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ORIGINAL ARTICLE

Towards statistical analysis of predictive parameters in competitive speed climbing

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Abstract
Competitive sport climbing progressed massively within the last quarter century. Development of technology enabling qualitative and quantitative analysis is required to withstand the challenges for athletes and trainers. This paper deals with the statistical study of a data set generated by the application of several image processing algorithms and neural networks on competition recordings. Therefore, calculated parameters are combined with random variables for the implementation of a linear mixed effect model. The resulting model enables the prediction of the end time of different athletes and the determination of its correlation with the input variables. Furthermore, analysis of velocity and path of the centre of gravity in different wall sections is done for all available speed climbing athletes. The observed data set consists of 297 runs in total divided into two subsets of 202 observations of 47 male and 95 of 25 female athletes. Among others, the statistical model was used for the validation of the measured parameters and the review and impact of proven techniques like the Tomoa skip in the start section. Likewise interesting is the high influence of the parameters, measured especially in the middle section of the wall, on the end time.

Keywords Performance analysis · Statistics · Computer vision · Sport science

1 Introduction

The participation at the past Olympic Games 2021 in Tokyo reflects beyond doubt the development of the climbing sport in the last few years. With the growth of popularity and media attention, also an increase of the requirements set to athletes and trainers is clearly visible. Especially with the temporary fusion of bouldering, lead and speed climbing to one evaluated Olympic discipline, the focus on specific training methods has changed. While the two classic disciplines lead climbing and bouldering share similar training efforts, speed climbing activates different body regions and is therefore not comparable. Therefore, the competition mode at the Olympic Games 2024 in Paris will separate speed climbing as a single discipline.

Due to the standardized and unique speed climbing route map, training sessions concentrate on the perfection on movements in different sections of the wall, namely the start, middle, and end section. The separation of the wall is exclusively defined by the speed climbing community and especially by trainers and athletes. Due to the specific arrangement of the climbing holds, a characteristic progress of velocity and acceleration is given. Therefore, before reaching the sixth hold, the athletes are accelerating their body in the start section before reaching a more or less constant velocity. At this point, this constancy remains within the middle section by executing a "ladder movement". Touching hold 12 the athlete enters the end section, where the velocity again drops due to the positioning of the following holds and a drop in the performance.[1]

Consequently, only a few combinations of possible hold sequences to reach the end buzzer have extracted. Especially, in the starting section, covering roughly the first third of the

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[1] The explanation about the division of the speed climbing wall is currently not scientifically investigated and therefore reviewed with trainers and confirmed by measured data of velocity and acceleration of the athletes' centre of gravity.

wall, the athlete's route maps differ from one another. To master the first part of the speed climbing wall and transfer high velocities to the next sections, the momentum arising from the explosive jump at the very beginning should be carried upwards. Thereby, three techniques originated in the last few years for the accomplishment of the start section: The Normal start, the Reza move, and the Tomoa skip.

Alongside the Normal start, the initial starting technique employing all hand and foot holds in the starting section, the the Reza move and Tomoa skip were invented to gain advantages in terms of time saving. By skipping the fourth hold on the far left, the centre of gravity follows a more vertical route resulting in the preservation of this momentum. This omission of the hold was first performed by the former world record holder Reza Alipour Shenazandifard in 2017 and hence has been named as Reza move. In 2019, the speed climbing athlete Tomoa Narasaki adapted the Reza move by skipping the third foot hold additionally. The therewith obtained reduction of the path of the body mass centre leads indeed to a deep squad position. According to previous studies [1–3], the resulting knee joint angles sharper than 90° lead to losses in jump height, ground reaction force, and thereby a possible minimum in velocity. Despite this critical loss of velocity at the start of the route map, the advantages of a shorter path length seem to predominate. Hence, most world class speed climbing athletes, including the current world record holder, favour the Tomoa skip.

These techniques demand high coordinative skills from the athletes and thus several training sessions under experienced trainers' watch. To further improve the technique and detection of possible mistakes, the usage of measurement units is also necessary. Therefore, this paper deals as an enhancement of the research in the field of the climbing sport, which is, compared to other Olympic disciplines, substandard.

The continuous determination of parameters describing the athletes' success is indispensable. Hence, research in sport climbing tries to tie up with other sports like running or cycling with the development of systems for the assignment of measurable parameters. Therefore, motion-describing variables like position, velocity, or acceleration of certain body key points and the athletes' force output can be combined with morphological parameters like height or arm span. The psychological influences on the performance must also not be neglected in the process. Several studies focus on the identification of psychological variables in sport climbing and their relation to the athletes' performance [4–6].

An example for the application of a measurement system for sport climbing purposes is introduced in [7, 8]. Combining both motion tracking and precise force measurements, it consists of a three-axis force measurement unit and a marker-less motion tracking framework based on the neural network OpenPose [9]. Accepting a loss in accuracy of the position of human body key points, it enables due to the simple installation a variety of measurement setups to determine several parameters while climbing. Nevertheless, this measurement set-up is not employable for speed climbing purposes. The mere modification of the unique route map with the addition of mentioned force measurement equipment to the holds would distort the athletes' movements.

