Statistical Interpretation of Predictive Factors of Head Impact Kinematics in Traumatic Brain Injury

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I. INTRODUCTION

When evaluating the risk of Traumatic Brain Injury (TBI) and mild TBI (mTBI), brain strain, particularly maximum principal strain (MPS), is an accurate predictor for brain injury and various pathology and is used in mTBI research [1-2]. To allow brain injury risks to be quantified quickly, many brain injury criteria (BIC) are developed to approximately quantify brain injury risks and often evaluated by their correlation with brain strain calculated by finite element (FE) modelling. The BIC use various head impact kinematic parameters, such as peak values of angular velocity, but contributions of different kinematic parameters in the evaluation of brain strain is not well understood. Beside the kinematic factors in their original maximum values, the underlying relationship between the kinematics and MPS may also be non-linear. The mathematical combination of multiple kinematic factors and the contribution of different factors, such as angular acceleration in different special axes, in the brain strain calculation remain to be further studied. To better develop BIC based on impact kinematics, the predictive power of kinematic parameters needs to be systematically investigated.

In this study, five datasets from various types of head impact are analyzed. With multiple statistical interpretation techniques, the predictive power of multiple kinematic parameters in the linear regression models of 95% MPS (MPS95) is evaluated. Three angles of kinematic factors are studied: the derivative order of the rotational kinematics (angular velocity, angular acceleration, angular jerk); the components in three spatial directions and the magnitude; and the power order of the kinematics (square root, quadratic, cubic, etc.).

II. METHODS

Data and kinematics factors

The datasets in this research include 2,130 simulated head impacts from a validated FE model [3] (dataset HM), 184 on-field college football head impacts [4] (dataset CF1), 118 on-field college football head impacts [5] (dataset CF2), 457 mixed martial arts (MMA) head impacts [2] (dataset MMA), 53 reconstructed head impacts by National Football League (NFL) [6] (dataset NFL), 48 car crash head impacts from NHTSA [7] (dataset NHTSA) and 272 numerically reconstructed head impacts in National Association for Stock Car Auto Racing (NASCAR).

The ground-truth MPS95 was calculated by the validated KTH model [8]. To build the MPS95 regression model, various features were extracted. As linear acceleration proves to contribute significantly less to MPS compared to rotational kinematics [10], only angular-velocity-based features are used in this study. We extracted factors (groups of features) that may contribute to the regression from three different aspects: (1) derivative order: the zero-order, first-order and second-order derivative of angular velocity; (2) spatial component and magnitude: the components of the rotational parameters derived from the components in three spatial directions, defined using the right-hand rule (x: posterior-to-anterior, y: left-to-right, z: superior-to-inferior). The magnitude of the rotational parameters was the fourth component; (3) power order: power of 1, 0.5, 2, 3, 4, 5 and 6 of those features was calculated and added to the feature set, respectively.

Statistical interpretation

We built linear regression models to quantify the contributions of factors to MPS95. The linear regression captures the most direct and explicit predicting effect of a factor and thus is used in this study to understand the most directly predictive factors in the prediction. To analyze the relative feature importance from linear models considering the linear correlation among features, four statistical interpretation approaches that focus on different angles of predictive power were used: zero-order correlation coefficients [10]; structured coefficients [11]; commonality analysis [12]; and dominance analysis [13].

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III. INITIAL FINDINGS

Regarding the predictive power of different derivative orders, according to both zero-order correlation coefficients and structured coefficients, on all datasets except dataset MMA and dataset NASCAR, the first-order features (angular acceleration) were the most predictive factor ($p < 0.05$, except that on dataset CF2 with structured coefficients there was no statistical significance; one paired t-test between the most predictive and the second most predictive factors for each dataset) while the second-order features (angular jerk) were the least predictive. On MMA and NASCAR impacts, both methods showed zero-order features (angular velocity) were the most predictive factor ($p < 0.05$). Commonality analysis showed that the common information of all three factors showed the highest predictive power on datasets HM, CF1, CF2 and NASCAR. On dataset MMA, the common information of zero-order features and first-order features manifested the highest predictive power. Dominance analysis showed that the first-order features dominated in every level on datasets HM, CF1 and CF2, while on dataset MMA and dataset NASCAR the zero-order features dominated in all levels.

