SIMULATION AND ANALYSIS OF HUMAN WALKING MOTION

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ABSTRACT

Simulation and analysis of human walking motion has applications in surveillance and healthcare. In this paper we discuss an approach for modeling human walking motion using a mechanical model in the form of a kinematic chain consisting of rigid links and revolute joints. Our goal is to discriminate different types of walking motions using information such as joint torque and angle sequences extracted from the model. The angle sequences are initially extracted using 3D geometry. From these angle sequences we extract the torque sequences using a recursive Newton Euler inverse dynamics algorithm. Time series models and Dynamic Time Warping of the torque and angle sequences are used to characterize and discriminate different walking patterns. A forward dynamics algorithm is also presented for synthesizing different walking sequences like limping from a normal walking torque sequence.

***Index Terms*—** Human walking, inverse dynamics, forward dynamics, ARMA, dynamic time warping

1. INTRODUCTION

Walking is one of the most common activities performed by humans. But the process of analyzing and simulating human walking motion is one of the most difficult problems to handle. Analysis of the problem has been done using various techniques and has been utilized for human recognition, abnormality detection and also medical purposes.

Human gait or walking motion can provide very rich and detailed information. Just by looking at the walking motion of a person we can detect whether he or she has some physical disability or even tired. In most of the cases we can also infer the person's gender. If the person is someone we know we can recognize him or her by observing the way he or she walks. Certainly all of these pieces of information are encoded in the walking patterns of the humans. However we can also say that they are not included in a specific frame, but we have to look at the dynamics of the walking process. We might not be able to say that a person is wounded or not from a picture, but if we are presented with a video sequence of a walking person, we can very easily infer about the pieces of information mentioned above.

In this work we attempt to capture the variations in human walking due to different loadings of the human body. By looking at a walking person we can usually infer whether he or she is carrying a backpack or not. The loading conditions can be carrying a heavy backpack or having something strapped to the chest or leg. We want to analyze the effect of these loadings on human walking through the use of a dynamic model for human locomotion.

The problem has been divided into two subproblems, namely

1. ***Inverse Dynamics to get the joint torques***: The inverse dynamics problem [1] is one of solving the joint torques from the joint angles along with their first and second order derivatives. In our work we have used the Newton-Euler recursive algorithm [1] for torque calculation.
2. ***Forward Dynamics***: This problem [1] estimates the joint angles from joint torques. It is done by representing the human body motion in the form of a differential equation and then numerically integrating the equation.

To the best of our knowledge discriminating human walking patterns using the angle and torque is a new work and has not been reported before.

Simulation and analysis of human walking motion has been a subject of interest in many fields like computer animation, biomechanics, robotics and computer vision. Specially in computer animation, human walking motion generation is an area where a lot of work has been done [2]. [4][3] has developed models which are physically realistic. Physically realistic models take into account all the different physical constraints like gravity and body muscle torques. The alternative to this is the use of kinematic methods [5][6].[7] have combined the methods. These methods use some biomechanical knowledge and some previously collected gait data for the generalization purpose.

In the robotics community bipedal locomotion is a very popular topic and we can find several works on the same. In general a biped can be represented as an inverted pendulum system. This system undergoes a constrained motion due to the interaction of the stance leg and the ground [8]. In [9] Chew and Pratt have explored the performance of their algorithms under different load variations.

Computer vision mainly uses human gait for recognition of humans. There are two types of methods, appearance based and model based. Appearance based models can be deterministic [10] or stochastic using a hidden Markov Model (HMM) [11].

The organization of the paper is as follows. Section 2 presents the human body and motion models used in our work. The overall system is described in section 3 along with inverse and forward dynamics calculation systems. A brief description of angle and torque vector modeling is provided in section 4. Section 5 presents the results of our experiments. Finally section 6 presents the conclusions.

2. HUMAN BODY MODEL AND MOTION MODEL

We have modeled the human body as a kinematic chain of rigid links. This type of a model has been used earlier in [12], but for a different

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purpose. They have used the model for capturing and representation of human motion from video sequences. We have used a similar model, but it has been used for analyzing and simulating human motion. There are in all eleven links. The link structure is shown in figure 1. All the links are assumed to be perfectly rigid with zero diameter. The center of mass of a link is at the center of its length.