However, within the field of speed climbing, research is still in an early stage of development. In the case of [10], the presented methodology deals with the determination of fluency and velocity, though for the usage in lead climbing. Nevertheless, the applied measurement equipment by Luxov (LUXOV Connecting Climbers, Chessy, France) is likewise used for the recording of contact times of the limbs in terms of modified standardized holds for speed climbing route maps. Reference [11] developed a drone-base camera system for the 3D motion analysis in speed climbing. With the tracking of a marker placed on the harness, the recording of its velocity and the spatial components enable, among others, the detection of critical phases in speed runs. In comparison, Ref. [12] introduced a statistical analysis of speed climbing runs studying the World Cup in 2019. Beside manual analysis of possible correlations between start reaction times and overall climbing times, different sections of the speed wall were parsed as well as error rates in various final rounds determined. Unlike these approaches, the described methods in [13] rely on the application of image processing algorithms for the calculation of several parameters within speed climbing trials through their recordings. Considering measurement uncertainty due to constraints like resolution, frame rate, or recording set-up, this solution allows an on-the-fly real time analysis of the motion of speed climbing athletes.

Based on this, the following sections will describe the structuring of a data set consisting of several measurable parameters. The combination of few neural networks will enable the calculation of motion-describing parameters especially position, velocity, and acceleration of different body key points and the centre of gravity (COG). With the determination of contact times for hands and feet, the athletes' movement can be even more parsed in detail. All these kinematic parameters reflect the performance of speed climbing athletes in different ways. With the analysis of the COG, for example, the detection of drops in the performance could be categorized as fatigue, error, or as basis for improvement by comparison with other athletes or among themselves. A statistical evaluation of the measured data and the composition of a model will allow a detailed analysis of motion patterns in single wall sections in speed climbing. Due to the novelty of speed climbing data, the main aim of this paper is the validation of the determined parameters with the proof of commonly known performance conclusions in speed climbing such as the application of established techniques.

Consequently, the achieved end time of every run is used as a performance parameter and through its correlation with several calculated and given variables, following hypothesis is proposed: The executed starting technique exhibits a significant correlation with the end time and therefore with the athlete's success.

2 Materials and methods

The absence of measurement equipment such as markers on the athlete's body leads to a deployment of a system for the joint recognition of the human body based on a convolutional neural network [9]. With the aid of the determined locations of the body key points and COG, the courses of their motion, velocity, and acceleration as well as all important joint angles can be computed. For the comparison of these parameters among different athletes and competitions, the transformation of pixel values to world coordinates is necessary. Therefore, several features on every frame are extracted [14–16] and used as input for the algorithms described in [13].

Applying these algorithms on all available recordings of speed climbing competitions results in a data set containing all calculable parameters describing the motion of the athletes. The following section deals with the description and preparation of the data set used for further statistical analysis.

2.1 Generation and preparation of the data set

Before a detailed statistical analysis can be started, the used data set should be carefully assembled and prepared. Since a meaningful analysis requires a large and significant data pool, all available videos recorded and published by the International Federation of Sport Climbing (IFSC) were included. In summary, about 400 recordings of 11 competitions in six countries and 139 athletes (69 females, 70 males) were used as input. The frame rate of all these recordings is limited to 25 FPS and the used camera setups differ for multiple IFSC events, which leads to unknown specifications like focal length or distance to the climbing wall. Therefore, the estimation of the camera parameters is part of the used algorithms. Due to missing video footage of qualifications, the data set consists of speed climbing races starting from the round of 16 up to the finals including a small final for the ranking of the third place. Beginning with runs in 2017 and excluding the year 2020 due to the Covid pandemic, all competitions hosted by the IFSC and therewith all participating athletes were analysed with the aid of the dedicated algorithms. Recordings generated at the Olympic Games 2021 in Tokyo are not considered due to the execution as a combined discipline and the thereby outlying performances of non-speed-climbers.

Since recordings published by the IFSC contain a whole competition day consisting of both female and male athletes, these videos need to be trimmed to obtain videos involving one speed climbing run of two duelling athletes. Simultaneously, each video editing is classified in following descriptive group variables: Competition, Year, Final round, Gender, Climber, Start technique, and End time.

By means of the declared algorithms in [13], all possible parameters describing the motion pattern of the speed athlete can then be calculated. The detection of the human body and its joints, the position of several holds and the following conversion from the image plane to a world coordinate system enables, among others, following calculations:

- Path length and velocity of the COG for different sections of the wall.
- Pasted time for different sections of the wall.
- Contact times for hands and feet.
- Angle between straight lines made up of the shoulder joints and hip joints.
- Deviation of the path of the COG from a straight vertical line.

All these parameters and their validity depend on the correct detection of the feature detection algorithms. Therefore, the inspection and filtering of the created data set are inevitable in terms of a valid statistical analysis.

In a first step, data points containing athletes with invalid trials due to falls before attaining the end buzzer or faulty detection or calculations are filtered out. Therefore, additionally to the mentioned determined parameters, the end time t_{est} of each athlete is estimated

$$t_{\text{est}} = \frac{\sum_{i=0}^{\tau} |\boldsymbol{x}_i|}{\tilde{\boldsymbol{v}}}, \tag{1}$$

with $\boldsymbol{x}_i$ as the position of the body centre of the ith frame and $\boldsymbol{v}$ as the median of the velocity vector of all frames. The value τ defines the sample number, at which the climber reaches the end buzzer. This moment is determined by analysing the motion of the body centre of the athlete. The vertical position of the COG (y-component) on the climbing wall is thereby rising to the point when the climber stretches to reach the end buzzer. The initiation of the following reverse movement of the COG indicates hence an approximation for τ. The calculation of the ratio between estimated and actual end time serves then as one filtering size, by defining a thresholding range of $\pm 5\%$.

