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Editorial

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Dear readers:

Welcome to the winter issue 2015 of the **International Journal of Computer Science in Sport (IJCSS).**

The issue contains three research papers and two project reports.

Hall used a two-tiered hierarchical linear modeling design that combined a number of specific on-court and off-court factors to assess both player and team performance at the NBA. The results show some statistically significant factors, including players' ages, entropy, and compensation.

Knudsen and **Andersen** introduce a method to detect gaps in a team's defence in soccer. Results showed that there is a critical passing speed, from which on gaps can occur in a soccer defence which cannot be defended anymore.

In their scientific report **Ting et al.** propose a novel lossless compact view invariant compression technique with a dynamic time warping algorithm which provides a badminton movement recognition and analysis framework.

The scientific report by **Thomas** establishes a predictive model capable of simulating and predicting the outcome of the 6th Rugby Sevens World Cup.

Finally, I would like to publicly announce that the IJCSS will become an open access journal. Starting with the summer issue 2016 (volume 15, issue 1) it will be published at de Gruyter Open. There still will be two issues per year, one in June and one in December. The submission and reviewing process will stay the same and will be organized on my part.
De Gruyter provides the publication platform and helps us improving the visibility of the IJCSS and, amongst others, applying for an impact factor. Authors who get an article accepted and published in IJCSS do not have to pay any publication fees.
The former IJCSS volumes will stay on the IACSS server and will be accessible as so far.

If you have any questions, comments, suggestions and points of criticism, please send them to me.

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A Hierarchical Linear Modeling Approach to Assessing NBA Player and Team Performance

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Abstract

With teams' annual payrolls nearing $100 million and valuations for some teams exceeding $2 billion, the National Basketball Association is big business. That being the case, many pro-basketball general managers are turning to analytics to discover ways to improve organizational performance. The purpose of this paper was to highlight the results of an analytics-based assessment of both player and team performance, using data from the regular 2012-2013 NBA season. The analytical paradigm described in this paper consisted of a two-tiered hierarchical linear modeling design that combined a number of specific on-court and off-court factors. The analysis also introduced a relatively new sports performance metric—entropy, which can be used to measure the degree of disorder at both the player and the team level. The target variable was Hollinger's Player Efficiency Rating. The results of the analysis revealed that a number of factors were statistically significant, including players' ages, entropy, and compensation. NBA general managers can use this modeling approach to evaluate both trade and draft opportunities.

KEYWORDS: NBA; ANALYTICS; HIERARCHICAL LINEAR MODELING; TEAM PERFORMANCE; PLAYER TRADING AND DRAFTING; ENTROPY

Introduction

The use of analytics throughout the sports universe is growing rapidly (Colemann, 2013; Davenport, 2014). This development is being driven by the continued economic growth of spectator sports both domestically and on a worldwide basis. For example, annual revenues for the 2012-2013 NBA season were estimated at $5 billion (Stern, 2012). To that end, analyses of individual and team achievements continue to receive attention in both popular and academic literature (Berri, 2010; Justin, 2007). Regression techniques, in particular, have found favor among analysts for evaluating a variety of basketball challenges, including arbitration, contract length, and competitive balance (Omidiran, 2013; Schouten, 2012). Not surprisingly, well-informed basketball prognosticators are turning to these more powerful statistical models that allow for the inclusion of many *complex predictor* variables. The NBA is particularly well suited for analytics use because player performance across different positions can be measured with the same set of statistics, unlike in the NFL or MLB, where different positions are measured using different metrics. For example, in MLB, pitchers are evaluated based on their earned run average, while the designated hitter is assessed using statistics like on-base percentage and slugging average. Analytics is the science of discovering and communicating meaningful patterns in data and developing actionable plans (Cooper, 2012). Typically, analytics can be divided into three broad categories: descriptive, predictive and prescriptive. Descriptive analytics is all about providing insights into what has already happened (e.g., player injury assessment). Predictive analytics focuses on generating forecasts about the future (e.g., player performance). Prescriptive analytics builds on both descriptive and predictive analytics to help identify solutions to specific problems and decision-making applications (e.g., drafting and trading). The predictive analytics category is replete with a wide range of models including those that are designed to examine hierarchical data structures.

Hierarchical linear modeling (HLM) allows for the analysis of complex nested data structures like those associated with organizations such as the NBA. One of the early applications of HLM involved educational research wherein students were nested within classrooms, classrooms were nested within schools, and schools were nested within districts (Ma, 2000; Schagen, 2003). The basic idea behind HLM, sometimes referred to as multi-level linear modeling, is that individuals associated with a particular cluster, such as a sports team, are likely to exhibit some degree of association with the other members of the cluster, namely their teammates. This behavior violates the classic assumption that each data observation is independent. HLM provides a vehicle to better examine relationships, which in turn should improve the resultant insights, enabling NBA management to make better player choices based on dependent, cluster data variables.

> *Obtaining the most talented and productive players on the team is perhaps the most important decision that NBA teams make. Constructing a team that can reach its full potential requires more than just acquiring talented players; these players have to fit well together (Ayer, 2012, p. 6).*

One of the basic goals of applying the analytics paradigm to sports in general and the NBA in particular, then, is to improve the decision-making process underpinning player acquisition and utilization. This paper is organized as follows: 1) a review of the relevant literature, 2) an analysis of the data on the regular 2012-2013 NBA season, and 3) a discussion on the application of the developed model for the purpose of improving team performance. This article's primary contribution to sports management is the introduction of a new sports performance metric— entropy—and the application of ensemble modeling featuring a hierarchical linear archetype.

Review of Literature

The nature of interaction between players and teams is both complex and dynamic. To capture the essence of these relationships calls for a comprehensive modeling approach. Typically, a number of broad factors are needed to explain both player and team performance, including: 1) economic, 2) management, and 3) system factors. In fact, sports analysts have taken a page from the equity market's play book by introducing compound factors like Hollinger's Player Efficiency Rating – PER (Sisneros, 2014). Hollinger's PER equation consists of a large number of metrics with a heavy emphasis on a player's offensive performance. To support this complex-factor approach, this paper introduces a performance variable called entropy, which is a measure of the randomness and disorder of a system that can be applied to both players and teams.

Entropy

Entropy is a relatively new concept in sports analytics (Couceiro, 2014; Fewell,2012). The first study examined player performance variability using entropy as a basis for developing an enhanced training plan. In the second study the findings suggest that team ball movement unpredictability, as measured by entropy, has a strong positive association with making the NBA playoff. Entropy has seen widespread use in the financial markets (Pincus, 2008; Zhou, 2013). Specific financial entropy applications include portfolio selection, asset pricing, and investor satisfaction. The basic idea with respect to equity markets is that more volatile securities are in a greater state of uncertainty than more stable securities. Continuing with the financial analogy, teams can be viewed as the broader markets while players are the individual stocks. As applied to the NBA, entropy can provide a measure of disorder based on a variety of performance metrics (e.g., point production at both the player and team levels). Two fundamentally different phenomena exist in which time-based data, like scoring patterns over the 82-game season, deviate from constancy in that they: 1) Exhibit larger standard deviations, and 2) Appear highly irregular.

These two phenomena are not mutually exclusive and as such, both can be used to characterize the uncertainty associated with fluctuations in a variety of performance-based time series data (e.g., point production). The standard deviation measures the extent of deviation from centrality, while entropy provides a metric to delineate the extent of the data set's irregularity or complexity. Two different time series can have the same standard deviation, yet significantly different entropy values. A time series containing many repetitive patterns will have a relatively small entropy value, while a less predictable process will produce higher values. Evaluating the subtle but complex shifts in series data is a primary prerequisite for exploiting the potential information contained therein. The related literature posits that entropy (ApEn) is both robust to outliers and can be applied to relatively small times series sequences with good reproducibility (Chen, 2009). However, with sample sizes under 200, approximating entropy can lead to bias since the ApEn-based process counts each sequence as a match for itself (Yentes, 2012). A second measure of system complexity that is often used to address this issue is called sample entropy (Maasoumi, 2009; Thuraisingham, 2006). Both approximate entropy and sample entropy utilize the following three inputs: 1) Time series, 2) Matching template length (M), and 3) Matching tolerance level (r).

For this study, the matching template length (M) utilized was two, which was predicated on the relatively short length of the time series (number of games = 82). The matching tolerance (r) was based on 20 percent of the standard deviation, which has been used in a variety of serial studies (Liu, 2011). Alternatively, it has been suggested that the selection of the tolerance level (r) should be based on the value that maximizes entropy (Lu, 2008). The computational process behind ApEn and SaEn is somewhat similar to the statistical non-parametric sign test. Smaller entropy estimates suggest that similar patterns will be followed by similar patterns (i.e., show more structured behavior). If the time series is highly irregular, then subsequent patterns will not mimic current patterns and the entropy metric will be larger (i.e., exhibit greater serial randomness). This information should provide useful insights regarding the future direction and behavior of the relevant time series, such as the scoring consistency of players and competitive team balance (Borooaha, 2012).

Hierarchical Linear Modeling

Like corporate management teams, sports teams are hierarchical in nature. Unfortunately, most classical analytic techniques (e.g., OLS) are based on the assumption of independent observations. This assumption is violated, however, when dealing with nested data structures like professional basketball. Typically, players drawn from a given team will be more homogeneous than players sampled from the NBA. Players from the same team tend to exhibit similar characteristics, suggesting that the observations are not fully independent. Therefore, using ordinary least squares regression in these cases tends to generate standard errors that are too small. This leads to a higher probability of concluding that relationships exist between the predictor variables and target variable, compared with the case involving independent observations.

Two classic approaches to addressing nested data are disaggregation and aggregation. In the former case (disaggregation), team performance data (Level 2) is assigned to each player (Level 1). Unfortunately, this results in violating the independent observation assumption since all players would be assigned team performance scores. In the latter approach (aggregation), average player characteristics are assigned to the team. This assignment results in two potentially serious problems (Bryk, 1992): 1) Upward of 90 percent of individual variability on the target variable is lost; and 2) The target variable can change significantly from individual achievement to average team achievement. Furthermore, both analytical strategies limit the researcher's ability to separate out the effects of players and the team on the target variable. To further illustrate the challenge at hand, consider a basketball team wherein the primary interest of each player is minimizing his own performance variance, while the focus of the coach is minimizing performance variance between team members. Hierarchical linear modeling (HLM) is specifically designed to address problems involving organizational nesting (Pan, 2008). Many HLM applications consist of a two-level arrangement such as the one found in this study. However, three- and four-level configurations are also possible. At Level 1, the parameters (intercept and slopes) representing the relationship between the Level 1 predictors and target variable are estimated (within). At Level 2, the intercepts and slopes for each Level 1 parameter are specified (between). The Level 2 process is analogous to the cross-level main effects model. A solution to the HLM framework was obtained by combining the two sets of equations (Level 1 and Level 2) into a single mixed model. HLM offers three distinct advantages over the use of traditional OLS in analyzing nested data structures: 1) separates out the target variable variance into within and between components. Therefore, the error terms are not systematically biased, 2) maximizes the use of the available information, and 3) permits testing for cross-level effects.

HLM is seeing increased applications in the study of sports team performance (Chen, 2010; Todd, 2005). The first study explored spectator satisfaction based on both service quality and win-loss performance. Specific questions of interest included: a) how many variances in spectator satisfaction existed at the spectator level and the game level, b) how many variances in spectator satisfaction could be explained by service quality and win-loss, respectively, and c) whether and to what extent the win-loss percentage damages or enhances the relationship between service quality and spectator satisfaction. In a similar way, the second study assessed player salaries as a function of player experience and performance (Level 1) and team talent and league (Level 2). The results indicated that the intercept and both of the slopes varied substantially across teams, which allowed for team-level explanations of those differences. These two studies provided the contextual framework for the present analysis.

Ensemble Modeling

This investigation specifically focused on explaining individual player performance, as measured by Hollinger's Player Efficiency Rating (PER), as a function of both team and individual player factors. PER embodies a large number of players' performance characteristics into a single compound metric (e.g., minutes played, assists). PER, which is not without its critics, is only one of a variety of possible player performance metrics (Fearnhead, 2011; Rosenbaum, 2007). The NBA's large variable set suggested the need for a multi-stage or ensemble modeling approach to examine the relationship between teams, players, and outcomes. Ensemble modeling refers to techniques wherein the predictions of a group of base models are combined to generate more accurate composite predictions (Moreira, 2007). The ensemble modeling paradigm consists of the following two steps: 1) Constructing an ensemble of base learners from training data, and 2) Combining predictions of the ensemble members into a composite prediction.

> *Ensemble forecasting has now become an established technique in medium-range prediction. The real value of ensemble prediction systems are not the probability forecasts, per se, but their ability to influence decisions across a range of applications sectors. However, as operational ensemble prediction continues to develop, so specific examples of the value of ensemble prediction for decision making will increase. Such specific examples will most likely arise when a specific application model is coupled to each individual member of the ensemble prediction system (Leutbecher, 2008, p. 3537).*

The first stage of the modeling process involved screening a large number of candidate explanatory variables using neural net analysis. Neural nets (NN) are seeing increased use in sports performance analysis (Loeelholz, 2009; Shamsoddini, 2012). Results from the first study revealed that that the NN outperformed so-called experts in predicting NBA game outcomes. NNs use complex network relationships to mimic the connections between sets of data. Among other things, NNs have the advantage of not requiring prior assumptions about the data or about possible relationships within the data, as is often the case with traditional analysis methods, such as regression. Once a more manageable and parsimonious set of promising explanatory variables were identified, the second stage utilized HLM as outlined above. The parsimonious principle, which states that the among competing models that predict equally well, the one with the fewest variables should be used, formed the basis for designing the final model (Vandekerckhove, 2015).

Results Analysis

The ensemble modeling approach outline in the previous section was used to explore player and team performance data for the regular 2012-2013 NBA season. Table 1 presents summary descriptive statistics for the assembled database. The overall player sample size was 326 (Level 1 = 326, Level 2 = 30). This study utilized approximate entropy, which was calculated for both players and teams based on point-scoring performance. It is interesting to note that the mean player entropy was less than the team entropy, which may appear somewhat counterintuitive. However, the player sample size is over ten times larger than the team sample size. A more helpful metric in this regard is standard deviation. To illustrate some possible Level-1 relationships, consider Figure 1. This graphic presents a plot of player salary versus PER. The resultant correlation coefficient of 0.55 suggests a moderate positive association between compensation and overall player performance. This relationship was also explored using the natural logarithm of salary, which revealed approximately the same degree of association. Figure 2 presents a plot of coaching experience with the current team versus the team-winning percentage (i.e., team-level variable). Notice that there is a moderately strong linear association, as highlighted by the correlation coefficient of 0.46.

Table 1 - Selected Descriptive Statistics (2012-2013 NBA Season)

Variable	Mean	Median	Min	Max	S.D.
Player Age	26.58	26.00	19.00	39.00	4.22
Player Salary ($MM)	5.19	3.50	0.28	27.85	4.77
Coach Exp. (yrs.)	3.17	2.00	1.00	17.00	3.25
GM Exp. (yrs.)	5.57	4.00	1.00	19.00	5.01
Attendance (000)	709.84	713.06	563.74	896.94	82.54
Team Entropy (Ap)[1]	0.63	0.65	0.32	0.81	0.13
Player Entropy (Ap)[1]	0.56	0.59	0.02	1.01	0.21
PER[2]	**14.53**	**14.16**	**5.95**	**31.67**	**4.08**

1) Ap = Approximate Entropy, 2) PER = Hollinger Player Efficiency Rating (15 average)

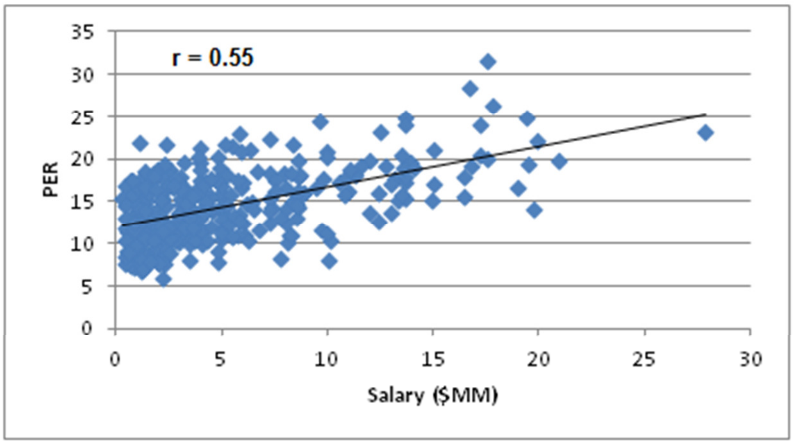

Figure 1 - Player's Salary versus PER (N=326)

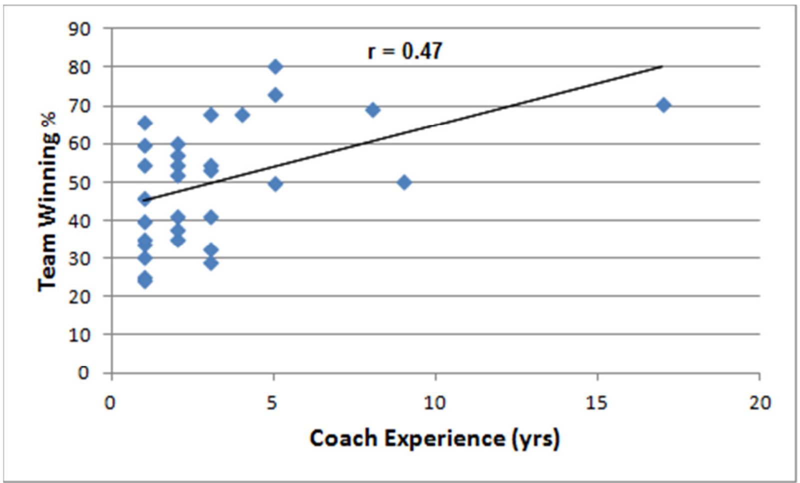

Figure 2 - Coaching Experience versus Team Winning Percentage (N=30)

A neural net model was used to prune the original candidate database down to a more manageable and parsimonious subset (Ward's Neuroshell predictor). The neural net model consisted of one input, one hidden layer, and one output layer. At the player level, examples of the variables that were pruned included personnel fouls per minute. The resultant dataset was then processed using HLM6 by Scientific Software International, Inc. The candidate HLM model is presented below. At Level 1, the target variable (PER) is described as a function of player age, entropy, and salary. The coefficients of the Level 1 model are described in turn by the coach's experience (years with the present team), the draft value, team entropy level, disciplinary actions, general manager's experience (years with the present team), and team payroll. The variable "Discipline" is defined as league or team disciplinary action taken during the regular season. There were a total of 59 disciplinary actions taken during the 2012-2013 season all of which were counted equally in this study. This assumption can be empirically tested with the model.

Negative media coverage is another potential factor that might be considered in this regard. There is a considerable body of literature on the relationship between negative media coverage and organizational performance, which includes specific metrics (Bednar, 2012). The variable "Draft Value" was estimated using an exponential decay model for first-round draft selection (Barzilai, 2009). For those teams without a first-round draft selection, a zero was assigned as the draft value. In the cases where teams had multiple first-round draft choices, the draft values were added. Ultimately, the best approach to addressing this issue was conducting an examination of the various accounting options. The resultant candidate Level 2 factors were those that management has either direct or partially direct control over. One example of the latter would be the team imposing discipline on a player. Another would be attendance, which can be influenced by yield management (dynamic ticket pricing) practices (Nufer, 2013).

Level-1 Model (Player)

$$Y\ (PER) = B_0 + B_1 * (Age) + B2 * (Player\ Entropy) + B3 * (Salary)$$

Level-2 Model (Team)

$$B_0 = G_{00}$$

$$B_1 = G_{10} + G_{11} * (Coach\ Exp.) + G_{12} * (Team\ Entropy)$$

$$B_2 = G_{20} + G_{21} * (Attendance) + G_{22} * (Discipline)$$

$$B_3 = G_{30} + G_{31} * (GM\ Exp.) + G_{32} * (Draft\ Value)$$

A graphical rendering of these hierarchical relationships is highlighted in Figure 3. Each of the team-level factors falls within the prevue of management either directly or indirectly.