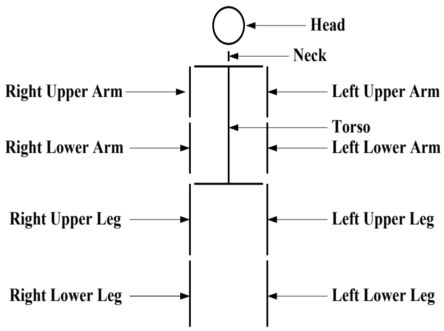

Fig. 1. Kinematic linked structure

The junctions of the links are connected in general by spherical joints which can rotate about all the three axes i.e. have 3 - degrees of freedom. Hence in general the total number of degrees of freedom with eleven joints is thirty three. In our work we have constrained the motion of the model in the sagittal plane i.e. the plane passing through the center line of a human body, dividing the body symmetrically into two equal halves. Hence the joints are modeled as revolute joints having their axis of rotation in the plane perpendicular to the sagittal plane.

The total number of degrees of freedom for the body model is then ten, and all the DOF's correspond to a revolute joint. We have added another degree of freedom to the stance leg where the leg rests on the ground. We have modeled the body ground joint as a revolute joint and torque is applied to this joint to move the body forward. All the above joints are actuated joints and appropriate torque is applied to the joints to generate the human motion.

Figure 2 shows the complete human model used in our work along with the ground connection modeled as a revolute joint

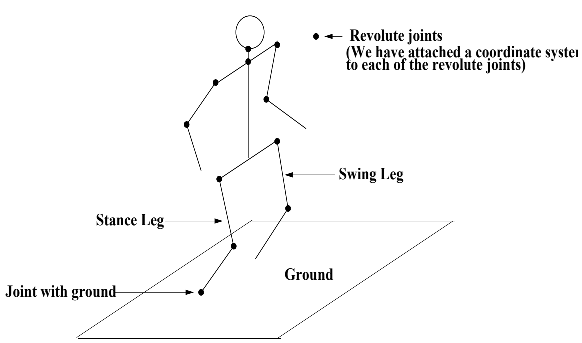

Fig. 2. Human model with ground connection.

We have adopted the following human motion model which has been used in many previous works [12]. In general, human motion can be described by three states and the body goes through all these states periodically. As the states are visited periodically, the human gait is generated. The states are

Double Support In this state the body is supported by both the legs

Right Support In this state the body is supported by the right leg (*support leg*) only and the left leg is the *swing leg*

Left Support In this state the body is supported by the left leg (*support leg*) only and the right leg is the *swing leg*

We assume that the time duration of the double support phase is very small and the transition from the left support to the right support or from the right support to the left support is instantaneous. In fact the simulation of this system alternates between the two phases.

3. THE INVERSE AND FORWARD DYNAMICS MODELING

A block diagram of the system is shown in figure 3. Initially, the joint angle data is manually extracted from a video sequence by hand marking the points of interest in the video frames or as in our case, the marker data collected in the Stanford Biomotion Laboratory is used to locate the joint positions of a human body. The points of interest for our case are the body joints. Since the motion of the model joints has been confined to one dimension only, the angles that are calculated are on the sagittal plane. As a result of this calculation for each frame, we capture the posture of the human model.

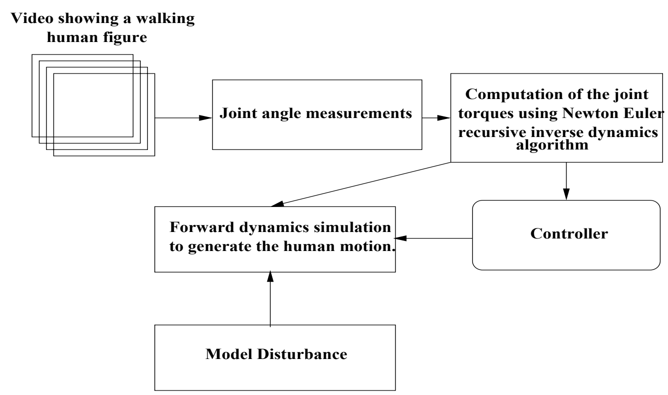

Fig. 3. System block diagram

The process of calculating the joint angles is represented by the block shown as "Joint Angle Measurement". These joint angle measurements are then fed to the inverse dynamics calculator for each frame. For the calculation of the joint torques we use the Newton Euler recursive inverse dynamics algorithm [1]. This block finds joint torques that are required to produce the desired human like motion. As mentioned earlier, all the joints are actuated in this model. The output is obtained in the form of a 11-dimensional torque vector. As a result of the computations mentioned above, we obtain a sequence of angle and torque vectors for a given video or marker data sequence.