In further steps, the data table is moreover analysed to eliminate outliers and achieve nearly normal distributed data columns. Therefore, all columns containing measured data are filtered by applying the interquartile rule to find and remove outliers. Thereby, the interquartile range (IQR), defined by the difference of the first (Q_1) and third (Q_3) quartile, is calculated and used for the elimination of an outlier o by meeting one of following conditions:

$$o \leq Q_1 - \mathrm{IQR} \cdot c \tag{2}$$

$$o \geq Q_3 + \mathrm{IQR} \cdot c. \tag{3}$$

The constant c defines the extent of the applied filter and is commonly set to 1.5. Besides, the data set is gender-dependent divided and filtered by end times describing successful runs (6.5 s for men, 8.0 s for women). Finally, the resulting data set consists of 297 speed climbing runs of 47 male and 25 female athletes, and 25 descriptive variables. It should be mentioned that the sample size of the data set needs to be carefully regarded and kept high in relation to the number of independent model parameters. Therefore, the filtering should be done regarding an acceptable data table height for further analysis.

2.2 Statistical analysis

After preparing the data set containing different parameters, the statistical analysis can be started. Therefore, the transformation of this data table to a model, which describes the behaviour of speed climbing athletes while competition is intended. By creating such a model, one should be able to get an idea of motion patterns, their single properties, and their correlations with the end time. Additionally, it should enable a prediction of the end time by knowing the model descriptive parameters. Using all or only a subset of the values described in the previous chapter results in an introduction of a so-called linear mixed effect model.

A linear mixed effect model is a statistical test, which is used for the prediction of a single variable (response) in dependency of two or more variables (random and fixed effects). Additionally, it describes the relationship between this predictable parameter and the ones defining the model. Initially the prepared data table should be classified in these two clusters. Continuous values such as all measured or calculated quantities are categorized as fixed effects. Fixed effects are non-varying parameters, which ideally follow a true regression line. They serve as explanatory values with the expectation to influence the response variable. Whereby parameters describing boundary conditions of a speed climbing run like “final round” or “year” belong to random effect due to their grouping behaviour. Although an influence on the response is expected, the analysis of an impact on the end time has less priority. As a rough guide, it can be defined that variables with less than five unique values belong to random effects. In the case of the starting version as a parameter, the assignment to one of these groups can vary depending on the type of analysis.

A formula describing the model parameters and their relation to the response variable and other variables is deployed with the aid of the so-called Wilkinson Notation. It allows the declaration of either fixed or random effects provided by the data set. The definition of possible correlations among parameters and the number of random intercepts and slopes distinguishes the mixed effect model from a common linear regression. The linear mixed effect model is defined as follows:

$$\boldsymbol{y}_i = \boldsymbol{X}_i\boldsymbol{\beta}_i + \boldsymbol{Z}_i\boldsymbol{u}_i + \boldsymbol{\varepsilon}_i, \tag{4}$$

where

- $\boldsymbol{y}_i$ is the known response vector ($n_i \times 1$) for observations in the ith group.
- $\boldsymbol{\beta}_i$ is the unknown vector of fixed effect coefficients ($p \times 1$).
- $\boldsymbol{u}_i$ is the unknown vector of random effect coefficients ($q \times 1$).
- $\boldsymbol{X}_i$ is the known matrix for fixed effects ($n_i \times p$) for observations in the ith group.
- $\boldsymbol{Z}_i$ is the known matrix for random effects ($n_i \times q$) for observations in the ith group.
- $\boldsymbol{\varepsilon}_i$ is the unknown vector of errors ($n_i \times 1$) for observations in the ith group.

The data set and especially the fixed variables should be validated and inspected for a possible correlation with the response and among themselves. Passing variables with a high correlation against the end time and eliminating those, which remain under a certain threshold and correlate with other parameters, lead to a further reduction of the data set.

2.3 Ethics statement

The ethics board approval was granted by the corresponding author’s university UMIT Tirol. Only recordings from the IFSC were used to generate the discussed data set. We received written permission from the IFSC to use their visual material published on YouTube.

3 Results

By means of the introduced algorithms and the therewith generated data set, a further statistical analysis is enabled. However, before studying the overall data set with the aid of the described mixed effect model, some variables and their influence on the end time are inspected.

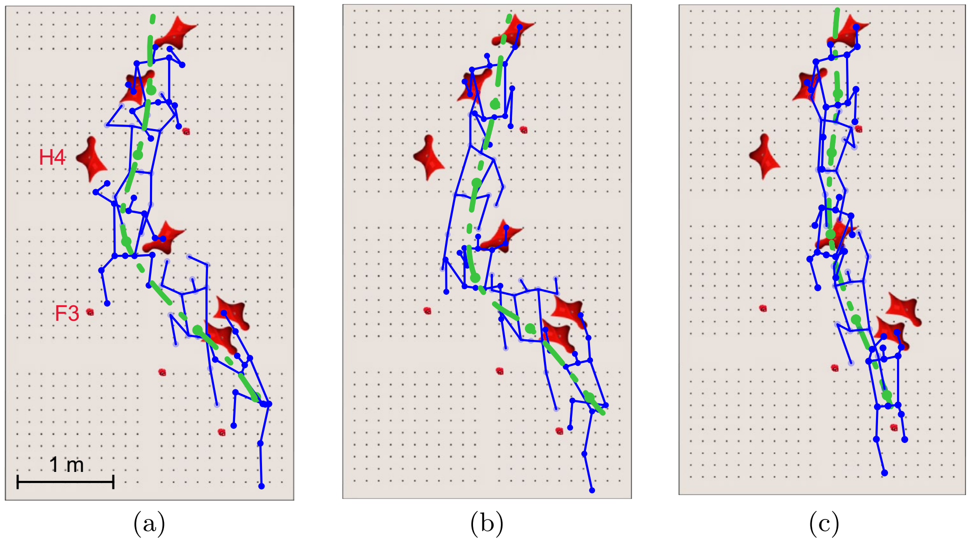

Fig. 1 Illustration of the three start techniques by the body skeleton at certain heights (blue) and the path of the COG (green) with marked fourth hand (H4) and third foot hold (F3); **a** normal start, **b** Reza move, and **c** Tomoa skip