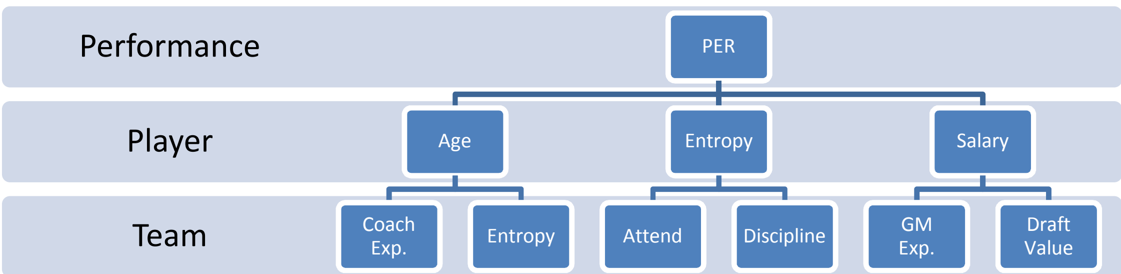

Figure 3 - Graphical Rendering of the Hierarchical Model

A comparison of the results from an OLS-Stepwise analysis (aggregate and disaggregate) and a candidate HLM is highlighted in Table 2. The data reports slopes and p-values for the three modeling approaches to the statistically significant variables. It is interesting to note that there was no variable overlap between the aggregate and disaggregate results. One of the challenges in interpreting the overall performance results of an HLM analysis is the lack of an appropriate R-square. In HLM analysis, the determination of an R-square is confounded by the presence of multiple variance components. Typically, in a standard step-wise OLS analysis, the final variable combination is based on maximizing R-square while minimizing collinearity. In the present analysis, there were a number of possible HLM representations. Again, the approach taken in this research was to develop a parsimonious HLM with only statistically significant variates that minimized overall deviance. A standard Student's t-test was used to compare the individual intercepts and variable slopes across the three classes of models (OLS Aggregate, OLS Disaggregate, and HLM). The *** in Table 2 indicate whether the intercepts and slopes, for a given row, resulted in a $p \leq 0.05$. For example, the computed slopes for player entropy for the OLD-disaggregate and HLM models were statistically different at the 0.05 level. The intercepts for all three models were near the league PER average of 15. The HLM modeling results for player entropy, for example, reported a slope over three times as large as the Disaggregate-OLS results. The overall statistics presented in Table 2 underscore the value of nested data analysis. The relatively low R-squares for both OLS schemes simply illuminate their limitations in addressing nest data applications. Specifically, HLM allows for random variation in both the intercepts and slopes at multiple levels, which in turn can yield more accurate coefficients. The negative HLM attendance coefficient suggests that as attendance increases, player entropy (performance variability) decreases.

Table 2 - Comparison of OLS and HLM Results

	OLS Aggregate*		OLS Disaggregate**		HLM	
Factor	B-Coeff.	p-value	B-Coeff.	p-value	B-Coeff.	p-value
Intercept	14.123	0.000	15.295	0.000	15.789	0.000
Player Age	-	-	-0.174	0.000	-0.209	0.000
Player Entropy***	-	-	2.130	0.015	7.445	0.007
Player Salary	-	-	0.511	0.000	0.587	0.000
Coach Exp.***	0.137	0.000	-	-	0.004	0.007
Attendance	-	-	-	-	-0.007	0.035
Draft Value	-	-	-	-	-0.002	0.002

*R-square = 0.219 (Aggregate), **R-square = 0.339 (Disaggregate), *** p< 0.05

Interestingly, the sign of the entropy coefficient was positive. A somewhat irregular pattern of point production for those high-scoring players appears to make sense, since it would be difficult to maintain consistency at the high end of point production game after game. Figure 4 compares the point-game production time series for Lebron James (MVP winner) and Courtney Lee (representing an *average* NBA player) for the 2012-2013 season. The data pattern for James showed a higher degree of irregularity than the one for Lee. This is reflected in James' larger entropy level compared with Lee's, as reported in Table 4. While the standard deviations for both players were similar, James' state of entropy over the season was nearly three times as large as Lee's. To this end, team management can use player entropy to support both trade and draft decisions. Team entropy could be used in a similar manner, and also by the league, to detect the presence of *tanking* as the season draws to a close.

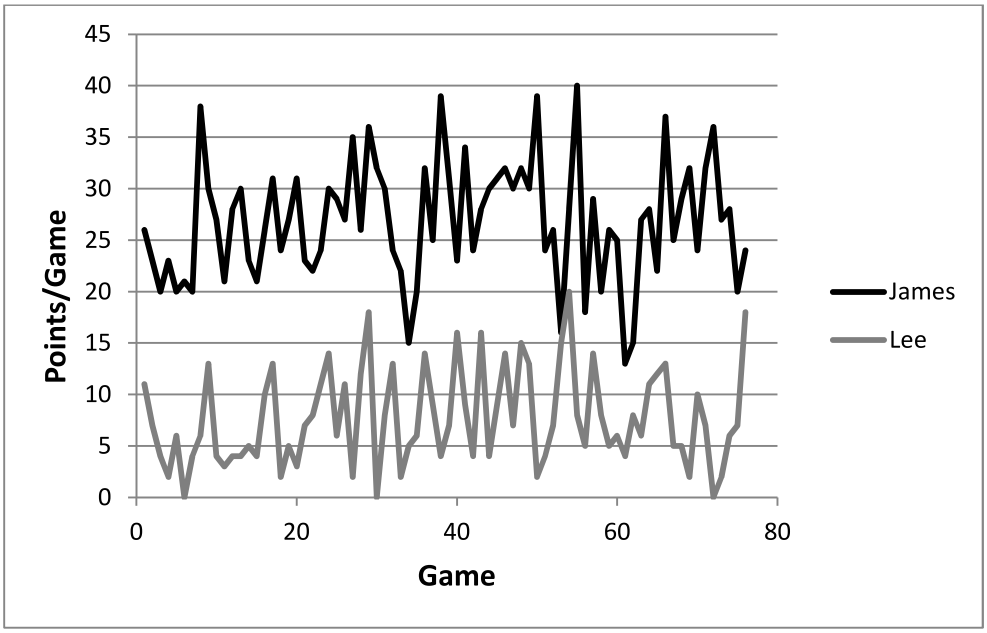

Figure 4 - Time Series of Points/Games for James and Lee (2012-2013)

Table 3 - Points/Game Descriptive Statistics Comparison for James and Lee

Statistic	James	Lee
Average	26.8	7.7
S.D.	5.8	4.7
Entropy	0.65	0.23

Table 4 - Inter-Level Correlations

Level 2/ Level 1	Age	Salary	Entropy
Coach Exp.	0.005	-0.063	-0.117
Attendance	-0.052	0.108	-0.158
Draft Value	0.170	-0.202	-0.113

Table 4 presents the inter-level correlations for the predictor variables. The relatively small correlation coefficients between Level 1 and Level 2 variates were a good indicator that multi-collinearity had been minimized.

The HLM methodology allows for the exploration of a number of candidate hierarchical relations, including alternative target variables (e.g., Player Value Added (VA)—the estimated number of points a player adds to a team's season total above a replacement player). The developed model framework can also be used to examine specific player performance factors, such as three-point field goals and rebounding. The results gleaned from the current study are consistent with those reported in the literature (Piette, 2011; Torre-Ruiza, 2012). Specifically, the first study found that current team members' past performance can have a negative impact on the initial performance of new recruits. This was comparable to the findings that age was statistically significant with respect to PER. The methodology in the second study was designed to search for players that are under-utilized. The specific goal was to look for players whose centrality score was small, but who over-performed statistically in one of the efficiency categories. Both of these findings can be further explored using the methodology outlined in this paper. The HLM results showed a positive correlation between player salary and player performance, as measured by PER.

> *We predicted that, in addition to performance mean, performance trend and variability would also affect compensation decisions. Results revealed that performance mean and trend, but not variability, were significantly and positively related to changes in compensation levels of NBA players. Moreover, trend (but not mean or variability) predicted compensation when controlling for future performance, suggesting that organizations over-weighted trend in their compensation decisions (Barnes, 2012, p. 3).*

Figure 5 illustrates how the proposed methodology could be used to assist management in improving overall team performance, such as the team's number of wins. The basic goal of this paradigm was to integrate all phases of basketball operations into one coherent decision-making process. Performance outcomes on the court, for example, will impact managerial decisions, which in turn affect player personnel decisions and thus on-field performance. This analytics-based management decision-making system was designed to minimize the impact of short-sided trading and drafting decisions. This decision-making paradigm provides a template to ensure a team's long-term success in an ever-increasing competitive environment. This approach was predicated on the Enterprise Resource Planning (ERP) paradigm, which is beginning to receive widespread consideration throughout the world of professional sports (Kartakoullis, 2013). Specifically, the proposal is to integrate all propositions of the enterprise into a unified, holistic, and values-centered organization, linking on-field performance variables to off-field metrics.

> *We look at a player's value in terms of not only what they do on the field ... but also how many more ticket sales can they generate, how many more hot dogs are they going to sell, how many more beers are fans going to buy, how many more jerseys (Goodfellow, 2015).*

To support the analytics process, the NBA has dramatically enhanced its data collection capabilities, such as by deploying SportsUV cameras at each stadium. The resulting performance tracking data is now available to the general public (Goldich, 2013). This development alone will greatly increase opportunities to employ advanced analysis techniques, such as HLM. While reliance on data analysis alone in making hiring and trading decisions can lead to problematic outcomes, the combination of analytics and human judgment will usher in a new era in sports management decision making (Mondello, 2014).

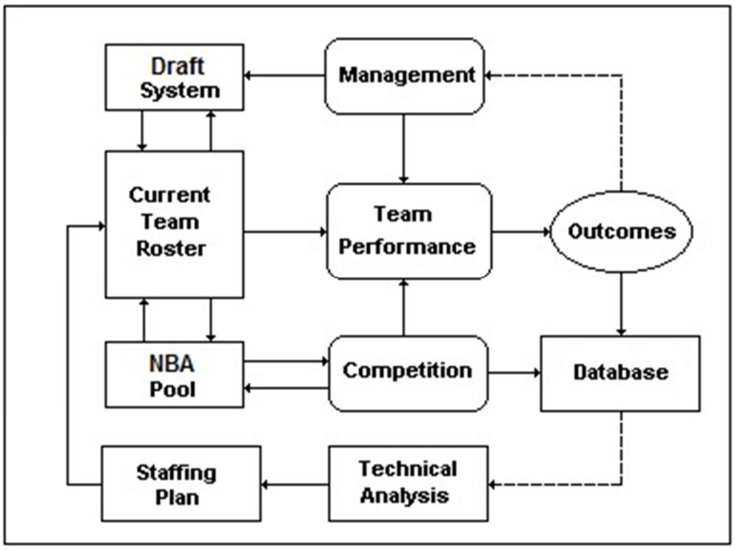

Figure 5 - Analytics-Based Performance Decision-Making Paradigm

Conclusion

Basketball's general managers are under growing pressure to field cost-effective teams as a result of enormous team payrolls and continuing fan demand to produce winners. One or two poor hiring decisions can not only cripple a team financially, but can also impact its performance on the court. Basketball teams are examples of hierarchical structures consisting of individual players, team management, and the league. The structural nature of interaction between players and the organization is both complex and dynamic and, as such, calls for a more sophisticated analytics approach.

The purpose of this paper was to highlight the results of a hierarchical linear modeling (HLM) analysis of player and team performance using data from the regular 2012-2013 NBA season. More specifically, the task was to identify specific determinates at both the player level and the team level that are related to overall player performance, as measured by PER. The target variable PER is only one of many possible candidates and was selected to illustrate the proposed HLM methodology. The HLM yielded a larger number of statistically significant factors than either the OLS-Aggregate or OLS-Disaggregate models. In addition, the modest R-squares associated with the OLS models simply accentuated the limitations of these schemes. The HLM results showed that players' ages, levels of entropy, and compensation are statistically related to player performance and that coaches' experience, attendance, and draft value are significant at the team level. The HLM modeling approach better reflects the reality of the hierarchical nature of the NBA in particular and many sport franchises in general. Team and player entropy represent a relatively new metric for both explaining and assessing both team and player performance. To that end, consideration should be given to expanding to a multi-year data assessment, since 82 games represents a lower limit to the minimum technical requirements for calculating entropy. Team entropy could also be used by the league to detect *tanking*, a notion that is receiving considerable attention throughout the NBA universe. Furthermore, a variety of additional performance factors, beyond point production, should be explored as candidates for entropy measurement.

The modeling approach presented in this paper can also be used to predict specific player performance attributes. For example, a team could be interested in adding a three-point shooter. In this case, the target variable would be players' three-point percentage. The pool of three-point shooters could be assessed using hold-out analysis. The study of NBA team outcomes using ensemble modeling can be expanded into a variety of areas, including the use of CART (Classification Analysis Regression Trees) for the purpose of classifying players based on a set of decision criteria. In its simplest form, candidate players could be classified using a binary format, which would significantly reduce the number of finalists for consideration in terms of either drafting or trading. In summary, the analytics-based approach outlined in this article can be used by NBA general managers to better align player trading and drafting with expectations of team performance.

References

Ayer, R. (2012). Big 2's and Big 3's: Analyzing how a team's best players complement each other. 6th Annual *MIT Sloan Sports Analytics Conference*, Boston, March.

Barnes C., & Reb, J. (2012). More than just the mean: Moving to a dynamic view of performance-based compensation. *Dionysius Journal of Applied Psychology*, 97, 711–740.

Barzilai, A. (2009). Assessing the relative value of draft position in the NBA draft. Retrieved from http://www.82games.com/barzilai1.htm

Bednar, M., Boivie, S., & Prince, N. (2012). Burr under the saddle: How media coverage influences strategic change. *Organizational Science*, 24, 910–946.

Berri, D., & Bradbury, J. (2010). Working in the land of metricians. *Journal of Sports Economics*, 11, 29–47.

Borooaha V., & Manganb, J. (2012). Measuring competitive balance in sports using generalized entropy with an application to English premier league football. *Applied Economics*, 44, 1093-1102.

Bryk, A., & Raudenbush, S. (1992). *Hierarchical linear models in social and behavioral research: Applications and data analysis methods*. Newbury Park, CA: Sage Publications.

Chen, Y. (2010). Hierarchical linear modeling in sport management: Using multilevel determinants of spectator satisfaction as an example. *North American Society for Sport Management Conference*, Columbia.

Chen, W., Zhuang J., & Wang, Z. (2009). Measuring complexity using Fuzzy En, Apen, and SampEn. *Medical Engineering & Physics*, 31, 61-68.

Coleman, B. (2012). Identifying the players in sports analytics research. *Interfaces*, 42:109.

Cooper, A. (2012). Making sense of Analytics: A framework for thinking about analytics. JISC CETIS Conference, Nottingham, February.

Couceiro, M., Clemente, F. M., Dias, G. Mendes, P., Martins, F. M. L. & Mendes, R.S. (2014). On an Entropy-based Performance Analysis in Sports. Proceedings from the *1st International Conference on Entropy and its Applications*, November.

Davenport, T. (2014). What businesses can learn from sports analytics. *MIT Sloan Management Review*, 10, Summer.

Fewell, J., & et. al .(2012). Basketball Teams as Strategic Networks. PLoS ONE, 7(11), 1-9.

Fearnhead, P., & Taylor, B. (2011). On estimating the ability of NBA players. *Journal of Quantitative Analysis in Sports*, 7(3), 1-16.

Goldich, M. (2013). Race for data feeds the sports analytics revolution. Retrieved from: http://newsarchive.medill.northwestern.edu/chicago/news-226402.html

Goodfellow, K. (2012). The revolution in advanced sports analytic systems. 6th *Annual MIT Sloan Sports Analytics Conference*, Boston.

Justin, K., Dean, O., Kevin, P.,& Rosenbaum, D. (2007). A starting point for analyzing basketball statistics. *Journal of Quantitative Analysis in Sports*, 3, 1-24.

Kartakoullis, N., Vrontis, D., Thrassou, A. & Kriemadis, T. (2013). Strategic resource planning for football clubs. *Journal International Business and Entrepreneurship Development*, 7(1), 1-20.

Leutbecher M., & Palmer, T. (2008). Ensemble forecasting. *Journal of Computational Physics*, 227, 3515-3539.

Liu, C., Liu, C., Shao, P., Li, L., Sun, X., Wang, X. & Liu, F. (2011). Comparison of different threshold values r for approximate entropy: Application to investigate the heart rate variability. *Physiological Measurement*, 32(2), 167-180. .

Loeelholz, B., Bednar, E., & Bauer, K. (2009). Predicting NBA games using neural networks. *Journal of Quantitative Analysis in Sports*, 5(1), 1-17.

Lu, S., Chen, X., Kanters, J., Solomon, I., & Chon, K. (2008). Automatic selection of the threshold value r for approximate entropy. *IEEETrans Biomed Engineering*, 55(8), 1966-1972.

Ma, X., & Kinlger, D. (2000). Hierarchical linear modelling of student and school effects on academic achievement. *Canadian Journal of Education*, 25(1), 45-51.

Maasoumi E., & Racine J. (2009). A robust entropy-based test of asymmetry for discrete and continuous processes. *Econometric Reviews*, 28, 246-261

Mondello, M., & Kamke, C. (2014). The introduction and application of sports analytics in professional sport organizations. *Journal of Applied Sport Management*, 6, 1-12.

Moreira, J., Soares, C., Jorge, A., & Sousa, J. (2007). Ensemble approaches for regression: A survey. *ACM Computing Surveys*, 45(1), 10-35.

Nufer, G., & Fischer, J. (2013). Ticket pricing in European football–analysis and implications. *Business and Management Review,* 3(3), 49-60.

Omidiran, D. (2013). Penalized Regression Models for the NBA, Cornell University Library.

Pan, Z.,& Hu, D. (2008). Hierarchical linear modeling of smoking prevalence and frequency in China between 1994 and 2001. *Health Policy and Planning*, 23, 118-124.

Piette, J., Pham, L., & Anand, S. (2011). Evaluating basketball player performance via statistical network modeling. 5th Annual *MIT Sloan Sports Analytics Conference*, Boston, March.

Pincus, S. (2008). Approximate entropy as an irregularity measure for financial data. *Econometric Reviews*, 27, 329-362.

Rosenbaum, D. (2007). The pot calling the kettle black: Are NBA statistical models more irrational than rational decision-makers? *NESSIS Conference*, Boston, September.

Sisneros, R. & Van Moer, M. (2013). Expanding plus-minus for visual and statistical analysis of NBA box-score data. The 1st Workshop on Sports Data Visualization, IEEE VIS, October.

Schagen I., & Hutchison, D. (2003). Adding value in educational research—the marriage of data and analytical power. *British Educational Research Journal*, 29(5), 749-765.

Schouten, D. (2012). Economics of salary dispersion in the national basketball association, *The Park Place Economists*, 20, 73-84.

Shamsoddini, A., & Trinder, J. (2012). Neural networks fusion for regression problems. *International Journal of Machine Learning and Computing*, 2 (3), 511-516.

Stern, D. (2012). Stern estimates NBA revenue up 20 percent to $5B, Associated Press.

Thuraisingham R., & Gottwal, G. (2006). On multi-scaling for physiological data. *Physica*, 366(1), 323-336.

Todd, S., Crook, T., & Barilla, A. (2005). Hierarchical linear modeling of multilevel data. *Journal of Sport Management*, 19, 387-403.

Torre-Ruiza J., & Aragón-Correaa, J. (2012). Performance of newcomers in highly interdependent teams: The case of basketball teams. *European Sport Management Quarterly*, 12, 205-226.

Vandekerckhove, J., Matzke, D., & Wagenmakers, E. (2015). Model comparison and the principle of parsimony, *Oxford Handbook of Computational and Mathematical Psychology*, 1-29.

Yantes, J., Hunt, M. Schmid, K. K., Kaipust, J. P., McGrath, D. & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of Biomedical Engineering*, 41, 349-365.

