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Automatic Selection of Task Spaces for Imitation Learning

Manuel Mühlig, Michael Gienger, Jochen J. Steil, Christian Goerick

Abstract— **Previous work [1] shows that the movement representation in task spaces offers many advantages for learning object-related and goal-directed movement tasks through imitation. It allows to reduce the dimensionality of the data that is learned and simplifies the correspondence problem that results from different kinematic structures of teacher and robot. Further, the task space representation provides a first generalization, for example wrt. differing absolute positions, if bi-manual movements are represented in relation to each other. Although task spaces are widely used, even if they are not mentioned explicitly, they are mostly defined a priori. This work is a step towards an automatic selection of task spaces. Observed movements are mapped into a pool of possibly even conflicting task spaces and we present methods that analyze this *task space pool* in order to acquire task space descriptors that match the observation best. As statistical measures cannot explain importance for all kinds of movements, the presented selection scheme incorporates additional criteria such as an attention-based measure. Further, we introduce methods that make a significant step from purely statistically-driven task space selection towards model-based movement analysis using a simulation of a complex human model. Effort and discomfort of the human teacher is being analyzed and used as a hint for important task elements. All methods are validated with real-world data, gathered using color tracking with a stereo vision system and a VICON motion capturing system.**

I. INTRODUCTION

When a robot with a high number of degrees of freedom, such as a humanoid robot, shall learn new movements by imitating a human teacher, a movement representation within so-called task spaces is often favorable in contrast to a joint space representation. Imagine for example the task of putting objects into a basket. A joint-level description is very inflexible towards new basket positions because the adaptation of the movement within the joint space is non-trivial. A good task space representation for this example is the movement of the object relative to the basket. Besides reducing the dimensionality of the data to learn, this also allows for additional generalization. In the mentioned example, the representation generalizes over different basket positions. Furthermore, if the robot shall learn from a human teacher instead of through kinesthetic teaching, a representation within task spaces eases the correspondence problem. This problem arises due to the different kinematic structures of human and robot. A direct mapping of the human's to the robot's joints is more difficult than the mapping of end-effector positions.

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Looking at the state of the art, many agree on the usefulness of representing movements in task spaces. However, most imitation learning frameworks that include this concept need a designer that chooses which task space fits best to the action that should be learned. This limits both the open-endedness of the system and the whole interactive process, because the robot cannot learn different movement tasks and their individual task spaces continuously. The authors of [2] review several task space control methods and emphasize that the use of task spaces in robots with many degrees of freedom is almost inevitable. However, they do not focus on applying task spaces to the imitation learning problem. Although there are numerous approaches to imitation learning with robots (e.g. [3]–[6]) and most of them use some kind of task space representation, almost none of them explicitly considers the problem of deciding which task space should be used for learning. Two of the few exceptions to this are [7] and [8] in which the teacher's gaze and pointing direction are used as priors for a Hidden Markov Model (HMM) or Gaussian Mixture Model (GMM) representation. Still, the movement is represented within a latent space extracted using techniques such as Principal Component Analysis (PCA), which may also contain elements that are irrelevant for the actual task.

Interestingly, the representation of movements in task spaces is not limited to the field of robotics but can also be found in biology. In [9], the analysis of human writing showed that the occurrence of several features was equivalent no matter if the writing was performed with the hand or with the toe. It seems that a mechanism exists that represents the writing trajectories on a level higher than pure motor control. According to [10], also human reaching is probably represented in multiple reference frames relative to objects in the environment or relative to the starting position of a movement.

This work contributes to the selection of task spaces for imitation learning. We make a step from using predefined task spaces towards automatic selection from a pool of possibly even conflicting task spaces. A selection method named *task space selector* is being introduced that analyzes the observed object trajectories and acquires task space descriptors that match the observation best. For this, several criteria beyond statistics are incorporated, such as a psychologically inspired criterion that is based on the robot's attention to the objects in the scene and a kinetic criterion that estimates *effort* and *discomfort* of the human teacher.

