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Body posture measurement in a context of example-based teaching

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Abstract. This paper presents a measurement process of body postures operated in a context of humanoid robot learning. The basic measured quantities are the angle joints of a human skeleton and the angle joints of a humanoid robot. Due to the differences between the two mechanical structures, the measurement results are expressed into a common representation space by the way of fuzzy scales. This paper shows how the common representation space can be defined, and presents a method to match weakly defined postures with uncertain measurements of a human posture.

1. Introduction

The era of humanoid robots now enters into a new step with the introduction of products for non-professional users. The set of applications of such robots is quickly growing and the conventional systems for the configuration and the robot programming stay dedicated to specific users. A solution to extend the set of potential *robot programmers* is to map education techniques on the context of robots. In particular, we suppose that it is possible to teach postures and gestures to a humanoid robot with a sample-based teaching method. The chosen process to perform such method is given:

- a human called teacher performs a posture,
- this posture is measured then interpreted,
- following the interpretation, the robot tries to perform the same posture.
- the robot posture is measured and compared to the teacher posture.

In order to be compared, the postures of the teacher and of the robot need to be expressed in a common space. Unfortunately, the numerical space in which the angles of the human joints are expressed cannot be the same than the numerical space used to represent the angles of the robots joints. This difference mainly comes from the distribution of the DOF (degrees of freedom) that differs between the teacher and the robot.

The solution we propose is to perform measurements with fuzzy scales [1][2]. This allows to represent a measurement indication as a fuzzy lexical set with dimension 6, each dimension leading to a part of the body : legs, torso, arms and head. For each dimension, i.e. for each body part, the posture of this part is represented with a usual Lexical Fuzzy Subset (LFS). A LFS is then a fuzzy subset of lexical terms, each lexical term being associated to a characteristic posture of this body part. The indication given by the measurement of the full body is then defined as a 6 components vector of LFSs.

The main advantage of this approach is that the same set of lexical terms can be used to characterise a part-posture of the teacher or the equivalent part-posture of the robot. This means that the measurements of full body postures of the teacher and of the robot are expressed into the same representation space and can be compared. It has been shown before that fuzzy scales are metrical scales and restrict the set of relations between measurement results to the comparisons of distances. But these relations are enough to perform the comparisons we need and to manage the measurement uncertainty.

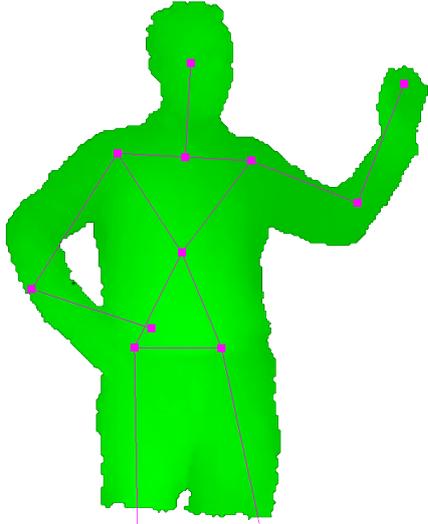


Figure 1. 2D representation of the body perceived by the depth sensor and of the measured joints.

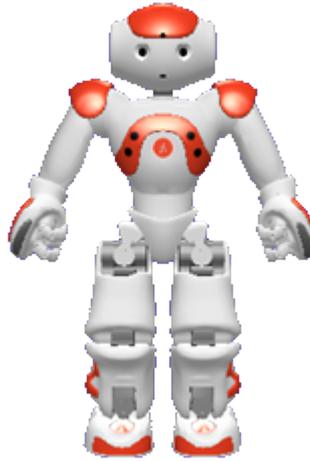


Figure 2. Robot used for the study. The joint states are acquired with proprioceptive sensors.

2. Numerical measurements

The body posture measurements of the teacher and of the robot are performed with 2 different systems. The body of the teacher is acquired with an image depth sensor (a Azuz Xtion pro in our case) [3]. A middle-ware extracts the body shape and computes the 3D coordinates of the joints to give a skeleton approximation as for [4][5]. Each joint is either a 1DOF joint or a 3DOF joint. Each 1DOF joint is characterized by a single angle. Each 3DOF joint is characterized by a normal rotation axe and an angle. The robot used for this study is a Nao robot from Aldebaran Robotics. It holds 13 joints with a total of 25DOF. Each rotation axe has a proprioceptive sensor that is used for the measurement of the body posture.

