

Video based Animation Synthesis with the Essential Graph

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Goal

Given a set of 4D models, how to generate realistic motion from user specified constraints ?

Input:

Output:

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- Video based 4D models of elementary movements
- Novel, user guided shape and appearance animation

Human animation generation:

Where:

- Digital media production :
 - Video Game industry
 - Motion Picture industry
 - Virtual Reality applications





Rise of the Tomb Raider, Cristal Dynamics

Game Of Thrones, HBO

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How:

- Physical modeling:
 - Computationally expensive
 - Model limitations





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- Example data Reuse:
 - Key-framing data:
 - Cost-wise expensive: 100-250\$ / character second
 - Time-wise expensive: 2-3 seconds of finished character animation per day



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Synthetic Motion

Rise of the Tomb Raider, Cristal Dynamics

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 - Motion capture data:
 - ✓ Real Motion



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CMU mocap dataset

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Rise of the Tomb Raider, Cristal Dynamics



Game Of Thrones, HBO

Synthetic Motion

Synthetic Shape



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3D character animated with mocap

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 - Surface capture data:
 - ✓ Real Motion
 - ✓ Real Shape
 - ✓ Real Appearance



Rise of the Tomb Raider, Cristal Dynamics



Game Of Thrones, HBO

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CMU mocap dataset





4D model, Thomas dataset

Surface Capture Reuse



Surface Capture Reuse



Data:

- Cyclic human movements: walk, run, jump, etc.
- Acyclic human movements: dance.



Thomas, Cathy

Surface Capture Reuse



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Data Reuse:

Thomas, Cathy

Generate continuous motion stream using basic operations on motion segments:

- Rigid transformations
- Concatenation
- Smooth transition generation



Issues and challenges

User control:

• Intuitive formulation of user defined constraints

Data organization:

• A data structure organizing the input sequences and encoding selected transitions between them

Motion synthesis:

- Generating synthetic motion transitions.
- Concatenating real and synthetic motion segments.



Numerical realism criterion:

Transition evaluation

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Numerical realism criterion:

Transition evaluation

Challenges :

- Limited data:
- Make exhaustive use of it
- User perceptual acuity:
- Reliable numerical realism criterion
- Optimal results in terms of said criterion

- Sensitive data:
- Robust mesh processing technique
- Complex dynamics:
- Robust transition generation technique

Comparison of Graph Based Approaches

	Input data	Automatic/ supervised	Data organization
Motion Graph(kovar02)(Arikan02)	Motion Capture	automatic	Motion graph
Surface Motion Graph(Huang09)	3D Surface Capture	automatic	Motion graph
4D Parametric Motion Graph(Casas13)	4D Surface Capture	supervised	Parametric motion graph
Essential Graph(Boukhayma et. Boyer15)	4D Surface Capture	automatic	Essential graph

Contributions

- An optimal structure for motion data organization and reuse:
 The essential graph
- Improving realism in synthetic motion transitions through dynamic time warping and variable length blended segments

A novel high-level constraint formulation for motion synthesis:
 3D behavioral path synthesis

Approach

Motion synthesis pipeline :







Graph structure:

- Node = frame/pose
- Edge = transition
- Edge weight = transition cost

0--0--0--0--0--0--0--0--0

0--<u>0-0-0-0-0-0-0-0-0-0</u>-0

Input sequences



Graph structure:

- Node = frame/pose
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Input sequences

We need to add new transitions :





Graph structure:

- Node = frame/pose .
- Edge = transition ٠
- Edge weight = transition cost •

Motion Graph(kovar02)

- Adding edges ٠
 - Local minima in similarity matrix _
 - Threshloding _

Input sequences





Similarity matrix,



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Motion Graph(kovar02)

- Adding edges
 - Local minima in similarity matrix
 - Threshloding
- Improvements
 - Interpolated Motion Graph(Sofanova07)
 - Well-Connected Motion Graph(Zhao08)
 - Optimization-based Motion Graph(Ren10)

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Input sequences







Essential Graph

- Creating a complete digraph
 - Connecting all nodes together with directed edges and transition costs as weights





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 - For each node
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shortest path tree:

the path distance from the root to any vertex in the tree is the shortest path from the root to the vertex in the complete digraph