In the next stage of the system these torque and angle sequence of vectors are used to discriminate the different walking patterns of humans by using autoregressive and moving average modeling [13] and Dynamic Time Warping (DTW)[13]. Using these techniques we discriminate the different walking patterns.

3.1. Inverse Dynamics

The inverse dynamics is calculated using the iterative Newton-Euler dynamic formulation which calculates the torque required to generate the given motion of the human model. The inputs to this algorithm are the position, velocity and acceleration $(\Theta, \dot{\Theta}, \ddot{\Theta})$ of the joint angles. The angle vectors are obtained as mentioned in the previous section. The velocity and acceleration vectors are obtained by taking finite differences of the angle vectors once and twice respectively. Along with these, we also need the knowledge of the kinematics and the mass distribution of the model for completing the calculations. To make the model authentic and realistic we have used the general human body characteristics [14] [15].

3.2. Forward Dynamics

For the forward dynamics [1] it is convenient to express the equation of motion of the model in a state space form that often hides the minute details of the system, but shows the underlying structure of the equation. The dynamic equation can be written as,

$$\tau = M(\Theta)\ddot{\Theta} + V(\Theta, \dot{\Theta}) + G(\Theta) \tag{1}$$

where $M(\Theta)$ is the *mass matrix* of the chain, $V(\Theta, \dot{\Theta})$ is a vector of centrifugal and Coriolis terms and $G(\Theta)$ is a vector of gravity terms. Each element of $M(\Theta)$ and $G(\Theta)$ is a complex function of Θ, while each element of $V(\Theta, \dot{\Theta})$ is a complex function of both Θ and $\dot{\Theta}$. To compute the forward dynamics, we use the inverse dynamics algorithm to find the matrix M and vectors V and G. This is a very convenient way of computing the forward dynamics.

4. MODELING OF ANGLE AND TORQUE VECTORS

We model the torque and the angle sequences as ARMA processes [13]. The dynamical model thus learnt is then used for identification of human walking motion variations due to loading by calculating the distance between the models. The models thus learnt are continuous state discrete time and since the model parameters lie in a non-Euclidean space the distance calculation is nontrivial.

The ARMA model that has been used is defined as

$$\alpha(t) = Cx(t) + w(t) \quad \text{where} \quad w(t) \sim N(0, R) \tag{2}$$

$$x(t+1) = Ax(t) + v(t) \quad \text{where} \quad v(t) \sim N(0, Q) \tag{3}$$

The cross correlation between w and v is assumed to be S. It is quite clear that the parameters of the model are A and C. However the matrices A,C,R,Q and S are not unique. Hence we transform the model to the "innovation representation" which is unique.

Distance between two ARMA model is defined in terms of the subspace angles [13] between the two models. The subspace angle between two ARMA models are defined as the principal angles $(\theta_i, i = 1, 2, \ldots, n)$ between the column spaces generated by the observability spaces of the two models augmented with the observability matrices of the inverse models. The Frobenius distance is then defined as

$$d_F = \sqrt{2 \sum_{i=1}^{n} \sin^2 \theta_i} \tag{4}$$

and the Gap distance is defined as

$$d_g = \sin \theta_{max} \tag{5}$$

Another method used is dynamic time warping. It is a nonparametric method for comparing two vector sequences. It is basically the best nonlinear time normalization used to match two sequences of vectors by searching the space of all allowed time normalizations. In this implementation we have used some temporal constraints. Further details are provided in [13]. The best warping function and the global warping error are efficiently calculated using dynamic programming. A global warping error measure is used to quantify the distance between models.

5. EXPERIMENTS AND RESULTS

We have conducted several experiments to judge the validity of our model. Most of the experiments have been done using the Stanford marker data. However the same tests can be run on any video data as long as we can extract the required information from the video sequence, which is a nontrivial problem. The data that are required from the sequence are the joint locations of the human body.

The experiments performed can be broadly divided into three categories.

- The Inverse Dynamics experiments
- The Forward Dynamics experiments
- Model validation

Figure 4 shows the angle data extracted from the Stanford marker data for a single individual walking normally.