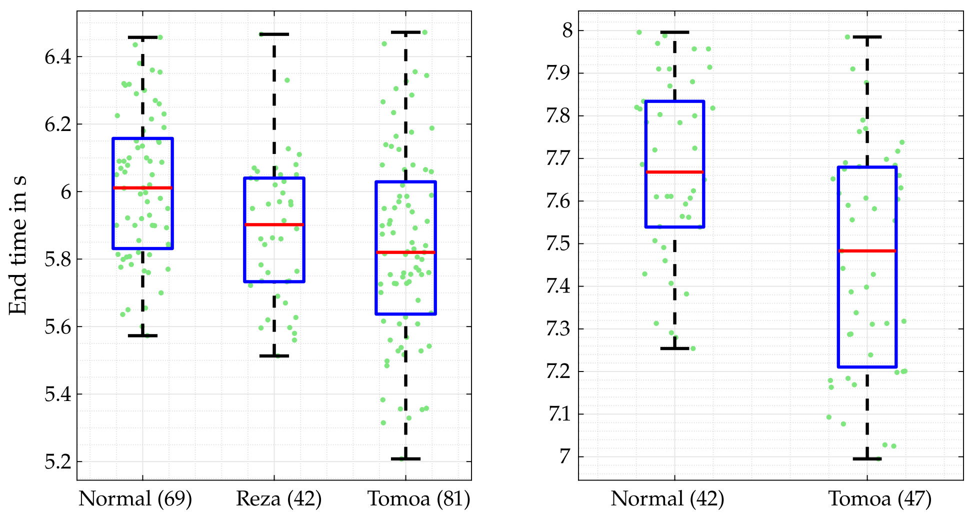

Fig. 2 Distribution of the end time depending on the applied start technique (with the number of participants in brackets) for male (left) and female (right) athletes

Due to the uniqueness of the speed climbing route map, the motion sequences of all athletes are similar. In general, the speed climbing wall is separated into three section: The Start section ending with the sixth hand hold, the Middle section including holds 6–12, and the End section containing the remaining holds. The greatest deviation of the movement is reported at the start section involving the first 5–6 holds. Thereby three different start versions are realized, mainly depending on the constitution of the athlete. Like previously described, these motion patterns differ from each other by the skipping of certain hand and foot holds. Figure 1 demonstrates the diversity of the single starting techniques by illustrating body skeleton postures and the resulting path of the COG.

What catches the eye immediately is the shortened path visualized in Fig. 1c, demonstrating the Tomoa skip. By skipping the fourth hand hold as well as the third foot hold, the athletes' body and its COG cling to a vertical line resulting in a reduction of the covered path. Compared to the other versions, the climber's initial posture differs a lot. Athletes using the Normal start or Reza move start with a far-right initial posture to reach the most left hand or foot hold or both. In contrast, the usage of the Tomoa skip allows a more central position of the initial COG and therefore the abstinence of a swinging motion of the torso. However, the usage of this technique requires a designated constitution, where especially the body height plays an important role. Therefore, female athletes prefer the usage of the Tomoa skip besides the Normal start (see Fig. 2).

The distribution of the end time grouped by the starting technique for male and female athletes is stated in Fig. 2. Thereby, advantages and disadvantages of using different techniques can be detected by the interpretation of the associated box plot. While median and minimum value are lower compared to the ones of athletes applying the Normal start, the maximum value and the length of the upper whisker

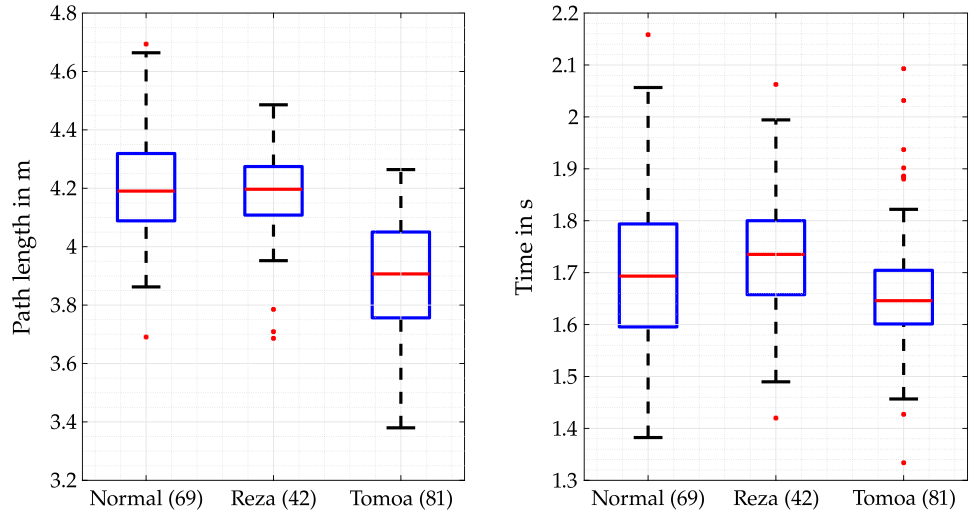

Fig. 3 Distribution of the path length and elapsed time in the start section depending on the applied technique (with the number of participants in brackets) for male athletes