The paper is organized as follows. Section II shortly reviews a previously developed framework for movement generation and imitation learning for the humanoid robot

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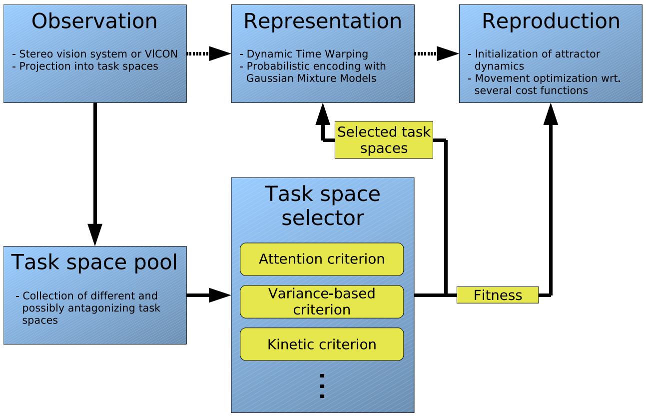

Fig. 1. Structure of the imitation learning process

ASIMO (see [1], [11]–[13]). Subsequent sections present extensions to this framework that aim for automatic task space selection. First, in section III, the task space concept is highlighted and different possible task spaces suitable for imitation learning are presented. These task spaces comprise the *task space pool*. Section IV presents the *task space selector* that evaluates the observations and automatically selects those task spaces from the *task space pool* that most probably contain important information. Finally, section VI concludes this work and presents a short outlook.

II. FRAMEWORK FOR IMITATION LEARNING AND MOVEMENT OPTIMIZATION

In recent work [1] and inspired from [5], [14], [15], we developed a framework for imitation learning with the humanoid robot ASIMO. The upper part of Figure 1 containing *Observation*, *Representation*, and *Reproduction* shows the structure of this framework. The lower part of the figure depicts the extensions discussed in later sections.

Several times, a human teacher demonstrates the movement task that the robot should learn. These demonstrations can be observed using either a stereo vision system with color tracking or a VICON motion capture system. The raw sensor data is mapped to a set of task spaces in which the movement is most conveniently represented. No assumptions about the teacher's or the robot's postures are made. As an example, for the task of pouring a beverage from a bottle into a glass, the relative position and orientations of the two objects may be used. Up to now, these task spaces are fixed and selected manually, which is a problem we address within this paper.

After the different demonstrations have been recorded, they are temporally aligned using Dynamic Time Warping. This results in meaningful inter-trial variance information, which is used as an importance measure for the movement generation later. Although it is a useful assumption to associate invariance over several demonstrations with importance, we show in section V that it should not be used as the only measure.

Gaussian Mixture Models are chosen to represent the mean and covariance information of the task. They are trained using a common Expectation-Maximization algorithm and K-Means initialization. The number of Gaussian components that are used for the representation is estimated using a fast heuristic based on the Bayesian Information Criterion. This results in a compact, probabilistic representation that can be used for both movement recognition and reproduction.

This probabilistic movement representation accounts for the robot's effector movement. However, it does not yet consider the limits associated to joint ranges, self-collisions etc. To handle these aspects, we incorporate a gradient-based trajectory optimization scheme [13]. It operates on an attractor-based trajectory generation [11] that describes the task space trajectories with attractor dynamics and projects these trajectories to the joint space movement with a kinematic whole body control system. The key idea is to optimize a scalar cost function by finding an optimal sequence of such task space attractor vectors that determines the robot's motion. This optimization scheme incorporates a *similarity criterion* that penalizes the deviation of the robot's task space trajectory from the observed one. The main idea is to apply an adaptive weighting scheme that weights the similarity with the inter-trial variance of the observation. By assigning a low weight to the similarity criterion, its effect will be reduced, as such giving higher influence to the other criteria governing the movement. This results in a movement that tracks the observed trajectory rather precisely in phases of low variance, while it is characterized by other criteria (joint limit and collision avoidance etc.) in phases of higher variance. The *similarity criterion* is implemented in a way such that the variance-based weighting is applied continuously over time and all dimensions of the task space.

Starting with this framework as a basis, we propose two extensions in order to solve the previously mentioned problem concerning the static task space selection. These extensions are the *task space pool*, described in the next section, and the *task space selector*, which is explained in section IV.

