Generalized and Probabilistic Modeling of Biomechanics Sensory Data

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Abstract**—**Through a robust and comprehensive analysis of data collected from XSens IMU sensors during a variety of exercises at varying weights, we propose a generalized and probabilistic modeling approach to quantitatively understand a subject's form and performance. This is for the objective of offering clinical practitioners useful and practical techniques to provide better guidance in training and rehabilitation. We conclude our approach provides a strong localized and global view into a subject's fitness behavior through data mining and simulated Bayesian estimation.

Keywords**—***biomechanics, kinematics, fitness, imu sensor, data mining, time series mining, bayesian estimation, probabilistic modeling, monte carlo simulation, markov chain*

I. Introduction

We analyze a series of fitness activities (bench press with varied weights, squats with varied weights, ball kick, and ball throw) for 2 objectives: 1. develop a method to help a physiotherapy clinic measure the power generated in rehabilitation exercises and 2. determine the repeatability of the exercise across repetitions (reps within a set) and across sets (different weights). The quantitative analysis regarding power output is supplemented by a suite of metrics to get a wholistic, generalized view into the activity. These supplementary metrics provide insight into potential injury or muscle/join strain. We additionally propose a Bayesian estimation method to analyze the distribution and uncertainty of power output and elbow/knee flexion/extension within a set's reps and between sets. Our paper is based on physiotherapy research papers, validated biomechanics quantitative methods, time series data mining strategies, and probability theory/stochastic modeling (see references).

II. Methods

To generalize a solution, we extract reps for each of the bench press and squat activities by finding the local minima and maxima bar z-axis value for each exercise and setting a threshold equal to half the distance between these values. The method for detecting a single rep is then any waveform peak followed by a trough and another peak where the distance between each consecutive feature is above this threshold. This correctly (based on visual inspection of rendered data) yields a list of triple integer tuples each referencing the frame boundaries of the eccentric phase and the concentric phase which we use to differentiate some of our metrics. For power, we first calculated the force by multiplying the mass of the weight of the bar plus the given plate weights by gravity (9.8m/s). Then we multiplied the force by the displacement, which is the change in segment position from the start and end of the positions in a rep yielding the work completed. Power is a function of work over some time, so power values were all calculated using the 60 HZ sampling frequency and are presented in watts.[1]

For grip width, we calculate that by finding the Euclidean distance between the x, y, and z positions for left- and right-hand segments, and the minimum bar depth is calculated by finding the difference in segment position between left/right hands and sternum (T8) which is anatomically the best approximation of the chest we have available.

The *sticking point* is a common training term for the location within a rep where the lifter stalls, and the position of the sticking point within the concentric phase has training implications [9]. For both the bench press and squat activities we calculate the sticking point by identifying the minimum power output in the concentric phase in a 0.2s window and report the value in time offset since the beginning of the concentric phase of the activity[2].

In the squats analysis, we find the pelvis depth by finding the displacement of the pelvis z position in the eccentric (lowering) phase. The degree difference between the hips/knees is established by first understanding that the knee flexion/extension would be 135 degrees if the thighs are parallel to the ground. Therefore, if we set 135 degrees at the baseline, we can find the relation of hips to knees by subtracting the knee flexion angle from the baseline. This yields the degree of separation the hips/pelvis has from the knees.

The amount of data provided is small – from a single subject over a few activities with five reps in each activity. Frequentist statistical methods are challenged to adequately describe the differences between samples at this level, and we present instead a Bayesian analysis based on sampling using the PyMC3 library.

[1] Equations omitted for brevity.

[2] We choose the lower bound of the range described by Van den Tilaar & Ettema [1] as cited in [2] due to the relatively rapid lifts. In the data sampled at 60 HZ this results in a window of 12 observances, and our reported times are centered on average minima across reps of the bar midpoint as approximated by the average of left- and right-hand sensor data.