Table 1 Path length and elapsed time in every wall section for all start versions described by mean and standard deviation analysed by one-way ANOVA

Start version	Path start (m)	Time start (s)	Path middle (m)	Time middle (s)	Path end (m)	Time end (s)
Normal	4.20 ± 0.18	1.73 ± 0.21	4.67 ± 0.08	1.96 ± 0.13	4.92 ± 0.26	2.37 ± 0.15
Reza	4.17 ± 0.17	1.73 ± 0.14	4.64 ± 0.07	1.92 ± 0.14	4.73 ± 0.29	2.26 ± 0.18
Tomoa	3.89 ± 0.19	1.68 ± 0.18	4.62 ± 0.07	1.90 ± 0.13	4.89 ± 0.22	2.33 ± 0.21
p-value	$\ll 0.001$	0.098	0.025	0.027	< 0.001	0.03

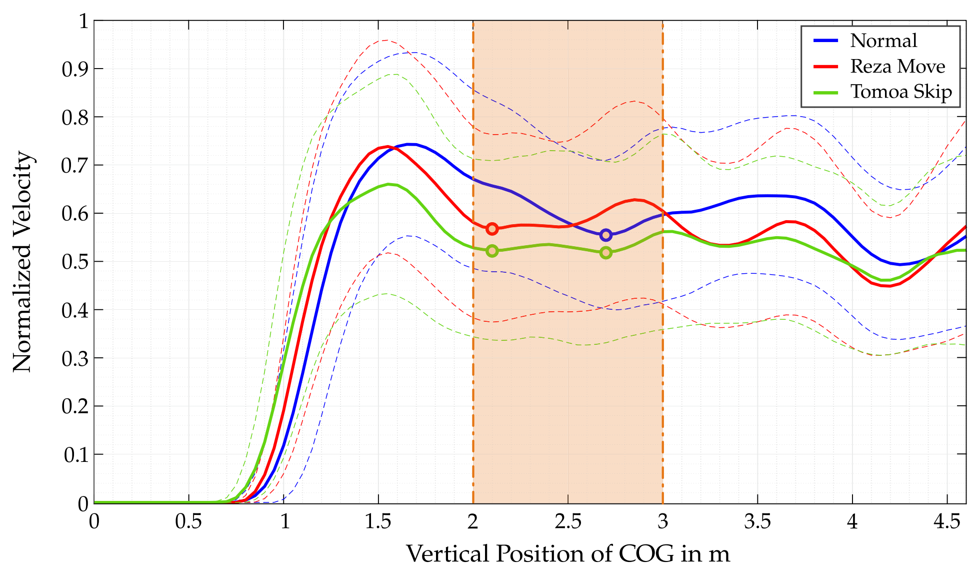

Fig. 4 Course of the normalized velocity represented by the mean (solid lines) and standard deviation (dashed lines) of male athletes using one of the three start techniques

indicate a similar failure rate for all versions. Due to the missing Reza move variety for female climbers, further analysis and comparison of the starting versions will be reduced to the male data (202 speed climbing runs).

The resulting path reduction compared to the other starting versions is significant (see Fig. 3). In terms of numbers, speed climbing athletes using the Tomoa skip save averaged around 0.3 m in the starting section, which corresponds to approx. 7.4% path length, compared to the Normal technique.

As appears from Table 1, the associated time saving corresponds to comparatively just about 50 ms (2.8%). Shortening the start section though leads to a deep squad position around the third hold and consequently to a local minimum of the COG's velocity. Figure 4 illustrates the mean velocity including the standard deviation of athletes

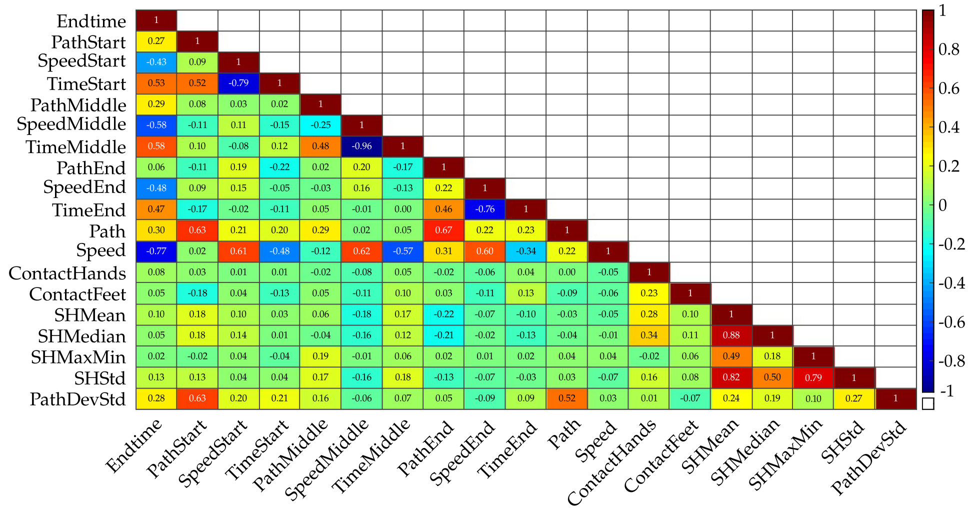

Fig. 5 Correlation matrix of the data set illustrating the magnitude of correlation from – 1 to 1

