A Deterministic Model of Human Motion Based on Algebraic Techniques and a Sensor Network to Simulate Shoulder Kinematics

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Abstract: Limiting the quantitative characterization of ambulatory mobility to only the two-dimensional sagittal plane through the investigation of key kinematic parameters, may still inform scientists and bioengineers of critical elements of joint locomotion. This paper presents the initial validation of a deterministic biomechanical gait model that was derived from an inverse kinematic analysis of three-dimensional upper extremity movement. Algebraic methods were applied to generate shoulder flexion and extension angles during a single gait cycle during normal walking. The direct kinematic measurements from a motion capture system were analyzed and compared to the predicted measurements from the algebraic model for eight healthy, human subjects. The predicted results over all subjects varied from the actual joint angle measurements with a nominal amount of mean error (23%), while correlations were quite strong (mean $R^2 = 0.97$). These findings indicate the potential value of deterministic modeling with algebraic techniques as an alternative to existing methods.

Keywords: Gait model, inverse kinematics, shoulder biomechanics, motion analysis.

INTRODUCTION

The medical community's interest in gait is often to classify the components of gait for the treatment of pathologically abnormal patients. Data collection of upper extremity movements in the gait cycle for the purpose of developing diagnostic methodologies may present problems for researchers. Upper extremity flexion and extension have a high degree of complexity for the shoulder in the gait cycle. Problems include poor marker measurements due to skin movement, spherical joint mobility at the shoulder that influences non-planar arm swing during gait, and occlusion of particular body segments [1-4]. However, data collection and analysis of the shoulder has improved through the use of medical imaging equipment, mathematical modeling, and sensor networks, leading to clinical advances, particularly for athletes and injured persons [5-8]. Although many studies emphasize medical diagnostics for abnormal gait characteristic determinations [9,10], the consequences of balance, center of mass, velocity, etc., also provide insight into more sophisticated data collection strategies for spatio-temporal pattern analysis [11,12]. A review of perturbed gait for the purpose of medical diagnostics called for the development of new clinical assessment methods to help reveal the influence of diseases (e.g., Parkinson's) on the control of postural tasks [13]. The assumption was that important parametric contributors could be identified that would be characteristic of a disease. The research appeared to indicate that various spatial tasks caused sagittal plane effects that could be correlated. The above, then, call for the use of alternative techniques to further enhance existing studies in pattern analysis in the sagittal plane. These approaches would also address skin marker challenges, joint mobility influences on arm swing, segment occlusion, and measurement error of upper extremity movements for the medical community.

Mathematical modeling of the shoulder typically tracks arm swing motion in three dimensions (3D). However, limiting the characterization of mobility to the sagittal plane through the application of key parameters still informs scientists and bioengineers of key elements of joint locomotion. A two-dimensional (2D) model of this nature would address joint mobility of the

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shoulder as well as segment occlusions. Importing gait data into the model from improved data collection techniques would address position marker variability through skin movement and measurement errors. Tracking motion through mathematical modeling, then, can provide a better understanding of shoulder joint kinematics while avoiding problems that have risen in previous studies [3,14-16], providing the field with alternative techniques for comparing normal versus abnormal shoulder flexion and extension.

Several kinematic and kinetic modeling techniques exist. Of these, inverse kinematic (IK) analysis has emerged as a common technique to model human motion [17,18]. However, this approach rarely incorporates a deterministic model. In general, most IK techniques apply probabilistic or optimization approaches [19-23]. While these approaches have broadened the field of biomechanics, further investigation is needed in deterministic modeling. The authors will illustrate the usefulness of one model in particular as introduced previously [24].

There are two types of kinematic problems. The forward kinematic problem is the computation of the position and orientation of a jointed flexible object in 2D or 3D space, and the IK problem is the process of determining all combinations of a jointed flexible objects in order to achieve a desired position and orientation in space [25]. In robotics, the IK problem is most widely used to determine object capability, efficiency, and accuracy for various robot manipulators. Previous efforts have successfully applied such research in robotics to human locomotion [26,27]. Investigators developed an optimization method that modeled a planar, kinematic chain with three degrees of freedom (DOF) for the upper extremities in the sagittal plane [27]. Results estimated body segment parameters (masses, center of gravity coordinates, joint angle measurements, etc.). Others have analyzed energy consumption during gait and used an optimization method based on a planar, five-link, open-chain robot manipulator to develop an algorithm to predict joint kinematics of the swinging limb [26]. These results supported other scientific studies that have concluded that gait is energy efficient. Previously, we contributed to this body of work by developing an improved methodology using a 2D model based upon algebraic techniques to simulate the movements of a three DOF planar human arm [24]. As an initial validation of this 2D model, we have applied the deterministic approach to original motion capture data collected from the upper extremities of human subjects. This paper will present the results of applying this model to shoulder flexion and extension during the gait cycle.

