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Statistical Analysis on the Human-Likeness of 3D Reaching Movements in Humanoid Robots

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Abstract. Human-like motion is often considered a key feature for intuitive human–robot interactions. In fact, this feature allows human peers to easily predict the robot's intention, which is perfectly aligned with the paradigm of collaborative industries, contributing to more human-centric and resilient industries. The *one-sixth power law* (1/6-PL) is well known in human motor control. In this work, the **H**uman-like **U**pper-limb **M**otion **P**lanner is used to generate three-dimensional (3D) movements of an anthropomorphic robotic arm. By applying direct kinematics, the position and orientation of the hand of the robot is determined. Subsequently, the respective curvature, torsion and velocity are computed. From a total of 600 movements, divided in six sessions, non-linear regression models are fitted and validated, in order to obtain the slope in the log-space of these movements. A statistical analysis of the parameters of the 1/6-PL is performed, and parametric and non-parametric tests are used to compare the results in each of the six sessions.

INTRODUCTION

Human-like motion is often considered a key feature for intuitive human–robot interactions, since they allow human peers to easily predict the final intention of a robotic movement. This is perfectly aligned with the paradigm of collaborative industries (or "Industry 5.0"), contributing to more human-centric and resilient industries [1].

Several relationships between the velocity and the geometry of a hand path have been found in studies on human arm motor control. The *two-thirds power law* (2/3-PL), originally introduced in [2], is a very well known model of human movements. It states that, the tangential velocity, v, of planar hand writing movements is inversely proportional to the path curvature, k, to the power of one-third, i.e. $v = \alpha\, k^{-1/3}$, where α is a constant. Pollick et al. in [3], have generalized the 2/3-PL, in the *one-sixth power law* (1/6-PL), which introduces the hand torsion in the mathematical formulation of the law. According to the 1/6-PL, the tangential velocity of the hand, v, is inversely related to the one-sixth power of the square of the curvature, k, multiplied by the torsion, τ, i.e. $v = \alpha \left(k^2|\tau|\right)^{-1/6}$.

In this paper, a set of unconstrained reaching movements, generated by the Human-like Upper-limb Motion Planner (HUMP), proposed in [4], is statistically analysed. Specifically, the kinematics of a robotic hand mounted on an anthropomorphic manipulator is studied to identify the similarities with the 1/6-PL. The aims is demonstrating that the HUMP algorithm is capable of consistently planning human-like end-effector three-dimensional (3D) trajectories that obey the 1/6-PL.

GENERATION OF THE REACHING MOVEMENTS

The **A**nthropomorphic **Ro**botic **S**ystem (**ARoS**) [5], consisting of a static torso, equipped with a seven degrees of freedom (DOF) anthropomorphic robotic arm, a three fingered robotic hand and a stereo vision system mounted on a pan-tilt unit, was used in the simulations. The dimensions of the torso were determined taking into account anthropometry studies by [6], enhancing functional anthropomorphism and promoting human-like behaviour to minimize people's aversion [7]. The posture of the arm and hand of the robot is denoted as a n-dimensional vector, where n is the number of joints involved in the motion planning, i.e. $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_n)^\top$. The movements which will be analyzed is the present work were simulated using the HUMP (see [4] for a detailed description). Preeminent inspiration was taken

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from the Posture-based Motion Planning Model proposed by [8] and [9], which explains how humans generate upper-limb movements in different goal-directed tasks and in presence of obstacles. Human-like movements are generated by a so-called *direct movement*, $\mathscr{T}_{direct}$, which results from the minimization of the angular jerk (i.e. minimization of $\dddot{\theta}$), over the period of the execution of the movement, T. $\mathscr{T}_{direct}(t;\boldsymbol{\theta}_{tar}) = (\boldsymbol{\theta}_{tar} - \boldsymbol{\theta}_0)\left(10\left(\frac{t}{T}\right)^3 - 15\left(\frac{t}{T}\right)^4 + 6\left(\frac{t}{T}\right)^5\right)$ brings the arm and the hand of the robot from a `start posture`, $\boldsymbol{\theta}_0$, to a `target posture`, $\boldsymbol{\theta}_{tar}$, correspondent to a given hand target pose (position and orientation) in the Cartesian space. The `target posture`, $\boldsymbol{\theta}_{tar}$, is the solution of a non-linear constrained optimization problem that minimizes the angular jerk of the related *direct* trajectory and is selected such that collisions with obstacles and the body of the robot are avoided [4]. T is the duration of the trajectory that is computed according to a human-like time parametrization [4]. After computing the trajectory of each joint, the position and orientation of the hand in 3D is obtained using direct kinematics. With these points it is possible to obtain the velocity, v, the curvature, k, and the torsion, τ, of each simulated movement.

