Fast Response and Quick Progressive Transitions using Body Part Motion Graphs

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Abstract

*Interactive applications where 3D character animation plays an important role need avatars ready to perform different activities. This objective has been accomplished in different works [LCR*02] [ZS09] that look for transition points in motion capture clips to allow transitions between them. These works ensure realism and smoothness but their responses and transition durations depend on transition points. Working with partial motions, such as body part motions, allows finding specific transition points for each part in order to optimize whole body transitions in a progressive way. This can be achieved with body part motion graphs (BPMG's) [FBM11]. In this work we want to show that progressive transitions generated by BPMG's have fast response and quick execution. In order to demonstrate this we have compared BPMG's transitions against standard motion graphs (SMG) transitions. The results we have obtained show that our method allows more reaction velocity and execution. Moreover BPMG's transitions are smoother than SMG transitions.*

Categories and Subject Descriptors (according to ACM CCS): I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—Animation

1. Introduction

Character animation in videogames and interactive applications is becoming more important and a mark of quality. Achieving real and plausible motions to drive characters is mainly done in two different ways: animating avatars by hand or concatening motion capture clips. The second option has motivated the development of several motion concatenation systems in the research community. One of the most important is motion graph. Motion graph appears in 2002 in various works such as [KGP02] [LCR*02] [AF02] and consists in embedding motion capture data in a graph structure associating frames under some constraints. Then, frames are connected satisfying user input using search algorithms of graph theory. In this manner, transitions between different behaviors are achieved.

A variety of graph-based motion synthesis systems have been developed after motion graphs appeared such as [KG04] [HG07] [BCvdPP08] [ZS09]. These systems have different peculiarities that hinder comparison between them. In [RP07] some methods are proposed for comparing perfomances of graph-based methods. This comparison is conduct based on a set of tasks and environment capabilities. In interactive applications, what is important is the response of characters and how quickly they change their behavior satisfying user commands. Wang and Bodenheimer [WB08] made an exhaustive study of transition length in linear transitions which is related with transition response. They focused on determining which frame length to use in order to achieve pleasant animations.

More recent works such [MP07] [LWB*10] are more focused on generating animations that respond quickly to application requests. Both works use continuous control of motion generation, unlike graph-based methods. Graph-based methods are discrete and they are focused on how to transition from one clip to another. [LWB*10] argued that discrete methods such as motion graph are slower in response (by a factor of two) than continuous one. We will show that body part motion graphs are up to three times faster than standard motion graphs in terms of response time.

2. Body Part Motion Graphs

Body part motion graphs (BPMG's) [FBM11] is a motion synthesis method based on standard motion graph (SMG)

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fundamentals. The main difference between BPMG's and SMG is how to deal with motions. In case of BPMG's, motions are treated as body part motions instead of whole body motions and this improves some problems of SMG. SMG generates whole body transitions at same time, so these are not optimal for all joints. Another issue is that motion graph assembling is based on posture distance between frames. Compute distance between frames using whole body causes that difference value overcomes threshold when only one or few joints are in different setup.

For better undertanding we review the BPMG's method in a brief summary. The method has two phases: Body part motion graphs construction and transition generation. The former consists on split whole body locomotions into body part (BP) motions according to the body segmentation shown in Fig. 1. Then, distance metrics between body part frames are computed and later, body part motion graphs are assembled. The transition generation consists in a conditioned search on BPMG's. The fact of having locomotions distributed in different graphs forces us to find BP transitions with close beginnings and ends for all BPMG's. These variations are included within a time window. Apart from these temporal constraints, motion synthesis criteria is based on finding the shortest paths for each BPMG. Later, transition paths are time scaled in order to synchronize all BP transition paths and then, the target motion clip is launched. This allows progressive transitions between locomotions. In this work we have been used the same parameters as in [FBM11].

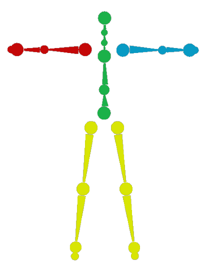

Figure 1: *Body parts. Joints in yellow color belong to lower-body; green joints belong to the trunk of the body; red and blue joints belong to right upper-body and left upper-body respectively.*

3. Transition Performance

In order to evaluate the performance of progressive transitions using BPMG's we have used a dataset C with different behaviors from CMU Motion Capture Database [Car04]. Dataset contains four different motions: Normal walking C_1, running C_2, long step walking C_3 and slow walking C_4. All motions in the dataset are locomotions and we want to study their transitions. We use these locomotions because they have different speeds and body postures and these difficults transitions between them. Motions have a framerate of 60 frames per second.