MATERIALS AND METHODS

Full body, 3D segment motions were gathered from healthy, male human subjects walking at normal speeds (n = 8, age range = 20 to 26 years, body mass index = 20.1 to 28.8). Anatomic data as well as passive optical motion capture data (Figure **1**) were collected at 60 frames per second using a 6-camera system (VICON Las Angeles, CA). Relative joint locations and rotation angles were defined in a manner consistent with published standards [28] and marker trajectories were filtered using a 2nd order Butterworth filter with a low-pass cutoff frequency of 6 Hz. In order to apply the 2D IK model, a dynamic system was created so that the shoulder and elbow centers were represented in the torso's sagittal plane with the shoulder joint center position constituting the 2D origin of motion [26]. Finally, all position and rotation data were normalized to a percentage of the gait cycle. During the first half of the cycle the shoulder is in flexion, while the shoulder is in extension during the latter half. All data post-processing was conducted using commercial software (MATLAB v7.5.0, Mathworks, Inc., Natick, MA; Excel, Microsoft Corp., Bellevue, WA).

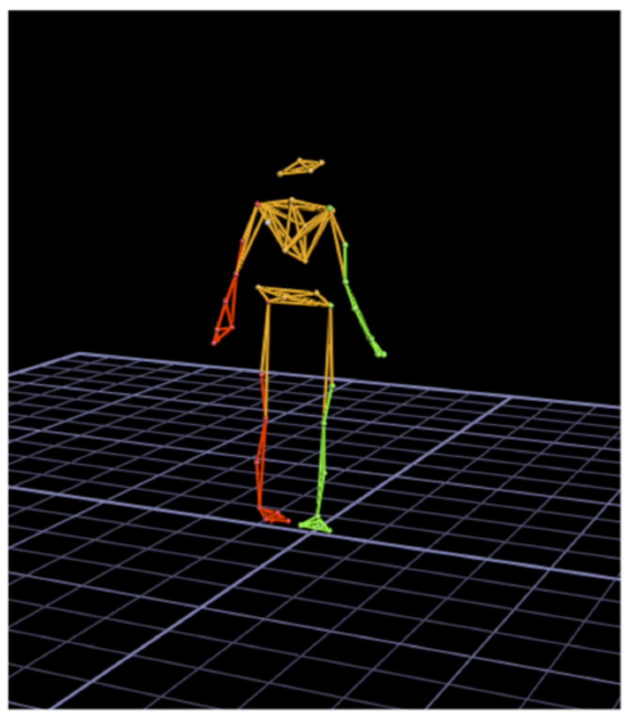

Figure 1: Representative three-dimensional motion capture image of a subject sampled from body-surface markers during a typical gait cycle.

The experiment allowed the test subjects to complete several gait cycles in a closed laboratory environment. The test subjects were given several strides (typically 3 to 5) to develop a normal gait pattern, upon which two gait cycles were recorded. The data were processed through the 2D geometric model (a kinematic chain of joint-link pairs) to determine the joint angle measurements of the elbow (θ_2) and shoulder (θ_1) [24]. The kinematic chain was projected onto an XY-Coordinate plane (sagittal plane) with the shoulder joint centered at the origin and the position of the wrist denoted as (x = a, y = b). Given the length of the upper arm, denoted L_1 and the forearm, denoted L_2, a system P, of four, non-linear polynomial equations was derived with four unknowns, *cos* θ_i and *sin* θ_i where i =1,2, such that:

$$P = \begin{cases} L_2\left(\cos\theta_1\cos\theta_2 - \sin\theta_1\sin\theta_2\right) + L_1\cos\theta_1 - a \\ L_2\left(\cos\theta_1\sin\theta_2 - \cos\theta_2\sin\theta_1\right) + L_1\sin\theta_1 - b \\ \cos^2\theta_1 + \sin^2\theta_1 - 1 \\ \cos^2\theta_2 + \sin^2\theta_2 - 1 \end{cases}$$