Assuming that the exponent of the 1/6-PL is unknown, i.e. $v = \alpha(k^2|\tau|)^{-\gamma}$, the constant α and the exponential γ will be obtained using ordinary least squares. Non-linear regression must be applied to find the best fit, by determining α and γ simultaneously. By applying the logarithm the following linear model is obtained:

$$\log(v) = \log(\alpha) - \gamma \log(k^2|\tau|). \tag{1}$$

The approximately least-squares regression values can be found by linear regression in the log-space, for determining $\log(\alpha)$ and γ (see e.g. [10, 11]). Note that, a constraint on the relation between curvature and torsion of the movements is imposed. Equation 1 shows a proportional relationship between the logarithm of the tangential hand velocity, $\log(v)$, and the logarithm of the square curvature multiplied by the torsion, $\log(k^2|\tau|)$. Therefore, this relationship can be verified by fitting a linear model on the points obtained by the planned movements.

A total of 600 reaching movements, divided in six sessions of 100 movements each, were generated by the planner in the 3D workspace. The position of the target hand is randomly selected from a 50 $cm \times 60$ $cm \times 60$ cm paralelepipedal in front of the robot. The points in the trajectory with absolute torsion, τ, less than 2 m^{-1} were excluded in order to avoid unreal cups raised when the torsion changes sign [3]. Also, the points with curvature, k, very close to zero were excluded to avoid numerical problems in the calculus of the logarithm.

RESULTS AND DISCUSSION

The analysis was performed using RStudio (version 1.4.1106) and R Statistical Software (version 4.0.5) [12]. For each reaching movement, the corresponding linear regression model was validated and residual analysis was performed, for a significant level of $\alpha = 1$ %. Next, a new database was built with the obtained results, namely: the estimates for $\log(\alpha)$ and γ and the corresponding standard errors; the p-values of the Shapiro- Wilk (SW) normality test and of the Durbin-Watson (DW) test; coefficient of determination R^2, the global and the marginal tests. The regressions presenting a p-value of the SW normality test and DW test, for the independence of the residuals, $< 1\%$ were excluded, since these models were not valid. Thus, a total of 367 movements, i.e. approximately 61% of the planned movements, are considered.

TABLE 1. Validation of the regression models and average, standard deviation and 99% Confidence Interval of γ.

Sample	R^2		F	$\log(\alpha)$	γ	Residuals	SW	DW	Slope, γ		
size	min	max	max p-value			Av.	min p-value		Av.	StD	99% CI
367	0.8713	0.9939	9.83E-05	1.62E-06	9.83E-05	0.53	0.0127	0.01	-0.202	0.007	[-0.203, -0.201]

Table I, shows that the coefficient of determination, R^2, of the regression are between, approximately, 0.8713 and 0.9939. Thus, at least 87.13% and at most 99.39% of the variability of the logarithm of the hand velocity, $\log(v)$, is explained by $\log(k^2|\tau|)$. It must be stressed that while R^2 indicates the strength of the regression model, verifying the adequacy of the model, as well as, performing the residuals analysis, is essential to evaluate the goodness of fit, and avoid the so called fallacy of R^2 (see e.g., [13] and [14]). Note that R^2 is not a measure of goodness of fit, and also thus not allow to compare models. In fact, a "wrong" linear models may have a large R^2 value.

The adequacy of these regressions is verified since, both the global F-test for significance of the regression, that determines whether a linear relationship exists between the response variable, $\log(v)$ and the explanatory variable $\log(k^2|\tau|)$, and the marginal tests, i.e. the individual regression coefficients tests, p-values are $< 1\%$.

Concerning the residual analysis of the 367 regressions, the p-values of the SW normality tests are $> 1\%$, thus it may be assume that the errors are normally distributed. Finally, the independence of the residual was tested using the DW tests, under the null hypothesis of mutual independence of the residuals. None of the 367 regressions presented p-values $< 1\%$. In summary, the 367 regressions for 3D reaching movements are valid.

Next, let us verify if there are significant differences between the distribution of the estimated model parameters ($\log(\alpha)$ and γ) and R^2, for the six sessions. Figure 1 shows the distribution of the estimated slopes (i.e. γ) over the six sessions. Note that, for each density curve, the height at any point is an estimate of the proportion of sample values per unit interval, locally at that point. These graphics suggest that there are no significant differences between the estimated slopes obtained in each session. In fact, the average slopes (vertical lines) of each session are quite similar. Also, the variability seems approximately the same. Furthermore, the slopes are all negative and mostly concentrated between -0.21 and -0.195.

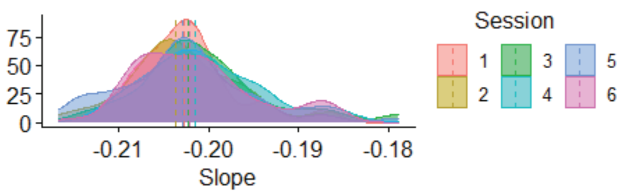

FIGURE 1. Distribution of the estimated slopes over the six sessions. The vertical lines represent the averages.

