Modeling Peripersonal Action Space for Virtual Humans by Learning a Tactile Body Schema

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Abstract. We propose a computational model for building a tactile body schema for a virtual human. The learned body structure of the agent can enable it to acquire a perception of the space surrounding its body, namely its peripersonal space. The model uses tactile and proprioceptive informations and relies on an algorithm which was originally applied with visual and proprioceptive sensor data. As there is not only a technical motivation for devising such a model but also an application of peripersonal action space, an interaction example with a virtual agent is described and the idea of extending the reaching space to a lean-forward space is presented.

Keywords: virtual agents, virtual environment, body schema, peripersonal space

1 Introduction and Related Work

In order to carry out sophisticated interaction tasks in a spatial environment like a virtual world, one requisite is to perceive how far away objects in the peripersonal space are in relation to the protagonist's own body. The peripersonal action space is the space which immediately surrounds our body, in which we can reach, grasp and manipulate objects with our limbs without leaning forward. It is thus to be conceived of as a sensory space to be delimitated from social perception of space as in social proxemics. The ability of virtual humans to perceive and adapt to their peripersonal space enables them to manipulate and also to avoid objects while moving their limbs through this space. Additionally, it raises more interpersonal interaction possibilities with other agents or with human partners.

In humans the representation of peripersonal space is intimately connected to the representation of the body structure, namely the body schema [6]. The most comprehensive definition of the body schema, as a neural representation, which integrates sensor modalities, such as touch, vision and proprioception, was provided by Gallagher [3]. This integration or mapping across the different modalities is adaptive and explains phenomena like tool use as an integration of tools into the body schema [9]. Learning of body schema is very versatile. We can not only learn configurations of a body structure, but according to Holmes and Spence [6] it also supports learning of the space surrounding the body.

To our knowledge, work on reaching space for embodied agents has yet been done isolated from body schema acquisition. In work by Goerick et al. [4] the concept of peripersonal space is used in order to structure the visual field of a robot. Work of Zhao et al. [13] and Huang et al. [7] aim at enabling a virtual agent to carry out reaching movements in their virtual workspace. Both approaches neither regard reaching space as represented in body-centered coordinates nor do they consider a body schema as basis for reaching or peripersonal action space, respectively. Although the topic of body schema acqusition is mainly treated by roboticists (e.g. [2]) and has yet not been applied to virtual agents, we want to point out how learning a body schema can also further the design of virtual humans and characters.

In this paper we will show how to model a tactile body schema for a virtual agent and how this can be used to build a representation of its peripersonal action space. Preconditions for the tactile body schema are our work on building touch sensors and motor abilities for a virtual agent. For learning a body schema, we base our computational model on the algorithm proposed by [5]. Unlike their approach, we will not use vision but will feed touch and joint information into the algorithm, in order to learn a tactile body schema, which therefore gets along without any visual information. Combining it with motor abilities, the virtual human is able to perceive its peripersonal space. This can also be regarded as a proof of concept which shows that the spatial representation of the body and peripersonal space, respectively, are not bound to visual information, since congenitally blind people are also able to perceive their peripersonal space.

For a fuller description of these ideas see [11]. Beyond this, the present paper describes how a virtual human's peripersonal space is related to reaching space and how it extends, by bending the torso, to a "lean-forward space".

The remainder of this paper is organized as follows. In the next section, we describe how virtual sensors were realized and prepared in order to feed our model of tactile body schema, described in Section 3. In Section 4 we present a demonstration scenario in which the tactile body schema can make an impact on peripersonal space. Finally, in Section 5 we give a brief conclusion and an outlook on future work concerning the interaction abilities of our virtual human Max.

2 Touch Perception and Proprioception for a Virtual Human

In this section we will first describe how a virtual sense of touch was realized for the virtual human Max [12]. In order to feed our computational model which we present in Section 3, we had to prepare the sensory data from the touch modality and complement it with sensory data from the motor modality.

The touch receptors were developed and technically realized for Max's whole virtual body. These receptors allow for differentiating between different qualities of tactile stimulation. Findings from studies on the human tactile systems were incorporated to build an artificial sense of touch for Max. Max has a segmented body, i.e. his virtual graphical embodiment consists of several geometry parts. Around every geometry representing a limb of Max's body, 17 proximity geometries were added forming a "proximity aura". Below the proximity aura, the surface of Max's body is covered with a virtual "skin". The virtual skin consists of flat quadrangle geometries varying in size,

