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Enhancing Robustness to Extrapolate Synergies Learned from Motion Capture

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Abstract

Reproducing the characteristics of human movements, is a crucial issue in studying motion. In the context of this work, an explicit model of synergies which can be parametrized is used for reproducing the main features of reaching motions. This paper evaluates the possibility to extrapolate learned parameters from a captured motion to new targets and shows how learning process is a key issue to ensure the robustness of parameters.

Keywords: synergy, motion control, learning, motion capture

1 Introduction

Using virtual humanoids has become a common trade in many applications like video games, virtual ergonomics or virtual training. However realism and autonomy of their movements is still an open challenge.

In previous work [1], synergies are modeled in a sensory motor loop to ensure both realism and autonomy in reaching tasks. This model of synergies uses explicit parameters to reproduce specific motion planning. A methodology is then proposed to learn these parameters from captured motion.

While attempting to extrapolate learned

parameters to synthesize motion towards another target, some parameters displayed poor capacity to extend features of the sample motion. In this article, differences between robust and non robust set of parameters are discussed. The learning process is enhanced to ensure robustness of parameters.

2 State of the art

Over the years, different methods aiming at producing natural gestures reproducing characteristics of real movements have been proposed [2]. This approach stands in the field of data-driven methods. In these approaches, the main objective consists of synthesizing new sequences of movements from existing ones.

On the first side, some methods try to learn the whole inverse function from a motion database [3, 4]. Both approaches produce natural-looking and physically plausible motions. However, these learning models require large set of motions.

An alternative is to use statistical learning to extract style from captured motions to guide inverse kinematics during synthesis [5, 6, 7] or to fit a sample motion to a new task [8, 9, 10, 11]. Relying on both an IK algorithm and real motions lowers the num-

ber of required data. However, dealing with implicit models prevents these approaches to study motor strategy of an individual.

A reduced set of parameters representing the dynamical effect of the synergies involved in reaching motions has shown to greatly improve the naturalness of the produced movements [1]. This work extends the methodology proposed to learn parameters from sample motion by evaluating their extrapolation to new targets.

3 Synergies

In this section, we consider the control of a kinematic chain \mathcal{C} which rotations are represented by the state vector Θ . Contrary to traditional inverse kinematics methods, trajectory of the end effector is not defined before synthesis. The motion controller thus uses an optimization loop, converging towards target's position \mathcal{X}_d (cf. fig. 1).

At each iteration, $\Delta\Theta$ is obtained using the optimisation function \mathcal{O} , based on the transpose of the Jacobian J^T or its pseudo-inverse J^+ . While transposed Jacobian has a lower convergence rate, it is more stable than pseudo-inverse which is sensitive to singularities [12].

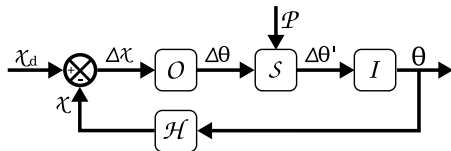


Figure 1: Motion control using synergies \mathcal{S} parametrized by \mathcal{P}

Synergies are defined as a function of time $\mathcal{S}(t)$ using both by a temporal function $\phi(t)$ (modeling the evolution with time of the motion), and a gain matrix M (representing how each DoF is involved in the motion). This function $\mathcal{S}(t)$ is then parametrized to represent physical characteristics of the subject performing a specific task.

To find the set of parameters representing a specific motor strategy, a global learning approach based on the comparison between synthesized and captured movement has been proposed. As motion synthesis is

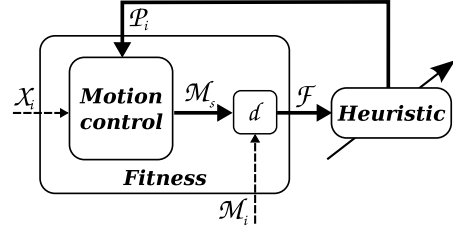


Figure 2: Iterative learning process used to evolve \mathcal{P}_i to fit motion \mathcal{M}_i towards \mathcal{X}_i .

non linear and iterative, finding the set of parameters \mathcal{P}_i corresponding to the reference motion \mathcal{M}_i cannot be done analytically, thus an heuristic [13] may be used to converge towards an optimal solution.

Optimality of \mathcal{P}_i is defined by a fitness function $\mathcal{F}(\mathcal{P}_i, \mathcal{M}_i)$. The given score represents the distance between synthesized motion using \mathcal{P}_i and original motion \mathcal{M}_i . A penalty is applied if target is not reached within a certain amount of time.

Using this fitness, it appears that parameters enhancing the realism of synthesized motions can be found without falling in local minima [1]. However, to our knowledge, no work has been done to evaluate whether learned parameters can be used when synthesizing motion toward new targets. Such a possibility would allow to extrapolate motor strategy of a sample motion towards new target-based motions.

