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Angular Momentum Primitives for Human Turning: Control Implications for Biped Robots

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***Abstract*—Human locomotion involves a number of different complex activities. Humanoid robots, if they are expected to work in a human environment, should be expected to navigate obstacles and transients as well as, or better than a human being. Turning is one aspect of human walking that is poorly understood from the perspective of biomechanics and robotics. It is an important task comprising a large percentage of daily activities through most human environments. During turning the body is subjected to torques that the leave the body unstable. By understanding the contributions of the spin angular momentum about the center of mass we can gain insight on how to design better controllers for bipedal robots. There are several different types of turning; using alternate legs as the stance leg to accomplish the turn and then recover and also, turning can be a steady-state phenomena as well as a more transient behavior depending on speed. The contributions of spin angular momentum to the center of mass is considered in the case of a spin-turn where the inside foot pivots and the opposite foot the direction of the turn returns the body to level ground walking. Motivations for control of human walking bipeds are discussed. Further, a theory is developed that turning is dominated by contributions from the swing leg producing angular momentum about the body during the turn.**

***Index Terms*—turning, angular momentum, humanoid, biped**

I. Introduction

Human locomotion has been well studied in the past and many important insights have been made into how humans accomplish locomotion. This has led to advances in humanoid robotics and the development of robust walking bipeds such as, ASIMO [1] have influenced the design of robotic prosthetics [2]. In terms of biomechanics less is known, however, about more complex human behaviors; turning, abrupt starts and stops, and walking on uneven terrain still have many unresolved questions that can be answered. In order to develop a humanoid robot, that will be able to live among us successfully, a large amount of flexibility in its control will have to be realized. Those bipedal robots that are able to learn from the behaviors of humans and successfully apply this knowledge to their locomotive control can be very successful.

Studies of human locomotion have allowed scientists to make predictions on what are the essential features of level ground walking that allow a mechanical model to accomplish a similar task. For example, the study of ground reference points like the Zero-Moment Point (ZMP) [3] have given us some knowledge of robotic control by treating the human body as an actuated system [7]. The understanding of these ground reference points have allowed designers of humanoid robots to successfully realize trajectories in a varied and diverse environment. The most famous example of this type of control is that implemented in Honda's Asimo humanoid robot, that calculates trajectories using a ZMP control strategy.

Some of the major challenged facing humanoid robots are,

1) planning of the predefined joint trajectories,
2) tracking the actualized predefined joint trajectories.

The over-arching goal of the field of humanoid robotics is to have robots that can produce biomimetic motions and at some-point even surpass the abilities of humans. To do this, trajectory planning algorithms should be able to address the following during pre-planning[9];

1) The joints have motions that be realized in a physical system. In particular, the resulting ground reaction forces are pointing upwards and the center of pressure (CP) is inside the foot support polygon.
2) The trajectory of the walking robot is optimized in such a way that large disturbances can be rejected by the control system.
3) Quick transitions, or transients, from the desired goal (e.g. negotiating a turn between two sections of level ground straight walking).
4) Various motion quality metrics are optimized. In particular the model in constrained by using the minimum energy expenditure to complete the assigned task.
5) Several tasks and subtasks can be completed concurrently (e.g. walking and picking up a glass of water)

Human being have managed to over come these significant control-level challenges with a high amount of energy economy. Then it would seem a good idea to motivate our controllers by the lessons obtained from biomechanical experimentation.

II. Experimental Methods

For the human motion experiments 2 subjects gave their informed consent to participate in this pilot study. Each subject was free of musculoskeletal and orthopedic problems by self-report. We collected kinetic and kinematic data from each subject during a 90° left turning task

Subjects were brought to a motion capture facility at the Computer Science and Artificial intelligence Laboratory at the Massachusetts Institute of Technology for trials. Kinematic data were collected with an AMTI force platform and a 16 camera motion capture system VICON 810i (Oxford Metrics, Oxford, UK) respectively. A total of 41 markers were placed on each subject according the VICON golem model specifications. Each subject completed a 90° left turn by pivoting for