To solve the system, an algebraic reduction algorithm (Buchburger's Algorthim) was computed *via* an algebraic software system (Magma Computational Algebra System V2, Computational Algebra Group, University of Sydney, Australia), reducing the set of equations to a simplified basis set [29]. Using lexographical order, *cos* θ_2 > *sin* θ_2 > *cos* θ_1 > *sin* θ_1, the following basis was produced:

$$G = \begin{cases} \cos\theta_2 - \dfrac{a^2+b^2-L_1^2-L_2^2}{2L_1L_2} \\ \sin\theta_2 + \dfrac{a^2+b^2}{aL_2} - a^2b + b^3 + \dfrac{b\left(L_1^2+L_2^2\right)}{2aL_1L_2} \\ \cos\theta_1 + \dfrac{b}{a}\sin\theta_1 - \dfrac{a^2+b^2+L_1^2-L_2^2}{2aL_2} \\ \sin\theta_1^2 + \dfrac{a^2b+b^3+b\left(L_1^2+L_2^2\right)}{L_1\left(a^2+b^2\right)}\sin\theta_1 + \dfrac{\left(a^2+b^2\right)^2+\left(L_1^2+L_2^2\right)^2-a^2\left(L_1^2+L_2^2\right)+2b^2\left(L_1^2-L_2^2\right)}{4L_1^2\left(a^2+b^2\right)} \end{cases}$$

A linear algebraic approach of group G (Variety G) allowed for the manipulation of the given equations to determine the solutions for the four unknowns [30]. Further, the denominators of terms in each equation provided information for additional cases when L_1, L_2, a ≠ 0 and (a^2 + b^2) ≠ 0. Thus, given the planar position of the wrist during walking and the lengths of the upper arm and forearm as input, the 2D geometric model determined the flexion/extension angles of the elbow and shoulder throughout the gait cycle.

During data collection, a single cycle of gait was divided into one hundred time increments ($\Delta t \approx 0.3$ s). The lengths of the upper arm and forearm (measured from joint center to joint center) and the position of the wrist were imported into the model through time. Inverse kinematic calculations predicted the flexion and extension angles of the shoulder for each of the time increments throughout the single gait cycle. These predicted results were then compared back to the measured joint angles produced directly from the motion analysis system software. Accuracy and correlation of the predictions were assessed by the root mean square (RMS) of the shoulder angle, the percent differences in the RMS (%Δ), and the coefficient of determination (R^2), respectively. An F-test was also conducted to assess the two-tailed probability of whether the measured or predicted variances are not statistically different.

RESULTS

Overall, the predicted extension and flexion angles were similar to those measured (Figure **2**). During the stance phase, the measured results increased on average until 50% of the gait cycle was completed, then decreased around toe-off and continued to decrease during the swing phase of the gait cycle. The predicted results closely matched those measured during the stance phase of the gait cycle. However, during the first 10% of the gait cycle, the predicted results varied on average by 3.66^o. The predicted results also varied at toe-off and at some parts of the swing phase. In particular, the predicted results increased higher than those measured around toe-off by an average of 10.0^o, this difference continued through the beginning of the swing phase. For 70 to 95% of the gait cycle, the measured results progressed, resulting in an average difference from those predicted of 3.24^o. Overall, the predicted results were closer to those measured for shoulder flexion, and varied for shoulder extension given the impact of toe-off and segment transition to and during the swing phase. Yet, the aggregate predicted results still follow the trends of the measured results.

Variance in the above results was generally due to the projection of joint motion onto the 2D sagittal plane. During an individual's gait cycle, the elbow bends slightly into a third dimension (medial-lateral orientation), not represented in the model. As a result, the perceived 2D total length of the arm (upper arm plus forearm) has a mean error of 7.8% through a single gait cycle (Table **1**). Given the above, the RMS and %Δ as estimates of the accuracy of the prediction indicate consistent differences for the entire gait cycle (Table **2**) as well as during the separate flexion an

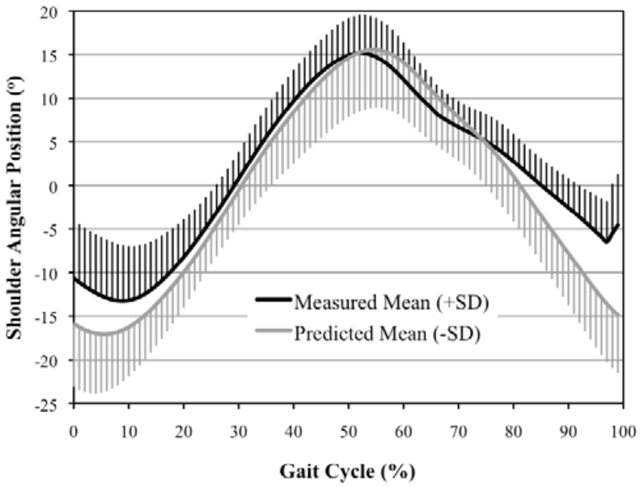

Figure 2: Aggregate mean (+/- standard deviation, SD) of the measured and predicted shoulder angles for all eight subjects through a single gate cycle. Flexion and extension angles are associated with the first-half and last-half of the gait cycle, respectively.

extension positions (Table **3**). In terms of precision, the correlation and variance testing indicate very consistent comparisons (Table **2**).