III. TASK SPACE POOL

The movement generation method allows for the task to be represented by a large variety of possible task space descriptions. Concerning the learning of object movements, task spaces may be composed of absolute object positions and orientations, relations between objects, additional constraints such as the restraint to only planar movements, and additional joint-level constraints. All these and more can be combined almost arbitrarily. However, this freedom comes with a price. Task spaces can be conflicting if they control the same end-effector for example. Thus, they cannot be active at the same time. Further, different movement tasks are best represented in different task spaces. As an example, the task of putting an object into a basket may be represented in form of absolute object positions or as relative object-basket positions. Although both representations are suitable for reproducing the task in the current situation, the latter one usually generalizes better because it is still valid if the basket is moved to another position.

a) absolute object positions:
$$\tau_a(R_j, o) = \left(\ldots pos(r_k^j, o)^T \ldots\right)^T \quad \text{(A.1)}$$
b) absolute object orientations:
$$\tau_b(R_j, o) = \left(\ldots ori(r_k^j, o)^T \ldots\right)^T \quad \text{(A.2)}$$
c) object positions relative to beginning:
$$\tau_c(R_j, o) = \left(\ldots \left(pos(r_k^j, o) - pos(r_1^j, o)\right)^T \ldots\right)^T \quad \text{(A.3)}$$
d) relative object positions:
$$\tau_d(R_j, o_1, o_2) = \left(\ldots \left(pos(r_k^j, o_1) - pos(r_k^j, o_2)\right)^T \ldots\right)^T \quad \text{(A.4)}$$
e) object positions relative to salient object:
$$\tau_e(R_j, o_s, o) = \left(\ldots \left(pos(r_k^j, o_s) - pos(r_k^j, o)\right)^T \ldots\right)^T \quad \text{(A.5)}$$

TABLE I

TASK SPACES AND THEIR MAPPING FROM THE RAW DATA

To tackle the problem of deciding which combination of task spaces to use, we introduce a discriminative approach. The idea is to map the observations into different task spaces that may be useful in imitation scenarios. These task spaces form the so-called *task space pool* from which the later described *task space selector* may choose those task spaces that fit the current movement best.

Formally, the creation of the *task space pool* $\mathcal{T}$ is performed using functions τ_i that map raw data $\mathcal{R}$ coming from the motion capture sensor system or vision system into the different task spaces:

$$\tau_i : \mathcal{R} \times \mathcal{O} \rightarrow \mathcal{T} \quad . \tag{1}$$

Symbol $\mathcal{O}$ denotes the set of all recognized objects o. The raw trajectories are already segmented into distinct demonstrations and for simplification this segmentation is predefined within this work (but see [16]). The segments are denoted as $\mathbf{R}_j \in \mathcal{R}$. Scalar D_R is the dimensionality of the raw data:

$$\mathbf{R}_j = \left(\mathbf{r}_1^{j\,T} \ldots \mathbf{r}_k^{j\,T} \ldots \mathbf{r}_{n_j}^{j\,T}\right)^T \text{ and } \mathbf{r}_k^j \in \mathbb{R}^{D_R} \quad . \tag{2}$$

Applying the individual functions τ_i to all demonstrations $\mathbf{R}_j$ results in the *task space pool* $\mathcal{T}$:

$$\mathbf{T}_{ij} \in \mathcal{T} \text{ with} \tag{3}$$

$$\mathbf{T}_{ij} = \left(\mathbf{t}_1^{ij\,T} \ldots \mathbf{t}_k^{ij\,T} \ldots \mathbf{t}_{n_j}^{ij\,T}\right)^T \text{ and } \mathbf{t}_k^{ij} \in \mathbb{R}^{D_{\tau_i}} \; . \tag{4}$$

The scalar D_{τ_i} denotes the dimensionality of the individual task space with for example being 3 for the absolute position of an object in Cartesian coordinates. Table I lists the task spaces used for the subsequently described experiments. The transformations are applied to all recognized objects o and, in case of relative descriptions, to all combinations of them. The functions *pos* and *ori* extract the position and orientation from the specific input source, respectively.

There are two ways to decide if task spaces are conflicting. One could predefine the pairs of conflicting task spaces, which is possible if all task spaces are known beforehand. Another way is to check if the resulting task Jacobian does not have a full row rank.

IV. TASK SPACE SELECTOR

In the previous section a *task space pool* is generated from the raw data. As already mentioned, this pool can contain redundant and conflicting task spaces, such as for example the absolute positions of two objects and their relative positions. Hence, it is unfavorable and sometimes impossible to learn the whole *task space pool*. Probabilistic representations, such as Gaussian Mixture Models as used within our imitation learning approach, suffer from noise in irrelevant task spaces. Therefore, we introduce the *task space selector* that analyzes the *task space pool* and selects only the important task spaces from it. For this, several criteria are used, which are described in the next section. These criteria calculate a score for each task space and, based on this score, the *task space selector* can influence the imitation learning process in two ways.