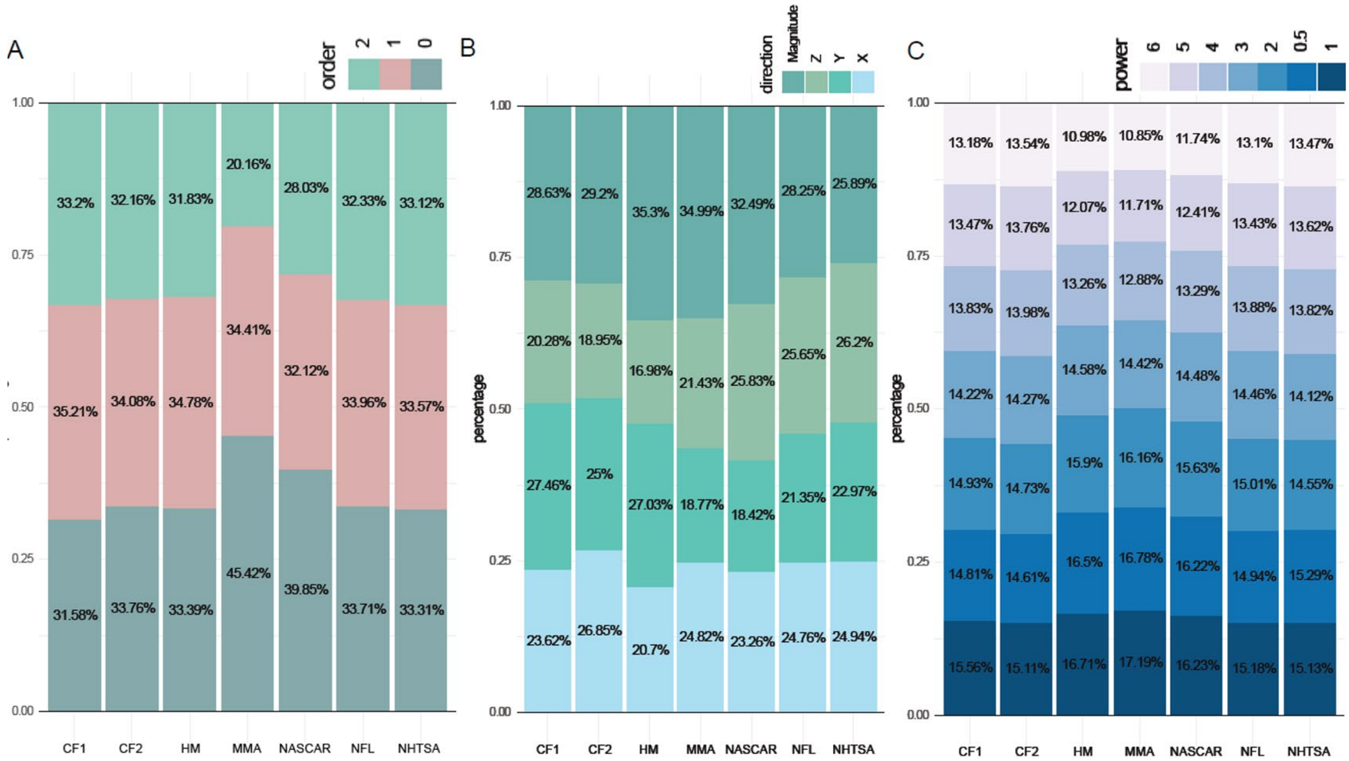

Fig. 1. Stacked bar plots of normalized mean R2 contribution of kinematic factors of three derivative orders, four components and six power orders in the regression of MPS95 using zero-order correlation coefficients (A-C).