Zhou, R., Cai, R., & Tong, G. (2013). Applications of Entropy in Finance: A Review. *Entropy*, 15, 4909-4931.

Methodology to Detect Gaps in a Soccer Defence

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Abstract

The purpose of the present study was to create a methodology which can provide information about gaps in an opposing team's defence. To illustrate the methodology, a defence was tracked during a game in the danish Superliga using ZXY radio tracking and analysed using the methodology. Results showed that at certain passing speeds, an opposing defence is well coordinated with no gaps, but if the passing speed is changed, gaps can occur that the defence is unable to defend. Even though the used methodology at time being is based on some crude approximations, it can at a later point be used to identify gaps in a defence for the offence to take advantage of.

KEYWORDS: RADIO TRACKING, COVERAGE, TACTIC, SOCCER

Introduction

In soccer, defence is of great importance for both the defending and attacking team. For the defending team, a well structured defence will prevent the attacking team in scoring, thus enhancing the chances for the defending team to win. On the other hand, the attacking team will try to find weaknesses in the defence of the opposing team utilizing these to try to score. In either case, the defence is ought to cover space for the attacking team in an attempt to capture the ball (Mitchell, 1996). Furthermore, the organization and thereby the tactic of the defence is of great importance in regards to a team's success.

Some studies define the covered area at the area spanned by the players of a defending team (Moura et al., 2012; Okihara et al., 2004). However, this is of limited tactical use of the coach, since the spanned area of the players gives little information about their ability to defend the spanned area and is independent of the motions of the individuals on the defending team.

A more useful study of the defence coverage area by Gréhaigne et al. (1997) uses the momentary velocity of the players to define and create sectors of play, which are areas the player can reach within 1 second. This gives a more realistic model for the area defended by the individual player, but lacks the ability to determine a player's ability to actually cover the defined area in time to e.g. intercept a pass through the sector. The sectors gives information of where a player can be within 1 second, but not where in the sector he can be at a certain point in time to intercept the ball. Accordingly, their study provides an overview of the defensive coverage capabilities, but lacks the ability to determine holes in the formations.

Other studies define the covered area as the dominant region of the defending team (Gudmundsson & Wolle, 2014; Taki et. al. 1996) dividing the field into areas the defending can reach before the attacking team. Though this method gives information about the defending team's ability to reach certain areas of the field, passes can still be made through the defended area without the chance of interception, if it is made to a dominant region of the attacking team.

To the best of our knowledge, no study has provided a methodology to determine areas on the field of play, which no defensive player can reach in time to intercept a pass being made into the area, so called gaps in the defence. This study wishes to create a methodology which can, based on the positions and velocities of the players and the position and pass velocity of a passer, give an insight of these gaps, where to passes can be made without the possibility of a defensive interception, and illustrate it by examples from professional soccer matches.

Methods

Data collecting

The data used is collected from a match in the danish Superliga played between FCM and Hobro on the 21st of March 2015. Each player on the home team is wearing a ZXY Sport Chip™ transmitting radio signals at 20 Hz. Using ten receiving sensors measuring the strength of the signal it is possible to triangulate the players, finding their position and velocity on the field at a given time during the match.

Defining the coverable area of players

For a player at a position on the field $\vec{P} = (X, Y)$ and with an initial velocity $\vec{v}(V_x, V_y)$ at angle $\omega = atan(V_x, V_y)$, the player will be able to reach and cover a certain point on the field $\overrightarrow{p_{i,j}} = (x_i, y_j)$ if he can reach this in the same time, T, it takes for the ball to be passed there. For an opponent with the ball at (x, y) passing with a velocity $v_b(t)$, which changes throughout the flight due to drag and friction, T will satisfy $\sqrt{(X-x)^2 + (Y-y)^2} = \int_0^T v_b(t)dt$.

For simplicity, the velocity curve used in this paper is given by $v(t) = \frac{20}{\pi} * \text{atan}(t)$, thus giving the player a maximum speed of 10 m/s (36 km/h). For a given initial speed $|\vec{V}|$ the player will be able to change his speed parallel to his velocity according to $v(t)$ starting at $t_i = \tan(\frac{\pi}{20} * |\vec{V}|)$ and ending at $t_f = t_i \pm T$ depending on whether the player is accelerating or decelerating. The player can also change his speed perpendicular to the velocity in a similar manner, starting at $t_{i\perp} = 0$ and ending at $t_{f\perp} = T$. Thus, a player can in the time T move a maximal distance of $d_a = \int_{t_i}^{t_i+T} v(t)dt$ parallel to his motion if he accelerates,

$d_d = \int_{t_i}^{t_i-T} v(t)dt$ parallel to his motion if he decelerates and $d_p = \int_0^T v(t)dt$ perpendicular to his motion to either side.

The initial coverable area of the player within the time, T, will thus be spanned by an ellipse with the semiaxes $a = \frac{d_a+d_d}{2}$ parallel to the players motion and $b = d_p$ perpendicular to the motion with center of the ellipse being placed at $x = \frac{2*X+\cos(\omega)*d_a-\cos(\omega)*d_d}{2}$,$y = \frac{2*Y+\sin(\omega)*d_a-\sin(\omega)*d_d}{2}$. However, to ensure that the player never exceeds his maximal speed or acceleration according to t, one must also create a circle with radius $r = d_a$ - the maximal possible displacement of the person in any direction.

Thus, the actual coverable area of the player is the intersection of both the ellipse and the circle defined. The development of the coverable area defined by this method can below be seen visualised as 1) a function of the time available to run and 2) as a function of the initial velocity:

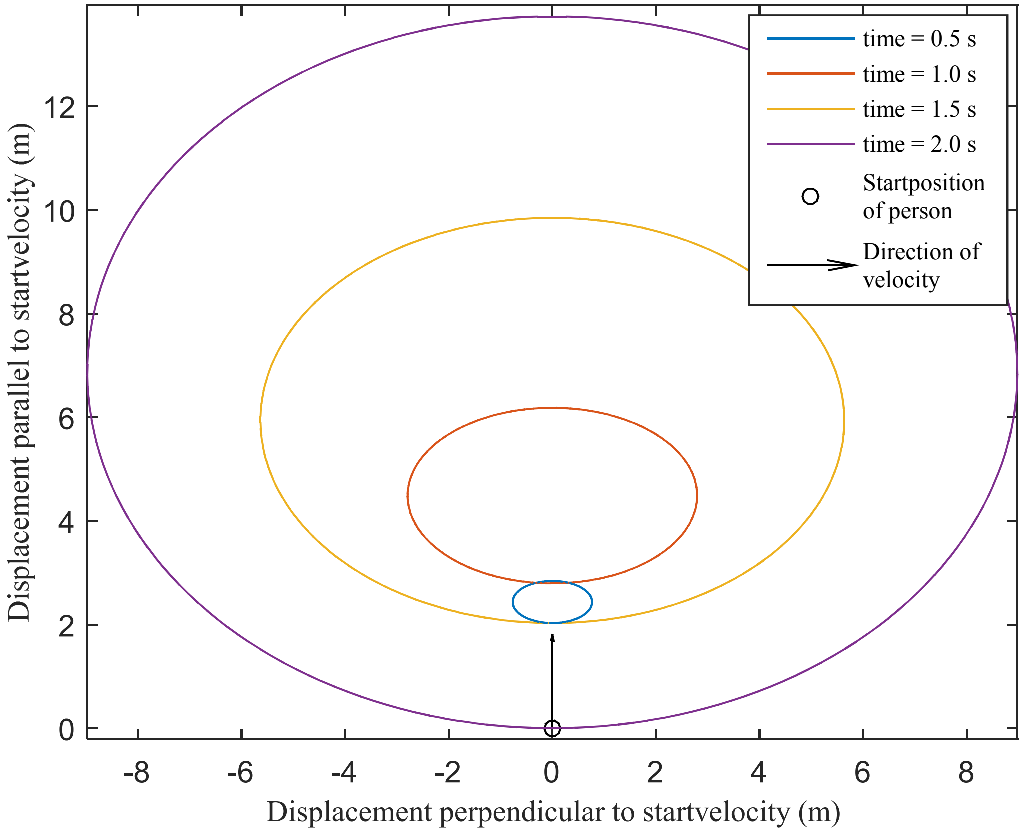

Figure 1. Plot of the development of the coverable area over time, with a initial velocity of 5 m/s and starting point at (0,0). Notice, that the starting point first can be covered after 2 seconds

To investigate whether $\overrightarrow{p_{i,j}}$ is covered, one simply checks if this point is inside the coverable area of the player. If this is the case, let the point $\overrightarrow{p_{i,j}}$ get the value $z_{i,j} = 1$, otherwise let $z_{i,j} == 0$.

To investigate the total covered area of the player, one simply let the method run through all the points on the field, from $i = 1{:}\,65$ and $j = 1{:}\,120$ (creating a heatmap of 1×1m squares). This gives a 120×65 matrix for z, consisting of 1 and 0. For the total team, one just adds the z-matrices of all the players together, creating a heatmap showing a) which parts of the field is covered/uncovered and b) how many players are covering certain areas of the field.

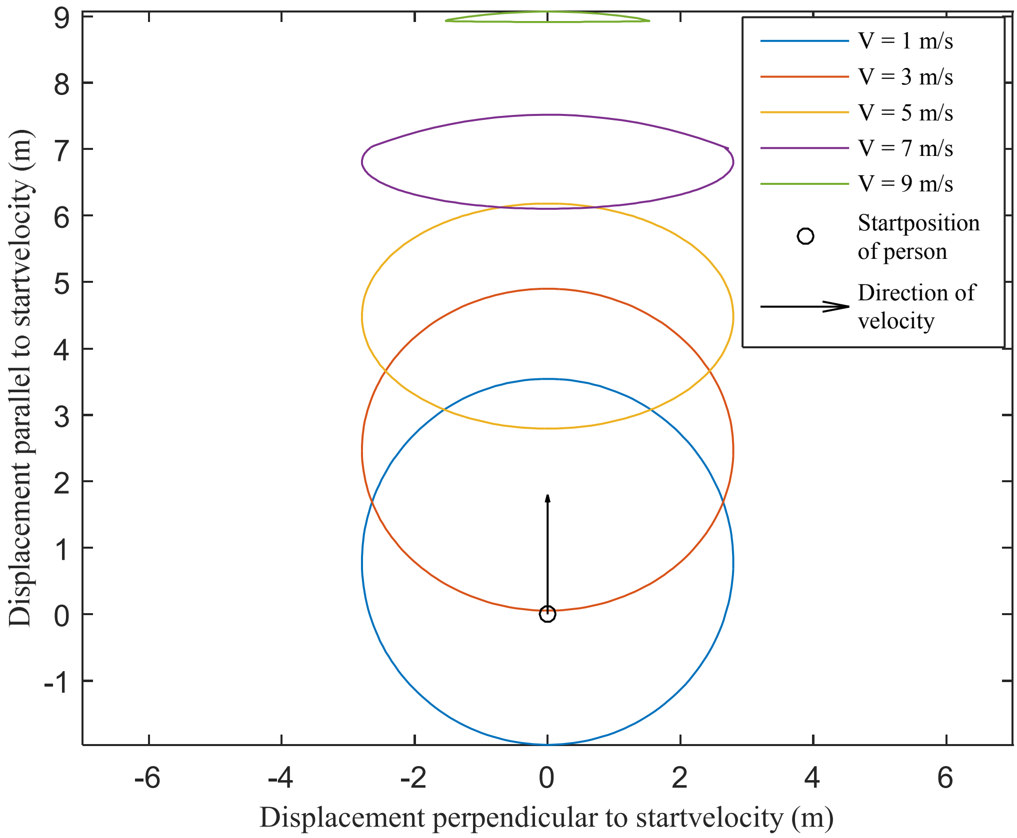

Figure 2. Plot of the coverable area after 1 s as function of initial velocity with starting point at (0,0).

Results

In order to illustrate the kind of results the mentioned methodology can provide, the 2nd minute of the match between FCM and Hobro has been analysed with regards to the positions and velocities of only the defending team, FCM, since no data was collected on the attacking team. The results are as follows:

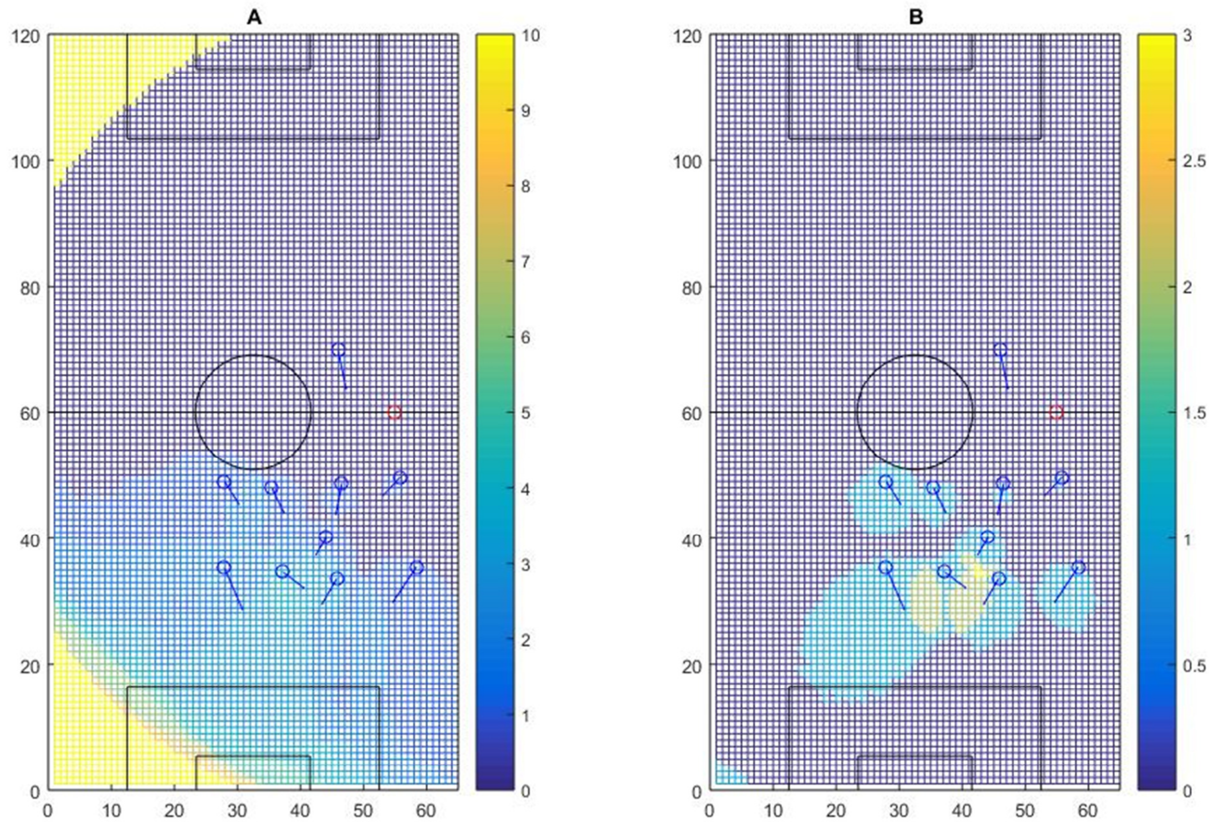

Figure 3. Plot of the defending players (blue circles), their velocities (blue vectors) and the area they cover (shade from blue to yellow). Note that the passer (red circle) has been placed on the field manually since there was no data on the opposing team in order to present the described methodology. In figure 3A the passing velocity has been set to 20 m/s, in figure 3B the passing velocity has been set to 25 m/s,

In figure 3, the defence seems to be well distributed across the defending half of the field. In figure 3A, with a passing velocity of 20 m/s, the defence looks rather compact with no gaps in the defence and some smaller areas of overlapping coverage. Note the far corners from the passer being yellow, resulting from the ball not being able to reach these areas with the chosen drag coefficient, friction and passing velocity. In figure 3B, the pass is made with 25 m/s, and at this passing velocity a gap appears between the midfielders and the defensive backs, where no player on the defending team can reach in time to intercept the ball. In both cases, a quadratic drag with drag coefficient $C_d = 0.12$ (Asai et. al. 2013) and a constant friction of 0.86 N (Hanson et. al.) is acting on the ball in opposite direction of the ball velocity. Figure 3 shows that, according to the passing velocity, gaps can form in the defence that the attacking and/or defending team might be unaware of.

Discussion

As the used methodology for this paper is a prototype, some approximations were made, which not necessarily are appropriate. Mainly the use of the antisymmetric atan-based velocity curve and the separation of the ability to change velocity tangential and parallel to the direction of motion to create figures 1 and 2 are crude approximations used in lack of actual velocity and change-of-direction profiles of the soccer players.

Although the work of Hader et. al. (2015) can indicate a velocity curve parallel to the direction of the motion to be approximated to an atan curve; they also show that the change of velocity tangential to the direction of the motion is dependent of the parallel speed of the player. The ability to change direction while maintaining some of the speed has not been included in the proposed methodology and would result in the defending players being better at defending laterally. An even better way to determine the coverable area would be to base them on actual measurements of the players, as proposed by Gudmundsson and Wolle (2014) and Fujimura and Sugihara (2005).

In addition, the change of speed of the ball due to drag is an approximation, and does not take into account that the drag coefficient of the ball has been shown to change as the velocity of the ball drops (Asai & Seo, 2013). The change of speed due to friction has in this model been added as a constant deceleration and implies that the passes are made so the ball does not leave the ground, which during normal game is highly unlikely to be the case. In addition, this also implies the friction coefficient being constant, which has been shown to be nonlinear (Weizman et. al. 2013).

The results from the presented methodology does at the time being not include the possibility of a pass being intercepted midways towards the undefended area as well as it only describes the field of play, the pass and the players as two-dimensional in the plane of the field. Thus, the results must be interpreted in such way that, if a player can make the pass to the presented gaps without the ball being intercepted, either by curving the ball around the opponents or by passing the ball over the defenders, the gap will be undefended. This interpretation does however not justify the approximation with the constant friction since a curveball will experience more friction due to a longer path, and passing over the defence makes the ball leave the ground thus not experiencing any friction at all. These issues must be corrected in future work.

The presented idea to discover holes in the defence is only half of the story, since for the attacking team to take advantage of the presented gaps they must have a player in position to receive the ball in the gap in time of arrival and a player in position to make the pass. The presented methodology can, in time, provide these data but the current data provided by ZXY only contained the defending team. Thus, it is not possible to show in this paper using the presented methodology a) whether the defending team is covering the opposing team's players and b) if a player on the opposing team is able to get in position to receive the pass in the gaps. In addition, a further investigation should aim to include both teams as well as the third dimension in order to determine true passable and usable gaps in the defence and, in time, give an estimate of the difficulty of the pass in terms of pass angle and velocity intervals.

Conclusion

This study has presented a methodology to provide information about a defending team's ability to cover the field in relation to their positions and velocities and in relation to a passing player's position and passing velocity. Although this methodology at present state only gives a crude estimate of the coverable area it can, in time, assist coaches in finding gaps in an opposing team's defence or identifying weaknesses in their own defence or be used as a coaching tool to visualize tactical aspects to the players.

References

Asai, T. & Seo K. (2013). Aerodynamic drag of modern soccer balls. *SpringerPlus, 2*,171.

Fujimura, A., & Sugihara, K. (2005). Geometric analysis and quantitative evaluation of sport teamwork. *Systems and Computers in Japan*, *36*(6), 49-58.

Gréhaigne, J. F., Bouthier, D. & David, B. (1997). A method to analyse attacking moves in soccer. In T. Reilly, J. Bangsbo and M. Hughes (Eds), *Science and Football III* (pp. 258-264). London: E & F.N. Spon.

Gudmundsson, J. & Wolle, T. (2014). Football analysis using spatio-temporal tools. *Computers, Envionment and Urban Systems, 47*, 16-27.

Hader, K., Palazzi, D. & Buchheit, M. (2015). Change of direction in soccer: How much breaking Is enough? *Kinesiology, 47*(1), 67-74.

Hanson, H., Harland, A., Homles, C. & Lucas, T. (2012). Method of understanding football ball motions using videobased notational analysis. *Procedia Engineering, 34*, 164-169.