using one of the three starting versions. With the switch from samples to the height of the COG on the wall, a synchronization of all velocity vectors is done. Additionally, the velocity of the COG is normalized relating to its minimum and maximum value within the start section. Therewith, a clearer understanding of crucial changes in the velocity data is accomplished. The orange marked rectangle in Fig. 4 labels an important area in the start section, where the transfer of the high momentum established at the first few milliseconds occurs. This part of the speed climbing wall signifies critical positions of athletes with great influence on further movements. The mentioned squad position resulting from the Tomoa skip happens within this range, from 2 to 3 m measured off the ground. Considering the distribution of the velocity of athletes using this technique, two local minima (green dots) appear at approx. 2.1 m and 2.7 m wall height, where the latter corresponds to the vertical location of the third hold and lowest position of the exerted squad movement. The first mentioned minimum seems to appear due to the change from an initial stretched body posture to one pulling hands and feet towards the centre of the body. Compared to that, the progression recorded for the Reza move and the Normal start exhibit one local minimum each. In the case of the Reza move (red dot), the turning point develops from a similar squad position causing sharp angles for the left and right knee. Athletes using the Normal start generate this point (blue dot) at the moment of a directional change of their body, caused by the motion towards, respectively, fromward the fourth hold. The transfer velocity into the middle section shows no significant differences for all three techniques.

The analysis of the starting version therefore shows a possible correlation with the athlete's success measured against the end time. Due to the grouping behaviour of this variable, it will be treated as a random effect in a first step. However, the demonstrated influence on, among others, the starting section allows likewise an application as fixed effect.

The deployment of an appropriate statistical model requires the investigation of all existing parameters from the calculated and filtered data table. For that reason, the computation of a correlation matrix covering the end time as well as all calculated fixed parameters is required. Figure 5 reflects the entries of this matrix within a range of – 1 to 1. The majority of the mentioned variables are summarized and described in [13]. Additionally, the parameter "PathDevStd" is added, to include the difference of the overall path from a straight line indicated by its standard deviation.

Not alone the correlation of the end time with any other variable reveals important information for further analysis, but also the correlation of these variables among themselves. The inclusion of fixed effects with a high correlation to other ones except the end time would lead to a corruption of the resulting model. Equally important is the exclusion of parameters with no influence on the end time, for example the contact times for hands ("ContactHands") and feet ("ContactFeet"). Similar to the formula in Eq. 1, the calculation of the time values in the single wall sections is done by variations of the limits of the sum. Therefore, their high correlations with the path lengths and velocity means lead to the omission of "TimeStart", "TimeMiddle", and "TimeEnd" from the model. Thus, the path and velocity (speed) parameters as well as a value for the shoulder–hip angle "SHStd" and "PathDevStd" are combined with the random effects "Final round", "Year", "Climber", and "Start technique".

The simplest line-up of the model specified in Eq. 4 is described by the subsequent notation [17]:

$$y \sim 1 + \text{fixed} + (1 \mid \text{random}). \tag{5}$$

In this composition, the inclusion of all fixed and random effects is ensured. Additionally, this definition clarifies the

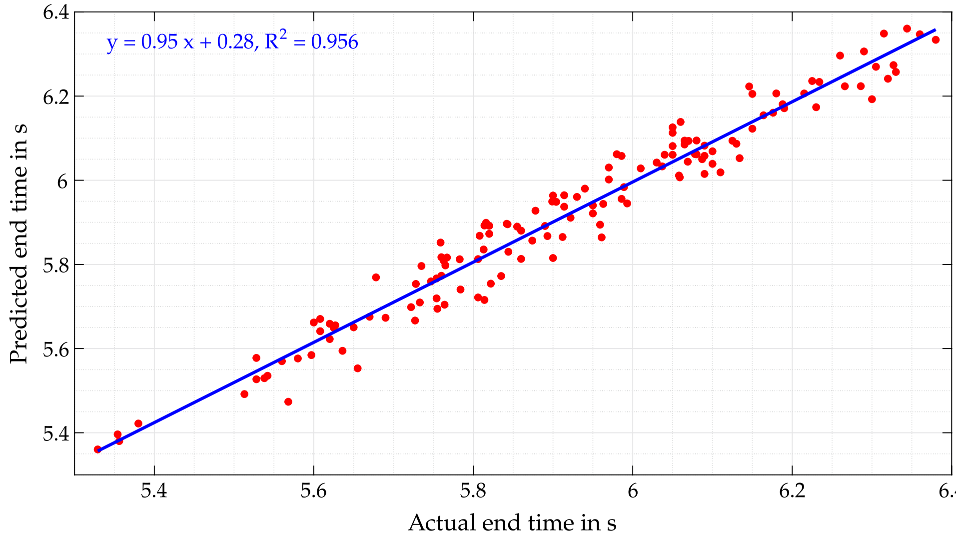

Fig. 6 Distribution of the response variable compared to the calculated fitting points for the end time of male athletes

existence of one random intercept for every cluster/group determined by the random variables and random slopes for every fixed variable. Since possible correlations of the applied parameters were previously excluded, interactions between continuous variables are not expected and hence not added to the formula.

With the aid of Matlab (Release 2022b, The MathWorks, Inc., Natick, Massachusetts, United States), the calculation of the linear mixed effect model for the presented data set is enabled. The next and almost most important step is the interpretation of the results with followed adjustments for the improvement of the model. The main aim of this statistical test is the determination of a model describing the motion patterns of speed climbing athletes and the detection of possible correlation of motion-describing parameters and the end time reflecting the performance and success. Before analysing input variables and their significant affect on the response variable, the calculated model should be freed from residuals. This removal should improve further analysis without shrinking the data set to a critical size. An additional calculation of the model with the omission of the residuals yields to the first comparable outcomes. Considering the *p* values of this model, the path and velocity parameters in single wall sections display a high significance relating to the end time. This expected result rather proves the validity of the inputted data set. In contrast, the parameter "PathDevStd" presents a *p* value of $p \ll 0.05$ and therefore a high statistical significance. In the case of "SHStd", its *p* value reaches with 0.58 a non-acceptable value for the rejection of the null hypothesis and consequently does not affect the end time at all. The remaining fixed effects are then analysed by the influence on the model by the computed slope values. Thereby, this model predicts better outcomes, respectively, lower end times for athletes with better performances especially in the middle section.

