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Motion Characteristic Capturing: Example Guided Inverse Kinematics
동작 특성 추출: 동작 모방에 기초한 향상된 역 운동학

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Abstract

This paper extends and enhances the existing inverse kinematics technique using the concept of motion characteristic capturing. Motion characteristic capturing is not about measuring motion by tracking body points. Instead, it starts from pre-measured motion data, extracts the motion characteristics, and applies them in animating other bodies. The resulting motion resembles the originally measured one in spite of arbitrary dimensional differences between the bodies. Motion characteristic capturing is a new principle in kinematic motion generalization to process measurements and generate realistic animation of human being or other living creatures.

1 Introduction

Animating human motion has been a great challenge. The task may appear easy at the first look since we can completely command an articulated figure by supplying joint angles. However, the difficulty stems from the fact that there are too many things to control. Human body has 206 bones and hundreds of muscles. A reasonable model of it can easily have 40 degrees of freedom. *Computing* such number of joint angles so that the resulting motion resembles that of a real human is not a trivial task. Among diverse approaches to solve this problem, inverse kinematics and motion capturing are just two. The algorithm proposed in this paper is about the half way between these two approaches.

Inverse kinematics was originated from robotics field. It computes joint angles that position the end-effector at a desired location. When the end-effector needs to follow a certain trajectory, the whole body motion can be generated by calling inverse kinematics repeatedly at the sample points along the trajectory.

In robotics, major interest is on the six DOF robots. Since the end-effector has six DOFs in general (three for position, and the other three for orientation), inverse kinematics on a six DOF robot gives a unique or at most four different solutions. However, if a model has 40 DOFs, there exist an infinite number of solutions, and only one of them is selected for the frame.

Because the selection is purely up to the numerical process employed, even though the end-effector follows anticipated trajectory, joint angles can make abrupt changes. Therefore neighboring frames won't have *coherence*, and simple replay of those frames may result in a jerky animation. Usually the numerical process picks a configuration that is reasonably close to the previous configuration. Therefore, in interactive demonstration, many times the *lacking coherence* is overlooked. When the above result is recorded into a video disk and replayed at a normal speed, however, the reasonable closeness is not acceptable to human eyes, and the lacking coherence produces quite unpleasant artifacts.

Motion capturing is an effective technique to measure and copy the complex motion of articulated characters. However, this technique at its current state has two major drawbacks. First, the measurement errors are far from negligible, and without elaborate manual processing the resulting animation looks shaky and unrealistic. The other drawback, which is directly relevant to this paper, is that the data is for a specific subject in performing a specific motion. Obviously, the anthropometric scale between the measured subject and to-be-animated figure will be different. Also, the target motion to be animated might be slightly different from the measured motion. Several partial solutions to this generalization problem have been proposed[13][11]. However, the motion characteristic capturing effort does not explicitly appear in their equations yet.

Motion characteristic capturing, the algorithm we propose in this paper, extracts the characteristics implicitly residing in a motion and applies them to other bodies to obtain similar motions. Some people in biomechanics mention it as motion copying[7]. This technique is practiced frequently in sports. Many coaches and athletes try to *copy the champion.* For example, to teach how to serve in tennis, coaches frequently adopt a service from currently successful players, and make his trainee repeat the motion until the motion pattern resembles the original one.

Our motion characteristic capturing is realized by *example guided inverse kinematics*, which combines motion capturing with inverse kinematics. A set of motion capture data is used as an example to be imitated. Before starting the inverse kinematics, the objective function is augmented with several extra terms that will drive the inverse kinematics solution to imitate the example configuration at that moment. The minimization of the objective function will have to do two things at the same time: minimizing the gap between the goal and current end-effector position, and imitating the original motion.

Motion characteristic capturing improves both inverse kinematics and motion capturing. As pointed earlier, the redundancy in the model causes the lacking coherence problem in inverse kinematics. In motion characteristic capturing, however, the surplus DOFs are involved in imitating the example motion. Therefore the selection among the multiple choices is not arbitrary. Instead the new inverse kinematics provides a single choice which is smooth as long as the original motion was smooth. Experiments(Section 2.3) prove that the resulting motion is coherent. Compared with motion capturing, the motion characteristic capturing uses measurements in a much flexible way. From a set of measurement virtually any number of variation is possible. Still the resulting variations all resemble the original motion in an optimal sense.

The concept of motion characteristic capturing is general, and applicable to any articulated structures. It is an effective technique to animate high DOF articulated models from a limited set of motion capture data.