The same interpretation methods were used to analyze the predictive power of four kinematic components. Both zero-order correlation coefficients and structured coefficients showed magnitude features were the most predictive features ($p < 0.05$) on all datasets except dataset NHTSA. Zero-order correlation coefficients showed the z-axis factor was the most predictive on dataset NHTSA ($p < 0.05$), but the result was not significant from structure coefficients ($p=0.17$). Commonality analysis showed that the predictive power varied with different datasets. On dataset HM, the common information of y-axis and the magnitude factors showed the highest predictive power. On datasets CF1/CF2, the common information of x-axis, y-axis, z-axis and the magnitude factors was the most predictive. On dataset MMA, the common information of x-axis, z-axis and the magnitude factors was the most predictive. Dominance analysis showed that magnitude factor dominated in most levels of analyses except for dataset MMA, where x-axis features dominated over other features on level 3.

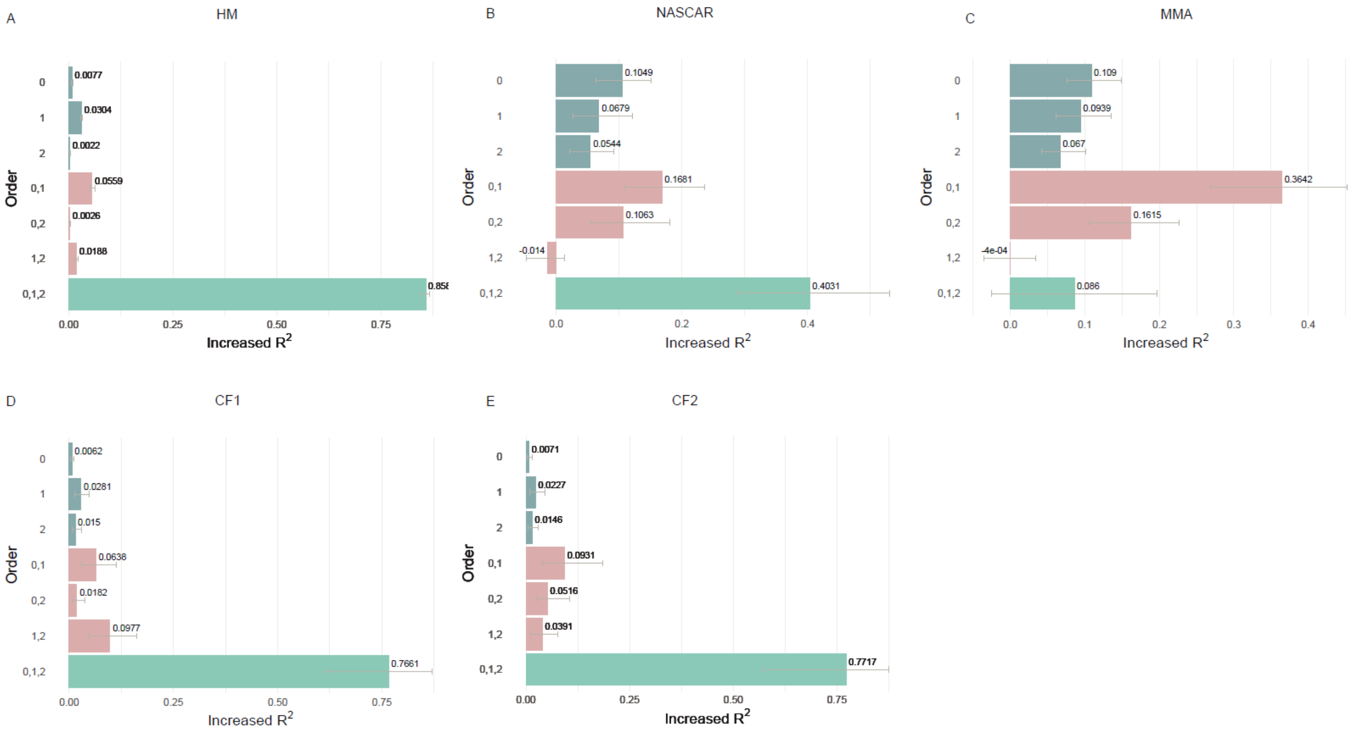

Fig. 2. Commonality analysis results for unique or common information of different predictors in the regression of MPS95 from features of three different derivative orders on five datasets.

