Modeling Joint Synergies to Synthesize Realistic Movements

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The need for making virtual humans more realistic keeps growing in domains like virtual reality, computer animation or interactive ergonomics. However, while many domains aim to enhance user's experience, applications in ergonomics mainly focus on the synthesis of realistic movements [1]. The number of works dealing with inverse kinematics to synthesize realistic movements highlights its difficulty. Among them, two categories can be sorted out of those works. On one hand, the whole inverse problem is learned from motion capture data and then reproduced [4]. On the other hand, a common method is used to solve the inverse problem and constraints are used to enhance realism. These constraints come from movement studies [2] or are extracted from captured data [5].

To enhance the realism of the synthesized movements, we propose a new constraint model based on the representation of joint synergies. Our constraint model integrates into the sensorimotor model proposed by Gibet et al. [3]. This sensorimotor model, based on the Jacobian transpose method, includes a non-linear gain function ("sigmoid" shape) to produce more natural pointing movements. We propose to replace this gain function by a new gain model learned from captured motions. After a description of our model, we present the learning process and the preliminary results that we obtained.

We propose to model joint synergies as a vector of gains $\overrightarrow{w}$, each w_i being applied successively to the n degrees of freedom. This gain can be a function of time (t), current posture ($\overrightarrow{q}_t$), current angular speed ($\Delta\overrightarrow{q}_t$) and previous computed gain. It is computed at each step of the sensorimotor loop. The gain function may also use some constant parameters $\overrightarrow{p}$ to differentiate individuals. The size m of $\overrightarrow{p}$ is independant of the number n of degrees of freedom. These parameters may constitute the signature of an individual movements. We thus obtain the following model of joint synergies :

$$\overrightarrow{w}_t = f_{\overrightarrow{p}}(t, \overrightarrow{q}_t, \Delta\overrightarrow{q}_t, \overrightarrow{w}_{t-1})$$

The choice of the function f is discussed in the results but has no influence on the learning process of the parameters presented below.

The goal is to find a value of $\overrightarrow{p}$ that makes possible the motion controller to reproduce recorded motions. We use a meta heuristic to adjust the parameters

$p_0, \ldots, p_m$ of the gain function. To evaluate a set of parameters, the meta heuristic fitness tries to reproduce captured motions using values of those parameters. It then computes a distance between the synthesized motions and the captured motions. Thus, the lower the distance is, the better are the parameters. By applying mutations to parameters, repeating the evaluation process and selecting the best sets of parameters, the distance can be minimized. We now provide some preliminary results that we obtained with this method.

During our first experiments, we tried three models for the joints synergies. Each model was trained over the same unique motion using the simulated annealing meta heuristic. The fitness was computed by superposing the captured motion to the corresponding synthesized motion and taking the average cartesian distance between the joints of each posture over the time.

The first model was a vector of constants : $w_i = p_i$ with $n = m$. The lack of representation of acceleration over time explains the poor results that we obtained with this model. We then defined a second model, using a scaled sigmoid with a temporal phasing for each joint : $w_i = p_{(2 \cdot i)} \times sig(t - p_{(2 \cdot i+1)})$ with $m = 2 \cdot n$. Bad results were also obtained with this function, despite that the sigmoid is suitable to represent the hand acceleration [3]. Our fitness taking account of the shape of the motion, our model must represent more than just acceleration. Better results were finaly obtained using a feed forward neural network with p_i being the weights of links between neurons. With this more complex structure, we got synthesized movements that are closer to the original ones.

We thus showed a new model that has the ability to represent joint synergies. Moreover, when applied to an existing motion controller, it enhances the realism of the synthesized movements. Further perspectives will be the learning of parameters that characterize the joint synergies over several movements in order to generalize our approach.

References

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