The teacher body and the robot body are decomposed into 6 parts that are the left and right arms, the left and right legs, the torso, the head. For each part, the information entities used to express indications and measurement results are vectors of numerical data.

Thanks to the proprioceptive sensors, the measurement uncertainty is negligible for the robot posture, but needs to be managed for the teacher posture. Actually the measurement process with an image depth sensor induces two kind of uncertainties. The first uncertainty is an ontic uncertainty [6] and comes from the common statistical dispersion of the 3D coordinates of joints and can be estimated with a type A evaluation [7][8]. The second uncertainty comes from the fact that a joint can be hidden by another part of the body or can simply be confused with another object (see figure 1). A third source of uncertainty named epistemic uncertainty [6] is not directly linked to the measurement but depends on the definition of postures that can be

imprecise. In this case a posture is no more defined with a value (actually a vector), but with a set of values. Such set doesn't define a probability distribution but a possibility distribution. As the simultaneous management of the measurement uncertainty and the epistemic uncertainty is not simply performed within a pure probabilistic approach, we use the Dempster-Shafer evidence theory that allows to handle in the same approach probabilities and possibilities [9].

3. The transferable belief model

The Dempster-Shafer evidence theory, also named the transferable belief model (TBM) is a general approach for uncertainty management based on the assignment of belief to sets. In this section, we present a short introduction to this theory.

The main element of the TBM is the *frame of discernment* denoted Ω and presented as a set of elementary events, or as a discourse set for the expression of the belief in a *piece of evidence*. The belief in a piece of evidence E is then expressed with a mapping $m[E]$ (or simply m) called *belief function*, or *basic belief assignment* (BBA). This mapping is defined from the set of subsets of Ω , denoted 2^Ω , to the set $[0, 1]$. It represents the distribution of a weight of belief over the event sets. A non null amount of belief assigned to an event set means that the occurrence of the given events are compatible with the *piece of evidence*.

Any belief function verifies:

$$\sum_{A \in 2^\Omega} m(A) = 1 \quad (1)$$

The set $\{A \mid m(A) > 0\}$ is called the set of focal elements of m , and the couple $(\{A \mid m(A) > 0\}, m)$ is called a body of evidence of a variable with values on Ω . The link with the probability theory is performed with the body of evidences of the form $(A \in \Omega, m)$. In this case the focal sets are singletons and the BBA m , qualified as a Bayesian BBA, is a probability distribution over Ω . The other categories of BBA used in our studies are the consonant BBAs which focal sets are nested sets. These last BBAs lead to possibility distributions.

The belief in two pieces of evidence E_1 and E_2 issued from 2 independent sources can be computed with a conjunctive combination operator:

$$m[E_1 \cap E_2](A) = \sum_{B \cap C = A} m[E_1](B)m[E_2](C), \forall A \subseteq \Omega \quad (2)$$

This operator can be used if both sources are reliable. In this case, it concentrates the amount of belief on events that are compatible with both pieces of evidence. This operator has the property to assign some belief on the empty set. The value $m[E_1 \cap E_2](\emptyset)$ is actually representative of the degree of conflict between sources. In order to moderate the degree of conflict it is possible to weaken the confidence into a source with a transfer of belief to the set Ω .

4. The fuzzy linguistic representation of the measured values

The method used to build a linguistic representation of measured postures is similar to the method previously used for hand posture measurement in [10]. In the initial study, only measurement indications were considered as measurement results. If we apply this approach to our case, each posture indication is represented by a LFS (Lexical Fuzzy Subset) defined on the cross product Ω of 6 lexical sets, each one corresponding to a body part. Within the scope of evidence theory used in this paper, Ω is interpreted as the exhaustive set of mutually exclusive representations of a posture. As an example, the item $\omega = (\text{vertical}, \text{front}, \text{down.open}, \text{down.open}, \text{behind.open}, \text{down.open})$ is a synthetic definition of a posture used to check hand. A posture indication is then a fuzzy subset $\{\mu_i/\omega_i\}$ where the membership degree μ_i to each item ω_i is directly interpreted as a Bayesian basic belief function in Ω .