Absent of guiding literature on the subject, we model the prior and likelihood using a Normal distribution parameterized by sample averages and standard deviations. For all analyses we create a model sampled with 3 Markov chains over 1,000 iterations and verified that the chains converge for each model reported and that $0.95 < \hat{R} < 1.05$. We model the likelihood as a Normal distribution with a Half-Cauchy standard deviation as the prior as suggested by Gelman [3] as a reasonable default when using weak priors.

To evaluate the periodicity of power for each weight/exercise, we find the autocorrelation Pearson correlation coefficient by overlaying a lagged power series over itself to see if previous time steps correlate to future values .

III. Results: Bench Press

There are numerous form factors to consider depending upon the injury or training regime a therapist is supporting depending upon the situation of the athlete in question and their training goals. Show in Table 1, we measured the average power at each hand (and overall) throughout the concentric phase of the activity. Hands were relatively matched with a slight bias to the left hand throughout each weight range, suggesting a greater range of movement (more distance was being covered in the same amount of time) on the left side. Power dropped dramatically in the last weight range, suggesting fatigue or that the athlete has hit their strength limit. To investigate the bias of power, both between hands within a rep and between reps, we plotted the Bayesian models for each weight set with a 94% highest density interval in Figure 1. Generally, the power models for each hand have highly overlapped HDI regions, suggesting minimal differences bilaterally in the athlete. However, the 25/35 Kg weight sets and the final 45 Kg weight set are significantly different, indicated by the lack of overlapping HDI regions. Clinically, the interpretation changes depending upon the goal of the athlete and training program – if the intention is to maintain levels of power across sets then the athlete should slow down on reps in the 25/35 Kg sets and focus training efforts on strengthening ability to increase power in the 45 Kg weight set.

The sticking point increases over as the weight sets increase. In the light weight sets the sticking point is early on, and likely is not a significant issue at light weights.[3] Being in the mid-range of the concentric movement for the heaviest weight, however, suggests further work by the athlete on the middle of the range could be beneficial.

Right and left elbow angles were compared across all sets (Table 2). A full discussion is omitted for brevity, however a Bayesian comparison (Figure 2) parameterized similarly to the previous models shows a concerning trend with respect to bilateral angle minimums (full or over extension, at the start of the eccentric movement and end of the concentric movement).

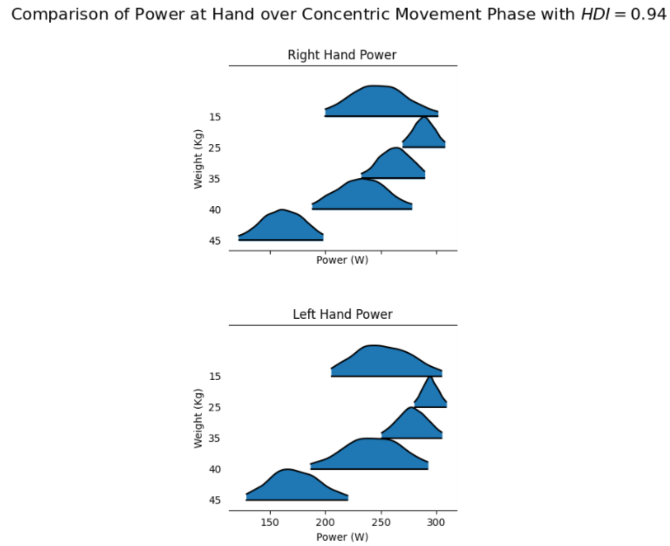

Figure 1: Bayesian credible intervals with HDI=0.94 comparing power between left and right hands across weight sets.