Table 1: Representative Anthropometric Error of the Upper Arm and Forearm (Subject 50) During a Gait Cycle

Subject 50	Upper Arm	Forearm
	Anatomic Lengths (mm)	
	352.2	269.9
Gait Cycle (%)	**Predicted Lengths (mm)**	
1	310.4	271.2
2	310.9	271.3
3	311.3	271.4
4	311.6	271.5
5	311.8	271.6
6	312.2	271.7
7	312.6	271.7
8	313.0	271.8
9	313.3	271.9
…	…	…
97	313.8	270.4
98	314.2	270.2
99	314.7	270.0
100	315.2	270.0
Mean %Δ From Measured Limb Length	-13.2%	-0.8%

Table 2: Comparison of Measured Versus Predicted Shoulder Motion During One Complete Gait Cycle. Although the differences appear large, a high correlation ($R^2 > 0.9$) and similar variances ($F < 0.05$) are generally indicated between the results of the motion capture data and the IK model

Subject #	RMS (°)			R^2	F- Test
	Measured	Predicted	%Δ		
50	9.12	11.87	30.3	0.9644	0.0064
51	10.67	12.64	18.5	0.9938	0.0694
52	11.52	13.68	18.7	0.9951	0.0724
53	10.09	13.01	28.9	0.9693	0.0509
54	14.09	17.81	26.4	0.9263	0.0309
56	9.40	11.82	25.7	0.9752	0.0430
60	4.72	5.67	20.3	0.9927	0.0648
62	8.35	7.07	-15.3	0.9691	0.3652

DISCUSSION

The results from this study demonstrated the useful albeit limited strength of the previously described model [24]. This model provides an alternate predictor of shoulder flexion, and requires further investigation to model shoulder extension in the sagittal plane of the gait cycle. To support future investigations, ongoing gait studies will develop and apply a 3D variation of the model through the use of motion capture and surveillance video. The ultimate goal is to provide an alternative analytical tool when characterizing normal and abnormal joint shoulder behaviors in the gait cycle.

Given that arm-swing motion assists with stabilizing body motion in the gait cycle, this study can support existing research in the analysis of the relationship between arm-swing motion and the angular motion about the vertical moment at the foot [31]. Research has also shown that different frequencies of arm-swing oscillation can be used to identify walking patterns in the sagittal plane [32,33]. The model in this study can be applied to simulate arm swing motion to further analyze experiment data capturing upper extremity occlusion [34]. For pathological gait patients, this approach can also contribute to the call from the medical community for more assessment methods to assist with diagnostics of diseases influencing gait.

Although the state-of-the-art in human motion analysis has moved into 3D kinematics, a validation of this deterministic model with 2D results is justified and comparable with the literature. Reducing complex

Table 3: A Comparison between the Distinct Flexion and Extension Phases of Shoulder Motion

Subject #	RMS-Flexion (°)			RMS-Extension (°)		
	Measured	Predicted	%Δ	Measured	Predicted	%Δ
50	7.74	10.12	30.7	5.04	6.46	28.2
51	7.40	9.07	22.5	7.89	11.48	45.4
52	7.90	9.42	19.4	8.39	9.92	18.2
53	8.18	9.54	16.5	5.90	8.88	50.5
54	11.29	13.18	16.7	8.42	11.98	42.2
56	6.63	7.014	5.7	6.66	9.51	42.7
60	3.39	4.70	38.4	3.28	3.18	-2.9
62	8.35	7.07	-15.3	8.40	7.01	-16.5

motion by projecting limb position into a single plane of rotation has been previously described for the hip and knee joints [35], the ankle [36], and the lower back [37]. The results here were similar in terms of precision with these previous works where body marker motion associated with skin displacement errors.

As described in the results, the comparison between the measured and predicted shoulder angular positions indicates that the proposed model may be highly precise but minimally accurate. The limitations in this work are strongly linked with characterizing 3D motion within a single 2D plane. The shoulder is a joint with three DOFs of rotation [38]. Each projection onto the sagittal plane will lead to compounded errors throughout motion. However, with additional 3D analysis, it is felt that these 2D errors can eventually be minimized.

This work represents an initial effort in validating a proposed deterministic IK model of human shoulder motion. The analytical approach described here will continue to be applied toward gathered data in an effort to therapeutically identify normal and abnormal motion. The implications of these and future findings will be used to enhance the clinical applications of motion analysis by providing refinements with which to improve diagnosis and guide therapy.

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