2 Example Guided Inverse Kinematics (EGIK)

Even though people are quite good at noticing the similarity between two motions, it is challenging to describe such a subjective criteria using quantitative terms. In this section we will look at different foci of imitation, define a measure of motion similarity, formulate the objective function for the example guided inverse kinematics, and show how weights can be introduced in combining the end-effector goal and the motion characteristic capturing goal to obtain the desired motion.

2.1 The Focus of Imitation

As a caricature is not a photo picture, our motion characteristic capturing is not motion copying. A caricature tries to emphasize unique characteristics of the character. Likewise, imitating a motion needs to have a focus. In general, people perceive that two motions look similar if the angles are kept the same at the corresponding joints. Such criteria can be easily satisfied when the ratio between the corresponding links is uniform.

When the anthropometric scale of the two articulated figures is not uniform, however, the above criteria do not have much sense due to the following two reasons.

- When there exists a closed loop, using the identical joint angles may violate important constraints.
- When the end-effector trajectory is the focus of imitation (e.g., when a person write the letter 'A' in the space with his finger tip, and another person is imitating it), simple joint angle copying may not imitate the end-effector motion pattern.

Because it is highly probable that the anthropometry of the measured subject is not proportional to that of to-be-animated figure, in most cases the joint angle following should be compromised with the end-effector following. The compromise should be based on what is the current focus of imitation. In this paper we consider two imitation foci:

- **The joint angle pattern (A-pattern)**
- **The end-effector motion pattern (E-pattern)**

These two types of imitation foci are not exhaustive, but are frequently used as the goal of imitation. And the other types of motion characteristic capturing can be augmented using a similar method if needed.

In the following subsection we will define the new objective function in which the above two types of imitation effort can be amalgamated.

2.2 The New Objective Function

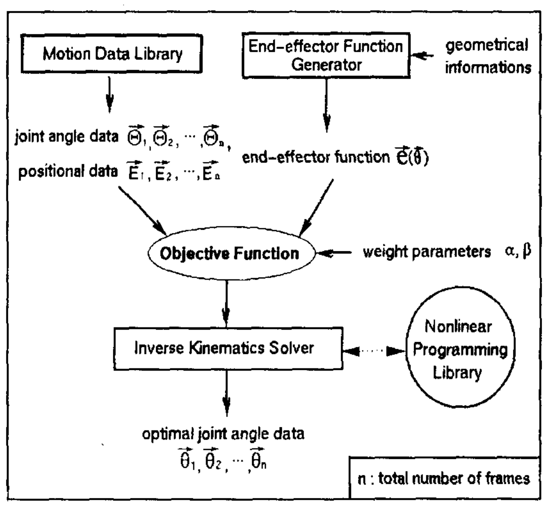


Figure 1: Overview of motion characteristic capturing.

Figure 1 is a diagram showing how motion characteristic capturing is carried out. The motion data library contains a number of exemplary data sets. A data set consists of the joint angle data $\theta_1, \theta_2, \ldots, \theta_n$ and the end-effector position data $E_1, E_2, \ldots, E_n$ at each frame of the motion. Here n is the total number of frames. The joint angle data θ_i is the J-tuple vector $(\theta^1_i, \ldots, \theta^J_i)$ where J is the number of joints, and the end-effector position data E_i is the three dimensional vector (E^x, E^y, E^z).

On the other hand, from the geometrical information of the to-be-animated figure, the end-effector function $e(\theta)$ is calculated using forward kinematics. The end-effector function $e(\theta)$, which is dependent on the joint variable, gives the global position of end-effector. In addition to the above, the weight parameters α and β (discussed later) participate in forming the objective function. Now the inverse kinematics problem can be solved to obtain the optimal joint angle data $\theta_1, \theta_2, \ldots, \theta_n$ for the new characteristic preserving motion.

The basic idea of example guided inverse kinematics is to allow a small fraction of error in end-effector position in order to imitate the joint angle pattern. We can think of two error terms, *E-error* and *A-error*. E-error is the end-effector's positional error $\|e(\theta) - E\|$, thus the small E-error means the E-pattern characteristics are accurately transferred. A-error is the joint angle error $\|\theta - \Theta\|$, thus the small A-error means the A-pattern characteristics are accurately transferred. The objective function of conventional inverse kinematics consists of a single term, i.e., $\|e(\theta) - E\|$. For our example guided inverse kinematics, A-errors are added as extra terms. Therefore our objective function is a weighted sum of E-error and A-errors at all frames during the motion, and looks like the following,

$$G(\theta) = \alpha \sum_n \|e(\theta_n) - E_n\|^2 + \beta\left(\sum_n \|\theta_n - \Theta_n\|^2 + \sum_n \|\dot{\theta}_n - \dot{\Theta}_n\|^2 + \sum_n \|\ddot{\theta}_n - \ddot{\Theta}_n\|^2\right)$$

where n is the total number of frames. We should minimize the function $G(\theta)$ to get the optimal motion.