First, the task spaces that should be used for the representation are chosen exclusively by the *task space selector* and all the remaining ones are discarded. The system only learns the important elements within its representation. This improves not only the representation quality and the generalization capabilities, but also defines clearly how the movement should be reproduced later.

But, solely influencing the representation has its limits. Imagine movements with not clearly distinguishable task spaces for their whole duration, for example, an object movement that is best described relative to one object at the beginning and to another one at the end of the movement. In such a case, the representation needs to contain both task descriptions. The *task space selector* can then modulate the movement reproduction with the robot by using a time-continuous fitness function that results from the score values of the different criteria. We have implemented this as a modification of the previously mentioned *similarity criterion* (see section II and [1]) that is used for imitating a learned movement. This *similarity criterion* was used to continuously weight the importance of different task spaces during the reproduction based on the inter-trial variance as an importance measure. The new formulation replaces this purely variance-based weighting with a so-called *Task Blending Matrix* $\mathbf{B}_t$ that accounts for the importance information of all criteria of the *task space selector*:

$$c_{\text{im}} = (\mathbf{x}_t - \hat{\boldsymbol{\mu}}_t)^T \mathbf{B}_t (\mathbf{x}_t - \hat{\boldsymbol{\mu}}_t) \quad . \tag{6}$$

During the optimization and for each timestep t of the reproduced trajectory, this cost function penalizes a deviation of the state of the task space vector $\mathbf{x}_t$ from the learned movement's mean values $\hat{\boldsymbol{\mu}}_t$, weighted with the time-dependent diagonal matrix $\mathbf{B}_t$. As an example, in the case of only using the variance-based criterion within the task space selector, the *Task Blending Matrix* is calculated using the estimated inter-trial variances $\hat{\boldsymbol{\sigma}}_t$ (see [1] for more details):

$$\mathbf{B}_t^{(ii)} = \begin{cases} w_i^{\max} - \frac{w_i^{\max}}{\sigma_i^{\max}} \cdot \hat{\sigma}_{ti} & \text{for } 0 \leq \hat{\sigma}_{ti} < \sigma_i^{\max} \\ 0 & \text{for } \hat{\sigma}_{ti} \geq \sigma_i^{\max} \end{cases} \quad . \tag{7}$$

In general, the *Task Blending Matrix* is defined by the fitness function of the *task space selector* that is based on all criteria:

$$\mathbf{B}_t^{(ii)} = \text{fitness}(t, i) \quad . \tag{8}$$

If the fitness for a specific task space i at timestep t is low, the deviation of the robot's movement from the learned movement does not result in high costs, thus allowing other task spaces to influence the reproduced movement stronger. Additionally, if two or more task spaces are conflicting, which allows only one of them to be active for the specific timestep, the fitness values are used to decide which of them.

The following section explains the different criteria that are evaluated within this work. In the future, based on the concept of the *task space pool* and the *task space selector* with its two possibilities to influence the imitation learning process, the framework is easily extendable with other criteria.

V. CRITERIA FOR AUTOMATIC TASK SPACE SELECTION

A. Attention-based criterion

The first criterion presented is based on the interaction between human and robot. Investigations in the field of parent-infant research [17], [18], which are partly based on a model proposed by [19] showed that parents modify their actions when teaching their children tasks, such as stacking cups. Parents start the interaction by highlighting and shaking the important object that is involved in the task and begin their demonstration when the child focuses on the object. There is evidence that humans approach robots in a similar way [20] and therefore it makes sense to incorporate such mechanisms.

We account for this by implementing a reactive behavior for the robot that detects and then focuses on the most salient object in the scene. This has the advantage that the teacher knows when the robot is attending to the right object before he or she starts the demonstration. Additionally, this criterion allows for another task space description, namely the position information of all objects relative to the salient one (see eq. A.5). Saliency thereby is calculated already during the observation phase in order to actively move the robot's head. It is defined using the weighted variances of each object's position and orientation over a specific number of timesteps. The object that is moved and shaked most strongly is selected as the salient one. Hence, the teacher is able to directly influence the robot's gaze direction. In order to avoid too hectic fixation changes if the teacher is shaking two objects alternately, a simple hysteresis is incorporated.