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shortest path tree:

the path distance from the root to any vertex in the tree is the shortest path from the root to the vertex in the complete digraph

- Union of shortest path trees rooted at every node
- This structure encodes all the optimal transitions with respect to the transition cost





Comparative case study:





Comparative case study:































Original frames Synthetic frames

Thomas dataset

Motion synthesis pipeline :





Edge weight = transition cost in terms of Realism criterion:







Edge weight = transition cost in terms of **Realism criterion**:



Interpolated Transition: Source and target motion segments gradual blending

- Dynamic time warping
- Variable length blended segments



Edge weight = transition cost in terms of **Realism criterion**:





Interpolated Transition: Source and target motion segments gradual blending

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Finding segment lengths lⁱ and l^j, and temporal warps wⁱ and w^j that minimize the total surface deformation cost:

$$D(i,j) = \min_{l^{i}, l^{j} \in [l_{\min}, l_{\max}]} \underbrace{\min_{w^{i}, w^{j}} \sum_{t \in [0,L]} d(w^{\bar{t}^{1}}(t), w^{\bar{j}^{1}}(t))}_{t \in [0,L]}$$

Dynalic Time Warping

Function d(.,.) is a static **pose distance**.





Edge weight = transition cost in terms of **Realism criterion**:



Interpolated Transition: Source and target motion segments gradual blending

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Motion synthesis level:

- **Pose interpolation** of matched frame along the transition
- Global displacements interpolation



Motion synthesis pipeline :





Skeleton parameterization for Mo-cap data

Riemannian manifold: $SO(3)^{n_{joints}}$





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Riemannian manifold: $SO(3)^{n_{joints}}$

Pose metric

 $\frac{1}{\sqrt{2}} \left\| \log(R_1^{-1}R_2) \right\|_F$ n_{joints}





Skeleton parameterization for Mo-cap data

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Skeleton parametrization for surfacic data:

- Mesh Ensemble Motion Graph(James07)
- One-to-Many(Zheng13)







Articulated plant model, James07

LBS skinning, Zheng13



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- Realism loss due to articulated model limitation



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Surface based parametrization for surfacic data:

- Surface Motion Graph(Huang09)
- 4D Parametric Motion Graph(Casas13) (Heck07)(Shin06)





Euclidean Parametrization $\Re^{3 \times n_{vertices}}$

- Pose metric : sum of squared Euclidean distances between vertices
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Surface Deformation based Parameterization for 3D triangular meshes:

Polar decomposition of Deformation Gradients: $T = (v_1 - v_3, v_2 - v_3, n)^{-1} . (v'_1 - v'_3, v'_2 - v'_3, n')$ T = R.S

Riemannian manifold: $(T_1, ..., T_{m_{triangles}}) \in (SO(3) \times S_3^+)^{m_{triangles}}$





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• Pose metric $d(.,.) = \sum_{m_{triangles}} \frac{1}{\sqrt{2}} \left(\left\| \log(R) \right\|_F + \left\| \log(S) \right\|_F \right)$





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- Pose metric $d(.,.) = \sum_{m_{triangles}} \frac{1}{\sqrt{2}} \left(\left\| \log(R) \right\|_F + \left\| \log(S) \right\|_F \right)$
- Pose interpolation
 - Geodesic transformation interpolation

$$\tilde{T} = e^{\lambda \log(R)} \cdot e^{\lambda \log(S)}$$

- Gradient deformation with interpolated transformation
- 3D Poisson Shape reconstruction



Motion synthesis pipeline :





Motion extraction casted as a graph search problem and solved using depth first search with Branch and bound





Motion extraction casted as a graph search problem and solved using depth first search with Branch and bound



- Motion Stream
 - Concatenate original and interpolated motion segments
 - Rigid alignment at segment junctions



Motion extraction casted as a graph search problem and solved using depth first search with Branch and bound



- reach specific poses at specific times
- Adapted to unstructured acyclic motion

2D path synthesis







Conclusion

- Realistic shape and appearance animation generation from user specified constraints
- Contributions:
 - An optimal structure for motion data organization and reuse
 - A method for improving realism in motion transitions
 - A novel high level constraint formulation
- Limitations:
 - Foot skate
- Future work:
 - Data annotation
 - Texture interpolation
 - More Data : Motion warping, Motion transfert, Merging parts motion.



Thank You !