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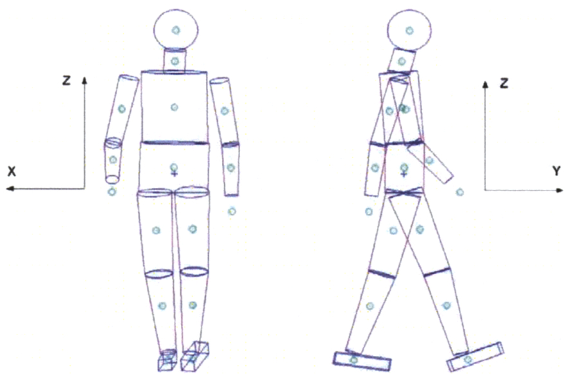


Fig. 1: This is a rendering of the morphologically accurate model [4] of the human body used to estimate the spin angular moment about the CM. The model has 38 external degrees of freedom, or 32 internal degrees of freedom. This corresponds to 12 for the legs, 16 for the arms, and six for the rest of the body. The radii and lengths of the truncated cones are taken from physiological measurements of each participant.

the turn on the left foot, so that the recovery foot is the right foot. The subjects walked at 1.5 m/s entering into the turn and wore bare-feet during the study.

III. Human Model

To estimate the angular moment contribution of each limb relative to the body's total center of mass a *truncated cone model*[4] is used. The model treats limb segments as truncated cones to account for differences in mass distribution about a specific limb, Figure 1.

The model [5] is comprised of 16 rigid body segments: feet, tibias, femurs, hands, forearms, arms, pelvis-abdomen, chest, neck and head. The segments representing the tibia, femur, forearms, and arms were modeled as truncated cones. The trunk was broken into lower (pelvis-abdomen) and upper (chest) segments, and the head is approximated as a sphere of a given radius.

The model has a 16 component vector corresponding to the relative mass distribution, M_R, of the human body model segments mentioned above. This vector can be written as a function of a single parameter α such that,

$$M_R(\alpha) = \frac{(M_R^{Exp} + a\bar{V}_R)}{1+\alpha}, \tag{1}$$

where V_R is a 16 component vector of relative volumes computed directly from the truncated cone model.

The relative volumes were computed as the ratio of the segment's volume over the total body volume. That is, if V^i is the i-th segment's volume, then the relative volume of the i-th segment, $V_R^i = V^i/V$. Using (1), in addition to, the total body mass and segments masses the 16 component vector density can be written as $\bar{D}^i(\alpha) = M_{subject} M_R^i(\alpha)/V^i$, where $M_{subject}$ is the total body mass and V^i is the volume of the i-th segment. The optimal setting of α, that is $\alpha = \alpha_{\min}$ that is found by the following optimization:

$$\min|\vec{D}(\alpha) - \vec{D}^{Exp}| = \min\sqrt{\sum_i [D^i(\alpha) - D^{Exp,i}]^2}$$

$$\Rightarrow \alpha_{\min} \Rightarrow \vec{M}_R = \frac{\vec{M}_R^{Exp} + \alpha_{\min}\vec{V}_R}{1+\alpha_{\min}}.^1$$

The moments and angular momentum of the in the model are estimated using the methods detailed in [5]. The *whole-body center of mass* is given by,

$$\vec{r}_{CM} = \sum_{i=1}^{16} M_R^i \vec{r}_{CM}^{\,i},$$

where M_r^i is the relative mass of the i-th body segment and $\vec{r}_{CM}^{\,i}$ is the CM location of the i-th body segment relative to the lab frame.

The whole-body angular momentum and moment are calculated using kinematic gait data and the human body model. The angular momentum, $\vec{L}$, is calculated as the sum of individual segment angular momenta about the body's center of mass (CM),

$$\vec{L} = \sum_{i=1}^{16} (\vec{r}_{CM}^{\,i} - \vec{r}_{CM}) \times m_i(\vec{v}^i - \vec{v}_{CM} + \vec{I}^i\vec{\omega}^i).$$

Where the first term in the cross product is the angular momentum as a result of the i-th segment's movement relative to the CM movement.