B. Variance-based criterion

The second criterion is based on the inter-trial variance. The basic principle of this is not new and its idea is that those

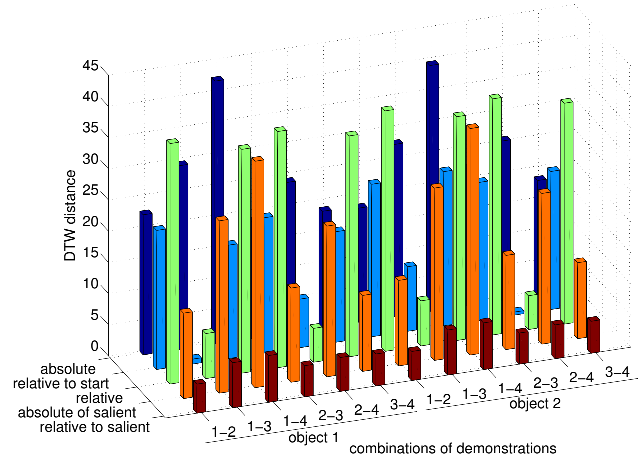

Fig. 3. Analysis of the positional task spaces for the *leapfrogging example*. It can be seen clearly that the demonstrations are most similar when using the relative position wrt. the salient object (dark red).

dimensions of the observation that are important for the task are similar over all demonstrations while the unimportant dimensions differ more strongly. This basic idea was already evaluated in our previous work [1] and other imitation learning approaches that use probabilistic representations [5], [7], [14].

In particular, the common process of imitation learning with probabilistic encodings can be seen as having a fixed set of task spaces for the representation and using the previously defined *similarity criterion* (eq. 6) with pure variance weighting (eq. 7) in the *Task Blending Matrix* to blend them during the reproduction phase. Additionally to this however, we define a method to select the task spaces before the encoding in order to learn only the necessary ones. This selection is based on the comparison of all demonstrations with each other within all possible conflicting task spaces.

Figure 2 shows 4 demonstrations of a *leapfrogging* toy example. The task to be learned is to move one object over another (top row). Note that the stereo camera head is actively moving and focussing the most salient object as it is defined in the *attention-based criterion*. The plots in the middle row show the absolute position of both objects during the 4 demonstrations of the task. It can be seen that the task is performed at different absolute positions and not always with the same object as the moving one. Further, although the demonstrations look similar, their temporal properties differ in a nonlinear way. To account for these nonlinear temporal distortions, the comparison of all demonstrations is done with Euclidean Dynamic Time Warping as a distance measure. The analysis of the positional task spaces of the *leapfrogging example* is depicted in Figure 3. For describing the movements of the objects, the *task space pool* contains the absolute object movements (eq. A.1), the movements relative to their initial positions (eq. A.3), their movements relative to each other (eq. A.4), the absolute movement of the salient object (eq. A.1) and the relative movement of the salient object wrt. the other object (eq. A.5). The figure

