**INTRODUCTION**

Although motion capture animation has become prevalent in the computer graphics industry, characters animated with this approach are only capable of the motions that have been previously recorded. The aim of this project is to address those limitations of motion capture animation. As a starting point, we focus on bipedal character walking in the sagittal plane. The idea behind our approach is to combine methods of robot modeling and machine learning: 1) A controllable dynamic five-link biped robot to simulate human walking and generate markers for the torso and two legs, 2) A learning machine uses the biped motion capture data to creates the remaining markers. In this way, our approach dramatically simplifies the implementation of human walking simulation, compared with the mechanical method of dynamic whole-body modeling.

**EXPERIMENT TOOL**

Cooper is a 3D human dynamic model by Cooper and Ballard [1] that uses ODE to generate the torques needed to create the movement. It consists of 23 body components with total of 41 marker-slots attached to them. When a human subject moves and generates motion capture data, Cooper attaches each marker to its corresponding slot using spring constraints to force those body components move appropriately. The above images show simulations of human walking and grasping. Blue boxes are body components and the red dots are the marker-slots. The images show the positions of the 41 named marker positions.

**REFERENCES**


**METHODOLOGY**

The goal of this project is to simulate a 50 degree of freedom(dof) bipedal character’s walking in sagittal plane. Our approach includes two components: a 2D five-link biped robot and an marker-estimation machine. The robot is a dynamic physical model that can walk according to a specified trajectory. Positions of markers for two legs and torso can be recorded while the biped robot is walking. The estimation machine then uses principal component analysis (PCA) to predict the positions of remaining markers, such as markers of head, arm, trunk, etc., at each frame. Its training data are from the existing motion capture data. Thus the biped robot can serve to constrain the motion of the larger dof character.

- **Five-link biped robot**
  - Mu.[2] provides a effective method for implementing a five-link biped robot walking in the sagittal plane. Figure A illustrates a schematic of single support phase of walking gait. The free end of the biped is swing leg while the other is the support leg. We assume that for a completed gait cycle step, when the swing leg contacts with the ground, an instantaneous exchange of the biped support leg takes place[3]. The equation of motion of the five-link biped SSP are derived using Lagrangian formulation as follows[2]:

\[
P = \sum_{i=1}^{5} \frac{1}{2} \sum_{j=1}^{m_i} m_i \dot{\mathbf{q}}_j^2 - \frac{1}{2} \sum_{i=1}^{5} \sum_{j=1}^{m_i} \sum_{k=1}^{m_i} C_{ijk} \dot{\mathbf{q}}_j \dot{\mathbf{q}}_k + \sum_{i=1}^{5} \mathbf{u}_i^T \mathbf{f}_i + \mathbf{d}^T \dot{\mathbf{q}}
\]

\[
K_{ii} = \frac{1}{2} \left( \mathbf{M}_{ii} \mathbf{I} + \frac{1}{2} \mathbf{J}_{ii}^T \mathbf{J}_{ii} \right) + \frac{1}{2} \mathbf{J}_{ii}^T \mathbf{C}_{ii} \mathbf{J}_{ii} + \frac{1}{2} \mathbf{J}_{ii}^T \mathbf{Q}_{ii} \mathbf{J}_{ii}
\]

\[
\mathbf{D} \dot{\mathbf{q}} + \mathbf{H} \dot{\mathbf{q}} \dot{\mathbf{q}} + \mathbf{G}(\mathbf{q}) = \mathbf{T}.
\]

- **Marker-estimation machine**
  - After the biped robot generates marker positions for two legs and torso, we use them as positions of base markers to estimate the remaining marker positions. Liu.[4] provides a data-driven, piecewise linear approach to modeling human motions. He found that motion data representing similar behaviors nearly lie in the same low-dimensional space, with similar shapes, orientations and pose distributions. The figure shown below illustrates projections of six walking sequences onto their two common leading principal axes. The curves of these walking sequences clearly have similar shapes and orientations. They differ mostly by mean positions and scales.

Due to the local linearity of human motion data, we can construct a low-dimensional, local linear model for walking motion using PCA as follows[4]:

Computer eigenvector matrix P from training data, and then form a 3k x d matrix U from P by taking the entries corresponding to the base markers, with a 3(m - k) x d matrix V taking the remaining entries.

Let s be the k known base markers positions at each frame and w a dx1 vector, be the projection of a frame on the leading principle component axes, we can get: \( \mathbf{Uw} = \mathbf{s} \)

Then we estimates the remaining m-k markers by: \( \mathbf{x} = \mathbf{Vw} + \mathbf{mean} \)

**EXPERIMENT**

- **Five-link biped robot**
  - We defined a trajectory shown in the figure below, then built a five-link biped robot to walk in the sagittal plane following the trajectory, and finally attached part of Cooper’s body to the markers generated by the biped robot.

- **Marker-estimation machine**
  - Figure B shows the motion capture data set that describes a person walking with small steps. We use it as the training data to reconstruct a person walking with long steps. Figure C is the original motion and figure D is the reconstruction.

- **Combination**
  - The training data is still the same. However the estimation machine will predict the remaining markers' positions based on the known markers generated by biped robot. The trajectory of biped robot is the same as described above. Left figure below shows the biped robot walking pattern while right figure shows the walking reconstruction.

**CONCLUSION AND FUTURE WORK**

The results provide a proof of concept that a low dof system can drive the dynamics of a larger system, however we need to refine our approach in two ways:

1) Increase the accuracy of marker estimation.
2) Extend 2D biped robot to 3D biped robot.

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