(a) Dominance analysis of different derivative orders on dataset HM.

Order	Mean R2	Additional Contribution		
		0	1	2
k=0 average	0.0000	0.9240	0.9630	0.8811
0	0.9240	0.0000	0.0493	0.0213
1	0.9630	0.0103	0.0000	0.0048
2	0.8811	0.0643	0.0867	0.0000
k=1 average	0.0000	0.0373	0.0680	0.0131
0,1	0.9733	0.0000	0.0000	0.0022
0,2	0.9454	0.0000	0.0301	0.0000
1,2	0.9678	0.0077	0.0000	0.0000
k=2 average	0.0000	0.0077	0.0301	0.0022
0,1,2	0.9755	0.0000	0.0000	0.0000

(b) Dominance analysis of different power orders on dataset HM.

Power	Mean R2	Additional Contributions			
		1	0.5	2	3
k=0 average	0	0.9664	0.9545	0.9201	0.8437
1	0.9664	0	0.0023	0.0028	0.0029
0.5	0.9545	0.0142	0	0.0126	0.0108
2	0.9201	0.049	0.0469	0	0.0482
3	0.8437	0.1256	0.1216	0.1247	0
k=1 average	0	0.0629	0.0569	0.0467	0.0206
1, 0.5	0.9686	0	0	0.0021	0.0024
1, 2	0.9691	0	0.0016	0	0.0023
1, 3	0.9693	0	0.0018	0.0021	0
0.5, 2	0.9671	0.0037	0	0	0.004
0.5, 3	0.9652	0.0058	0	0.0058	0
2, 3	0.9684	0.0031	0.0027	0	0
k=2 average	0	0.0042	0.002	0.0034	0.0029
1, 0.5, 2	0.9708	0	0	0	0.0016
1, 0.5, 3	0.971	0	0	0.0013	0
1, 2, 3	0.9714	0	0.0009	0	0
0.5, 2, 3	0.971	0.0013	0	0	0
k=3 average	0	0.0013	0.0009	0.0013	0.0016
1, 0.5, 2, 3	0.9723	0	0	0	0

(c) Dominance analysis of different components on dataset HM.

Directions	Mean R2	Additional Contributions			
		X Abs Max	Y Abs Max	Z Abs Max	Mag Max
k=0 average	0	0.5544	0.7182	0.4525	0.9406
X Abs Max	0.5544	0	0.3917	0.1196	0.4047
Y Abs Max	0.7182	0.2279	0	0.1948	0.2467
Z Abs Max	0.4525	0.2216	0.4605	0	0.4984
Mag Max	0.9406	0.0185	0.0243	0.0103	0
k=1 average	0	0.156	0.2922	0.1082	0.3833
X Abs Max,Y Abs Max	0.9461	0	0	0.0162	0.0255
X Abs Max,Z Abs Max	0.674	0	0.2883	0	0.2938
X Abs Max,Mag Max	0.9591	0	0.0125	0.0087	0
Y Abs Max,Z Abs Max	0.913	0.0494	0	0	0.0581
Y Abs Max,Mag Max	0.9649	0.0067	0	0.0062	0
Z Abs Max,Mag Max	0.9509	0.017	0.0202	0	0
k=2 average	0	0.0243	0.107	0.0104	0.1258
X Abs Max,Y Abs Max,Z Abs Max	0.9623	0	0	0	0.013
X Abs Max,Y Abs Max,Mag Max	0.9716	0	0	0.0037	0
X Abs Max,Z Abs Max,Mag Max	0.9679	0	0.0075	0	0
Y Abs Max,Z Abs Max,Mag Max	0.9711	0.0042	0	0	0
k=3 average	0	0.0042	0.0075	0.0037	0.013
X Abs Max,Y Abs Max,Z Abs Max,Mag Max	0.9754	0	0	0	0

Fig. 3. Dominance analysis results on dataset HM.