4 Extrapolating synergies

A system is qualified as a "robust" one if it is capable of coping well with variations in its operating environment with minimal alteration or loss of functionality. Following this definition, a set of parameters \mathcal{P}_i is defined as robust if it can extrapolate the features of the motion \mathcal{M}_i – towards a target \mathcal{X}_i – to a target $\mathcal{X}_j \neq \mathcal{X}_i$.

While using the presented learning method, extrapolating parameters to a new target led to instabilities of the controller in some cases (cf. fig. 3). By studying the results of the learning process, it appeared that the heuristic, given the fitness

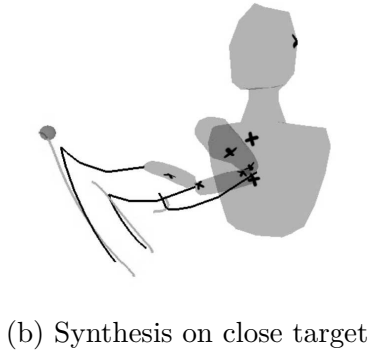
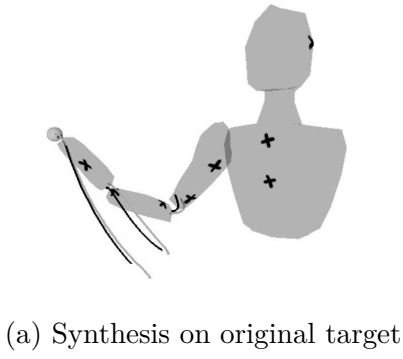


Figure 3: Joints trajectories from training motion (grey) and synthesized one (black) for the original target (a) or a new target (b).

presented below, may converge towards a solution where motion does not stop on the target but passes through it. In fact, stopping the motion on the first contact [1] did not account of whether the target was reached with non-zero velocity (cf. fig. 4).

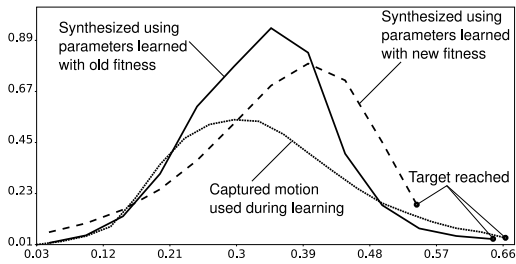


Figure 4: End effector's velocity for motions: captured (dotted), resulting from original (dashed), or enhanced (plain) fitness.

To overcome this problem, the fitness has been enhanced to ensure that the arm actually reaches the target. In order to ver-

ify whether the target is reached or passed through, motion synthesized after the first contact is analyzed. If the end effector remains within the target's sphere, we assume that target is reached. Otherwise a penalty is applied. Fitness can thus be expressed as: $\mathcal{F}(\mathcal{P}, \mathcal{M}) = \max(p_1, p_2) \cdot d(\mathcal{M}_s, \mathcal{M})$, with \mathcal{P} the set of parameters, \mathcal{M} the original motion, \mathcal{M}_s the synthesized motion, p_1 the penalty applied if target is not reached, and p_2 the one applied if the end effector passes through the target.

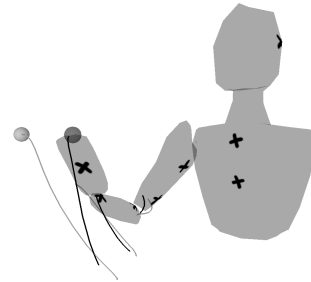
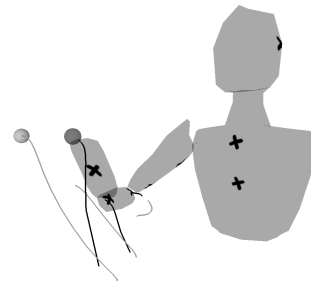


Figure 5: Motion with synergies extrapolated (b) is compared to a motion synthesized without synergies (a). Joints trajectories displays capacity of synergies to reproduce feature of the recorded motion (in grey).

Finally, robustness of synergies learned with new fitness is tested. Results demonstrate a good capacity to extrapolate features of a motion to a new target (see elbow's trajectory in figure 5). The velocity of synthesized motion displayed in figure 4, shows that target is reached with a close to

zero speed.

5 Discussion

Previous work [1] has proved to improve the realism of synthesized reaching movements using parametrized synergies. However, when trying to extrapolate the obtained synergies to reach new targets, learned synergies appeared to have poor results in terms of robustness.

The enhancement proposed in this paper for the fitness shows capabilities to improve the robustness of the learned synergy parameters. To go further, the fact that a synergy can be extrapolated to reproduce features of an original motion over a portion of space brings numerous perspectives.

Our first perspective is to study how far from the original target learned synergies can be used. Depending on results we may also be able to propose a statistical model allowing to represent a mapping between target's position and synergy parameters.

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