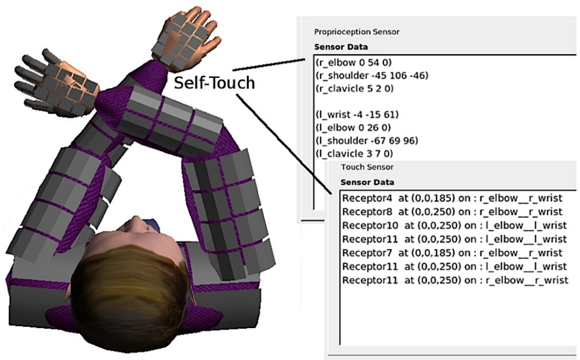

Fig. 1. Tactile body schema learning: For each random posture, sensory consequences are output by the sensory systems. The touch sensor provides an ID of the receptor the limb it is attached to, and the position in the frame of reference (FOR) of the corresponding limb. Angle data for the involved joints are output by the motor system, representing the proprioceptive information.

each representing a single skin receptor (see Figure 1). In humans, the somatosensory modality is represented in body-part-centered reference frames [6]. This aspect is also modeled by the virtual proximity auras. Each skin receptor is assigned to a unique body limb, that means, the receptors' locations and distances are not centrally encoded. Any geometry's collision with a skin receptor is regarded as tactile stimulus. This also includes skin receptors colliding with each other which is crucial for identifying self-touch. In the computational model described in Section 3, for each triggered skin receptor, the touch sensor provides the assignment to the unique body limb and its position in the frame of reference (FOR) of that corresponding limb.

In addition, we need proprioceptive information about Max's body, i.e. his sense of the orientations and positions of his limbs in space. We will refer to it as the angle configuration of the joints in Max's body skeleton. The virtual agent's body has an underlying anthropomorphic kinematic skeleton which consists of 57 joints with 103 Degrees of Freedom (DOF) altogether [8]. Everytime Max is executing a movement, the joint angle informations of the involved joints are output. Synchronously with the tactile informations, the proprioceptive informations can be observed. In Figure 1 we can see the data for a sample posture, where Max is touching his own arm. In the next section we will explain how these input data can be integrated to form a body schema.

3 A Computational Model of Peripersonal Space

For the purpose of perceiving and acting in peripersonal space, a tactile body schema is sufficient. We do not need a precise representation of the physical properties of the body, rather we need the kinematic structure and functions of the body for controlling and predicting the sensory consequences and movements with regard to tactile stimulations coming from objects located within the reaching space. In this section we present our model on how to learn a tactile body schema for our virtual human Max. The idea is

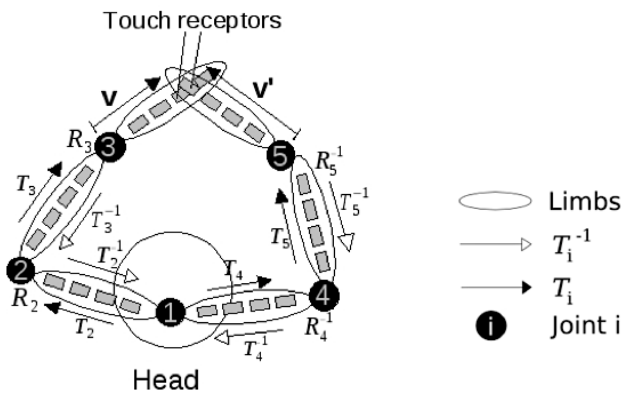

Fig. 2. Kinematic schema of Max touching himself. The following composition transforms the position **v** (given in the FOR centered on joint 3) of a touch receptor into the FOR centered on joint 5: $\mathbf{R}_5^{-1} \circ \mathbf{T}_5^{-1} \circ \mathbf{R}_4^{-1} \circ \mathbf{T}_4^{-1} \circ \mathbf{T}_2 \circ \mathbf{R}_2 \circ \mathbf{T}_3 \circ \mathbf{R}_3$. Note that retracing the same chain in the opposite direction transforms the position of the other touch receptor **v'** (given in the FOR centered on joint 5) into the FOR centered on joint 3.

to integrate tactile and proprioceptive information from his virtual body. In a first step, Max executes random motor actions resulting in random body postures. For each posture he perceives proprioceptive data from his joints and tactile stimuli when touching himself (see Fig. 1).