Mitchell, S. A. (1996). Improving invasion game performance. *Journal of Physical Education, Recreation & Dance, 67*(2), 30-33.

Moura, F. A., Martins L. E. B., Anido R. D. O., De Barros R. M. L. & Cunha, S. A. (2012). Quantitative analysis of Brazilian football players' organisation on the pitch. *Sports Biomechanics, 11*(1), 85-96.

Okihara, K., Kan, A., Shiokawa, M., Choi, C. S., Deguchi, T., Matsumoto, M., & Higashikawa, Y. (2004). Compactness as a strategy in a soccer match in relation to a change in offence and defense [Communications to the Fifth World Congress on Science and Football]. *Journal of Sports Sciences*, *22*(6), 515.

Taki, T., Hasegawa, J. I., & Fukumura, T. (1996). Development of motion analysis system for quantitative evaluation of teamwork in soccer games. In *Image Processing, 1996. Proceedings., International Conference on* (Vol. 3, pp. 815-818). IEEE.

Weizman, Y., Fuss, F. K., & Doljin, B. (2013). A method for accurate measurement of the non-linear rolling friction coefficient between an instrumented ball and a surface. *Procedia Engineering*, *60*, 496-500.

Kinect-Based Badminton Movement Recognition and Analysis System

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Abstract

In sports science, two widely used approaches to perform movement recognition and analysis are through manual annotation of sports video and physical body marker attached to athlete's body. The use of physical body markers, however, requires expertise on visual annotation which is obviously time-consuming and inconvenient for the athletes. Badminton is one of Malaysia's most popular sports but there is still a lack of scientific research on movement recognition and analysis focusing on this sport. Therefore, in this paper, a novel lossless compact view invariant compression technique with a dynamic time warping algorithm is proposed to cater for both badminton movement recognition and analysis frameworks. Our experimental dataset of depth map sequences composed of 10 types of badminton movements with a total of 600 samples performed by 20 badminton players. The dataset varies in terms of viewpoints, human body size, clothes, speed, and gender. Experimental results revealed that nearly 95% of average recognition accuracy was accomplished for badminton movement recognition framework. In addition, badminton movement can be analyzed in detail and compared by using the movement analysis framework. The present research will be beneficial to sport scientists, badminton coaches, and potentially useful in enhancing the performance of badminton players.

KEYWORDS: BADMINTON, MOVEMENT RECOGNITION, MOVEMENT ANALYSIS, DTW, KINECT

Introduction

The roots of the sport badminton has can be traced back to the ancient civilization of Europe and Asia more than 2000 years ago. Badminton, in ancient time was known as *battledore* and *shuttlecock*, which was prevalent in India, China, Japan, and Greece where a paddle was used to hit the shuttlecock back and forth (Guillain, 2004). Later, British military officers revolutionized the game with an added net, namely Poona in British garrison town *Poona* (now Pune) in mid-18th century British India (Connors *et al.*, 1991). Today, badminton is one of the most popular racquet sports in Malaysia and in many other countries. It is played within a center netted rectangular court by two opposing players in a singles match or opposing pairs in a doubles match. In addition, it is the fastest racquet sport in terms of shuttlecock velocity along with tennis (Tsai and Chang, 1998). Although badminton is one of the most popular racquet sports in the world, there is still lack of scientific research on this sport as compared to other racquet sports such as tennis.

In sports science, a common method for analyzing performance based on body movements is to film the athletes and manually annotate the footage offline using a video digitization system. It is a popular method in many sports but requires expertise from the system operator to annotate the videos in order to highlight important components of the video contents. An alternative way is to use a motion tracking system that can extract a skeleton model of the athlete automatically using physical body markers and perform manual analysis later in an offline mode. This method produces a more accurate representation of the human body but requires cumbersome placement of body markers. Furthermore, such a method is time-consuming and inconvenient, especially to the athlete. Within the last two decades, biomechanical analyses of sports motions were mostly of qualitative nature. However, due to the recent technological advancements regarding input acquisition sensors and computer hardware, computerized motion recognition and analyses for athletes are becoming more prevalent. Recently, several studies have been conducted to analyze the movement of a badminton player, such as *smashing* (Salim *et al*., 2010; Hussain and Bari, 2011; Nagasawa *et al*., 2012; Ning, 2013), *service* (Yoshikawa *et al*., 2010; Hussain *et al*., 2011; Teng and Paramesran, 2011), and *swing* (Liu *et al*., 2014). Most of the literature above, however, analyze badminton movements based on spatiotemporal (*x*-*y*-*t*) information without depth information, which leads to discriminative performance degradation. In fact, human body movements are four dimensional (*x*-*y*-*z*-*t*) in the real world. Additionally, the placement of physical body markers tends to affect the performance of a badminton player.

Due to the emergence of inexpensive, reliable and robust algorithms to capture the depth information, human motion tracking using the Microsoft Kinect sensor is becoming more prevalent. The Microsoft Kinect sensor was originally released with the intention to improve human computer interaction in gaming for the Xbox 360 game console. Despite being targeted mainly for the entertainment market, the sensor has gained enormous interests within the vision and robotics research community for its broad applications (Goles, 2010). Since then numerous human activity recognition studies with the Kinect sensor were published. Generally, there are two main approaches in depth-based human activity recognition, space-time and skeletal tracking-based approaches. The space-time approach represents each depth sequence as a 3-dimensional (3D) volume along spatiotemporal axes. The depth sequences can be processed either as a whole (Ni *et al*., 2011; Wu *et al*., 2012) or as a bag of local feature points (Li *et al*., 2010; Zhang and Parker, 2011; Malgireddy *et al*., 2012). These methods are, however, suitable for simple human activities, such as clapping, waving, walking, and running. Due to the limitations of the space-time approach a skeletal tracking-based approach was proposed where 3D human body parts tracking has become feasible for high-level recognition tasks. Shotton *et al*. (2011) developed a new method to predict 3D positions of body joints from a single depth image rapidly and accurately. This 3D body joints information brings benefit to human centric computer vision tasks. Basically, feature extraction modes in the skeletal tracking-based approach can be classified into two major groups which are point-based and orientation-based. The point-based feature extraction (Reyes *et al*., 2011; Lin *et al*., 2012; Wu *et al*., 2013) might be affected by rotation and scale factors. In contrast, orientation-based feature extraction (Raptis *et al*., 2011; Sempena *et al*., 2011; Miranda *et al*. 2012) is invariant to rotation and scale factors. However, most of them adopted lossy compression techniques in order to reduce the dimensionality of data before a human activity is classified. As such, the loss of information reveals in time domain and deteriorates the accuracy of recognition.

In this paper, a cost-efficient Microsoft Kinect sensor with a novel lossless compact view invariant compression technique using dynamic time warping algorithm is proposed for badminton movement recognition and analysis. Moreover, badminton movements are chosen because they represent significant movement of arms, torso, legs, and their combinations. Furthermore, the study is an extension of the paper (Ting *et al*., 2014) where the proposed technique is refined and implemented for badminton movement recognition. Additionally,a technical badminton movement analysis without consideration of the amount of force being exerted by players are presented and discussed. Moreover, the proposed system enables badminton players to benchmark their performances either by themselves or together with experts. Therefore, the present research will be beneficial to sports scientists, badminton coaches, and badminton players.

Methods

Figure 1 illustrates an overview of our proposed system, which consists of movement recognition and analysis frameworks. Generally, both badminton reference and sample movements are acquired by Microsoft Kinect sensor and skeletal joints are estimated subsequently. Then, the tracked joints coordinates are mapped to range of movement index. Finally, recognition and analysis results are obtained by mapping two time-series data using dynamic time warping algorithm.

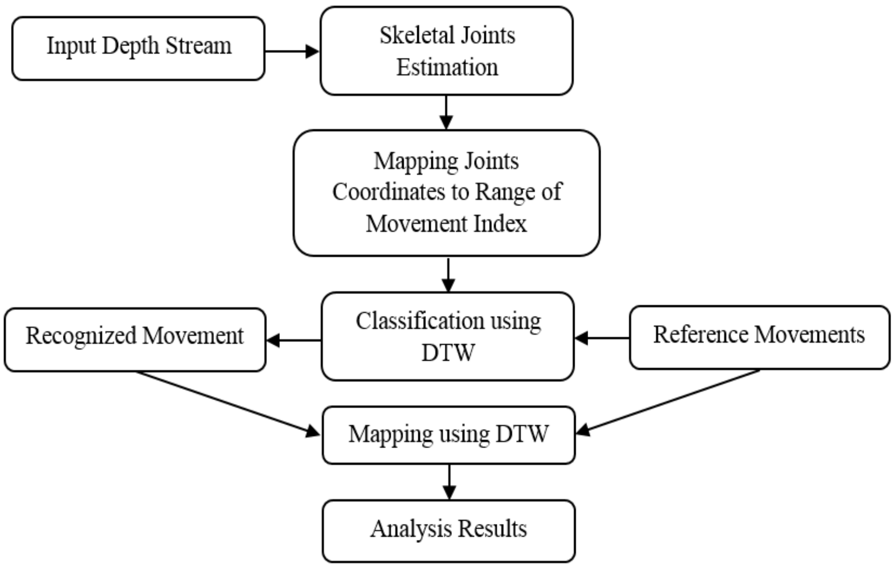


Figure 1. An overview of the proposed system.

Skeletal Model

In real-time, the Microsoft Kinect sensor generates depth map sequences which provide the human body silhouette. From the body silhouette, the body joints are estimated using the method from Shotton *et al*. (2011) and the skeletal model is constructed subsequently. The skeletal model, also known as "*stick model*", encompasses 20 body joints as illustrated in Figure 2. The 3D coordinates of these 20 body joints are tracked in real-time. Moreover, the skeletal model is quite robust to variations in shape and size of human body, the color and texture of clothing, and background. In this research, however, we have excluded head joint during the feature extraction process due to insignificant contribution.

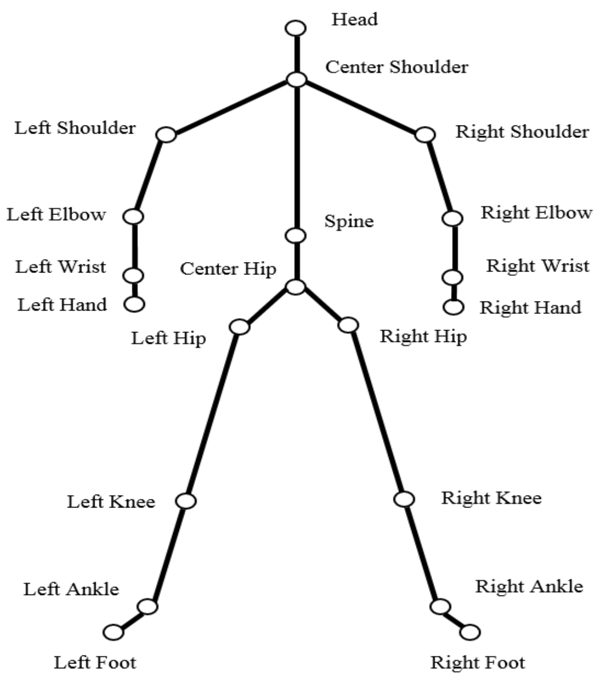
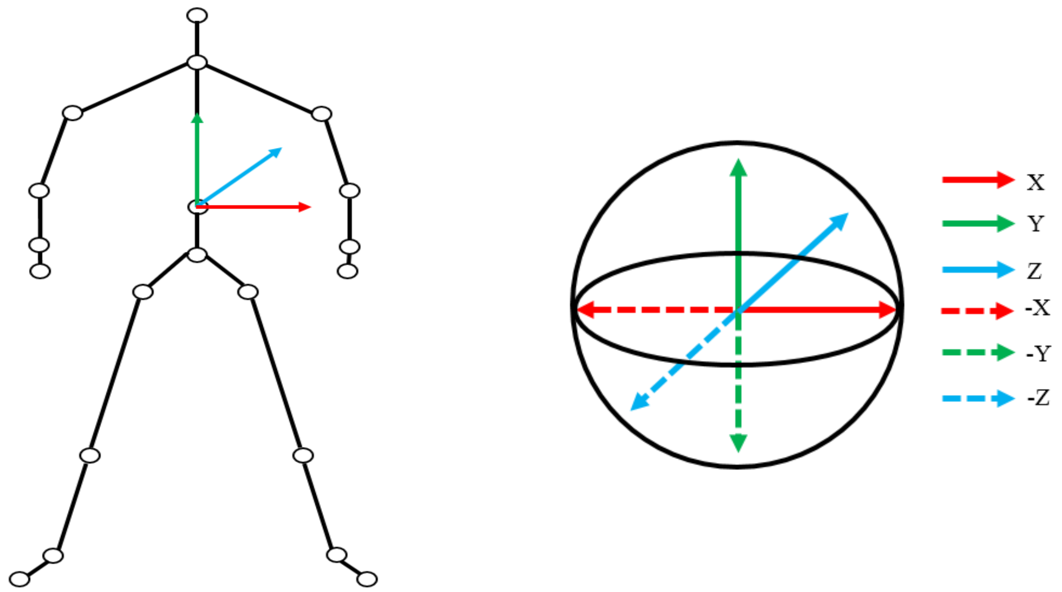


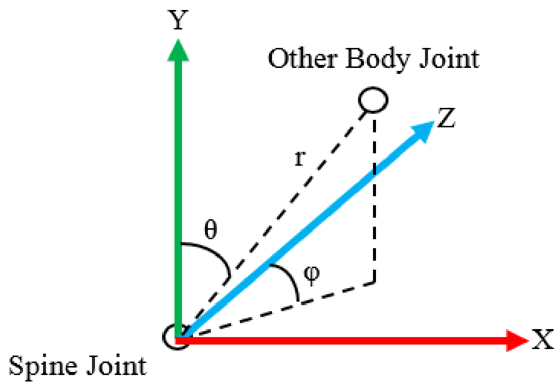
Figure 2. Skeletal model.

Range of Movement Index

In this section, we propose a novel lossless compact viewpoint invariant compression technique, namely range of movement index (RoMI). From the tracked skeletal frame, three axes (orthogonal) are defined at the spine joint where the *Y* axis lays on the spine bone as presented in Figure 3(a). Then, eight distinctive ranges based on the axes signs are determined as shown in Figure 3(b). The construction of the range of movement serves as a platform to locate the body joint respective to the spine joint. The label of the range corresponding to the signs of the axes is shown in Table 1.



(a) (b)



(c)

Figure 3. (a) Defined axes centered at spine joint, (b) eight distinctive ranges based on the axes signs, and (c) spherical coordinate system of body joint respective to spine joint.

Table 1. The label of range corresponding to signs of axes.

X-axis sign	*Y*-axis sign	*Z*-axis sign	Label, *R*
+	+	+	0
+	+	-	1
-	+	-	2
-	+	+	3
+	-	+	4
+	-	-	5
-	-	-	6
-	-	+	7

In each range a spherical coordinate system is constructed to describe the radius, the inclination, and the azimuth angles of a body joint with respect to the spine joint as displayed in Figure 3(c). Equations (1) to (3) denote the radius (r), theta (inclination), and phi (azimuth) angles in spherical coordinate system, respectively.

$$r = \sqrt{x^2 + y^2 + z^2} \;\; ; r \geq 0 \tag{1}$$

$$\theta = \arccos(\frac{y}{r}) \tag{2}$$

$$\varphi = \arctan(\frac{x}{z}) \tag{3}$$

where x, y, and z are the 3D human body joint coordinates. In our research, we regard the range of the theta angle for the frontal position from 0 to 180 degrees and for the back position from 0 to -180 degrees. On the other hand, we set the range of the phi angle for the right position from 0 to 180 degrees and the left position from 0 to -180 degrees.

In order to represent the spherical coordinate in a specific range more compactly, RoMI is formed. The RoMI I is denoted as

$$I = (r \times \theta_{\max} \times \varphi_{\max}) + (\theta \times \varphi_{\max}) + \varphi \tag{4}$$

where $\theta_{\max}$ and $\varphi_{\max}$ is the maximum angle of inclination and azimuth in each range respectively. Then, the RoMI is normalized and added with the label R which is shown in equation (5) to provide a distinctive representation of the RoMI in each range for each joint.

$$M = R + normalized\{I\} \tag{5}$$

Thus, a normalized RoMI body pose descriptor, $G=(M_1,\ldots,M_{19})\in\mathbb{R}^{19}$ is formed.

Furthermore, the RoMI is a lossless compression technique where radius, theta, and phi angles can be retrieved using equations (6) to (8), respectively.

$$r = \frac{I}{\theta_{\max} \times \varphi_{\max}} \tag{6}$$

$$\theta = (\frac{I}{\theta_{\max}}) \bmod \varphi_{\max} \tag{7}$$

$$\varphi = I \bmod \theta_{\max} \tag{8}$$

Dynamic Time Warping

In this research, the extracted features from a badminton sample movement are required to map to a reference movement. Since both, the badminton sample and the reference movement, are of arbitrary length, dynamic time warping (DTW) is proposed. DTW is a well-known algorithm in many areas, particularly in speech recognition. Moreover, the algorithm is popular due to its efficiency in time-series similarity measurement which minimizes the effects of shifting and distortion in time by creating a warping path to detect similar points with different phases (Senin, 2008).

In our framework, we denote the time-series normalized RoMI for both the badminton reference and the sample movements as displayed in equations (9) and (10), respectively.

$$R = [G_{r1}, G_{r2}, \ldots, G_{rn}] \tag{9}$$

$$S = [G_{s1}, G_{s2}, \ldots, G_{sm}] \tag{10}$$

To align two sequences R and S, we define an $m \times n$ cost matrix; the cost associated with time instant (i, j) is given by:

$$cost(R_i, S_j) = \sum_{p=1}^{d} \| R_{G_{p,i}} - S_{G_{p,j}} \| \tag{11}$$

where d = 19 body joints and $\|.\|$ is the Euclidean distance between d pairs of corresponding joints in the skeletal model.

In order to find the alignment between R and S, the path cost is defined as follows:

$$P = \{p_1, \ldots, p_T\}; \quad \max(m,n) \le T < m+n+1 \tag{12}$$

The warping path is defined as a set of "contiguous" matrix elements that construct a mapping between R and S. The warping path between R and S is typically subjected to several constraints:

1. **Boundary conditions:** The starting and ending observation points are aligned to each other for the reference and the sample actions.

$$p_1 = (1,1) \text{ and } p_T = (m,n) \tag{13}$$

2. **Continuity:** No observation points for the reference and the sample actions are to be skipped.

$$\begin{aligned} &\text{Given } p_{t-1} = (a',b');\ p_t = (a,b); \\ &a - a' \le 1 \text{ and } b - b' \le 1 \end{aligned} \tag{14}$$

3. **Monotonicity:** The observation points are monotonically spaced in time.

$$\begin{aligned} &\text{Given } p_{t-1} = (a',b');\ p_t = (a,b); \\ &a' \le a \text{ and } b' \le b \end{aligned} \tag{15}$$

In particular, the optimal alignment between R and S is the path that minimizes the warping cost given by:

$$DTW(R,S) = \min\left(\sum_{k=1}^{T} p_k\right) \tag{16}$$

where p_k are the elements in a warping path P that represents a mapping between R and S. For the badminton movement recognition, the costs between a sample movement and all reference movements are obtained. Obviously, the smaller the cost is, the more similar the sample and the reference movements are. Therefore, the least cost is determined in order to find the movement label for the current sample movement.

During the alignment procedure for two time-series badminton movements there are several segments where one to many (shorter sequence maps to longer sequence) or many to one mapping (longer sequence maps to shorter sequence) occur. In order to make the mapping results more presentable to badminton coaches or players, the system will perform a second stage of mapping, which is also known as segment mapping to align the length of the sample sequence to the reference sequence. If the sample sequence is longer than thereference sequence, the shortest distance in the segment (where many to one mapping is going to occur) of the sample sequence is selected. On the other hand, if the sample sequence is shorter than the reference sequence, the one to many mapping scenario is usually executed during the DTW stage. That particular single value is then appended in the segment in order to make the sample sequence longer.