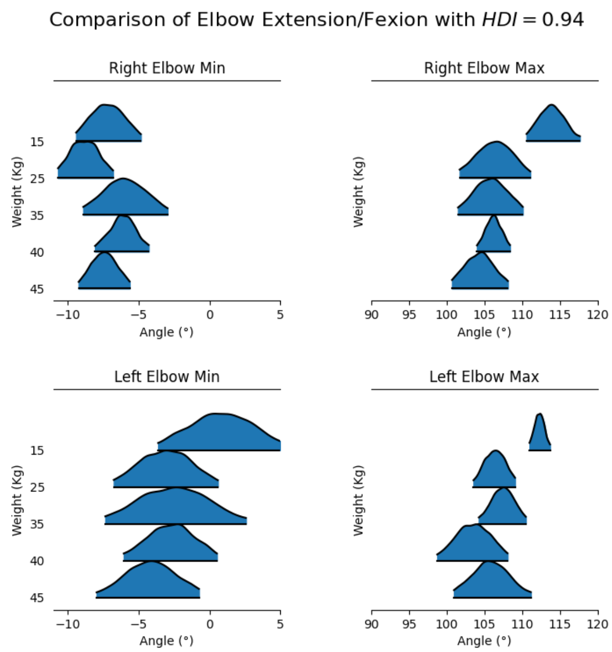

Figure 2: Bayesian credible intervals with HDI=0.94 comparing minimum and maximum elbow angles.

While HDI regions do overlap, the consistent skew of regions across all reps suggests that the athlete must overextend on the right-hand side compared to the left.

IV. Results: Squat

For squat, we similarly assess the activity from eccentric & concentric phases to evaluate form and performance from a

[3] Due to the limited time for the challenge and that sticking point was not a recommended feature of interest we chose not to do a model comparison across weights, however we expect that the sticking point for the lightweight sets is highly variable and essentially noise, while it may be more interesting for the heavy weight sets and building strength.

variety of metrics. We evaluate the average power (bilateral variation), average velocity, the sticking point, and max ankle dorsiflexion in the concentric phase while assessing hip flexion in the eccentric phase. Shown in Table 4, we see a strong decline in power after repetitive increase after 60 kg, indicating that the subject started to experience fatigue around that time. We do see a slightly larger average power output for the right hand, but this does make sense due to the subject being right-handed. The sticking point in the back squat does not seem to happen as frequent; we see the subject stalling in .47 seconds with the 80 kg weight but hardly stalling in lower weights. This could be suggestive of a high sticking point pattern, so the trainer may want to watch out for weaker back strength relative to legs. Our analysis also shows a good range for the left/right ankle dorsiflexion for general fitness purposes (27-31 degrees) which reflects a full or near full range of motion. The form for squat depth is consistent and stable for these 7 sets, with the hips never dipping below the knees hovering at about 95-110 degrees (Table 5).

We break out right/left knee flexion (Table 3)to appropriately bilaterally assess means and variation within & between sets. The Bayesian estimation (Figure 4) shows us, with 94% high density intervals, less variation (and a higher power output) generally for the 40-60 kg sets. This contrasts with the high variation and a low output at 80 kg and low variation and low output at 20 kg. Along with this, we see the max flexion of the right knee containing quite a bit of distribution overlap with the max flexion of the left knee, but still averaging higher values. This could translate to a recommendation of more bending of the left knee to ensure proper balance. The variation amongst knee flexions is quite significant as well, but we see best performance and form in the 60 kg set as there is minimal variation in flexion and a high/consistent power output.