Note that the above function contains the error sums of velocity and acceleration in joint space. In animation, the velocity and acceleration characteristics have significant impacts as well as the static positional characteristics. Especially, velocity is susceptible to human eyes. Therefore it must be considered for realistic animation.

Here, α and β are weights specified by the animator interactively. For example, α=1,β=0 is the case of pure inverse kinematics, α=0,β=1 is the case of pure joint angle copying, and α=0.5,β=0.5 is the case in which E-pattern and A-pattern are considered with equal weights. This means that by having different values of α and β, we can control the extents of the E-pattern and A-pattern characteristic transfers, and generate an infinite variety of motions.

In the inverse kinematics, achieving the end-effector goal is the primary target. The reader might worry a nonzero value of β causes failure in achieving the end-effector goal. However, it was one of our most surprising results that a small value of β (e.g., α=0.99,β=0.01) could transfer the motion characteristics quite well, while the error in end-effector positioning was negligible (less than 0.1\% of the total link length in the worst case). Section 2.3 describes more details on this.

We admit our EGIK is very similar to the Gleicher's work in that he addressed the problem of adapting an animated motion from one character to another preserving original qualitiey. In his optimization method he imposed end-effector

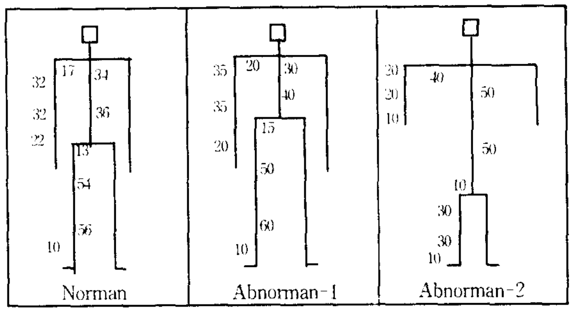


Figure 2: Human models.

constraints stringently, so he could fulfilled the end-effector

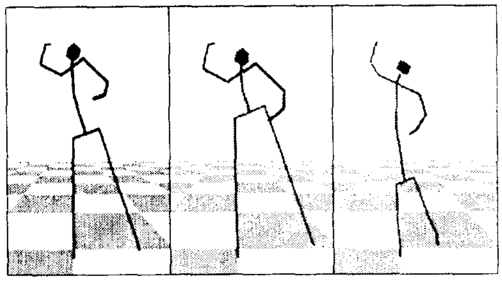


Figure 3: Snapshots of throwing motions of *Norman and Abnromans.*

goals exactly. But due to this stringency, the resulting motion may include undesirable data in a singular point. One remedy to this is to allow some flexibility to the end-effector. Because in EGIK the E-error and A-error are dealt with in one objective function as a primary task, we can imply this flexibility of the end-effector. As a result, tolerating some small end-effector errors, it is possible to obtain a rather robust motion data even in the singular moments.

2.3 Experiments

Our motion characteristic capturing algorithm was implemented on Silicon Graphics Octane MXI workstation.

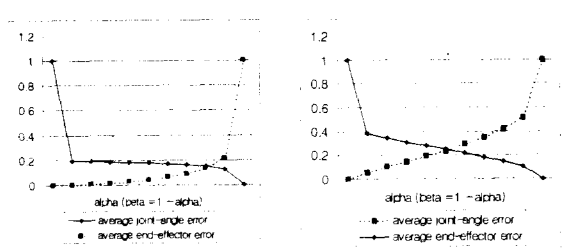
We modeled three articulated human figures. The first one, called **Norman**, is the subject whose motion was measured. The second and third ones are called **Abnorman-1** and **Abnorman-2**, respectively. As shown in Figure 2, Abnorman-1 has longer limbs and shorter torso than Norman, while Abnorman-2 has excessively shorter limbs and longer torso. These two figures are out of proportion on purpose, in order to demonstrate that in spite of the anthropometric differences our algorithm is capable of producing the similar motion.