Following Hersch et al. [5] we consider the body schema as a tree of rigid transformations. The kinematic tree is prescribed by the skeleton of the virtual human Max with the hip joint as the root node. In this tree each node corresponds to a joint in Max's skeleton and each edge corresponds to a limb between two joints (for more details see [11]). In our model the touch receptors are attached to the limbs (see Section 2) and their position is represented in the limb's FOR. In the kinematic tree representation, the touch receptors can therefore be represented as located along the edges. Following any path linking one joint to another represents a kinematic chain which transforms the FOR centered on one joint to the FOR centered on the other joint. Max's skeleton prescribes the hierarchy of the FOR transformations. We can transform the position for one touch receptor, given in the FOR of the corresponding limb, into any other touch receptor position also given in the FOR of its corresponding limb. Following an edge in direction to the root node a FOR transformation $\mathbf{T}_i$ and a rotation $\mathbf{R}_i$ associated to the respective joint i (numbers are free chosen) have to be carried out, in the other direction we use the inverse FOR transformation $\mathbf{T}_i^{-1}$ and rotation $\mathbf{R}_i^{-1}$ (see Figure 2).

So far, we use the number of joints and the hierarchy of Max's skeleton as prior knowledge about his body structure. However, what is not yet known is the position and orientation of these joints which also determine the limb lengths. This is where the algorithm proposed by Hersch et al. (see Eq. (14) and (15) in [5]) comes in. We can use the algorithm straightforward, since it provides a new and general approach in online adapting joint orientations and positions in joint manipulator transformations.

Our challenge in using this algorithm is the adaptation to a case different from the one it was originally applied to. In our case we do not use visual and joint angle data but instead, replace all visual by tactile information in order to update all the rigid transformations along the generated kinematic chains. In order to use the algorithm, we have to start with an onset body schema which is an initial guess of Max's target body schema. It is described on the one hand by known parameters and on the other hand by initially guessed parameters. The parameters which are not known yet are the joint orientations and their positions ($\mathbf{a}_i$ and $\mathbf{l}_i$ for joint i), determining the body segment lengths. Thus we choose the orientations randomly and assign the segment lengths with small values. The randomly assigned parameters can then be adapted and updated by the algorithm.

Algorithm 1 Pseudo code: Tactile learning process

```
repeat
  for all torsojoints do
    choose random angle θ
    set torsojoint of current body schema to θ
  end for
  if two touch receptors trigger then
    pos_i ← position of touch receptor with ID i
    pos_j ← position of touch receptor with ID j
    joint_n ← joint of limb n where pos_i is attached to
    joint_m ← joint of limb m where pos_j is attached to
  end if
  Set Transformation T ← kinematic chain (startnode ← joint_m, endnode ← joint_n)
  pos_j = T ( pos_i )
  for k = startnode to endnode do
    update Δl_i
    update Δa_i
  end for
  if pos_j not transformed yet then
    Set T ← kinematic chain (startnode ← joint_n, endnode ← joint_m)
    pos_i = T ( pos_j )
    GOTO 14
  end if
until (pos_j - T(pos_i)) = 0
```

For modeling peripersonal space we start with learning the schema for Max's torso, which includes all nodes above the hip joint to the wrist joints. We then have to choose random joint angle configurations for the torso. For each randomly generated posture where skin receptors are touching each other the sensor data is processed. The algorithm takes as input a given position $\mathbf{v}_n$ in a FOR attached to one joint, its given transform $\mathbf{v'}_n$ in a FOR attached to another joint, and the corresponding rotation angles θ_i at joint i. In our case the input data are the positions of two touch receptors touching each other in the FOR of their corresponding limbs, both provided by the touch sensor (see

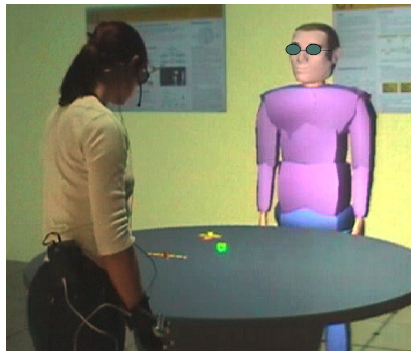

Fig. 3. Virtual agent Max with a human interaction partner standing around a table in a CAVE-like Virtual Reality environment. By means of his peripersonal space Max may perceive objects located on the table in front of him as near or far away from his body.

Figure 2). Interestingly, both positions can take over the role of the input vectors $\mathbf{v}_n$ and $\mathbf{v'}_n$. This is also illustrated in the pseudo code for the tactile learning process in Algorithm 1. Additionally, the angle values of the joints involved in the current posture are input to the algorithm. It then takes the sensor data for updating its guesses of the joint orientations ($\Delta\mathbf{a}_i$) and positions ($\Delta\mathbf{l}_i$) of the involved kinematic chain. In the adaptation process the idea is to use the update algorithm from Hersch et al. two times for each posture (see Algorithm 1, Line 18-22). In a first process the transformation of the position $\mathbf{v}_n$ of one touch receptor is transformed into the FOR of the other touch receptor (Line 13). This is used to update the current body schema (Line 14-16), in a second pass the angles of the postures stay the same, but the kinematic chain linking the two touch receptors is retraced to transform the position $\mathbf{v'}_n$ of the other touch receptor. Note that this "double-use" is only possible in the case of learning a tactile body schema. After completion the learned body schema expectedly contains the kinematic functions derived from the sensory input. This can be used to control Max's movements with regard to tactile stimuli.