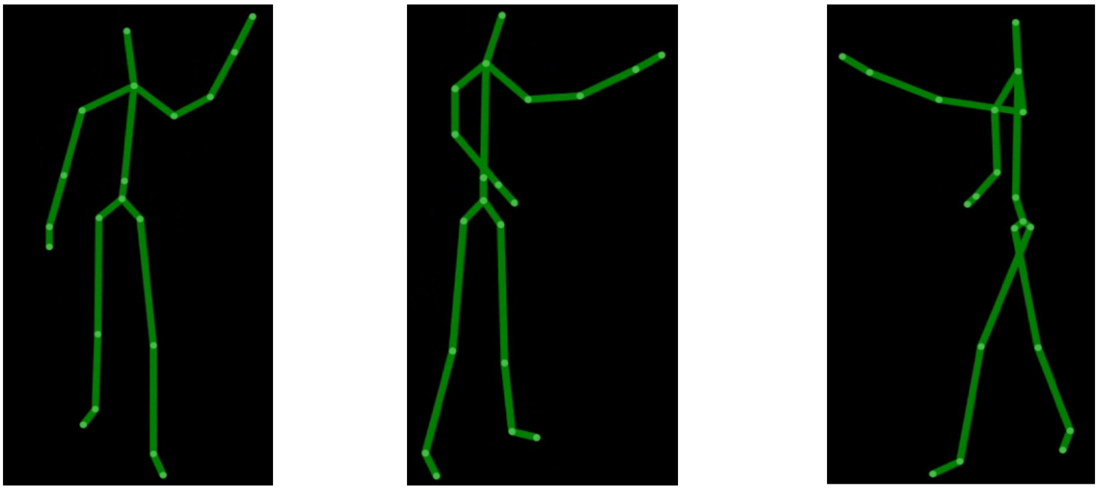
Let Q_r and Q_s denote the reference and sample vectors respectively after the segment mapping is executed. Thus, similarity index in percentage between reference and sample movements is computed using:

$$D_{RS} = \frac{Q_r . Q_s}{\| Q_r \| \| Q_s \|} \times 100 \tag{17}$$

Results and Discussion

Dataset and Setup

To-date there is no publically available badminton movement datasets in the form of depth map sequences for result benchmarking. In order to put the algorithm to test, we collected a dataset that contains ten essential and basic badminton movements needed by badminton players at all levels. The movements are: *backhand lift*, *backhand lob*, *backhand net*, *backhand serve*, *forehand lift*, *forehand net*, *forehand serve*, *forehand side*, *forehand lob*, and *overhead forehand clear* from 20 right-handed female and male badminton players for each movement. In this experiment, a Microsoft Kinect sensor with a maximum depth range of 5m and depth resolution of 25mm at three meters (Khoshelham and Elberink, 2012) was utilized to measure the movements. The depth map sequences were acquired with 30 frames per second by the Microsoft Kinect sensor with a dimension of 640 × 480. Each player performed the predefined badminton movements three times, about three meters from the sensor with three different views (Figure 4). The badminton players varied in terms of skin color, clothes, height, weight, and speed. Moreover, the same badminton movements were acquired from the coach as benchmark movements for the recognition framework. Looking into the dataset, there are certain aspects that are important to highlight. These aspects add up to the existing challenge in classifying the movements. The first being small visually perceived inter-class variations between two classes. Some obvious examples would be *forehand lift* and *forehand side*; *forehand lob* and *overhead forehand clear*. The second aspect is the existence of different views for a single movement such as frontal, left, and right views to highlight our representation as presented in Figure 4(a), 4(b), and 4(c) respectively.



(a) (b) (c)

Figure 4. Three different skeletal views. (a) Frontal view, (b) left view, and (c) right view.

Badminton Movement Recognition

In this experiment, there were 600 badminton movements in total to be classified. Basically, the framework generates cost values between the compared sample and reference movements. Subsequently, the smallest cost value is determined in order to assign a label to the sample movement. Figure 5 demonstrates the recognition accuracy confusion matrix for the proposed framework. According to Figure 5 *forehand side* achieves the lowest recognition accuracy in this experiment. 15% of *forehand side* movements were misclassified as *forehand lift*. The major reason for such result is that both movements have similar patterns except the right arm segment shows a different pattern. A full arm swing is required for the *forehand lift* movement in order to hit the shuttlecock up high and all the way back to the baseline. In contrast,the *forehand side* movement is mainly focusing on the wrist segment. In addition, some of the *overhead forehand clear* movements were categorized as *forehand lob* movement because of the small variation between the two movements. The major difference between the two movements involves the forearm merely “brushing” the top of player’s head before straightening the arm for the *overhead forehand clear* while the *forehand lob* is rather performing a throwing ball movement. Overall, the proposed framework attains average recognition accuracy of 94.5%.

However, instability of the joints localization was discovered in this experiment, particularly in the left skeletal view of badminton movements. This mainly occurs due to self-occlusion. The most obvious case in this experiment is the *forehand side* movement where the right arm segment might be occluded by the torso or other body parts when the movement is captured from the left view of a right-handed badminton player. Therefore, instability of the joints localization might be one of the factors leading to the high misclassification rates. Moreover, research from Obdrzalek *et al*. (2012) concluded that the Microsoft Kinect skeleton tracking framework struggles with occluding body parts or objects in the scene. Additionally, Wei *et al*. (2015) reported that tracking results would be more valuable for side view acquisition when the body parts are closer to the Microsoft Kinect sensor.

	Backhand Lift	**Backhand Lob**	**Backhand Net**	**Backhand Serve**	**Forehand Lift**	**Forehand Net**	**Forehand Serve**	**Forehand Side**	**Forehand Lob**	**Overhead Forehand Clear**
Backhand Lift	60									
Backhand Lob		57							3	
Backhand Net			60							
Backhand Serve				60						
Forehand Lift					51			9		
Forehand Net						60				
Forehand Serve							60			
Forehand Side					15			45		
Forehand Lob									60	
Overhead Forehand Clear									6	54

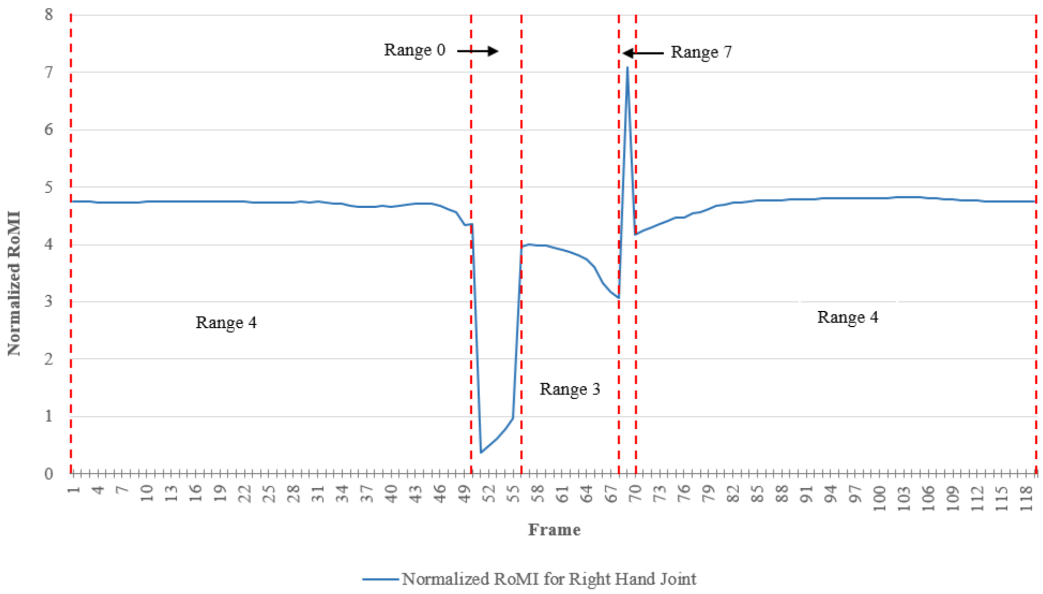
Figure 5. Badminton movement recognition accuracy confusion matrix.

Badminton Movement Analysis

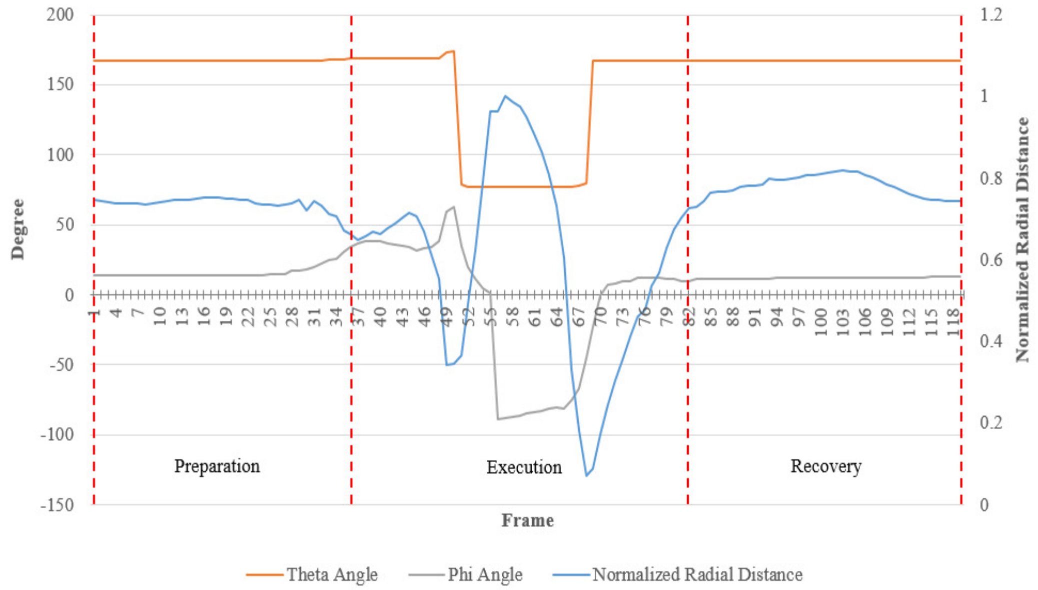
In this section, the results of two complex badminton movements namely *forehand lift* and *overhead forehand clear* (Figures 6 and 7) which were performed by badminton coaches are further analyzed and discussed. Although the algorithm is able to track up to 20 body joints, we only focus on the right hand joint movement in our study. Generally, results shown in Figure 6(a) and Figure 7(a) are generated using equation (5) in order to identify the location of the movement range for the right hand joint relative to the spine joint for *forehand lift* and *overhead forehand clear,* respectively. The right hand and spine joints were tracked in real-time to compute spherical coordinates (equations (1) to (3)) over frames and converted to RoMI subsequently. The interval scale of *Y* axis indicates the location of the range. In addition, Figure 6(b) and Figure 7(b) show the results of the inverse RoMI (using equations (6) to (8)) from Figure 6(a) and Figure 7(a), respectively. Besides, Figure 8 demonstrates the effectiveness of the lossless compression technique with a badminton movement using the right hand joint. The solid and dotted lines in Figure 8(a) indicate the temporal features of the original movement and the reconstructed features using the RoMI from Figure 8(b), respectively. We can clearly observe that the difference between original and reconstructed features is zero. The reconstruction of temporal features from RoMI is particularly useful when badminton coaches or players want to further examine the execution.

The badminton movement *forehand lift* is analyzed as illustrated in Figure 6. The transition of movement range for *forehand lift* movement is: 4-0-3-7-4. Such a transition of movement range states that the right hand joint is raised and executes a diagonal top left swinging motion. Then, the right hand joint returns back to the original position. In addition, the details of the movement in terms of spherical coordinates can be seen in Figure 6(b). Generally, there are three main stages, which are preparation, execution, and recovery. From the spherical coordinates graph, we can observe that the preparation and recovery stage almost have a similar pattern. During the execution stage, the theta angle relative to the *Y* axis of the spine joint is starting to decrease, indicating an elevation of the right hand joint. Moreover, when the phi angle encounters a drastic drop, the normalized radial distance almost hits its peak. This pattern demonstrates that badminton players perform a big swing motion to the left in order to hit the shuttlecock up high and all the way back to the baseline. After that, the right hand joint returns to the original position.

Figure 7 illustrates the badminton movement analysis for *overhead forehand clear*. Obviously, the movement demonstrates higher complexity as compared to *forehand lift*. In Figure 7(a), the transition of movement range for *overhead forehand clear* is: 4-0-1-0-4-7-4. The core movement of the skill is to execute an overhead full arm swing. Such an execution can be visualized from the first five ranges of transition. Basically, the right hand joint is raised “brushing” over the head (phi angle is reaching nearly zero degree) and performs a full swing motion to clear the shuttlecock to the baseline. Such overhead full swing motion can also be observed in detail as shown in Figure 7(b) where the theta angle rapidly decreases and increases within a small frame interval. Furthermore, the normalized radial distance reaches its peak in order to take the shuttlecock at the highest point.

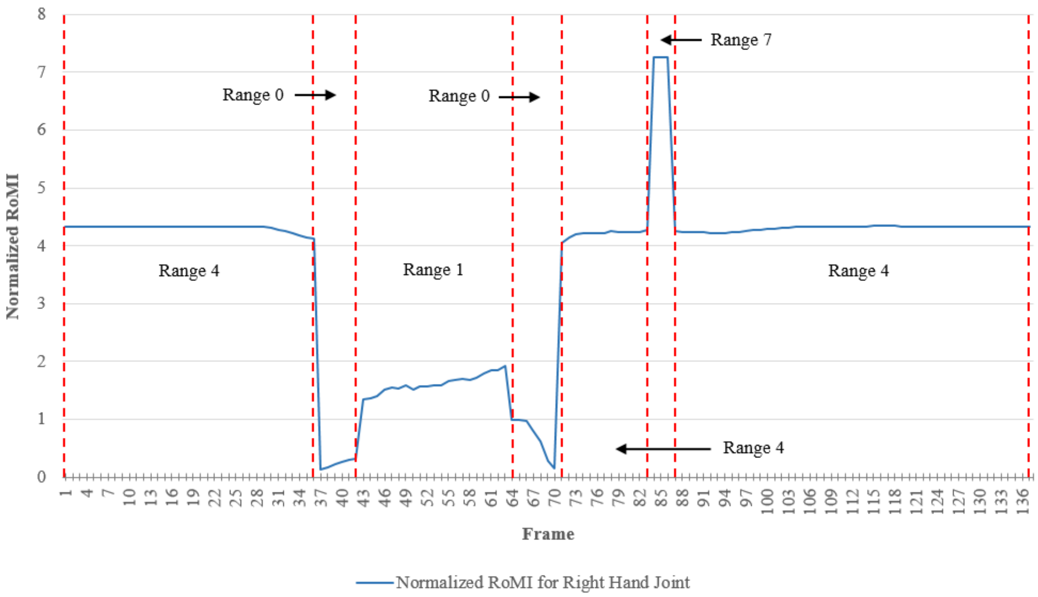


(a)

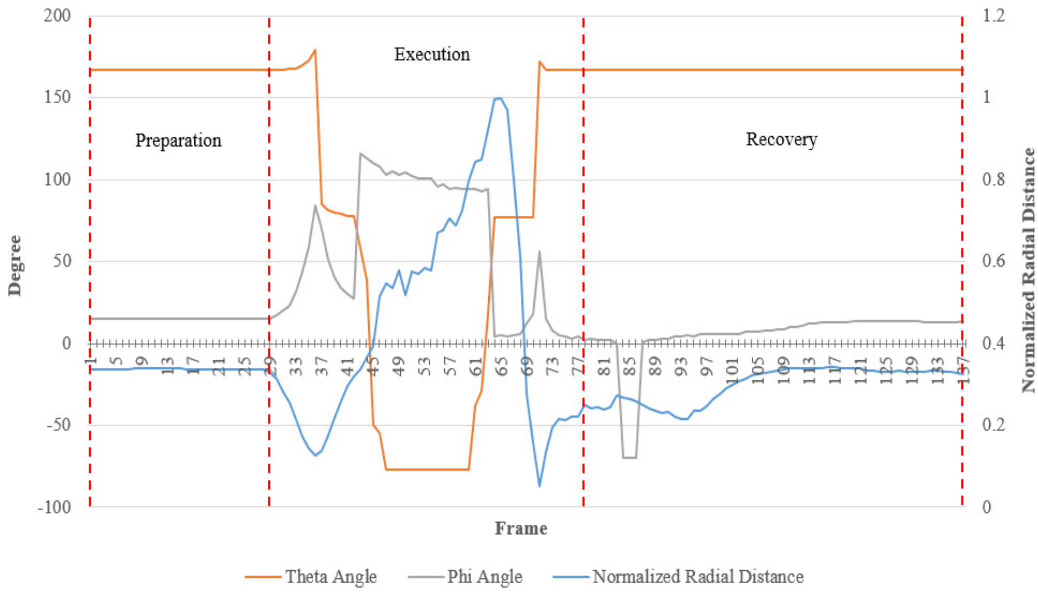


(b)

Figure 6. Badminton movement analysis for *forehand lift* that was performed by a badminton coach. (a) Right hand joint normalized RoMI graph and (b) spherical coordinates graph.

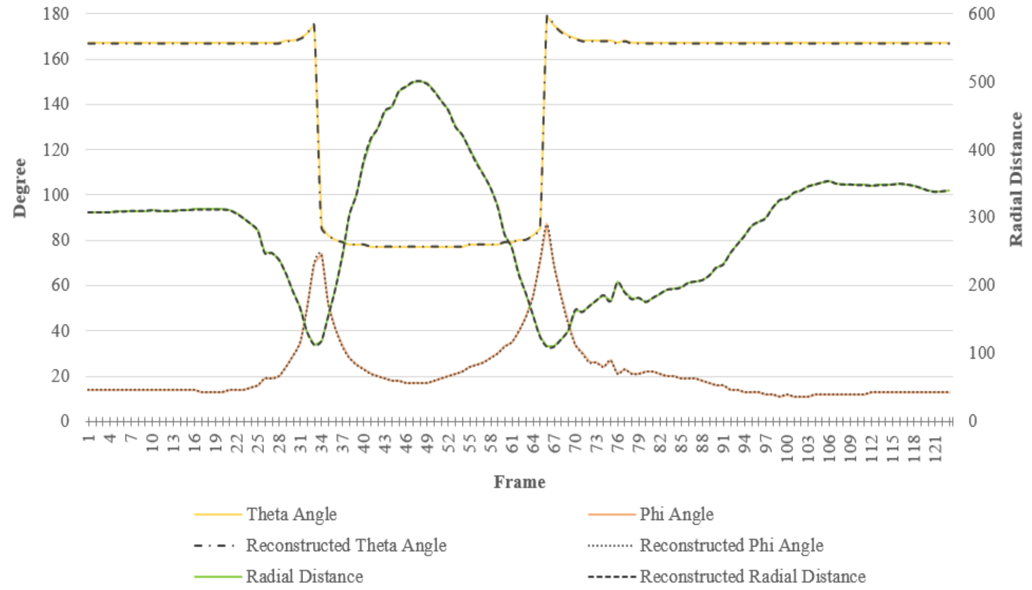


(a)

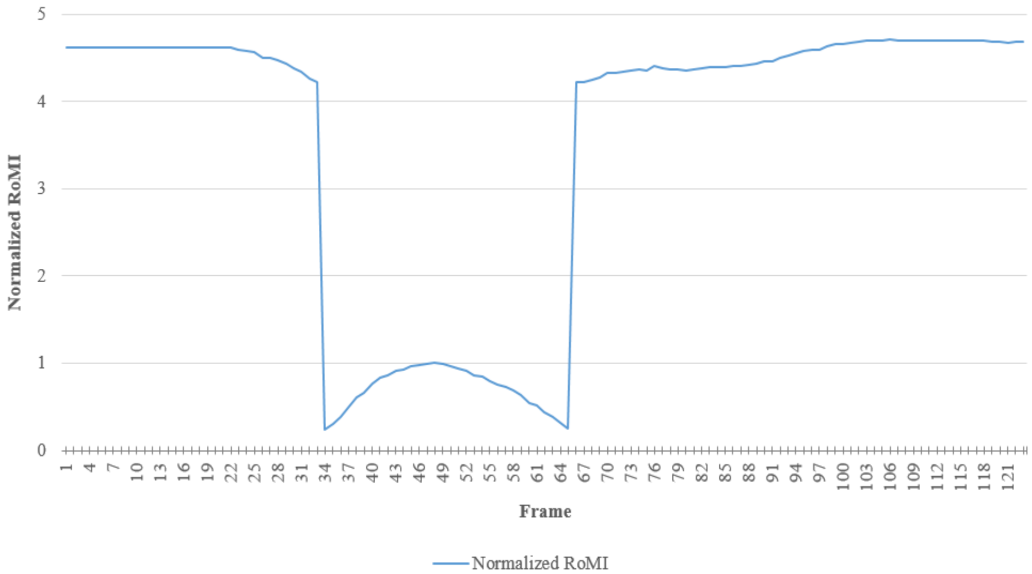


(b)

Figure 7. Badminton movement analysis for *overhead forehand clear* that was performed by a badminton coach. (a) Right hand joint normalized RoMI graph and (b) spherical coordinates graph.