IV. Principal Component Analysis of the Morphological Model

Principal Component Analysis Background

Principal component analysis (PCA) [8] is a powerful method for reducing the dimensionality of a data set.[2]. Our experiment involves a set of observations $x_1, x_2, \ldots, x_N$ that can be represented by a rank-q linear model $f(\lambda) = \mu + \mathbf{V}_q\lambda$, where μ is a vector in $\mathbf{R}^p$ that indicates location, and $\mathbf{V}_q$ is a $p \times q$ matrix with q orthogonal unit vectors as columns, and λ is a vector of length q.

Then to fit the model to the data we minimize the reconstruction error,

$$\min_{\mu,\{\lambda_i\},\mathbf{V}_q} \sum_{i=1}^{N} ||x_i - \mu - \mathbf{V}_q\lambda_i||^2.$$

Then partially optimize the reconstruction error for μ and λ_i to get $\hat{\mu} = \bar{x}$ and $\hat{\lambda}_i = \mathbf{V}_q^T(x_i - \bar{x})$. From here our optimization is to find the orthogonal matrix $\mathbf{V}_q$ that minimizes,

$$\min_{\mathbf{V}_q} \sum_{i=1}^{N} ||(x_i - \bar{x}) - \mathbf{V}_q\mathbf{V}_q^T(x_i - \bar{x})||^2.$$

[1] In this work $\alpha_{\min} = \frac{1}{2}$.

[2] Newer methods exist [10], but for this work we only use this relatively simple technique to extract principal components

For simplicity assume that the mean of the observations is 0, i.e. $\bar{x} = 0$. Then the projection matrix is given by $\mathbf{H}_q = \mathbf{V}_q \mathbf{V}_q^T$ that maps each observation, x_i onto its rank-q reconstruction $\mathbf{H}_q x_i$, which is the orthogonal projection of x_i onto the subspace spanned by the columns of $\mathbf{V}_q$.

Given a set, X, of N observations in $\mathbf{R}^p$ if $N > p$ then we can perform a *Singular Value Decomposition* and write,

$$X = UDV^T.$$

Here U and V are orthogonal matrices that are $N \times p$ and $p \times p$, respectively. The columns of U are the left singular vectors, columns of V are the right singular vectors, and the diagonal elements D are the singular values. Each solution corresponding to rank q, that is a solution o $\mathbf{V}_q$ consists of the first q columns of V. The principal components of X are then the columns of the matrix UD.

PCA analysis of the human body model

PCA has been recently applied to the reduction of dimensionality in a human body model for level-ground walking[5][9]. The observations obtained from each link's spin angular momentum, associated with the kinematic data of a trial, was used to perform a PCA dimension reduction. This was done by treating each link of the morphological model as a component in the analysis.

The components of spin angular momentum are listed in the following order: c_1 = Left Foot, c_2 = Right Foot, c_3 = Left Shin, c_4 = Right Shin, c_5 = Left Thigh, c_6 = Left Hand, c_7 = Right Hand, c_8 = Right Thigh, c_9 = Left-Forearm, c_{10} = RightForearm, c_{11} = LeftUpperarm, c_{12} = RightUpperarm,c_{13} = UpperTorso, c_{14} = LowerTorso, c_{15} = Neck,c_{16} = Head.

PCA was performed on each link's angular momentum for each cartesian direction. The eigenvalue problem, the SVD, was computed using a 16×16 covariance matrix. Then the eigenvalues were ordered in by their magnitude. Then from the eigenvectors a new 14 dimensional orthonormal basis was obtained with basis vectors, $\vec{P_i}$ that are linearly independent and ordered by the magnitude of their associated eigenvalue.

V. Control

Though, at this time, no controller has been implemented to use these angular momentum primitives, now that we have identified them we should use this knowledge to control a biomimetic biped robot.

The motivating work for this paper [9], searched for a joint reference trajectory that minimized the error between the model's angular momentum distribution and the biologically determined distribution.