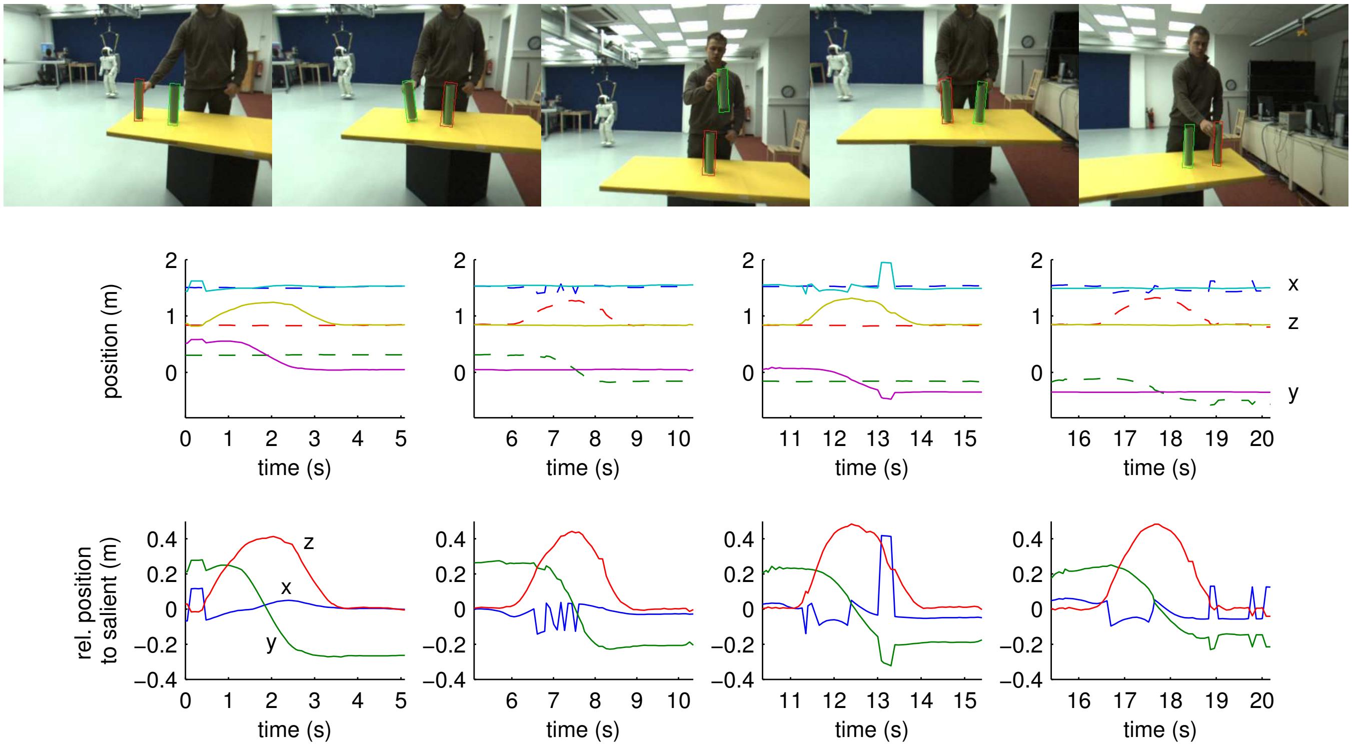

Fig. 2. The top row shows shots of the *leapfrogging example*. The middle and the bottom row show 4 demonstrations of the task and their representations within absolute world coordinates and in coordinates relative to the salient object, respectively. The x-axis of the right-handed world coordinate system points towards the demonstrator and the z-axis to the top.

shows clearly that the latter task space is best suited to represent the *leapfrogging example* because within this task space all demonstrations are most similar. This can also be seen in the bottom row of Figure 2. Based on a winner-takes-all selection the *task space selector* chooses this task space to be learned with the imitation learning system.

C. *Kinetic criterion*

Using the similarity over several demonstrations as a criterion for what to imitate is a reasonable approach. However, it cannot be applied to all aspects of imitation learning. Imagine for example, the robot shall learn to reproduce gestures performed by a human. It seems useful to track the positions of the teacher's hands, maybe even wrt. his shoulders, generate the task space pool and select the task space in which all gestures looked similar. But, there are limits to what similarity can explain. If for example the gesture involves only one moving hand and the other hand is held still during the performance, no information about the importance of the resting hand is available. It may be important to hold the hand still exactly at the observed position, but it is also possible the hand is completely uninvolved and is held still because it is comfortable for the demonstrator.

We think that in order to overcome these limitations, additional information from a model-based criterion can efficiently be incorporated into the task space selection. This is motivated by neuroscientific findings, such as the mirror system in humans [21] and by experiments as they were carried out in [22] where it was shown that humans tend to

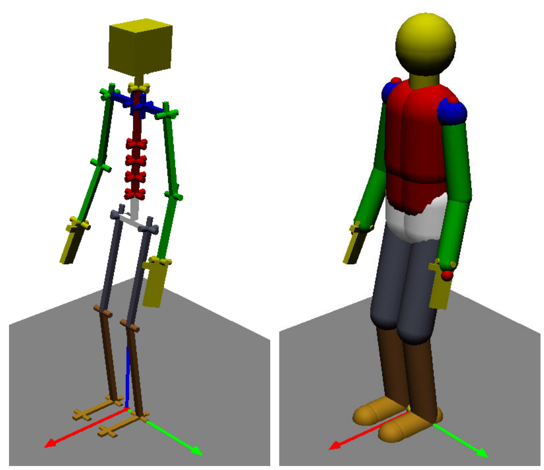

Fig. 4. 49 DOF skeleton and collision model of a human in its resting position.

include their own motor model for prediction while observing hand movements. Therefore, the criterion presented in this section maps the observation onto a human body model and then analyzes the postures that the human teacher went through during the demonstrations. The basic heuristic is that exhausting or uncomfortable postures are more likely to be task-relevant because they would have been avoided otherwise.