$$\Omega = L_{Body} \cdot L_{Head} \cdot L_{RightLeg} \cdot L_{LeftLeg} \cdot L_{RightArm} \cdot L_{LeftArm} \quad (3)$$

$$L_{Body} = \{vertical, bent, left, right\} \quad (4)$$

$$L_{Head} = \{front, left, right, up, down, leftbent, rightbent\} \quad (5)$$

$$L_{RightLeg} = L_{LeftLeg} = \{down, up, behind, outside\}.\{open, square, closed\} \quad (6)$$

$$L_{RightArm} = L_{LeftArm} = \{down, up, behind, outside, bodyside\}.\{open, square, closed\} \quad (7)$$

5. Building the epistemic knowledge

The first step before any measurement is to define the universe of discourse on which any measurement is expressed. In our approach, the universe of discourse is made of labels that identify postures. So each posture is identified by a unique label but a label fits with a set of postures. For example, the label *chekingHand* identifies several postures with several left arm locations.

According that, the sets of postures are learned with examples, we propose to model the knowledge on postures with belief functions. Indeed, this knowledge is acquired from various sources and cannot be simply limited to the definition of the labels. It also hold an epistemic uncertainty. The process is the following:

First the meaning of each lexical set L_i is defined as a fuzzy partition of the numerical set such that:

- An observation of the posture is performed and gives an indication expressed as a LFS on each lexical set.
- An aggregation is performed to compute a LFS on the general lexical set Ω .

The membership of the observation to each lexical term is interpreted as a Bayesian basic belief assignment m_1 on Ω^2 . The definition of postures can be interpreted as a classification building problem. The idea is to build a BBA that includes the knowledge related to a posture. We suppose that for a given posture to learn, we have a set of samples given by a teacher and represented by LFSs. One possibility is to consider all samples as independent sources and use the conjunctive combination to build a BBA consistent with all samples. This approach is consistent if the samples are close from each other but cannot be used in our case because a posture is imprecisely defined. In [11] Denoeux proposed to weaken the confidence into samples that are not similar with the previous learned samples. But this option stays unsuitable in our case where two dissimilar samples can be strongly representative of the same posture. Another possibility is to aggregate the Bayesian BBA associated to each sample with a simple mean operator. The resulting Bayesian BBA is then translated into a consonant BBA using the discrete version of the Yamada's algorithm [12].

Step 1: Let m_1 be the Bayesian basic belief assignment to translate. Let $j = 1$ be an iterator.

Notice that all focal sets are singletons.

Step 2: Let $A = \{\omega_i \mid m_j(\{\omega_i\}) \neq 0\}$ be the set of focal sets of m_j that are singleton. Let a be the smallest belief assignment on a singleton in A .

Step 3: Transfer the amount a of belief assignment from each singleton in A to the set A .

$$\forall \omega \in A, m_{j+1}(\omega) = m_j(\omega) - a \quad (8)$$

$$m_{j+1}(A) = \sum_{\omega \in A} a = a \mid A \quad (9)$$

Step 4: If m_{j+1} has at least one singleton as focal set, increment the iterator j and go to step 2.

At the end of this process, each archetype posture P is weakly defined by a BBA $m[P]$. These BBAs are consonant BBAs and are therefore considered as possibility distributions (see figure 3).

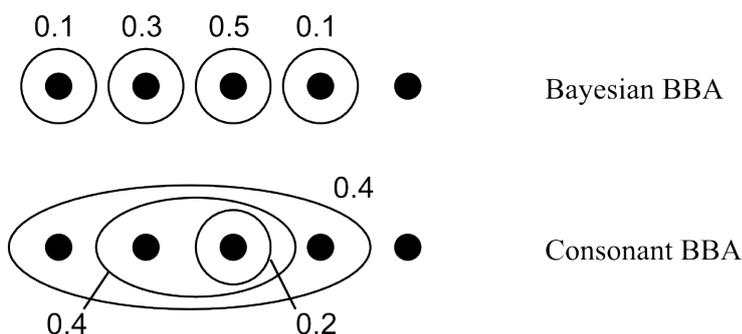


Figure 3. Example of a transformation of a Bayesian BBA into a consonant BBA on a frame of discernment Ω made of 5 symbols. The figure gives for each BBA the focal sets and their belief assignment.