In the following, six groups, one per session, are considered. For deciding which is the most suitable statistical test for testing significant differences between the estimated slopes obtained in each session, it must be verified the assumption of homoscedasticity, i.e. homogeneity of variance, and also the normality of the six independent samples.

TABLE 2. Comparison of the slopes obtained on each of the six sessions for 3D reaching movements.

	ANOVA		**Brown-Forsythe**		**Kruskal-Wallis**	
	F	p-value	F	p-value	χ^2	p-value
Slope, γ	1.71	0.131	0.6	0.701	7.77	0.169

To test whether there are significant differences on the variability of the slope of the six groups, the Brown-Forsythe test for homogeneity of variance is used. This test uses the median to compute the center of each group, therefore, it is a more robust test than the most commonly used Levene's test, that uses the mean. For a significance level of 1%, there is no statistical evidence to reject the null hypothesis, H_0, that the variances of the estimated slopes obtained in each session are equal, given that p-value $= 0.701$ (see Table II). Therefore, there are no significant differences between the variability of the six groups. Since all the samples have more than 50 observations (more precisely, 56 and 57 for sessions 3 and 5; 63 for sessions 4 and 6; and 64 for the two first sessions) the normality may be assumed.

Since the homogeneity of the variances was verified, to compare the means of the slopes for the six groups (independent samples), Analysis of Variance (ANOVA) was used. The p-value of the ANOVA is > 0.131, thus, there are no significant differences between the mean slopes of the regressions obtained on the six sessions.

The non-parametric Kruskal–Wallis (KW) test by ranks was used for testing whether samples originate from the same distribution, in order to get a more robust analysis. Since the distributions for all groups are identically shaped and scaled (Figure 1), the null hypothesis of the KW test is that the medians of all groups are equal. For this, p-value$= 0.160 > 0.01$. Therefore, the null hypothesis is not rejected, and it may be concluded that are no significant differences between the medians of each group.

As it was showed, both from the parametric ANOVA test and the non-parametric KW test, there are no significant differences between the slopes of the regressions estimated for the six sessions.

For all the 367 regression, the average values of the slope, γ are approximately -0.202 and it presents a small standard deviation (Table I). Furthermore, the coefficient of variation, computed as the ratio between the standard deviation and the average, is 3.5%, showing consistency of the regression slopes. This is also observed on the 99% confidence interval (CI) $[-2.02, -0.201]$. The estimated slopes are all negative (see Figure 1), which goes in line with the observations made with human subjects. The maximum slopes was approximately $-0.1788 < -1/6$, only three of the regressions present $\gamma \geq -0.18$ and 1% have slopes ≥ -0.1839. Furthermore, the 99% CI does not include -1/6. Similar results were also observed in human experiments. E.g. in [3] the slopes range between -0.21 to -0.15 for different human subjects, -0.18 in average.

CONCLUSIONS AND FUTURE WORK

The present work contributes to the research on the generation of human-like movements in anthropomorphic robots, with a concise and complete statistical analysis. Non-linear regressions were adjusted, using ordinary least squares, to unconstrained reaching movements generated by the Human-like Upper-limb Motion Planner [4]. The regression models found were validated and residual analysis was conducted. A careful statistical analysis of the parameters of the model, called the $1/6$-PL that was observed in human movements, was performed.

It is concluded that all fitted models, as well as its coefficients, are statistically significant. Furthermore, residuals are normally distributed and independent. Coefficients of determination, R^2, larger than 0.8713, reveal a high degree of explainability of the non-linear models. Both parametric and non-parametric tests, show that there are no significant differences between the parameters of the non-linear regressions obtained in the six sessions. The obtained slopes are significantly negative as observed in experiments with humans. In fact, the average slope is approximately -0.20 and are consistent depicting small standard deviations (< 0.01) and coefficients of determination, in line with what was observed in human experiments.

Most works on this topic, present only the coefficient of determination, R^2, when analysing the regression. It is not clear if model validation and residuals analysis was performed. Relying only on R^2 may fall in the so-called fallacy of R^2 (see e.g. [13] and [14] for further details), and lead to wrong models. Thus the results obtained are not valid. We consider important that model validation and residual analysis are included in the papers on this topic.

One of the drawbacks of the present work is that the model presented in Equation (1) exhibits an explicitly constrains curvature and torsion. The use of the multivariate non-linear regressions, such as proposed in [3], could be a significant contribution in our future work. It is worth noting that, the results, obtained on several unconstrained reaching movements, confirmed the tight relationship between the application of the minimum-jerk model on motion generation and the implications with hand speed and curvature in a power law [15]. We expect that the present work contributes to more deeply understand this relationship for any humanoid agent.

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