4 Peripersonal Space in Interaction

Based on the work presented in Section 2, we devised the computational model in Section 3 for building a body-representation for the virtual humanoid Max. This model can enable him to acquire a perception of his peripersonal space. In an interaction scenario Max is to interact in a CAVE-like environment with a human partner as shown in Figure 3. In our test scenario both partners are standing at a table with several objects located on it. Let us assume that Max is (technically) "blindfolded". The interaction partner, aware of Max's inability to see, asks him to reach out for an object near to his body. Max then explores his peripersonal space with one hand. As soon as he touches it, the partner could ask him to carry out tasks, such as touching the object with the other hand or putting it as far away from him as possible. The first task is supported by the tactile body schema which contains the kinematic transformations relating two touch receptors. This can be used to compute a movement to the respective position.

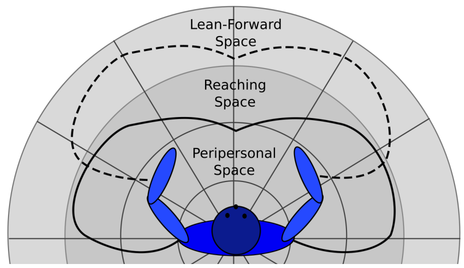

Fig. 4. Peripersonal space as subspace of Reaching space (spanned by body rotation) which extends to Lean-forward space (dashed line) by employing the hip joint.

The task of putting or reaching an object as far away as possible is an interesting aspect relating to peripersonal action space. McKenzie et al. [10] showed that at the age of 8 months, human infants perceive that leaning forward extends their effective reaching space in order to grasp objects, moreover at the age of 10 months they additionally perceive the effective limits of leaning and reaching. Applied to Max this means he has to learn the kinematic function of leaning forward in order to shift his peripersonal space. We can distinguish two cases similar to the work of Huang et al. [7]: Reaching objects within the peripersonal space, only using the arms and reaching objects outside of the reaching space, moving the whole torso. We refer to the latter case as "lean-forward space" shown in Figure 4. We can model the cases by relating the joint movements to human movement behavior; humans tend to adopt joint angle configurations which are comfortable [13]. The cases differ in the amount of joints included: In the first case shoulder, elbow and wrist joints are needed, whereas in the second case the hip joint supplements the movement. It is for example unlikely to lean forward when a target is near to the body and easy to reach, since we need more effort for bending the whole torso.

Our approach is to model this effort by using cost functions assigned to joints, similar to work of Cruse et al. [1]. Unlike them, we want to describe locations in peripersonal space depending on the distances in relation to certain body parts. The summed cost values depend on all involved joints of a whole posture. The more proximate an object is in relation to the body, the lower are the total costs. More distant locations can e.g. only be reached by including the hip joint, therefore the cost for moving it is high. Associating cost with peripersonal action space, hence, brings in a "feel" for the effort involved to reach an object.

5 Conclusion and Future Work

In this paper, we proposed a computational model for building a tactile body schema for the virtual humanoid Max, which can enable him to acquire a perception of his peripersonal space. The proposed computational model uses tactile and proprioceptive informations and relies on an algorithm, which was originally applied with visual and proprioceptive sensor data. In order to feed the model, we presented work on obtaining the nessessary sensory data from touch sensors and the motor system. Based on this, we described the learning process for a tactile body schema. The proposed approach of learning the body structure can not only be applied to other virtual agents but also to robots, provided that they have tactile sensors. The next step in our work will be to test the proposed model for its online learning features. This is especially very relevant for sophisticated computer games where players can design and predefine creatures even with more unusual kinematic structures, not comparable to humanoid ones. Therefore methods which take this pre-knowledge for learning body structures lend themselves for an immediate use in character animation. Based on the motivation to gain an understanding on how humans develop a sensation for the space surrounding their body, in future work we will investigate how spatial perspective models of two agents can be aligned. The aspect of computer games and the planned work on spatial perspective models are discussed in some more detail in [11].

Acknowledgment

This research is carried out in the context of the Collaborative Research Center 673 "Alignment in Communication" granted by the Deutsche Forschungsgemeinschaft. This paper is a preprint version of an article published by Springer-Verlag. The original publication is available at `http://link.springer.com/chapter/10.1007/978-3-642-04617-9_65`

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