6. measurement of postures

Each observation gives an indication I in the form of a LFS. Such LFS is directly interpreted as a Bayesian BBA $m[I]$ on Ω . For each defined posture P we have a consonant BBA and the conjunctive combination of the 2 BBAs gives the simultaneous belief into the indication value and a posture definition.

The result is a BBA where the focal sets are singletons and the empty set. The amount of belief assigned to the empty set after the combination $m[I \cap P](\emptyset)$ gives the degree of conflict between the indication and the interpretation of the measurement with P . This last information is representative of the impossibility to believe into the assertion *the posture P represents the indication I* .

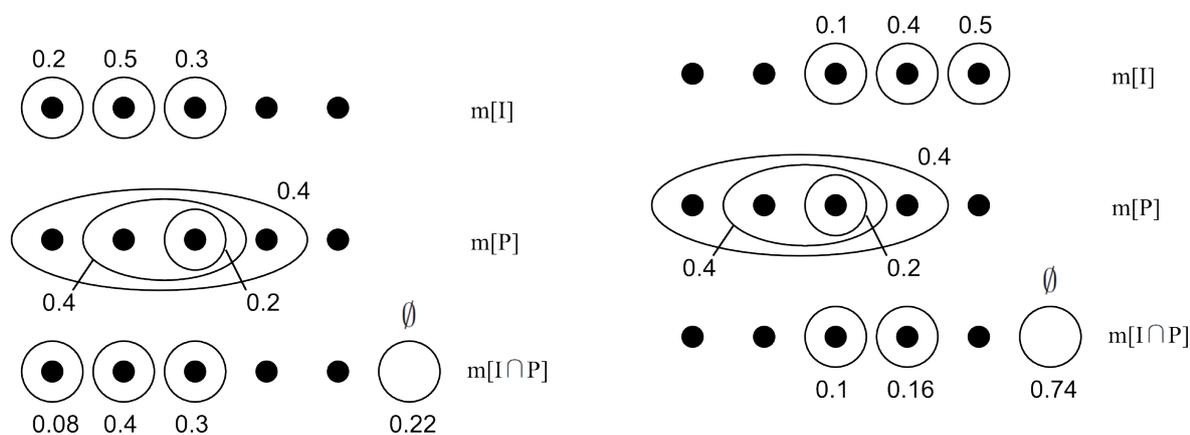


Figure 4. Conjunctive combination of an indication and a posture definition where the indication globally fits with the posture.

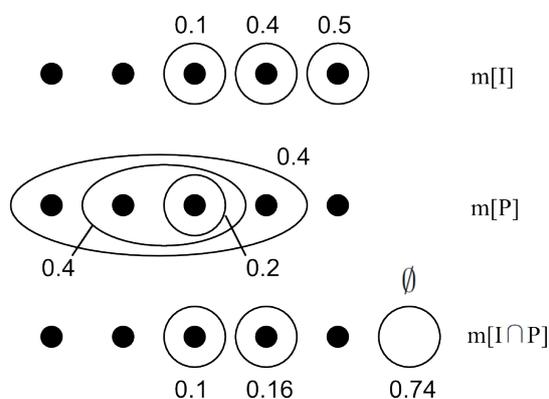


Figure 5. Conjunctive combination of an indication and a posture definition where the indication partially fits with the posture. The empty set holds the majority of the belief assignment.

Conclusion

As for psycho-physical scales, the scale built for human posture recognition depends on a knowledge on the posture definitions: an epistemic knowledge. Thus, the definitional uncertainty known as the epistemic uncertainty is more related to the consistency of the knowledge than

related to statistical events. Such uncertainty is then preferably modeled in the frame of possibility theory that allows to model unknown events. The management of ontic uncertainty issued from measurements is based on statistical approaches and are preferably modelled in the frame of the probability theory that gives a large set of mathematical tools. In this paper ontic and epistemic uncertainties interact at two steps. First when the epistemic knowledge is built with a set a measured samples. Then when a measurement indication is compared with the epistemic knowledge. We see in this paper that the immersion of these two kind of uncertainties into the transferable belief model allows to manage them together.

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