The model used was an eight degree of freedom humanoid model that had eight rigid links or appendages. This includes a pair of feet, a pair of shanks, a pair of thighs, a pelvis and abdomen as one link and a thorax. However, differing from this work we would like to remove the constraint that the model can only walk in the sagittal direction and allow movement in full 3D.

VI. Results

A. PCA Results

Note Fig. 3, the three components, c_2, c_4, c_6 accounted for the majority of contributions to the spin angular momentum about the CM. This suggests that our subjects used specific parts of their body to complete the turn.

Fig. 2 shows the plot of the principal components for each cartesian direction in the lab frame. Note that in all three directions the first principal component accounts for 85.1533% of the variance observed in the data when averaged over the two subjects. This means the majority of the contributions of the angular momentum about the center of the mass can be explained by the variance in the first principal component of each subjects' trial averages.

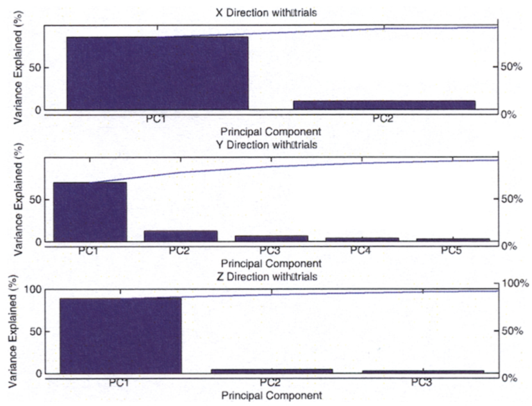


Fig. 2: The average principal components for three axes (X, Y, Z) representing the contributions to the spin angular momentum about the CM for two subjects taking a turn. Note that the first principal component explains the majority of the variance observed in the data.

Subject	$\vec{P_1}$	$\vec{P_2}$
1	85.33%	10.9%
2	84.97%	9.4%

TABLE I: Percentage of variance explained by each principal component, $\vec{P_i}$. Note that the first two components account for $< 90\%$ of the variance in the data.

B. Angular Momentum Results

Fig. 3 shows the averaged angular momentum for two subjects. This curve is similar to those found for level ground walking in [5].

VII. Discussion

The results in the preceding section indicate that while angular moment is tightly controlled about the CM, during a turn angular momentum become highly unregulated and

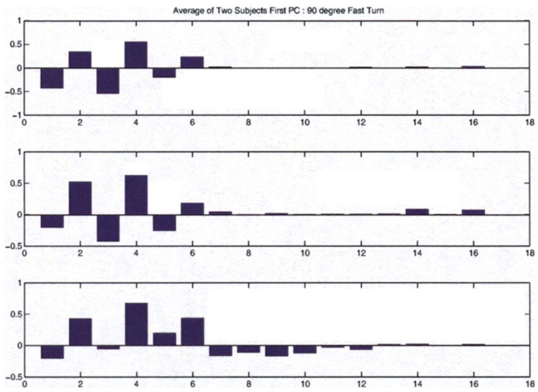


Fig. 3: The first averaged PC for two subjects taking a left turn with the right leg swing out during the turn. The last graph shows the contributions from each segment to the angular momentum about the CM. The majority of contributions come from c_2, c_4, c_6 that are the foot, shin and thigh of the right leg, respectively.

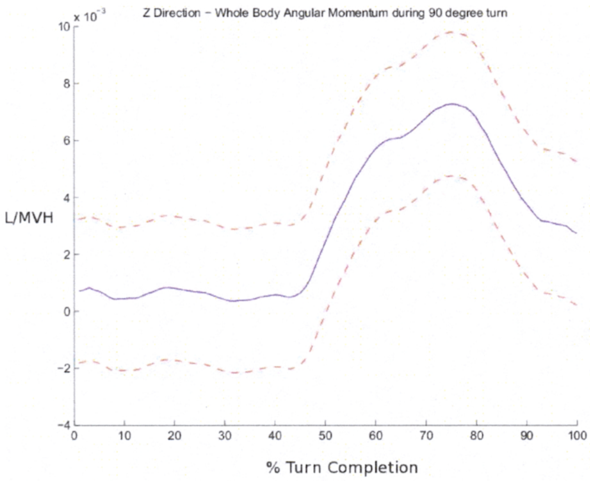


Fig. 4: This shows the angular momentum, L, is scaled to a unit-less value by $M_{subject}V_{subject}H_{CM}$, where $M_{subject}$ is the mass of the particular subject begin tested, $V_{subject}$ is the average velocity of the subject through the trial, and H_{CM} is the average height of the CM through the trial.