At different values of α and β, the characteristics in the throwing motion of Norman(Figure 3) was transferred to Abnormans. Figure 3 shows snapshots during the characteristic transfers. When A-pattern is given more emphasis than E-pattern (small α, large β), Abnormans will imitate the global pattern of Norman's motion, and when E-pattern is given more emphasis than A-pattern (large α, small β), Abnormans will put relatively more effort on following the end-effector trajectory of Norman. In animating Abnormans, it would be reasonable to scale the end-effector trajectories proportional to the *size* of to-be-animated figures. However, we did not scale the end-effector trajectories in the experiment to demonstrate the adaptability of our algorithm.

Figure 4 shows A-error and E-error of Abnormans at different values of α and β. As expected, a larger α value ($\beta = 1-\alpha$) reduces the end-effector errors but increases the joint-angle errors. In the first of Figure 4, the errors of Abnorman-1 are reduced rapidly even with a small value of α or β. In the second of Figure 4, the errors of Abnorman-2 drop slower than those of Abnorman-1. It is predictable; the anthropometric discrepancy of Abnorman-2 is a lot more excessive than that of Abnorman-1.

The graphs in Figure 5 show the shoulder angle variations of Abnormans during the throwing motion. The fluctuating solid line is the pure E-pattern case($\alpha=1, \beta=0$), the fine dotted line is pure A-pattern case($\alpha=0, \beta=1$), and the other two lines are the cases of $\alpha=0.9, \beta=0.1$ and $\alpha=0.99, \beta=0.01$. Here what attracts our attention is the cases of $\alpha=0.9, \beta=0.1$ and $\alpha=0.99, \beta=0.01$, in which joint motions follow the original joint angle pattern quite accurately if the anthropometric difference is not

Figure 4: Normalized average errors of Abnormans.



excessive. At the same time the end-effector errors are considerably small. (In Figure 5(b), due to the excessive anthropometric difference, a small value of β could not imitate Norman's joint angle pattern.)

In most cases, a value between 0.9 and 1 was a reasonable choice for α. This result can be explained by Figures 4 and 5. In Figure 5(a), if $0.9 < \alpha < 1.0$, E-error is almost negligible. Even though A-error goes high at this value of α, the joint angle curve doesn't have sharp edges (Figure 5). Moreover, the global pattern of the joint curve is similar to the original pattern (the case when $\alpha:\beta = 0:10$) as shown in Figure 5(a). When the anthropometrical gap is huge, even though the pattern of joint angle deviates quantitatively from the original one (Figure 5(b)), the animated result still seems to preserve the original motion characteristics. Refer to the animation put on the web introduced below.

Table 1 summarizes the end-effector errors at a few (α, β) choices. With $\alpha=0.9, \beta=0.1$, Abnorman-1 and Abnorman-2 could follow the end-effector trajectory within 0.02% and 1% errors, respectively. When we use $\alpha=0.99, \beta=0.01$, the errors are reduced almost to zero, while the joint angle pattern is

(a) Abnorman-1.

preserved quite well. If the anthropometric difference is not excessive, for example in Figure 5(a), joint angle error of the two cases(9:1, 99:1) was not distinguishable, but the end-effector error could be reduced significantly. We present these animation results as movie file in "http://graphics.snu.ac.kr/document/paper/journal/invkin/".

α	β	Abnorman-1	Abnorman-2
0.0	1.0	0.048	0.17
0.5	0.5	0.0017	0.047
0.9	0.1	0.0002	0.011
0.99	0.01	0.000034	0.00053
1.0	0.0	0.0	0.0

(b) Abnorman-2.

Figure 5: Shoulder angle variations of *Abnormans*.

Table 1: Average errors of end-effector. (Normalized with respect to the *total-link-length* of each figure.)

3 Conclusion and Future Work

The motion characteristic capturing is a kinematic generalization, a new attempt to imitate a motion in a characteristic-preserving way. It improved the existing inverse kinematics technique remarkably. By sacrificing just a small fraction (0.1% of total link length) of end-effector goal achievement, we could produce natural motion preserving the original joint angle motion pattern. In most animations, 0.1% error is almost negligible even in tasks such as grasping in which the end-effector goal is a critical element. Also, we extended the algorithm to the exampleless inverse kinematics. Our algorithm can contribute to the applications that need elaborate control of inverse kinematics.

Here are some items left for future work.

- A-pattern and E-pattern were easily converted to quantitative terms. But there are many other qualitative aspects such as slow/quick, gentle/wild. All these should be added to the objective function in the future.
- Dynamic soundness [8] should be considered. Copying the

motion kinematically is not feasible sometimes, because of the difference in the strength of the two bodies, or some other factors. Dynamic aspects are not negligible in realizing the motion of non-zero mass entities in the physical world. Therefore our kinematic imitation should be further refined by dynamic adjustment.

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