The effect of the defined random effects on the statistical model is first proven with the calculated random intercepts, respectively, the deviation from the overall intercept value. A convergence of this estimate (standard deviation for each random effect) against 0 indicates no statistical influence on the response variable. Likewise, the calculation of the percentage from the total variance value of all random effects including the model error leads to an interpretation of the contribution of the variability to the response.

Figure 6 illustrates the fitted data points (140 observations) generated with the aid of the calculated linear mixed effect model against the given end time as response. The relatively high value of approx. 0.96 for the coefficient of determination (adjusted R-squared) implies a statistically good linear model for the prediction of the response variable in dependency of the discussed fixed and random effects.

It should be mentioned that for the deployment of this model, exclusively parameters with high correlations with the end time were used, explaining, among others, the high linearity of the fitted data. Because of the novelty of this data set and its descriptive algorithms, a relatively basic model was presented. It serves as an access in statistical analysis of speed climbing data, which can be easily adapted for the usage of more complex parameters.

4 Discussion

With the introduction of a linear mixed effect model, a statistical analysis of speed climbing athletes and their motion patterns is enabled. Therefore, the corresponding data set consists of computed parameters as a result of image processing algorithms applied on several speed run recordings, as well as manually registered variables. After several filtering iterations and the removal of several outliers, this statistical model allows the calculation of a potential correlation of diverse motion-describing parameters with the end time associated as the success variable. Additionally, the fitted model serves as a predictor of the response variable in dependency of the explanatory parameters.

Due to the unified speed climbing route map and the related comparability of motion sequences, studies about video analysis and automated human skeleton detection were brought into focus. Another statistical analysis presented in Chen et al. [12] included a data set consisting of 384 runs (192 female, 192 male athletes), compared to the one here described covering 397 recordings (178 female, 219 male athletes). Based on the manual analysis of competition recordings, the system is limited to parameters like start reaction time and error rate. As it includes only one climbing event, an extensive assessment of single athletes is not practicable. Similar to this approach, video-based analysis in [18] was done for 362 runs including 55 world elite climbers with the aid of the human pose estimator OpenPose [9]. Since the results were not merged to one common global coordinate system, the comparison of the performances of athletes among each other is not given, and hence, it is not suitable for statistical approaches. The study described in [19] covers motion analysis of speed climbing trials with a set-up camera system and the use of OpenPose. The recording of the whole wall and single athletes enables a qualitative evaluation of few runs, but is not applicable for already existing video material. The usage of a drone based-system [11] for the analysis of self-recorded speed climbing runs allows the inclusion of the third spatial coordinate for precise measurements and further use for biomechanical applications. Due to the high cost of this system, the usage besides training purposes is on account of present requirements set by the IFSC currently not possible. The only established system so far is the one of Luxov. Its deployment at the Olympic Games in Tokyo 2021 enabled the measurement of contact times [10, 20]. However, the use of only three Luxov holds restricted the analysis to three data points. Also worth mentioning is the psychological impact of the modification of route map using black holds. Therefore, the main idea of the research described in this paper was to build up a non-invasive system for speed climbing athletes and trainers for the evaluation of training and competition with nothing more than computing power. Through the calculation and compilation of a comprehensive data set, the access to efficient performance analysis is granted for the sport climbing community.

The presented results reflect the potential of such data sets describing the outcomes of speed climbing trials of different athletes and the application of several statistical tests. Besides implementations of linear regression models, an analysis of important variables by means of illustrations of their distribution enables first steps into the understanding of the available data. Especially in the case of random predictors such as the group of starting versions, these pre-investigations help to decide, which parameters could correlate with the response and therefore improve the fitting model. The assignment of different techniques in the start section, involving approx. the first 5 meters of the speed climbing wall, shows a noticeable impact on the elapsed time. With a significant reduction of the travelled path of the COG, athletes using the Tomoa skip achieve averaged lower periods within this wall section. However, the usage of this cut-off leads to two local minima in the velocity caused by critical body postures. Most notably, the deep squad position at the height of the third hold shows a non-negligible loss of the athlete's velocity. Among others, this body pose requires a certain constitution and is therefore not applicable for every athlete, whereby especially female speed climbers favour this technique. The benefit of the shortened path length prevails though, since the other two starting versions also cause velocity drops with the extensive movement of the body towards, respectively, fromward the fourth hold.

A further validation of the statistical model yields a low significance of the random effect "Climber", grouping the investigated speed athletes. Since the model error prevails, the influence of this parameter is negligible. This result is a consequence of the limitation of the data set. The final data quantity of about 140 observations leads to an averaged number of three athletes, whereby some athletes, especially the current world record holder, only appear once or twice in this data set. This insight disables the deployment of a statement about the influence of this random effect on the model. The random parameters "Year" and "Final round" have no influence on the success regarding the available data set. Also, the random intercept generated by the cluster "Start technique" yields no divergence from the model intercept. This result is explained by the application of the path length and mean velocity in all of the three defined sections of the speed climbing wall for this statistical analysis. Since all parameters within a section were calculated independently, the grouping of the data set with the starting technique as a random effect does not influence the resulting model. Alternatively, the inclusion of motion-describing variables in the starting section into the model could take place with the implementation of the parameter "Start technique" as a fixed effect. Though, this modification would not lead to a significant enhancement of the model due to the previous proven dependency of the path and elapsed time in the start section to the applied technique (see Fig. 3 and Table 1).