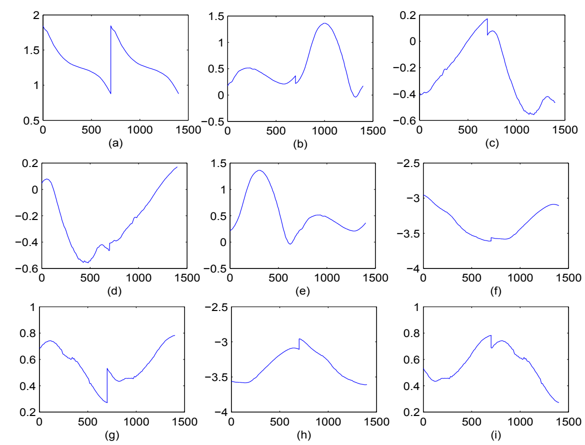

Fig. 4. The plots of angle data input to the inverse dynamics system block for a single gait cycle. Angle between (a) Ground and the shin of the support leg (b) Right shin and right thigh (c) Right thigh and torso (d) Left thigh and torso (e) Left thigh and shin (f) Torso and left upper arm (g) Left upper arm and lower arm (h) Torso and right upper arm (i) Right upper arm and lower arm

Figure 5 shows the similarity matrices for the inverse dynamics experiments. For all the matrices the columns correspond to twenty normal walking sequences, twenty backpack carrying sequences and twenty limping sequences. The rows contain the same sequences. The matrices show that there is considerable similarity between sequences of the same type and hence can be used for identification of different loading conditions. Specially the similarity matrices using dynamic time warping even show the similarity of walking styles of the individual subjects in the form of the small diagonal squares. Hence these sequences can also be used for recognition purposes.

For forward dynamics experiments we used the torque data of the inverse dynamics simulation as inputs to the system. We simulated the following walking patterns of a human

- Normal walking
- Walking with a heavy backpack

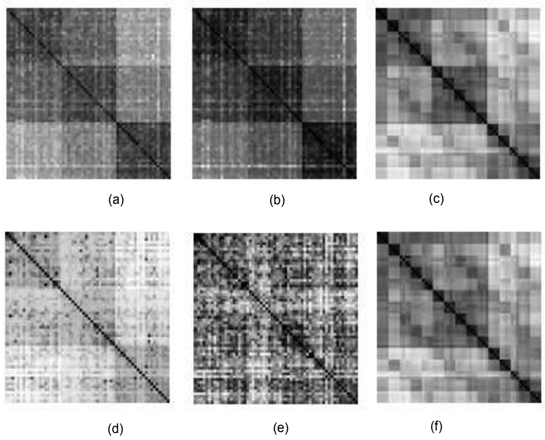

Fig. 5. Inverse dynamics similarity matrices for angle sequences using (a) ARMA modeling and gap distance (b) ARMA modeling and Frobenius distance (c) dynamic time warping. Corresponding torque sequence similarity matrices are shown in (d), (e) and (f)

- Waking when the right upper leg is loaded

In the validation experiments, the synthesized torque and angle sequences in the forward dynamics experiments were compared with those extracted from the Stanford marker data. Figure 6 shows the similarity matrices. The rows correspond to the sixty sequences present in the Stanford dataset. The five columns of the matrices correspond to the synthesized sequences with one normal sequence, two backpack carrying sequences and two limping sequences. The similarity between the synthesized data and the Stanford marker data empirically validates the model.

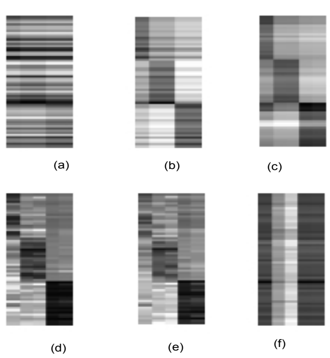

Fig. 6. Validation similarity matrices for angle sequences using (a) ARMA modeling and gap distance (b) ARMA modeling and Frobenius distance (c) dynamic time warping. Corresponding torque sequence similarity matrices are shown in (d), (e) and (f)

6. CONCLUSION

We presented a dynamic model for simulating human walking and also identification of some loading conditions of the walking person like limping and carrying a backpack. The work clearly shows that the torque data and also the angle data has discriminative power to identify the loading conditions of the human body. The forward dynamics problem has been solved to generate human walking patterns under different loading conditions. The artificial walking patterns are very similar to the actual human marker data, validating the use of the model. An important extension of this work is to integrate the model with unconstrained video. The torque and angle sequences can be used for recognition purposes too.

7. REFERENCES

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