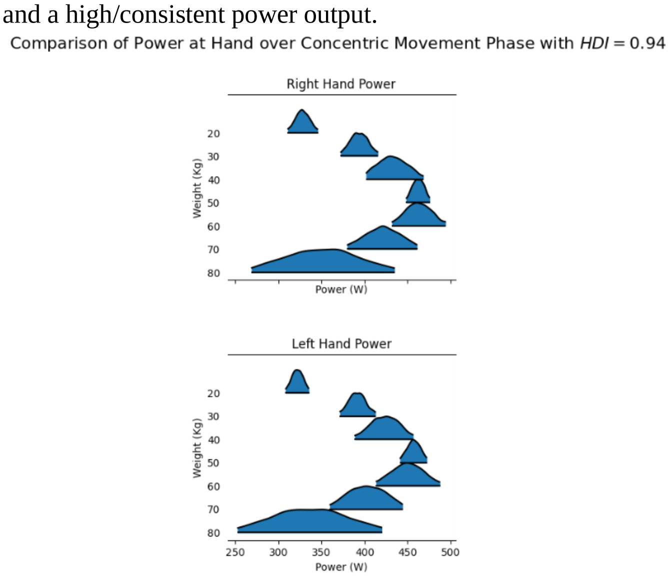

Figure 3: Bayesian credible intervals with HDI=0.94 comparing power between left and right hands across weight sets

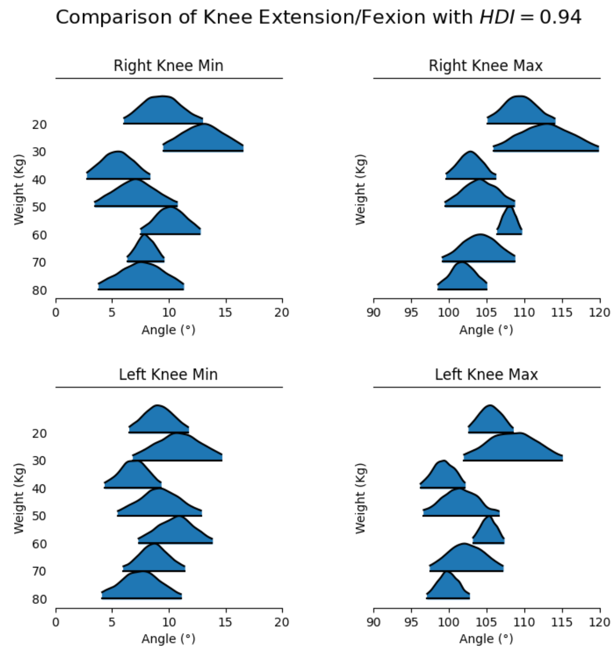

Figure 4: Bayesian credible intervals with HDI=0.94 comparing minimum and maximum knee angles.

V. Results: Other

In addition to assessing averages per rep, we can evaluate the periodicity of power over time for a given weight as well. This is done through finding the autocorrelation of power for left- and right-hand z-axis positions, which allows us to see how much variation there is in the sequence over time. Although the overlayed correlation decreases as weight increases, as expected, we see that there is relative stability in the periodicity of power with the Pearson correlation coefficient $R > 0.5$ for each weight for bench press and squats, which is significant indication of autocorrelation, or periodicity correlation in the time series of power output[4].

The approach to determining power for both ball kick and ball throw is based on how the authors approach determining the work done by a pitcher throwing a baseball. The work done by the thrower and the kicker in each repetition is determined by calculating the kinetic energy of the ball immediately after the ball has been thrown or kicked. Since we do not know the velocity of the ball, the velocity of the right hand/foot along the x axis is used as a proxy in its place. For calculating power we also need the delta time for each repetition. For every throw, the start time for a repetition is the frame in which the avatar's feet have stopped moving and the end time is the frame in which the thrower's right hand is perpendicular to the ground. For every kick, the start time for a repetition is the frame in which the avatar's left foot is firmly planted and the end time is the frame in which the kicker's right foot is no longer parallel to the ground. Since we only have a set of reps for each, there is not many conclusions we can draw with these two activities but

[4] according to Durbin-Watson Statistic

there does seem to be high variation in each so little consistency in how the ball is kicked or thrown is exhibited (Table 6).