We use a simplified human model with 49 angular degrees of freedom (see Figure 4), which is structured similar to the Santos$^{\text{TM}}$ model [23]. It includes segment masses and limb lengths of an 1.8m tall male human with a weight of

81.4kg. The model's properties are suited for the experiments within this work. However, it should be noted that in order to apply the method to teachers with different proportions, some kind of automatic scaling of the model needs to be incorporated. The model itself is controlled using a whole body motion algorithm [12], which includes several criteria mapped into the null space, such as joint-limit avoidance or collision avoidance.

Our experiments focus on human arm movements that are recorded using a VICON motion capture system[1]. The observed movements are mapped onto the human model by using task space control that accounts for the relative positions of the hand markers wrt. the shoulder markers and the absolute head position. The marker positions are depicted in Figure 4 as small, red spheres on the collision model. Similar to [24] and [25], it is possible to define cost functions based on this model. But, instead of predicting human upper body postures, we use such cost functions to evaluate arm movements of a human teacher.

We define two cost functions for both arms, *effort* and *discomfort*. *Effort* is a cost that is based on the torque of the arm joints, caused by the masses of the arm segments. A high overall torque is associated with an exhausting arm posture. It is calculated using the center of gravity Jacobians $\mathbf{J}_{\mathrm{COG}i}$ that relate the velocities of the segment masses to the joint velocities of the human model. For all segment masses i that belong to one arm, the torque that they generate is defined through:

$$\mathbf{M} = \sum_{i \in \mathrm{arm}} \mathbf{J}^T_{\mathrm{COG}i} \mathbf{m}_i \tag{9}$$

with $\mathbf{m}_i$ being the gravity force due to the segment's mass. The effort costs are calculated as squared measures, multiplied with a diagonal selection matrix $\mathbf{S}$ to include joints of the specific arm only:

$$C_{\mathrm{effort}} = \mathbf{M}^T \mathbf{S} \mathbf{M} \tag{10}$$

$$\mathbf{S}^{(jj)} = \begin{cases} 1.0 & j \text{ is arm joint} \\ 0.0 & \text{else} \end{cases} . \tag{11}$$

Note that for simplification we only include the static torques in our equations. We ignore the dynamic torques because we use the cost function only to evaluate parts of movements, which the variance-based or the attention-based criterion cannot cope with, namely the static parts.

The *discomfort* cost function is defined by the deviation of each arm joint j from its resting state. Figure 4 shows the resting posture of the human model. The deviation is weighted with the overall range between default q_{0_j} and extreme angular positions q_{min_j} or q_{max_j}:

$$D_j = \begin{cases} \left(\frac{q_{0_j} - q_j}{q_{0_j} - q_{\mathrm{min}_j}}\right)^2 & \text{for } q_{\mathrm{min}_j} \leq q_j \leq q_{0_j} \\ \left(\frac{q_j - q_{0_j}}{q_{\mathrm{max}_j} - q_{0_j}}\right)^2 & \text{for } q_{0_j} < q_j \leq q_{\mathrm{max}_j} \end{cases} \tag{12}$$