We have created standard motion graphs and body part motion graphs with different threshold values using this dataset. Transitions from both methods have been globally analyzed (Dataset Transitions) and particularizing the performance between behaviors (Behavior to Behavior Transitions). We have compared transition duration and transition response from both points of view.

3.1. Transition scheme

Before showing interactivity results it is important to know how exactly transitions work in BPMG's. After searching process and transition path scaling are done we get a transition scheme like in Fig. 2. For each body part motion graph p, we have an origin frame i_p, a transition path p_p, an end frame j_p. Transition path length is defined by l_p. So, each transition is composed by origin frames vector $\bar{I}$, transition paths duration vector $\bar{L}$ and end frames vector $\bar{J}$. We will use this nomenclature for the following formulas.

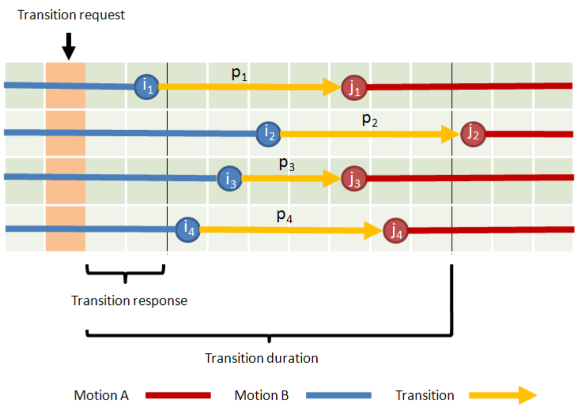

Figure 2: *Transition scheme.*

3.2. Dataset Transitions

As a first measure of the interactivity of BPMG's we have computed time between frames [ZS09]. Time between frames (TBF) consist in compute the average transition time between all pairs in the dataset. In SMG, transition time is computed straightforward by counting how many frames elapsed from transition request until the target motion is running. In case of BPMG's, transition time is computed doing

$$T(f_{req}, C_t) = (i_p - f_{req}) + l_p + (max(\bar{J}) - j_p) \qquad (1)$$

where f_{req} is the frame which user has requested the transition, C_t is the target motion clip, p indicates any body part index and $max(\bar{J})$ is the later end frame of body part transition paths. Note that this formula can be operated using any possible value of p.

Time between frames shows how quickly we can achieve the target motion. On the other hand, we want to evaluate when transition is started after user has requested one. Transition response (see Fig. 2) is the amount of frames between the requested transition frame and the beginning of this transition. To compute this value in SMG we have to substract the starting transition frame from the requested transition frame. As we have mentioned, in BPMG's not all joints transition at same time but they do progressively. So, if one body part starts to transition means that the avatar starts to react. Then, BPMG's transition response is computed by $min(\bar{J}) - f_{req}$, where $min(\bar{J})$ is the first starting frame of body part transition paths and f_{req} is the requested frame.

We have calculated TBF and response varying the treshold from 0.06 to 0.165. The results of these tests are shown in Table 1. Comparing both methods, we notice that BPMG's transition duration is lower than SMG transition duration when both have the same threshold and even when the treshold is larger for BPMG's. This means that BPMG's transitions are quicker than SMG and also smoother. Besides this, it should be highlighted that BPMG's achieve connection to all clips in the dataset with a lower threshold than SMG. In Table 1, cells have different background color depending on how many behaviors we can transition with the corresponding threshold. Cells in color yellow means connectivity with two behaviors; color green for three behaviors and color magent for four behaviors. As seen, SMG achieves connectivity with all behaviors at 0.165 and BPMG's at 0.105.

	SMG		BPMG's	
Threshold	TBF	Response	TBF	Response
0.06	19.99	14.24	17.24	4.34
0.075	19.65	13.61	17.28	4.42
0.09	18.95	13.30	17.27	4.41
0.105	18.43	12.92	17.30	4.40
0.12	18.18	12.74	17.30	4.37
0.165	18.20	12.53	17.30	4.37

Table 1: *Transition duration and response in BPMG's and SMG. All results are in frames (60 fps). Color yellow denotes that transitions can be achieved between two behaviors; color green for three behaviors and color magent for four behaviors.*

In the case of transition response, the difference between BPMG's and SMG is more evident. The set of response values belonging to SMG is between 12.53 frames and 14.24 frames. However, BPMG's provides results between 4.34 and 4.40 frames. So, we have an improvement of more than 3 times in terms of response time.