(a)



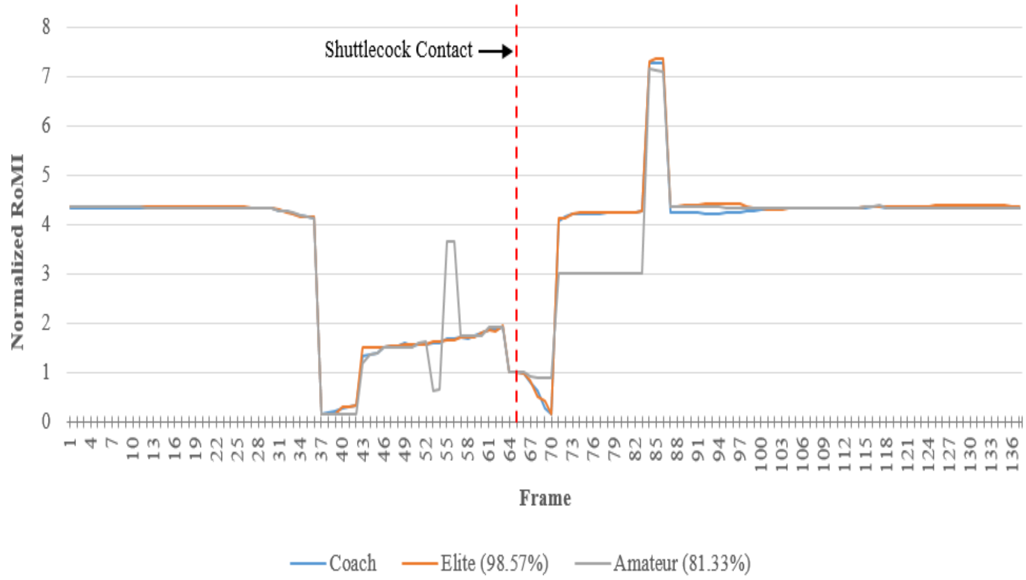
(b)

Figure 8. (a) Comparison of temporal features for original movement (solid line) and reconstructed movement (dotted line) from (b) normalized RoMI.

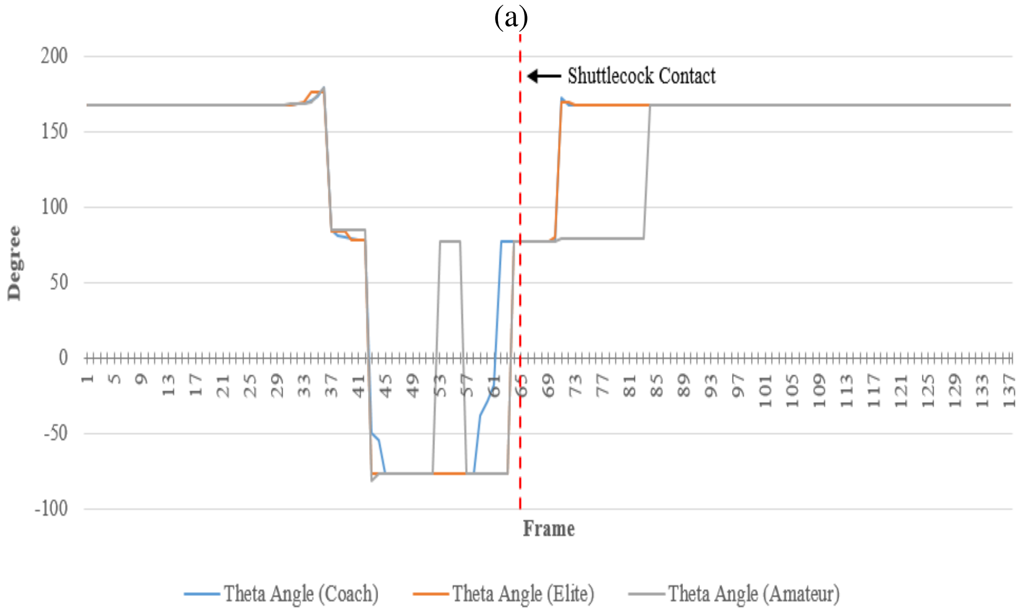
Benchmarking

Two different levels of badminton players which are elite and amateur perceived as expert players and intermediate players from the training group were selected to benchmark movements with a badminton coach. This module serves as a template for the badminton coach to compare and differentiate the movement of badminton players quantitatively. Moreover, the coach would be able to provide insightful feedback or rectification steps to the badminton players by referring to the benchmarked results. The benchmarking module is essential to prevent badminton players from developing "bad habits" in their technical approach to the game. Generally, time-series movements from the coach and a player are aligned using the DTW algorithm and the similarity index (SI) between two movements is computed using equation (17).

Figure 9 presents the benchmarking results for *overhead forehand clear* between the badminton coach and the players. In Figure 9(a), the expert player performed an almost identical movement as the coach and accounted for by an SI of 98.87% while the intermediate player achieved an SI of 81.33% from the normalized RoMI graph. Furthermore, the intermediate player had the same theta angle for a while after the shuttlecock was hit by the racquet (frame 65) (see Figure 9(b)). Also, the phi angle for the amateur player in Figure 9(c) significantly declines after the shuttlecock contact, which further justifies the transition range of movement for the right hand joint (from 0 to 3) in Figure 9(a). Figure 9(d) depicts that the expert and intermediate players strike the shuttlecock at the maximum radial distance. Thus, the possible feedback from the coach to amateur players is to execute an overhead straight swinging motion for *overhead forehand clear*. Moreover, badminton players can use the system to measure the consistency of movement by self-benchmarking.



(a)



(b)

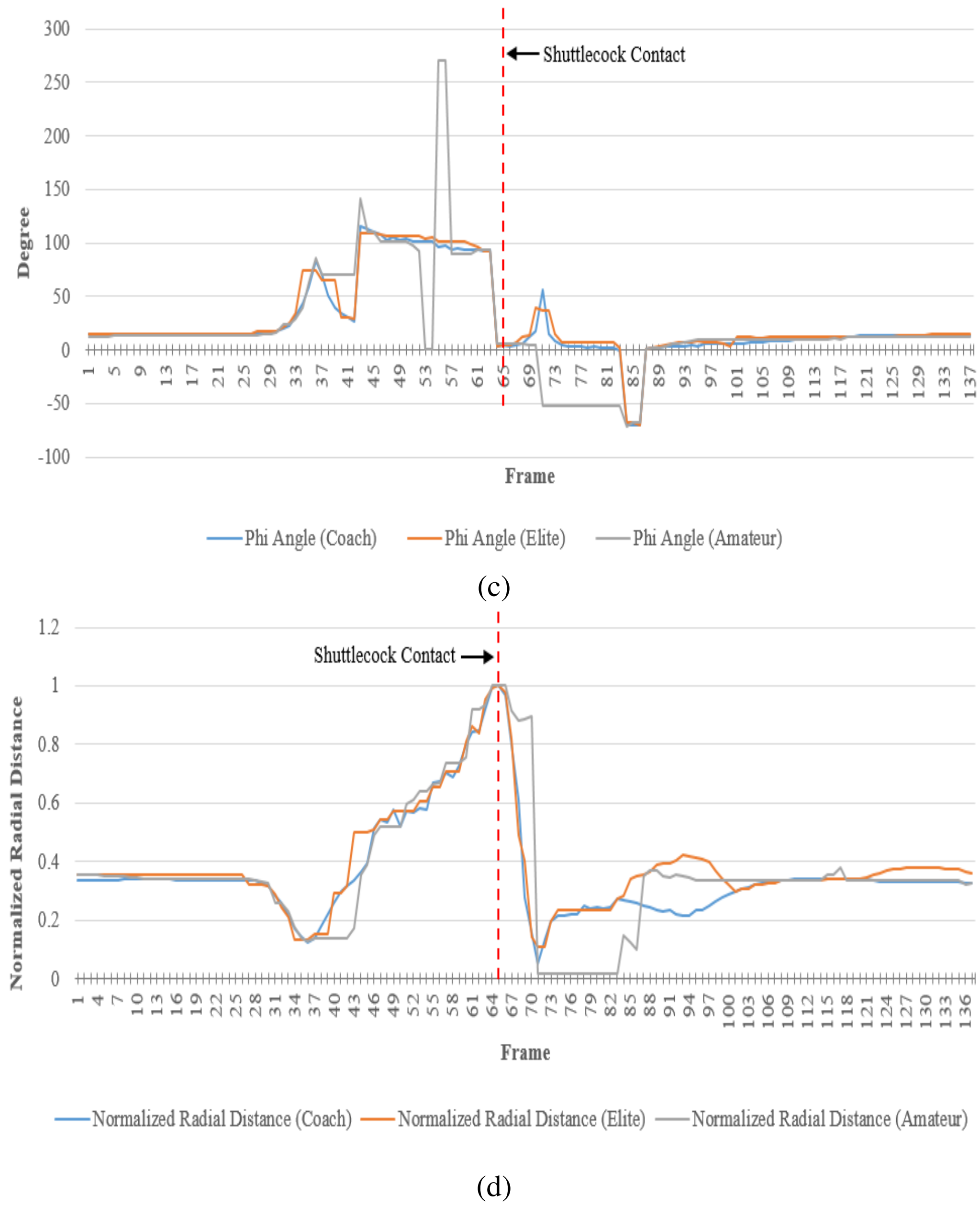


Figure 9. Badminton skill levels benchmarking results between badminton coach and players for overhead forehand clear. Comparison skill levels for (a) normalized RoMI, (b) theta angle, (c) phi angle, and (d) normalized radial distance.

Conclusion

In this paper, we present an approach to analyze and recognize badminton movements using depth map sequences acquired by the Microsoft Kinect sensor. A novel lossless compact view invariant compression technique with the dynamic time warping algorithm is proposed in order to cater for both recognition and analysis frameworks. The movement recognition framework was validated with a dataset which varies in terms of viewpoints, human body size, clothes, speed, and gender with a total of 600 samples from 20 badminton players. Experimental results have clearly shown the promising performance of the movement recognition framework with an average recognition accuracy of 94.5%. In addition, the system is capable to perform movement analysis in detail using the movement analysis framework. The proposed system also enables badminton players to periodically benchmark their performances either by themselves or with an expert. As such, feedback can be obtained in order to enhance their performance. Therefore, as a tool for performance analysis, the proposed system can be beneficial to sports scientists, badminton coaches and most importantly the players themselves.

References

Connors, M., Dupuis, D. L., & Morgan, B. (1991). *The Olympics Factbook: A Spectator's Guide to the Winter and Summer Games*. Visible Ink Press. 195.

Goles, J. (2010). Inside the race to hack the Kinect. *New Scientist*, *208*(2789), 22.

Guillain, J. Y. (2004). *Badminton: An Illustrated History*. Publibook.

Hussain, I. & Bari, M. A. (2011). Kinematical analysis of forehand and backhand Smash in badminton. *Innovative Systems Design and Engineering*, *2*(7), 20-25.

Hussain, I., Ahmed, S., Bari, M. A., Ahmad, A., Mohammad, A., & Khan, A. (2011). Analysis of arm movement in badminton of forehand long and short service. *Innovative Systems Design and Engineering*, *2*(3).

Khoshelham, K. & Elberink S. O. (2012). Accuracy and resolution of kinect depth data for indoor mapping applications. *Sensors*, *12*, 1437-1454.

Li, W., Zhang, Z. & Liu, Z. (2010). Action recognition based on a bag of 3D points. *In Proceeding of IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 9-14.

Lin, S.Y., Shie, C. K., Chen, S. C., Lee, M. S. & Hung, Y. P. (2012). Human action recognition using action trait code. *In Proceeding of 21st International Conference on Pattern Recognition*, 3456-3459.

Liu, G., Zhang, D. & Li, H. (2014). Research on action recognition of player in broadcast sports video. *International Journal of Multimedia and Ubiquitous Engineering*, *9*(10), 297-306.

Malgireddy, M., Inwogu, I., Govindaraju, V. (2012). A temporal bayesian model for classifying, detecting and localizing activities in video sequences. *In Proceeding of IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 43-48.

Miranda, L., Vieira, T., Martinez, D., Lewiner, T., Vieira, A. W. & Campos, M. F. M. (2012). Real-time gesture recognition from depth data through key poses learning and decision forests. *In Proceeding of 25th SIBGRAPI Conference on Graphics, Patterns and Images*, 268-275.

Nagasawa, M., Hatori, Y., Kakuta, M., Hayashi, T., & Sekine, Y. (2012). Smash motion analysis for badminton from image. *In Proceeding IIEEJ 3rd Image Electronics and Visual Computing Workshop*.

Ni. B, Wang, G. & Moulin, P. (2011). RGB-D-HuDaAct: A color-depth video database for human daily activity recognition. *In Proceeding of IEEE International Conference on Computer Vision Workshops*, 1147-1153.

Ning, Y. (2013). Research of badminton forehand smash technology based on biomechanical analysis. *Journal of Chemical and Pharmaceutical Research*, *5*(11), 172-177.

Obdrzalek, S., Kurillo, G., Ofli, F., Bajcsy, R., Seto, E., Jimison, H., & Pavel, M. (2012). Accuracy and robustness of Kinect pose estimation in the context of coaching of elderly population. *In Proceeding of Engineering in Medicine and Biology Society, 2012 Annual International Conference of the IEEE*, 1188-1193.

Raptis, M., Kirovski, D. & Hoppe, H. (2011). Real-time classification of dance gestures from skeleton animation. *Eurographics Symposium on Computer Animation*, 147–156.

Reyes, M., Dominguez, G. & Escalera, S. (2011). Featureweighting in dynamic timewarping for gesture recognition in depth data. *In Proceeding of IEEE International Conference on Computer Vision Workshops*, 1182-1188.

Salim, M. S., Lim, H. N., Salim, M. S. M., & Baharuddin, M. Y. (2010). Motion analysis of arm movement during badminton smash. *In Proceeding of Biomedical Engineering and Sciences*, 111-114.

Sempena, S., Maulidevi, N., Aryan, P. (2011). Human action recognition using dynamic time warping. *In Proceeding of International Conference on Electrical Engineering and Informatics*, 1-5.

Senin, P. (2008). *Dynamic time warping algorithm review*. Honolulu USA.

Shotton, J., Fitzgibbon, A. W., Cook, M., Sharp, T., Finocchio, M., Moore, R., Kipman, A., & Blake, A. (2011). Real-time human pose recognition in parts from single depth images. *In Proceeding of Computer Vision and Pattern Recognition*, 1297-1304.

Teng, S. L. & Paramesran, R. (2011). Detection of service activity in a badminton game. *In Proceeding of IEEE Region 10 Conference*, 312-315.

Ting, H. Y., Sim, K. S., & Abas, F. S. (2014). Kinect-based badminton action analysis system. *In Proceeding of 3rd International Conference on Key Engineering Materials and Computer Science*.

Tsai, C. L. & Chang, S. S. (1998). Biomechanical analysis of differences in the badminton smash and jump smash between Taiwan elite and collegiate players. *In Proceeding of XVI International Symposium on Biomechanics in Sports*, 259-262.

Wei, T., Lee, B., Qiao, Y., Kitsikidis, A., Dimitropoulos, K. & Grammalidis, N. (2015). Experimental study of skeleton tracking abilities from microsoft kinect non-frontal views. *In Proceeding of 3DTV-Conference: The True Vision - Capture, Transmission and Display of 3D Video*, 1-4.

Wu, D., Zhu, F., & Shao, L. (2012). One shot learning gesture recognition from RGBD images. *In Proceeding of IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, 7-12.

Wu, J., Konrad, J. & Ishwar, P. (2013). Dynamic time warping for gesture-based user identification and authentication with Kinect. *In Proceeding of IEEE Internation Conference on Acoustics, Speech and Signal Processing*, 2371-2375.

Yoshikawa, F., Kobayashi, T., Watanabe, K., & Otsu, N. (2010). Automated service scene detection for badminton game analysis using CHLAC and MRA. *World Academy of Science, Engineering and Technology*, *4*, 841-844.

Zhang, H. & Parker. L. E. (2011). 4-Dimensional local spatio-temporal features for human activity recognition. *In Proceeding of International Conference on Intelligent Robots and Systems*, 2044-2049.

A Statistical Model of the 2013 Rugby Sevens World Cup

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Abstract

The purpose of this study was to establish a predictive model capable of simulating and predicting the outcome of the 6th Rugby Sevens World Cup, held in Moscow on the 28th to the 30th June 2013.

Following a review of predictive modelling approaches in sport, a multivariate regression model was attempted, using International Rugby Board (IRB) ranking points and various travel effect descriptors (relative time zone, altitude, average temperature, estimated flight time and circadian rhythm offsets) to predict points-difference of international Rugby Sevens matches. A whole database approach was used to generate the model, based on the outcomes of all IRB Series matches dating from 2004 to the fifth round of 2013 (n = 3240). A step wise approach to establishing a model was attempted, though none of the travel effects tested correlated, with only IRB ranking difference between teams improving the model. Accordingly a bivariate model was used in simulating the tournament structure. The model correctly predicted New Zealand as tournament winners, as well as six of the eight cup quarterfinalists, which is in line with the tournament seeding. Half of the tournament final standings were within +/- 1sd of the prediction.

The current research establishes that international Rugby Sevens match outcomes are dominated by difference in relative strength demonstrated over previous ranking events, and are largely insensitive to the travel effects estimated in this study. Meanwhile analysis of the input dataset revealed a 24.7% upset frequency in the period 2004-2013, which is higher than that presented in other texts for fifteen a side Rugby Union.

KEYWORDS: REGRESSION, TRAVEL EFFECTS, RUGBY SEVENS

Introduction

Modelling has been applied widely with the intention of advancing the knowledge of various sports (profiling) in order that future performance can be predicted with a reasonable degree of confidence (Reed, et al., 2005). Various methodologies have been applied, with varying success in (for example) football (O'Donoghue *et al.,* 2003), tennis (O'Donoghue, *et al.,* 2010), rowing (Mikulic, *et al.,* 2009) and rugby union (O'Donoghue *et al.,* 2004; O'Donoghue, 2013).

One of the more popular approaches is regression modelling, which can be thought of as a methodology for determining the extent to which one or more independent variables are able to describe a dependent variable, by using varying coefficients to minimise the combined size of residuals. A strength of regression modelling is the ability to output results in terms of points difference (Reed *et al.*, 2005) rather than just Boolean win-loss outcomes. This allows actual tournament rules to be applied, in events where pool standings and seedings are influenced by measures of points scored and conceded, and in doing so more fully capture the element of chance within a particular event. Furthermore, they are able to incorporate opposition effects by using the relative strength of the opposition as an independent variable (O'Donoghue, *et al.,* 2011). The flexibility of the number of additional variables that can be included as part of a multivariate approach means that sophistication of the model can be improved in light of correlation with additional independent variables. Meanwhile, they have tended to perform better as an input to tournament modelling than in Neural Network approaches (O'Donoghue, 2003), which demand a large database (Reed et al., 2005), and are conceptually challenging.

