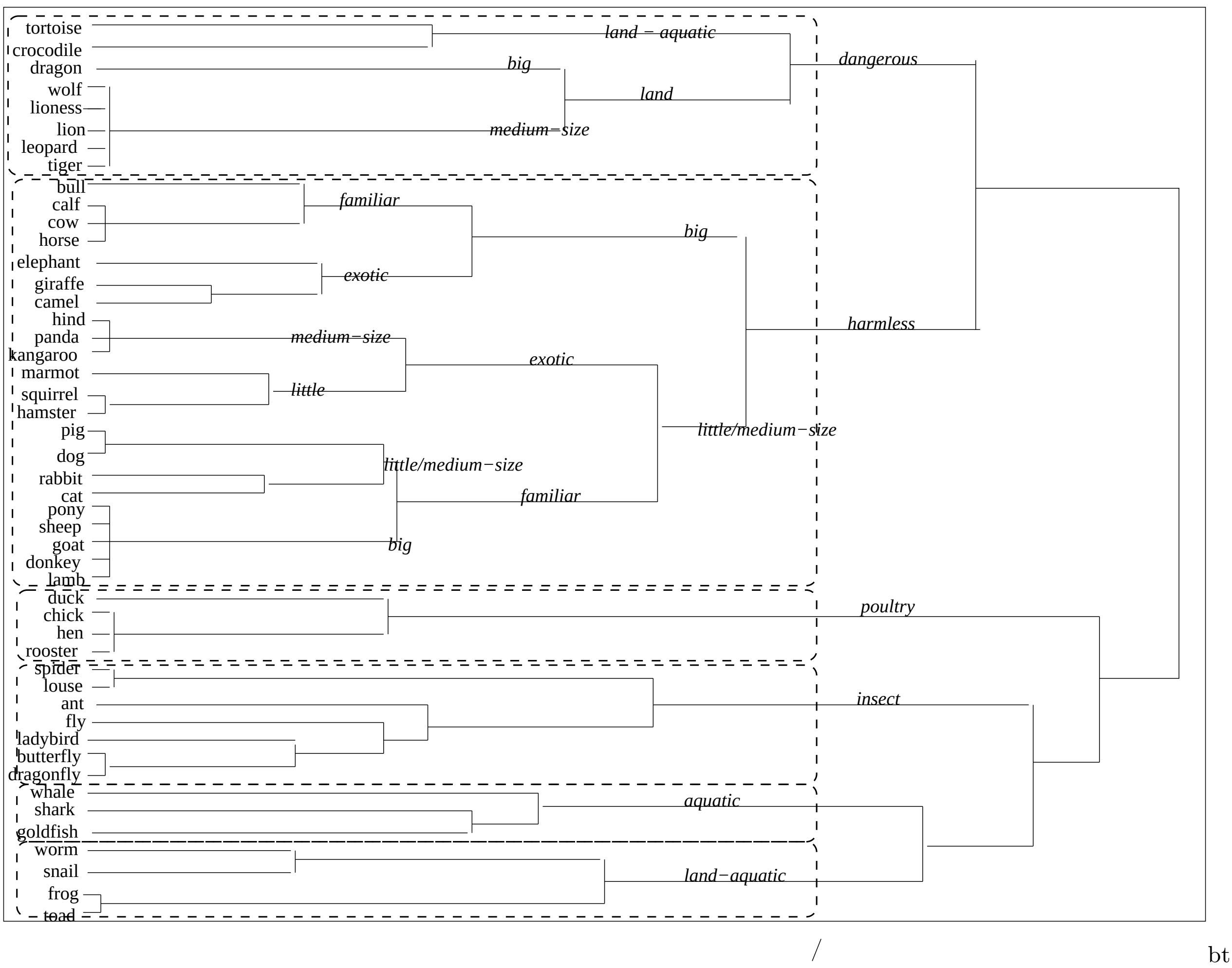

Figure 2: Animal dendrogramme resulting from hierarchical ascending classification with Ward criterion.

	exterior covering					number of legs				size		
	hear wool	feathers	naked skin	scales	other	0	2	4	>4	big	medium	little
lamb	1	0	0	0	0	0	0	1	0	0	1	0
frog	0	0	1	0	0	0	0	1	0	0	0	1
ant	0	0	1	0	0	0	0	0	1	0	0	1

Figure 4: An example of data for hierarchical ascending classification.

   (a) Big mammals, familiar (*cow*) or exotic (*elephant*).
   (b) Little or medium mammals, familiar (*dog*) or exotic.

6. Dangerous big or medium size animals which are split into two sub-classes:
   (a) Mammals: *wolf, lion,* etc.
   (b) Others: *crocodile*, etc.

Despite this coherent classification, the algorithm shows that the data must be improved and some properties added. For example, *bear, hedgehog* are badly classified (they are not shown here). *Tortoise* is classified with *crocodile*, with a lot of dangerous animals according to its properties: the two words share the rare modality *scales*, since other variables do not compensate for that link.

Other algorithms such as Kohonen [3] artificial neural networks have to be used in order to refine the classification and our taxonomy. They will favour the idea of proximity and bring out new classification meta-criteria.

4. APPLICATIONS - PERSPECTIVES

The models of phrase or sentence generation which we currently use are very simple since we have only canonical simple phrases such as *(adjective, noun)* or sentences such as *(subject, intransitive verb)*, *(subject, transitive verb, complement)* or *(subject, indouble transitive verb, complement1, complement2)*. Moreover, we generate affirmative sentences only. Presently, we are conceiving linguistic games, suitable for the targeted children and able to distract them. For example, we implemented a game in which a participant has to formulate a sentence which begins with the last word of the previous sentence formulated by his opponent, while ensuring a coherent meaning to the sentence.

Future prospects will require a great deal of work to develop the cognitive and linguistic capacities of our system. The language acts will need to be worked on and different types of sentences introduced, such as interrogative or imperative sentences. Furthermore, the emotional state of the child, as well as the linguistic context should be taken into account (realistic, funny, artistic, etc.). We will also need to create some linguistic games, and more generally to extend the linguistic reaction patterns of the robot. Another major difficulty of this work is its evaluation. The first objective of the projects Emotirob and MAPH is to improve the comfort of weakened children. Our work is a part of a global project whose evaluation is a difficult challenge. A less ambitious possibility is questionaires, where people are asked if the linguistic reactions of the system are satisfactory.

5. ACKNOWLEDGMENTS

We thank the region of Brittany (France) for the interest and the support which it brings to the project. We also wish to thank Dominique Bassano for her collaboration by giving us access to her child corpus.

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