VI. Clincal Relevance and Application

Our solutions propose novel quantitative approaches to enable trainers/physiotherapists to understand the nuance for a given activity, within a set and between sets. We highlight not only the averages for each weight so the clinic can see general trends, but we also quantify the uncertainty of those estimates which gives insight into the variation. If a subject were consistent in their workout, we would see distributions with minimal variation and all concentrated around the same means. This is largely what we find when evaluating left/hand power for squats – there is a lot of balance between both hands. In contrast, if a subject is inconsistent then we would see high variation and means moving around. This is what we find when we evaluate the power distributions across the weights for one hand, especially as the weights increase. When we look at the elbow/knee flexion/extension we are looking for not only balance between the two joint angles, but also that they align with one's goal. For general fitness purposes, trainers may want to see if individuals display ample mobility and joint range of motion. In the squat, for example, this typically requires at least 15-20 degrees of ankle dorsiflexion and 120 degrees of hip flexion [4], otherwise a person may be at a greater risk of injury to the knees, hips, or lower back [5.6]. If a person has had history of knee injury and are undergoing recovery, then they should restrict knee flexion to 50-60 degrees to minimize posterior shear forces [7]. Our method enables trainers to work with patients, depending on their goal, see the common patterns at various weights that they move their joint angles to see if they are adequate given the patient's scenario. The clinical relevance of the averages of about 5 reps per weight class is limited as it only shows a generalized view into a few workouts, but there is significant relevance of quantifying the uncertainty and distribution of that workout as it allows clinical practitioners to see beyond just one or a few workouts through simulations and probabilistic modeling. Getting precise and accurate estimates and qualified understanding of uncertainties when it comes to clinical settings is imperative as usually, they are working with a small sample of a subject's workouts/fitness regimen. Our approach allows clinical practitioners to look beyond the data to draw inferences and make recommendations.

VII. Discussion

Our chosen methods to calculate power (average over a series of reps and Bayesian estimation) provided two crucial views into the activity, but they each have their limitations for interpretation. For the average over a series of reps, it is difficult to make inferences for changes in activity from a macro perspective as we do not know how 'normal' that average is. A solution to this would be to have the subject take endless reps/sets so you can keep taking averages, but this can be costly (time and money). Due to this, we propose the averages as a micro-approach for trainers to advise specific changes that should be done during that one training session and recommend the Bayesian estimation approach to see macro-methods. The Bayesian estimation approach allows trainers to quantify how 'normal' a given rep or set was as it provides uncertainty estimates based on some prior knowledge which reflects the central limit and variation within and between an activity. This enables inferences to be drawn about the consistency, stability, and bilateral balance of an activity through simulated repetition. Both methods can be paired simultaneously with time series analyses to show real-time trends and updates to the micro- & macro- methods.

VIII. Conclusion

In this study we look at each set by finding the periodic repetitions and calculating average metrics to generalize the activity to a reasonable degree. We focus primarily on the concentric phase of each rep, and this allows us to see whether the subject's power output, joint angle flexion, grip width, squat depth, and more are within means given the height, weight, and objective of the subject. We add outputs of the sticking points in the bench press and squat to see when there is dramatic decrease in the power output in the concentric phase, which can reflect different potential points of injury/strain and different remedy strategies. The issue with only looking at averages for an activity is that it provides a microscopic view into a given set or a minimal set of workout exercises and this inhibits the trainer from having a macro perspective of coaching a subject to achieving their goals. Due to this, we conduct Bayesian estimation through Monte Carlo Markov Chain models to estimate the probability distribution of power output and elbow/knee flexion which yields insight into how concentrated and variable a given workout was. This approach allows the trainer to conduct simulated models of a workout for a subject which can save the clinic/subject money and time without sacrificing rehabilitation. For future improvements, we would recommend adjusting the weakly informative priors in our models with stronger priors advised by physiotherapists/trainers that allows more precise knowledge to be embedded in the modeling. Additionally, we believe a machine learning predictive approach can also be leveraged to predict what activity a person is doing based on their biometrics and sensor data, and depending on the activity/their performance, these quantitative analyses could be triggered to provide real-time suggestions to encourage better form and performance.