The following assumptions are outlined as pre-requisites of the application of regression analysis. Firstly there must be no outliers in the independent variables or residuals, although it has been argued that outliers in sport are in fact valid inclusions to the model, as they relate to events which have already happened, rather than measurement error (O'Donoghue et al., 2011). Secondly residuals should be independent, homosecedastic and normally distributed (O'Donoghue, 2012). Finally there should be no correlation between independent variables. However, it has been demonstrated in several texts that violating these assumptions may actually lead to an improved prediction (O'Donoghue, *et al.,* 2011).

The size of the data set is of interest, with too large a sample being seen as inflexible and insensitive to form (Hughes, et al., 2001), and too little being unlikely to satisfy the key regression assumptions (Ntoumatis, 2001). However, the creation of a large dataset allows for later refinement of a model (Reed, *et al.*, 2005). Similarly, a larger sample population may reduce the requirement to extrapolate beyond the dataset, which is cautioned against in certain texts (O'Donoghue, 2012), while demonstrated as wholly inappropriate in others (Heazlewood, 2006; Berthelot et al., 2008; Thibault et al., 2010). A review of this literature underlines the importance of applying a model that successfully reflects the mechanics of the relationship, rather than approximating it over a small portion of the population. It may also be the case that greater belief in the model and subsequent predictions can be found in developing it from a larger database.

The 6th Rugby Sevens World Cup held in Moscow in July, 2013 presented an interesting opportunity to assess the relative strengths of competing nations, as well as the seeding procedures adopted by tournament designers. The pan global nature of Sevens, with between 16 and 24 nations competing at each of the 9 stages of the HSBC IRB Sevens Series, held at venues spanning four continents over the course of each season, presents an opportunity to review the sensitivity to travel effects, that is often cited by coaches as justification of underperformance (Friday, 2013; www.irbsevens.com, 2013). A multivariate regression approach was selected, as a means of understanding the relative sensitivity of performance in Sevens to various travel effects, and founding the prediction of likely outcomes of the 2013 Sevens Rugby World Cup (RWC), in keeping with the aims of predictive modelling as described above. As data collection was required, the entire online dataset was collated for examination, with the intention of subsequent refinement as required (Reed, et al., 2005).

This study is particularly pertinent in light of the increase in media coverage and available funding made available to competing nations since the sport's inclusion into the Olympic program (Pengelly, 2013, in press). Furthermore, Rugby Sevens is hitherto an underresearched area, with research to date centring on physiological demands (Van Rooyen et al., 2008; Suarez-Arrones *et al.,* 2012) and match patterns (Hughes et al., 2005).

Method

The seedings for the 2013 Sevens Rugby World Cup are determined based on the number of tournament points accrued by each of the competing nations during the Hong Kong and Shanghai Banking Corporation (HSBC) IRB Sevens Series over the 2010-2011 and 2011-2012 series, as well as the first five rounds of the 2012-2013 series (www.rwcsevens.com, 2013) as presented in Table 1. The justification for using the 25 previous tournaments to determine RWC seedings was examined, and is discussed in the next section.

Table 1 - RWC Sevens Seeds and ranking points (www.rwcsevens.com, 2013)

Tournament Seed	Team	Points	Tournament Seed	Team	Points
1	New Zealand	429	13	Canada	77
2	Fiji	349	14	Portugal	49
3	South Africa	338	15	Spain	42
4	Samoa	324	16	Russia	19
5	England	304	17	Tonga	19
6	Australia	227	18	Zimbabwe	12
7	Wales	197	19	Japan	10
8	Argentina	183	20	Hong Kong	5
9	France	144	21	Georgia	0
10	Kenya	113	22	Tunisia	0
11	Scotland	93	23	Philippines	0
12	USA	79	24	Uruguay	0

In all cases independent variables were examined in terms of their ability to influence the dependent variable, Points Difference (PD) between the two teams, as defined by the equation 1:

$$PD = \text{Points for Team A} - \text{Points for Team B} \quad (1)$$

where Team A and Team B are the first and second teams listed in the match schedule by www.IRBSevens.com, respectively. Thus, a victory for Team A would result in a positive value for PD. All independent variables were expressed as differences between Team A and Team B in the same manner. One of the prime tenets of interacting performance theory is that the relative strength of the opposition is a key affecting variant in sports performance (O'Donoghue, 2009). Accordingly, the difference between ranking points of the two teams, RankDiff25, was used to assess the relative strength of the teams, and is given by Equation 2.

RankDiff25 = (#Tournament Points for ***Team A*** *in the previous 25 tournaments) - (#Tournament Points for* ***Team B*** *in the previous 25 tournaments* **(2)**

RankDiff25 was selected in preference to seeding position, as it was assumed to contain a better reflection of the relative strength of two teams, and is consistent with previous studies in the field of Rugby Union (O'Donoghue, 2013). However, the assumption of improved correlation was not statistically tested in this study.

Travel effects are often cited in the press as reasons for varying sports performance, with altitude, environmental differences and training disruption (Youngstedt *et al.,* 1999), general travel disruption (McGukin *et al.,* 2012) and in particular Jet Lag (du Preez *et al.,* 2007; Forbes-Robertson, *et al.,* 2012) presented as contributing factors. Distance Penalty was assessed as the point to point distance between capital cities of competing nations and the venue, the hypothesis being that any travel effects would be a proportional to the distance travelled (O'Donoghue, 2003). The variable Distance Penalty is given by Equation 3. Data was downloaded from http://www.worldweatheronline.com/.

DistancePenalty = ABS(Distance from ***Team A*** *capital city to Tournament Venue) - ABS(Distance from* ***Team B*** *capital city to Tournament Venue)* - **(3)**

The effect of flight time was also examined, under the hypothesis that the dehydration, blood pressure, and training disruption effects of air travel (Auger *et al*., 2009) are more likely to be a function of time in the air than distance travelled. FlightPenalty is given by Equation 4. The minimum flight time used was the fastest route that could be found from www.skyscanner.net between each team's capital city and the airport nearest to the tournament venue, in lieu of detailed travel plan information which would have been prohibitively difficult to gather in study of such sample size.

FlightPenalty = ABS(Minimum flight time from ***Team A*** *capital city to Tournament Venue) - ABS(Minimum flight time from* ***Team B*** *capital city to Tournament Venue)* - **(4)**

Two dependent variables were used to assess the effects of jet lag. Firstly, the number of time zones difference between each team's capital city and the tournament venue was compared, as Equation 5. However, circadian disruption follows a sinusoidal, rather than linear, model (Forbes-Robertson, et al., 2012), and so a variable representing a broadly sinusoidal relationship between circadian disruption and pan time zone travel was considered for analysis, developed under the assumption that the relative disruption could be determined by superimposition of circadian waveforms. The adopted model is described given in Equation 6. Figures 1 and 2 explain the development of this model, using the example of Fiji v England, in the final of the 2004 Dubai Sevens, played at 18:40pm local time.

UTCPenalty = ABS(time zone offset between ***Team A*** *capital city and tournament venue) - ABS(time zone offset between* ***Team B*** *capital city and tournament venue)* - **(5)**

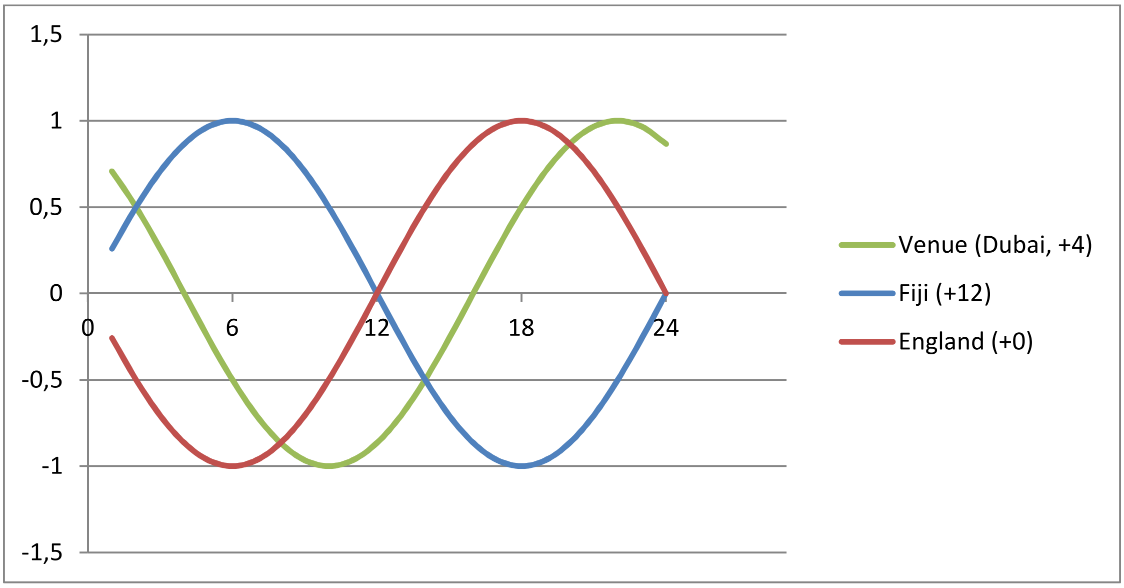

Figure 1 – Sinusoidal Curves used to simulate circadian rhythms

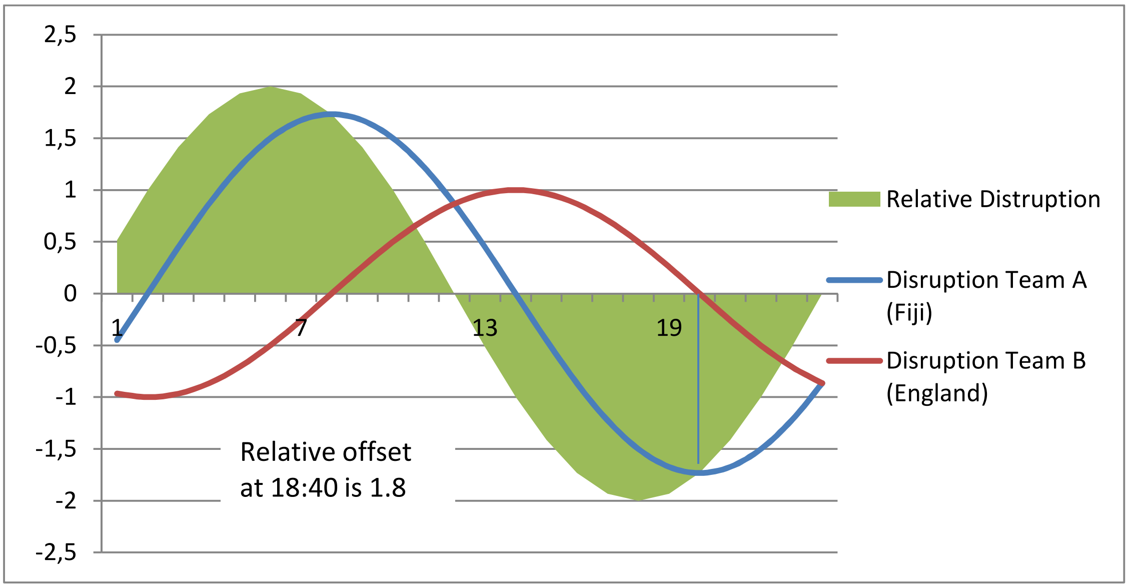

Figure 2 – Superimposition of circadian rhythms

CircDisruption = Abs{sin((Local time – 12 – **TeamA** Home City Time Zone)/24) – sin((Local time – 12 – **Venue** Time Zone)/24)}- Abs{sin((Local time – 12 – **TeamB** Home City Time Zone)/24) – sin((Local time – 12 – **Venue** Time Zone)/24)} - **(6)**

Time zone offsets were expressed in terms of Coordinated Universal Time, UTC, and were downloaded from http://en.wikipedia.org/wiki/List_of_UTC_time_offsets. Altitude were defined similarly, with the temperature being the average monthly temperature for the month that the tournament was played in. Data was obtained from http://en.wikipedia.org/wiki/List_of_capital_cities_by_altitude (altitude) and http://www.worldweatheronline.com/ (temperature). These variables are presented in Equations 7 and 8.

AltitudePenalty = ABS(Difference in altitude between **Team A** capital city and Tournament Venue) - ABS(Difference in altitude between **Team B** capital city and Tournament Venue) **(7)**

TemperaturePenalty = ABS(Difference in average temperature between **Team A** capital city and Tournament Venue) - ABS(Difference in average temperature between **Team B** capital city and Tournament Venue) - **(8)**

Recovery time between games was not assessed. However, the database created in the current study lends itself to subsequent analysis of this variable in future studies. The reliability of the selected regression model was tested by modelling a tournament which had already been played at the time of writing, yet occurred after the tournament seedings were determined, hence had not been included in the dataset used to generate the model. Predicted results for pool standings and overall winners were then compared to the actual data. Finally, confidence in the results was assessed using a convergence statistic, to ensure that the simulation had been run enough times for the results to stabilize, a method borrowed from Finite Element Analysis programs used in Mechanical Engineering. The convergence statistic chosen was stability of chance of each country winning the cup, plate and bowl competitions of the tournament.

Data Processing and Analysis

Initially the ability of tournament points to predict match results was assessed, in an attempt to validate the number of tournaments included in the RWC Sevens Seeding process, the initial hypothesis being that the ranking system is over-damped, or un-reactive to changes in form. Match data from all tournaments (2004-2013) (n = 3240) and tournaments points that were achieved by all teams (2002-2013) was downloaded from www.irbsevens.com and copied to Microsoft Excel. Data cleaning subroutines were written in Visual Basic for Applications (VBA), to standardize the data (e.g.: "NZ" rather than "New Zealand") and to extract the match scores for each team. Kick off times were extracted formulaically within Excel. A function was written to assign what would have been the relative tournament ranking points for each team in all matches in the dataset, accessed from preceding tournament information. The function looped, to assign ranking points for different numbers of tournaments, from 1:25. Formulae were applied in Excel to determine consistency of ranking point disparity between sides and actual results, as the number of upsets versus ranking points. Upsets were calculated as follows by Equation (9), where if the signs of the two variables differ, the lower ranked side unexpectedly scored more than the higher side. Where the ranking difference was not equal to zero, draws were also treated as upsets.

If RankDifference(A,B) * PointsDifference(A,B) < 0 then Upset - **(9)**

Increasing the number of tournaments included in the model showed greater prediction of results, with 25 tournaments performing best across all seasons, as shown in Figure 3. As a result, the 25 preceding tournaments were included in the independent variable RankDiff25, and the choice of tournaments included in the seeding process adopted in the RWC Sevens can be considered valid.

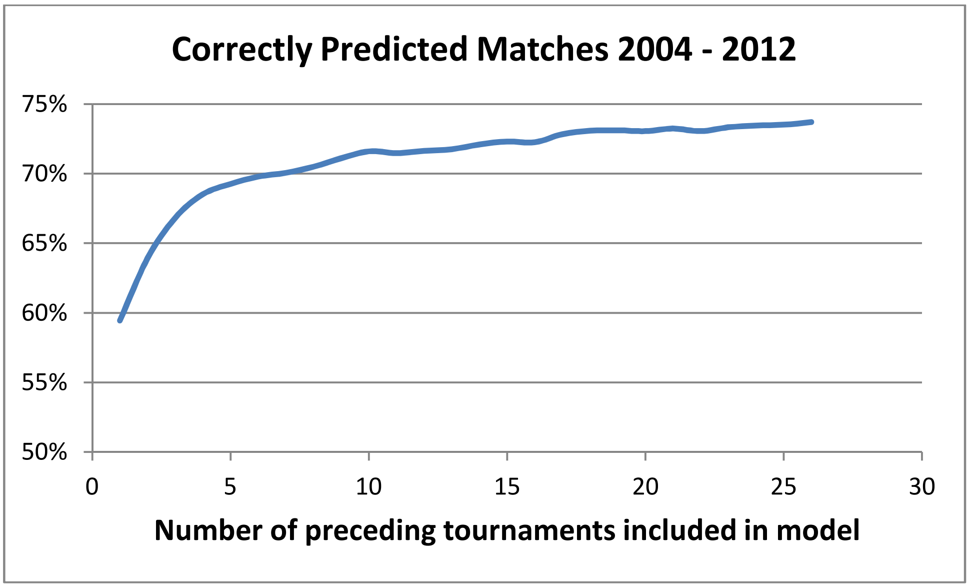

Figure 3 – Tournament Points Prediction of Match Results.

RankDiff25 values were again assigned on an individual match basis, along with travel and environmental independent variables. A programmatic approach was adopted (VBA) for simplicity and runtime issues, in response to the computational demands of including volatile Excel lookup functions in a large dataset. The dataset was imported into Matlab once teams that would not compete in the 2013 RWC had been excluded (n = 2478). Each variable was assessed for correlation with PD, with R^2 values and linear regression coefficients returned. Correlation to the residual values of the linear model of RankDiff25 and PD was subsequently examined for all other independent variables. These values are presented in Table 2.

Table 2 – Regression coefficients of independent variables to PD

	Correlation to PD			Correlation to residuals of RankDiff25 vs PD		
	R^2	gradient	intercept	R^2	gradient	Intercept
RankDiff25	0.294	0.059	2.130	-	-	-
Altitude	0.000	0.000	8.060	0.000	0.000	-0.009
DistancePenalty	0.004	0.000	7.912	0.000	0.000	0.005
FlightPenalty	0.005	-0.002	7.909	0.000	0.000	0.015
TempPenalty	0.009	0.187	7.913	0.001	-0.055	0.047
UTCPenalty	0.015	-0.334	7.713	0.000	-0.036	-0.039
RelativeDisruption	0.000	0.375	8.068	0.000	0.132	-0.001

Matlab's stepwise regression tool was used in an attempt to produce a multivariate model, though no variable improved the model beyond the influence of RankDiff25, and so the multivariate approach was abandoned in favour of a bivariate model, given by Equation 10 and illustrated in Figure 4. Note that the positive bias of the dataset is indicative of the tendency of tournament organisers' tendency to list the higher ranked team first in the fixture list.

$$TeamAPD = 0.0588 * RankDiff25 + 2.1305 \qquad - \qquad \mathbf{(10)}$$

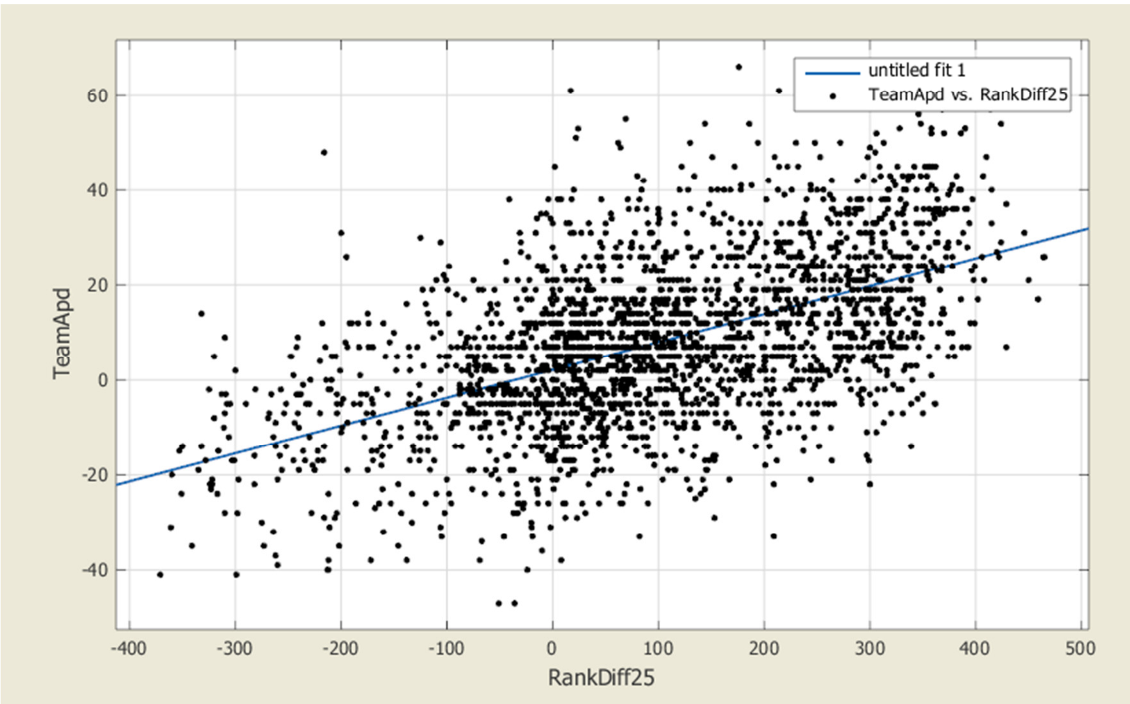

Figure 4 – Matlab Output of Linear Regression Model of RankDiff25 and TeamApd

Each competing nation's performance against the regression model was expressed in terms of mean and standard deviation of the residuals of actual results, and were extracted in Matlab along with the number of games featuring each side, and are presented in Table 3.