The observation of the available fixed effects is mainly done with the aid of a correlation matrix. First, this should clarify the existing correlation of all measured variables with the end time and among themselves. In the case of the contact times for hands and feet, their independency regarding the end time can be explained by the finite frame rate of the recordings. This limitation leads to a possible corruption of the actual contact times. Additionally, the reduction to one descriptive value like the mean probably leads to a broad scattering within the data set. Considering the shoulder-hip parameter, describing the angle between two lines connecting the shoulder and hip joints, the importance of this value is recognizable for athletes of all three sport climbing disciplines. In the case of bouldering and lead climbing, this variable is an indicator for energetic optimization of motion patterns. Thereby, the contortion of both body halves leads to a high variation of the shoulder–hip parameter. Compared to that, such variations in speed climbing runs are associated with directional changes of the COG and deviations from an optimal path. Despite the apparent interaction with the end time, verified by the correlation matrix, the combination with other effects results in an exceeding of the corresponding *p* value and its exclusion from the model. Here too, an increase of the recordings' frame rate and resolution could affect the calculations positively.

The remaining parameters used for the description of the linear model exhibit high correlation. The distribution of the computed slopes displays a section wise influence on the response variable. This shows the highest correlation within the middle section, followed by the end and start section. One possible explanation of this arrangement is given with the consideration of the training methods. The speed climbing wall for training purposes consists of the common competition route map. Additionally, a route map omitting the start section is placed at the beginning of the wall. This enables a specific training of the middle and end section by skipping the first approx. 5 meters. Since the athlete starts without the transfer velocity from the start section, the trained performance in the middle section is not applicable to competition. Therefore, the perfection of motions within the starting section reflects the matching of performances of different athletes, whereas the calculated parameters in the middle section serve as performance indicators separating the wheat from the chaff.

Even though there are currently enough videos of speed climbing competitions available, not every athletes' runs can be used for further analysis. Especially when examining the applied starting technique, the low portion of athletes using the Reza move stands out (see Fig. 2). Due to the absence of data for female athletes using this start version, a gender-based analysis in this case is not given and therefore not part of the statistical evaluation. Therefore, a more precise investigation of the remaining two versions should be done. Despite the separation into these three main starts, there are several modifications implemented by different athletes to succeed the possible results in dependency of their bodily constitution. Due to the missing information about anthropometric parameters of each athlete, their consideration in the data set is not possible. The sourcing of these values would enable a more precise analysis of different techniques and the determination of a possible correlation with the end time.

Since the calculated parameters highly depend on the outcome of human body key point and random feature detectors, the camera setups of several recordings lead to faulty results. This deep dependency demands the filtering of several speed runs, a significant decrease of the available data set and, therefore, a loss of information describing the success of speed climbing athletes. A great part of the calculated parameters highly depend on the output of the human body detector OpenPose, where bad recognition due to, e.g., covered joints contribute to deviations. An improvement of the used marker-less motion method should be considered. With the training of the neural network for the detection of speed climbing relating motion patterns or even the application of an alternative pose estimation network [21, 22] would lead to significant better results and hence to a larger data set. Another limitation of the described system is the simplification to a two-dimensional problem due to the usage of conventional recordings. The missing third dimension affects the precision of the detected joints. By comparison, Pavllo et al. worked on a method for a 3D human pose estimation on recordings with dilated temporal convolutions over 2D key points [23].

It must be pointed out that, in addition to the discussed parameters, additional measurable and also non-measurable variables should be considered. The psychological impact as well as competition-describing variables play a great role and have major influence on the performance of professional athletes. Therefore, periodic evaluation of reliable psychological tests combined with the monitoring of external influences like temperature or humidity would increase the informative value of the data set.

5 Conclusion

All these results clearly describe the amount of information gained by a large data set and its need for the improvement of the competitive climbing sport. Only with the usage of IFSC recordings of speed climbing competitions with different and unknown camera setups, the system enables the composition of an unprecedented data volume. With the knowledge of the influence of single motion-describing parameters and the accomplishment of predicting possible success in speed climbing, the described methods define a new milestone in the analysis of this sport.

After investigation of the path length and velocity in the start section of the COG and their inclusion in the linear mixed effect model, a correlation of the end time with the executed starting technique is given. Especially athletes using the Tomoa skip achieve better results in average than those who perform the Reza move or Normal start.

Nevertheless, it must be mentioned that also the measured parameters in the middle and end section exhibit significant correlations with the athlete's success. This result is assigned to the design of training units, which focus on the perfection on motion sequences particularly in the first third of the speed climbing wall.

Considering that, by now, no comparable research is available, the herewith described model serves as an entry point for statistical analysis within speed climbing. With the introduction of more descriptive variables and the enhancement of described ones with the expansion of the data set with more recordings of competition as well as rateable training sessions, the potential of the application of different statistical models can result in an improvement of existing training methods and the athlete's performance. The combination of the takeaway from the statistics with the longstanding experience of speed climbing coaches enables an even more precise evaluation of motion sequences.

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Data availability As the data set was generated by the analysis of exclusively IFSC recordings (publicly accessible, YouTube), the data is not available to this paper as we do not have the explicit permission to share it.

Declarations

Conflict of interest No potential conflict of interest was reported by the authors.

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