$$C_{\mathrm{discomfort}} = \sum_{j \in \mathrm{arm}} D_j \quad . \tag{13}$$

[1]located at the CoR-Lab, Bielefeld University

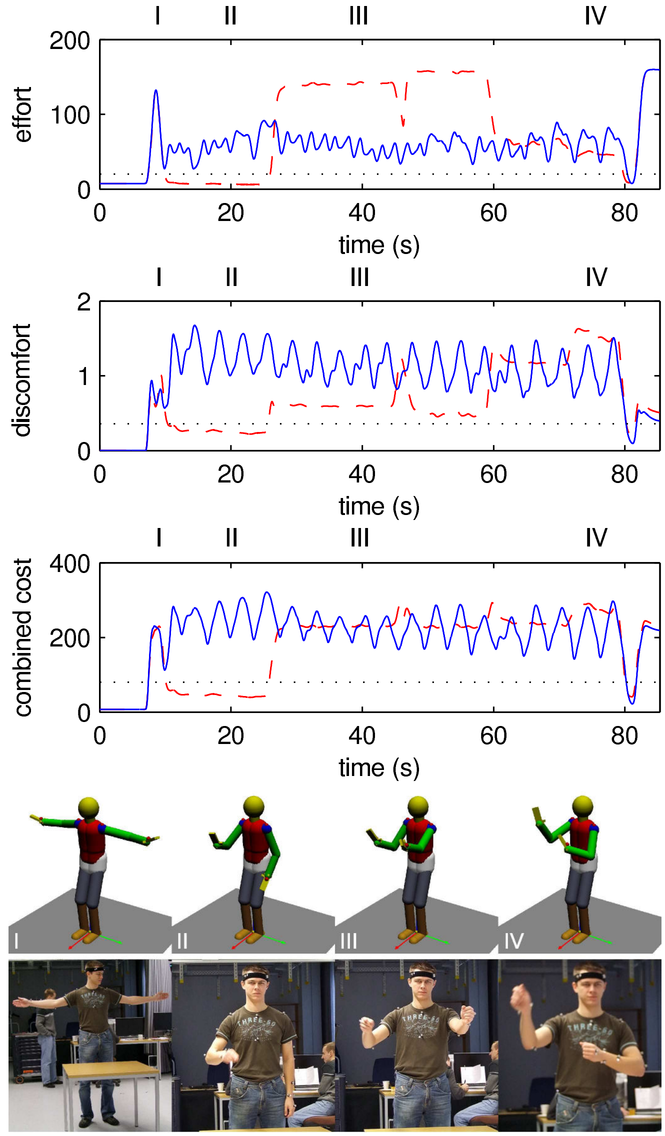

Fig. 5. The plots show the *effort*, the *discomfort* and their combination for the observed movement depicted on the bottom. The blue, solid lines and the red, dashed lines represent the right and left hand, respectively.

Figure 5 shows a movement that is evaluated with the kinematic model and the cost functions. The demonstrator begins the movement with a default posture, which can be seen in the first subfigure (I). Afterwards, the right hand continuously draws the symbol "8" into the air and the left hand is held still at different positions (subfigure II-IV). During this, only the left arm posture in subfigure II is comfortable for the demonstrator. The recorded movements are used to control the human model and *effort* and *discomfort* is calculated for each arm. The upper two plots show clearly distinguishable phases of high and low *effort* and *discomfort*. Further, both cost functions complement each other as illustrated in the third plot of Figure 5, which shows the weighted sum of both cost functions. Applying thresholds, such as indicated by the dashed lines, can account for the distinction between importance and unimportance for an arm that is held still.

As initially mentioned, this criterion obviously provides advantages in cases where the observation cannot be explained through variance-based measures. Based on the combined costs, the *task space selector* is able to choose if the movement of a specific arm should be learned or not. Note that although only human arm movements are investigated within this work, the same method can account for whole body movements.

VI. SUMMARY AND FUTURE WORK

This work investigated a method for the automatic selection of task spaces. These task spaces can be used to efficiently represent movements that a robot should learn through imitation. In order to determine an effective representation, a discriminative approach was presented that analyzes the observed movement within a pool of possibly even conflicting task spaces. Based on the score of several different criteria, the *task space selector* can choose a subset of this *task space pool* for representation and influence the movement reproduction with the robot by adapting the *Task Blending Matrix*.

The incorporated criteria do not solely rely on variance-based analysis, where a low inter-trial variance is associated with importance, but also on psychological and physiological measures. An attention mechanism is used to enable the robot to determine task-relevant objects and reactively orient its gaze direction towards it. Further, a step towards model-based task space analysis with the help of a kinematic simulation was made. The *effort* and *discomfort* cost functions based on this model can be used as reliable importance measures in cases where the other criteria fail.

Future work will further investigate the topic of task spaces and their use in imitation learning systems. More insights from the field of neuroscience shall be included in the generation of the *task space pool*. Further, we want to emphasize the task-dependence of task spaces and therefore incorporate more higher-level information about task goals. Quality measures for selecting suited task spaces shall include this additional information.

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