3.3. Behavior to Behavior Transitions

Measuring the average transition time and transition response of whole dataset gives an idea of how both methods works. Although, we do not have any information about behaviors specifically. Reitsma and Pollard [RP07] proposed local maneuverability (LM) measurement to evaluate how long it takes the character to perform any other action of the dataset. This measure was created for working with action motions since it takes into account the beginning and the end of dataset behaviors. In our case, we are evaluating local maneuverability of locomotions so we have used an adaptation of the known formula for computing this measure. In human locomotions it does not matter when the motion is started or ended because all time is performing the locomotion. So, we look for how fast we can transition from a locomotion to any instance of another locomotion. A behavior to behavior LM is computed as

$$LM(C_K, C_L) = \frac{1}{\|K\|} \sum min(T(k, L)) \tag{2}$$

where C_K is the origin behavior, C_L is the target behavior, $\|K\|$ is the amount of frames of clip C_K, and $min(T(k,L))$ is the duration of the minimum transition from instance k of behavior C_K to any instance L of behavior C_L. We have also computed transition response between behaviors. In order to do it we have used (2) but swapping transition duration term for transition response. In this manner, we can evaluate response and transition duration between behaviors.

In Table 2 there are results for LM and response times between behaviors. We have used different thresholds for both methods. The thresholds chosen are the minimum values that allow transitions between all clips of the dataset. Threshold values are 0.165 and 0.105 for SMG and BPMG's respectively. BPMG's transition times and response are better than SMG results in all cases.

If we look at the highest values of SMG results, we notice that C_2 as target motion is the one further away. Specifically, if we want to transition from C_4 to C_2 using SMG, it took 25.00 frames of duration. However, if we use BPMG's the values are 9.40. So, BPMG's is more than two times better in transition duration in the slowest transition between behaviors. And if we pay attention to the response time in the same case, BPMG's response time is close to zero while SMG is 18.23 frames. In fact, there are many zero values in response between behaviors. Specifically there are 7 zero values of 12 possible transitions between behaviors. So, in these cases when a transition is requested the avatar starts to transition to the target motion inmediatly without delay.

4. Discussion

We have used a set of measurements to evaluate progressive transitions using BPMG's. We have focused on how quickly

	C_1	C_2	C_3	C_4
C_1	0	10.71 / 6.35	3.68 / 0.43	3.40 / 0.63
C_2	4.26 / 0.84	0	5.26 / 0.84	7.26 / 0.84
C_3	5.71 / 2.52	15.86 / 11.50	0	5.23 / 2.91
C_4	3.73 / 0.01	25.00 / 18.23	2.86 / 0.00	0

	C_1	C_2	C_3	C_4
C_1	0	5.91 / 0.00	3.90 / 0.00	2.61 / 0.02
C_2	2.41 / 0.00	0	4.97 / 0.00	3.29 / 0.00
C_3	5.11 / 0.06	9.54 / 1.53	0	3.95 / 0.15
C_4	3.40 / 0.00	9.40 / 0.01	3.10 / 0.00	0

Table 2: *Behavior to behavior transition duration (frames) and response (frames). Above, SMG results; Down, BPMG's results. Motion clips are normal walking C_1, running C_2, long step walking C_3 and slow walking C_4.*

we can execute transitions and how long it takes the system to begin such transitions. We have evaluated whole dataset and behavior to behavior transitions in order to have a global perspective and a specific one focused on behaviors. These measurements have been done for BPMG's and SMG in order to compare both methods.

Results show that progressive transitions using BPMG's have better response and better execution than standard motion graphs. It should be noted that these results are achieved using threshold values for BPMG's lower than SMG. So, BPMG's transitions are smoother than SMG. Apart from this, the fact that BPMG's work with body part motions allows better connectivity between behaviors, although thresholds are lower. Because of this, we believe that BPMG's improve some of the deficiencies of discrete methods such as SMG and offer a new way to generate transitions between locomotions. In the future, we plan to examine the plausibility and realism of BPMG's transitions with a user study.

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