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[10] 10.2 - Autocorrelation and Time Series Methods (The Pennsylvania State University, 2018)

IX. Appendix of Tables

	Concentric Phase					Overall		
Weight (kg)	Average Power (W)	Average Power Left (W)	Average Power Right (W)	Time (s)	Sticking Point Time (s)	Min Bar Depth (cm)	Grip Width (cm)	Total Activity Time (s)
15	249.6	251.2	248.1	0.47	0.24	10.5	53.9	1.07
25	291.7	294.5	288.8	0.52	0.46	9.9	52.9	1.13
35	270.8	278.6	263.1	0.67	0.67	9.6	54.2	1.26
40	237.4	242.2	232.6	0.83	0.83	8.9	56.2	1.46
45	166.6	171.5	161.7	1.25	1.1	9.6	55.8	1.96

Table 1: Bench press activity measures across weight sets

	Right Elbow				Left Elbow			
	Minimum		Maximum		Minimum		Maximum	
Weight (kg)	Average	Std	Average	Std	Average	Std	Average	Std
15	-7.16	1.23	113.8	1.79	0.80	2.34	111.3	0.73
25	-8.83	1.01	106.3	2.49	-3.06	1.98	106.4	1.50
35	-6.06	1.58	105.8	2.29	-2.50	2.53	107.4	1.64
40	-6.10	1.01	106.20	1.14	-2.71	1.74	103.6	2.50
45	-7.43	0.97	104.36	2.03	-4.12	1.94	105.8	2.65

Table 2: Bench press elbow angles, in degrees, across weight sets

	Right Knee				Left Knee			
	Minimum		Maximum		Minimum		Maximum	
Weight (kg)	Average	Std	Average	Std	Average	Std	Average	Std
20	12.9	1.72	109.5	2.34	12.7	1.60	105.5	1.62
30	13.1	1.57	112.9	3.70	11.6	1.04	108.4	3.60
40	6.8	1.71	102.7	1.71	8.3	1.15	99.4	1.56
50	7.6	1.27	104.2	2.49	9.3	.93	101.4	2.65
60	11.3	1.81	108.0	.86	11.6	1.93	105.1	1.01

70	9.6	1.87	103.9	2.53	10.5	1.63	102.2	2.60
80	8.2	.85	101.5	1.81	7.3	1.09	99.5	1.58

Table 3: Squat knee angles, in degrees, across weight sets

	Eccentric Phase	Concentric Phase							
Weight(kg)	Average Max Hip Flexion	Average Power (W)	Average Power Left (W)	Average Power Right (W)	Average Velocity (m/s)	Time (s)	Sticking Point Time (s)	Average Max Left Ankle Dorsiflexion	Average Max Right Ankle Dorsiflexion
20	99.5	325.4	321.9	328.0	.81	.52	.2	27.1	30.8
30	95.2	392.9	390.7	393.7	.78	.55	.2	27.5	33.7
40	105.0	428.2	423.8	432.0	.68	.59	.2	27.4	26.5
50	99.9	461.2	457.1	462.3	.63	.64	.2	28.8	27.0
60	99.7	458.2	449.6	421.2	.55	.74	.2	30.8	29.9
70	95.9	413.8	402.7	421.2	.44	.87	.2	29.9	28.2
80	101.6	344.2	335.8	349.3	.32	1.16	.47	29.1	27.6

Table 4: Squat activity measures across weight sets

	Overall		
Weight (kg)	Average Pelvis Depth (cm)	Degree Diff. Hips/Knees	Total Activity Time (s)
20	-.35	27.5	1.60
30	-.36	24.4	1.38
40	-.32	33.9	1.53
50	-.33	32.2	1.52
60	-.35	28.4	1.64
70	-.32	31.8	1.81
80	-.32	34.1	2.15

Table 5: Squat pelvis measures

	Power (W)	
	Throw	Kick
Rep 1	4.6	76.7
2	14.0	87.3
3	9.8	176.9
4	11.5	111.8
5	9	246.6
6	6.7	147.4
7	--	140.4
Average	9.3	141.5
Std dev	3.3	57.7

Table 6: Ball throw and kick measures across reps