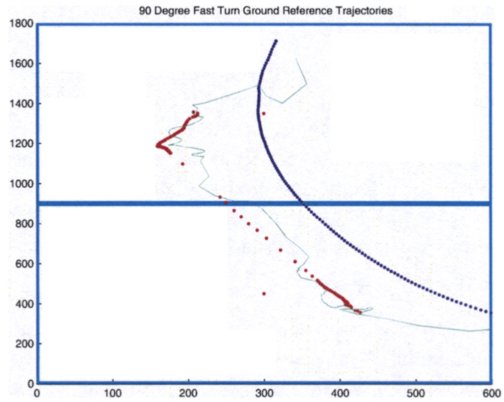
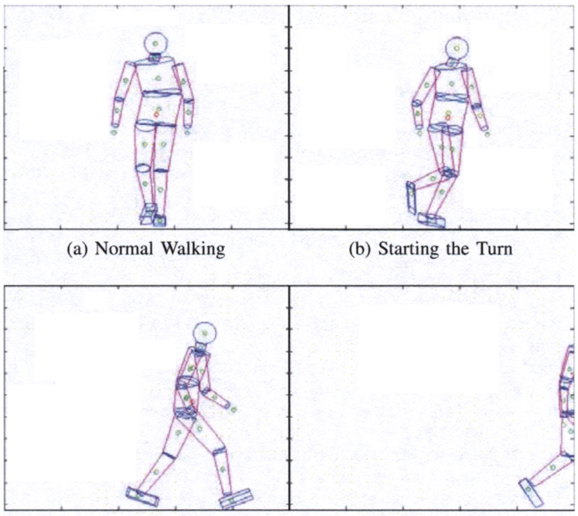


Fig. 5: Depicted above are the two force-plates with the ground reference trajectories, CM (blue), CMP(green), COP(red). The walking direction is from the top of the picture down.



(a) Normal Walking (b) Starting the Turn

(c) Landing the Swing Foot (d) Return to Normal Walking

Fig. 6: Example Left Turn Trial

perturbs the otherwise stable bipedal system. The fact that the turn can be explained by angular momentum contributions from the feet, shins and thigh indicates that better control of those segments should provide better stability of the whole body during a turn.

Finding the principal components that account for the angular momentum for a particular action in a human indicate a possible procedure for developing a controller that can actuate a subject of the available joints in a humanoid robot.

Some of the limitations of the experimental methods are the in ability to regulate human turning and speed in a reliable way. There is some error introduced from the combination of activities into the calculations for the angular momentum about the CM.

The method of PCA is a basic statistical method to choose the more parsimonious model to explain the variance in a model. However, newer methods, such as Bayesian PCA, might provide better model reduction by taking into account the prior distribution the data is drawn from there-by more succinctly explaining the data. This will be the focus of follow up work on model selection for a wider range of human motion activities.

The next logical step, and one regrettably not included in this paper, is developing a simulation that utilizes a control of the ankles and legs to successfully complete a left turn at 90°. This will be the subject of follow-up work. Also, other transients and movements that occur in the direction other than sagittal can be perfectly analyzed with this method. Another followup work will look at the effect of angular momentum contributions for rapid accelerations on level ground.

VIII. Conclusions

In this paper we showed that during a turn a high dimensional model of the human body can have a reduced representation by a smaller number of principal components that account for the contributions to the spin angular momentum about the CM. Limitations of this method are separating different activities from the primary one of interest are cited and possible extensions using Bayesian PCA are mentioned.

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