In the power order analysis, both the zero-order correlation coefficients and the structured coefficients showed that on all datasets, except NHTSA, the first-order-powered factor was the most predictive ($p < 0.05$), while the square-root-features were the most predictive on dataset NHTSA ($p < 0.05$). The power orders smaller than 3 were significantly more predictive than the remaining power orders. Beyond the power order of 2, the factors showed decreasing predictive power in the regression as the power order increases. According to the results of commonality analysis, the common information of all factors had the highest predictive power, which indicates that not too much new information was provided by changing the power orders. The dominance analysis showed that the first-order-powered factor generally exhibited dominance – except on dataset MMA and dataset NASCAR, where different factors exhibited dominance on different levels, which indicates that the predictive power of different factors was not clearly ranked on dataset MMA and dataset NASCAR.

IV. DISCUSSION

This study applied four statistical interpretation approaches to analyze the MPS95 regression and quantify the predictive power of different factors of impact kinematics. In terms of the predictive power among factors when viewed individually (the direct effect defined by Budescu [14]), the zero-order correlation coefficients and structured coefficients show that the following kinematic factors generally show the highest predictive power: (1) features based on the first derivative order of angular velocity (angular acceleration); (2) features based on the magnitude of the kinematics; and (3) features of power order 1. These findings were generally reinforced by the dominance analysis, which showed that these three factors dominated in most levels of analyses.

There were several dissimilarities across the datasets. First, both zero-order correlation coefficients and structure coefficients showed that angular velocity features exhibit significantly higher predictive power on dataset MMA and NASCAR (Fig. 1). The dominance analysis also supported the findings that the zero-order features dominated in every level on dataset MMA and NASCAR while the first-order features dominated on the other datasets. The higher predictive power of the angular velocity on MMA impacts may be related to the fact that the duration of MMA impacts is generally shorter than their counterparts in other datasets. For short-duration impacts, angular velocity tends to be more predictive of brain strain [9]. On the two football datasets (CF1 and CF2), besides the most predictive magnitude features, the x-axis features and y-axis features show higher predictive power than the z-axis features. This finding suggests a potential explanation that the side or rear impacts are more likely to lead to obvious performance decrement (OPD) of the players [15].

According to this study, in terms of brain injury criteria design, new mathematical forms can be developed and validated to quantify the brain injury risks more accurately. For instance, the brain injury criteria can include both angular acceleration and angular velocity [9], the magnitude and the components in different directions, and the first-order-powered and also the square-rooted math forms for better risk evaluation in a wider range of head impacts. Furthermore, an understanding of the most predictive factors in the head impact kinematics will facilitate the development of improved concussion-prevention technologies, focused on more predictive features. For example, in the design process of protective headgears, such as football helmets [16], the peaks of the angular acceleration magnitude can be the metric to guide the design.

V. REFERENCES

[1] Wu, S., *et al.*, *Biomech Model Mechanobiol*, 2020.
[2] O'Keeffe, E., *et al.*, *J Neurotrauma*, 2020.
[3] Giudice, J. S., *et al.*, *Ann Biomed Eng*, 2019.
[4] Camarillo, D. B., *et al.*, *Ann Biomed Eng*, 2013.
[5] Liu, Y., *et al.*, arXiv, 2020.
[6] Sanchez, E. J., *et al.*, *Clin Biomech*, 2019.
[7] NHTSA NHTSA, United States, https://www.nhtsa.gov/data.
[8] Kleiven, S., SAE Tech. Paper, 2007.
[9] Gabler, L. F., *et al.*, *J Biomech Eng*, 2018.
[10] Nathans, L. L., *et al.*, *Pract Assessment, Res Eval*, 2012.
[11] LeBreton, J. M., *et al.*, *Organ Res*, 2004.
[12] Date, P. U. B., *et al.*, 1999.
[13] Budescu, D. V., *Psychol Bull*, 1993.
[14] Budescu, D. V., *et al.*, *Organ Res*, 2004.
[15] Bartsch, A. J., *et al., Ann Biomed Eng*, 2020.
[16] Vahid Alizadeh, H., *et al.*, *J Biomech Eng*, 2020.