Table 3 – Distribution of residuals against bivariate model of PD v RankDiff25.

Team	μ	sd	n
Argentina	-1.90	14.08	325
Australia	-0.36	14.40	553
Canada	-0.22	14.27	263
England	-0.56	14.90	605
Fiji	0.14	14.75	342
France	-0.69	14.54	311
Georgia	11.90	19.42	35
Hong	1.29	14.07	327
Japan	4.56	16.04	87
Kenya	-0.13	15.02	321
New Zealand	0.72	14.10	610
Philippines	0.00	14.79	0
Portugal	-0.03	13.50	217
Russia	3.68	15.93	110
Samoa	-1.89	13.72	334
Scotland	-0.10	14.80	523
South Africa	0.55	14.21	519
Spain	-2.79	13.75	81
Tonga	-2.14	15.62	118
Tunisia	5.27	15.39	68
Uruguay	6.70	15.28	39
USA	-0.68	13.71	535
Wales	-0.24	14.09	274
Zimbabwe	2.28	14.66	100

The validity of the assumption that each team had a significantly different data set was tested with a one way ANOVA, using Excel's statistical analysis add-in, returning a P-value of 0.21 which is reasonable given the size of the database and the large number of subsets. The requirement for normality of residuals was tested with Anderson-Darling, returning acceptable values of skewness for all teams, and kurtosis only evident in teams with small source populations (Japan and Zimbabwe). Heteroscedasticity of residuals was not apparent, though this was not statistically tested. Pool Standings and seedings for the knock out stages of the Sevens RWC is in part determined by tries scored (tournament rules, www.rwcsevens.com), and so a prediction of tries was required for realistic tournament simulation. Try scoring rate per team was assessed as the number of tries scored by each team in the 2011-2012 series (IRB, 2012). Where no data was available for a competing nation (EG: Tunisia, The Philippines, and Georgia) the global mean was used (0.16), in the expectation of the fact that the relatively low ranking of these teams would suggest that any inaccuracies in the number of tries scored would be outweighed by the impact of points difference to the extent that any effect would be negligible.

Each match was played independently, with the points difference determined by Equation 11, incorporating a random number generated from a normal distribution based on the pooled means and standard deviations of the two sides.

$$diff = 0.0588 * RankDiff25 + 2.1305 + Rand_{(normal,\ PooledMean,\ PooledSD)} \quad - \quad \textbf{(11)}$$

The score for each team was calculated by Equations 12 and 13, where 18 was selected as the mean value, as this is the mean score during the 2011-12 Sevens Series.

$$ScoreTeam\ A = 18 + 0.5 * diff \quad - \quad \textbf{(12)}$$

$$ScoreTeam\ B = 18 + 0.5 * diff \quad - \quad \textbf{(13)}$$

Scores were then adjusted programmatically to ensure no impossible scores occurred according to the scoring system of Rugby Sevens, and the tries for and against each team was calculated. Tries scored was calculated by multiplying the team's score by their scoring rate as given in Table 5. Points and tries scored (for and against) were recorded in the six pool tables, along with the tournament points (3 for a win, 2 for a draw, 1 for a loss). The tournament fixtures and draw was constructed, and pools standings and seedings of the knock out stages were determined according to the tournament rules (sorting by, in order: pool position, result between teams, tournament points, match points difference, try difference, match points for, tries for) once the pool games had been completed (www.rwcsevens.com, 2013). Winners, losers and point-difference of each game were recorded, as was the number of upsets. The tournament was run 10000 times, and the descriptive statistics described in the previous section were recorded and automatically output to Excel for subsequent analysis and visualization of data. Model convergence was assessed by examining the stability of the percentage of cup, bowl and plate winners, in 1000 tournament increments, and was shown to converge to <0.25% for all countries by 8000 iterations, giving confidence in the stability of the result.

The validity of the approach was tested by repeating the exercise above, using the 2013 London Sevens as a pilot study (iterations = 1000) and compared to the actual results. London was selected as it was not included in the original dataset, and like the Sevens RWC also uses seedings to determine the knock out stages, rather than pure pool positions as is the case in other tournaments in the IRB Sevens Series. The London simulation correctly identified the tournament winner on 49% of occasions (New Zealand), the top seed on 62% of occasions (New Zealand again), one or more of the pool winners on 93% of occasions, and two or more of the pool winners on 38% of occasions. However, the four top seeds were only correctly identified on one occasion out of 1000, and then not in the correct order. Furthermore there was no discernible relationship between the actual upsets, and those predicted as likely upsets by the model. It is worth mentioning, however, that the tournament was not of equal value to all teams; New Zealand had already mathematically secured the IRB Sevens series in the preceding round (www.irbsevens.com).

Results

The tournament simulation model identified that New Zealand (43%) were the most likely winners of the 2013 RWC Sevens, as well as most likely to enter the knock out stages as top seeds (45%). More than half the teams have a less than 0.1% chance of winning the overall competition. The most likely winners of the Cup, Plate (2nd Tier) and Bowl (3rd Tier) tournaments are presented in Tables 4a, 4b and 4c, while the full summary of the expected finishing position is presented in Figure 5.

Table 4: Most likely winners of the Most Likely Winners of RWC Sevens, the RWC Sevens Plate Tournament (2nd Tier) and RWC Sevens Bowl Tournament (3rd Tier) tournaments are presented in Tables 4a, 4b and 4c

(a)

Team	**Chance**
New Zealand	43.4%
Fiji	16.8%
South Africa	16.4%
Samoa	10.2%
England	7.8%
Australia	2.6%
Wales	1.2%
Argentina	0.6%
France	0.5%
Kenya	0.2%
Scotland	0.1%
Canada	<0.1%
USA	<0.1%
Russia	<0.1%
Spain	<0.1%
Zimbabwe	<0.1%

(b)

Team	**Chance**
Scotland	7.5%
USA	7.1%
Argentina	7.1%
Canada	7.0%
Wales	6.9%
Kenya	6.8%
Russia	6.2%
France	6.0%
Portugal	5.5%
Zimbabwe	5.0%
Spain	4.2%
Georgia	3.9%
Tunisia	4.2%
Uruguay	3.9%
Tonga	3.3%
Japan	3.1%
Hong Kong	2.8%
Australia	2.8%
Philippines	2.6%
England	1.9%
Samoa	1.1%
Fiji	<1%
South Africa	<1%
New Zealand	<1%

(c)

Team	**Chance**
Georgia	12.7%
Japan	10.4%
Uruguay	9.6%
Hong Kong	7.6%
Phillipines	7.3%
Tunisia	7.0%
Tonga	6.2%
Portugal	5.2%
Canada	4.8%
USA	4.7%
Russia	4.6%
Zimbabwe	4.5%
Spain	4.2%
Scotland	2.7%
Kenya	2.4%
France	1.9%
Argentina	1.9%
Wales	1.2%
Australia	<1%
England	<1%
Samoa	<1%
Fiji	<1%
New Zealand	<1%
South Africa	<1%

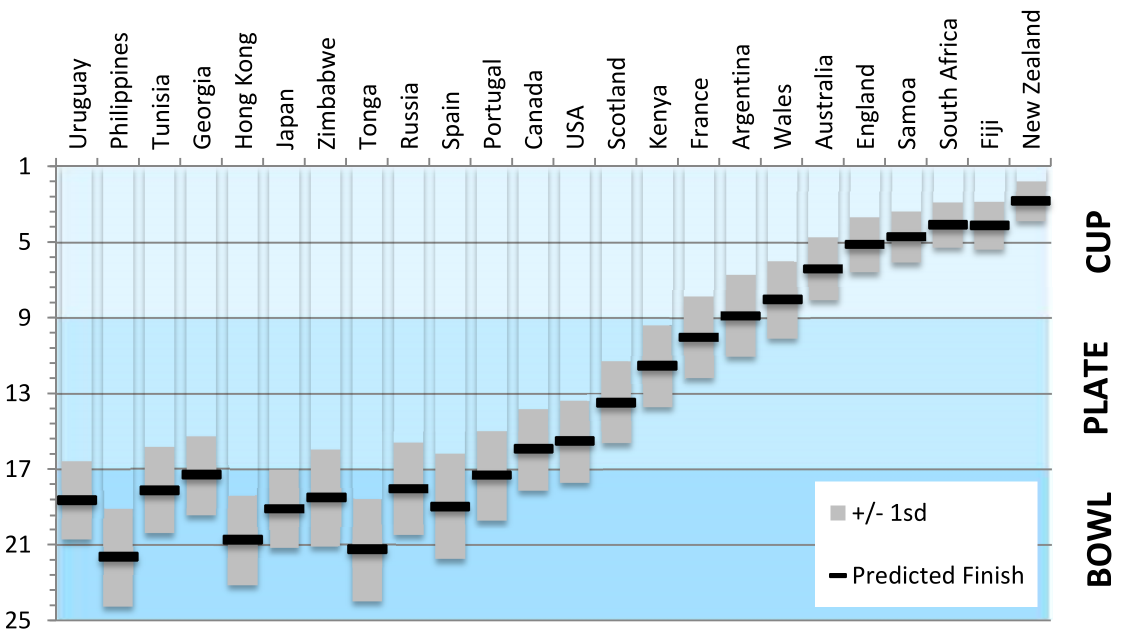

Figure 5 – Expected Finishing Position of Each Team (+/- 1SD) *(1st = Cup final Winner, 2 = Runner up, 3 = playoff winner, 4 = playoff loser, 8 = losing Quarterfinalist, 9 = plate winner, etc)*

Analysis of seeding results predicted that the top seed would only win the tournament on 36% of tournaments run under this model. The expected distribution of seeds entering the knockout stage presented in figure 6. Note that South Africa are expected to out-seed Fiji, despite being ranked lower, while the two teams have an equal chance of winning the tournament.

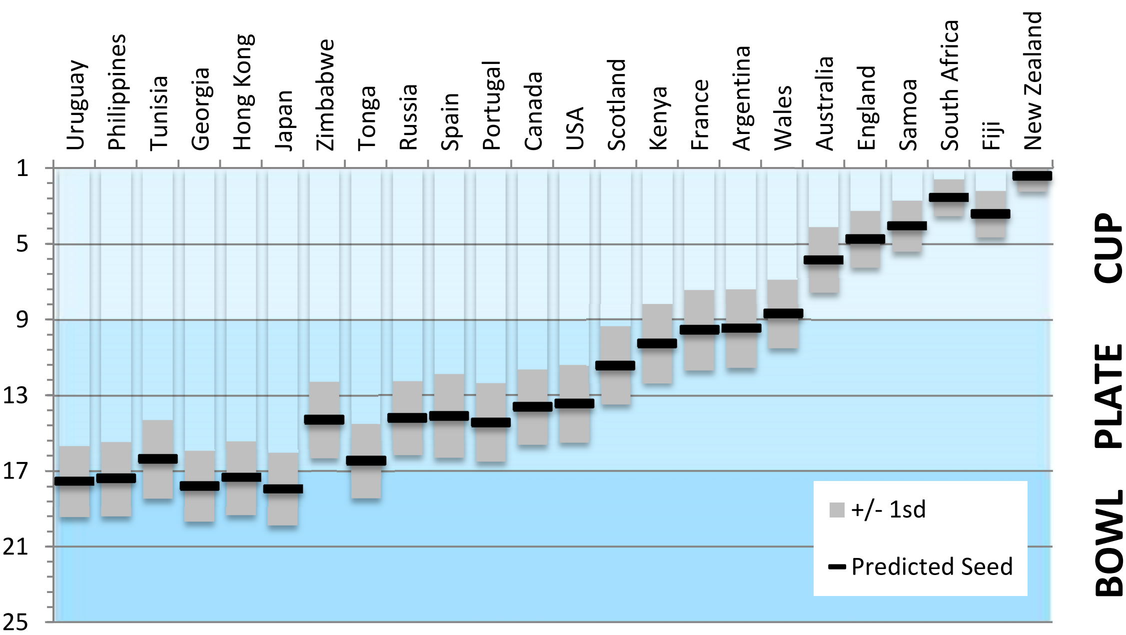

Figure 6 - Distribution of expected seedings for knock out stages.

The most likely victors of each of the six pools are Australia (60%), South Africa (87%), Samoa (76%), New Zealand (94%), Fiji (77%) and England (68%), though it is predicted that all six will top the pools concurrently in only 20% of tournaments. All iterations included at least one of these teams as pool winners. Half of the competing nations had a 5% or less chance of winning their pool, including everyone in New Zealand's pool other than themselves. Uruguay and Georgia were identified as having a 1% chance of topping their respective pools. 1.8% of the pool games were likely to result in draws (approximately one per tournament), while 2.4% of the knock-out games were likely to go to extra time. 26.7% of all games were likely to produce upsets.

Performance of Model against Actual Tournament Results

The Sixth Rugby World Cup Sevens tournament was held in Moscow from the 28th to 30th June 2013. Actual results were downloaded from www.rwcsevens.com and compared to the predictions of the current study. Table 5 details the finishing positions against tournament seed and model prediction, below, with teams that differed from their predicted position by more than 1 standard deviation deemed to have either an under / over performance. Figure 7 illustrates the final positions of each team, against the model prediction. Teams are presented in IRB ranking order.

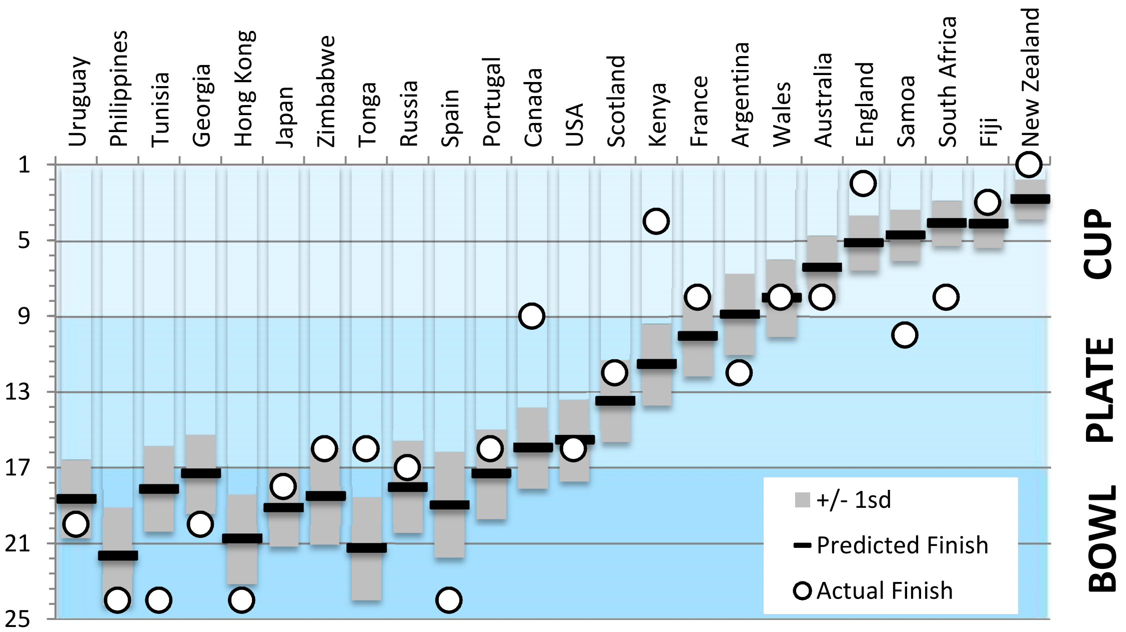

Figure 7 - Model Prediction and Actual Tournament Performance

The model correctly predicted six out of the eight teams that progressed to the cup competition, and also the overall winner, New Zealand, while twelve teams' performances closely matched the prediction (*i.e.*: within 1sd of their individual model prediction). Only four teams produced results that might be considered unexpected, occurring more than 3 standard deviations from their expected performance. These were Samoa (-4 sd), South Africa (-3.3 sd), Kenya (+3.5 sd) and Canada (+3.2 sd). The model's suggestion that all six predicted top seeds were unlikely to occur simultaneously was borne out, with the actual combination of pool winners being the fifteenth most likely to occur. Two of the thirty six pool games resulted in a draw (5.5%), which is higher than the model predicted.

Table 5 – Model Prediction and Actual Tournament Performance (over/under performing teams in **bold**).

Position		Team (RWC Seed in brackets)	Prediction	Performance
1	Cup Winner	New Zealand (1)	*2.8 +/- 1*	+1.7 sd
2	Runner Up	England (5)	*5.1 +/- 1.4*	+2.2 sd
3	3rd place runner up	Fiji (2)	*4.1 +/- 1.2*	+0.9 sd
4	**Fourth**	**Kenya (10)**	***11.5 +/- 2.2***	**+3.5 sd**
8	**Losing Quarterfinalist**	**South Africa (3)**	***4.1 +/- 1.2***	**-3.3 sd**
8	Losing Quarterfinalist	Australia (6)	*6.4 +/- 1.7*	-1 sd
8	Losing Quarterfinalist	Wales (7)	*8 +/- 2*	+0 sd
8	Losing Quarterfinalist	France (9)	*10 +/- 2.2*	+0.9 sd
9	**Plate Winner**	**Canada (13)**	***15.9 +/- 2.1***	**+3.2 sd**
10	**Plate Runner Up**	**Samoa (4)**	***4.7 +/- 1.3***	**-4 sd**
12	Losing Plate Semifinalist	Argentina (8)	*8.9 +/- 2.2*	-1.4 sd
12	Losing Plate Semifinalist	Scotland (11)	*13.5 +/- 2.2*	+0.7 sd
16	Losing Plate Quarterfinalist	USA (12)	*15.5 +/- 2.2*	-0.2 sd
16	Losing Plate Quarterfinalist	Portugal (14)	*17.3 +/- 2.4*	+0.5 sd
16	Losing Plate Quarterfinalist	Tonga (17)	*21.2 +/- 2.7*	+1.9 sd
16	Losing Plate Quarterfinalist	Zimbabwe (18)	*18.5 +/- 2.6*	+1 sd
17	Bowl Winner	Russia (16)	*18 +/- 2.4*	+0.4 sd
18	Bowl Runner Up	Japan (19)	*19.1 +/- 2.1*	+0.5 sd
20	Losing Bowl Semifinalist	Georgia (21)	*17.3 +/- 2.1*	-1.3 sd
20	Losing Bowl Semifinalist	Uruguay (24)	*18.6 +/- 2.1*	-0.7 sd
24	Losing Bowl Quarterfinalist	Spain (15)	*18.9 +/- 2.8*	-1.8 sd
24	Losing Bowl Quarterfinalist	Hong Kong (20)	*20.7 +/- 2.4*	-1.4 sd
24	Losing Bowl Quarterfinalist	Tunisia (22)	*18.1 +/- 2.3*	-2.6 sd
24	Losing Bowl Quarterfinalist	Philippines (23)	*21.6 +/- 2.6*	-0.9 sd

However, set against Kenya's 2012-13 IRB Series form, finishing in the top four in five out of nine events, a fourth place finish should not be seen as out of the ordinary. Figure 8 shows the tournaments at which their RWC ranking points were accrued, and there is a clear concentration of higher scores in the tournaments immediately preceding the event, with the accrual rate increasing sharply in the 2012-13 series. It would seem therefore that the regression model used in this study was insensitive to Kenya's recent and sustained improvement in form. Note also that Kenya's strong showing extended into the four tournaments which took place after the ranking period, which may further explain the model's under-estimation of performance.

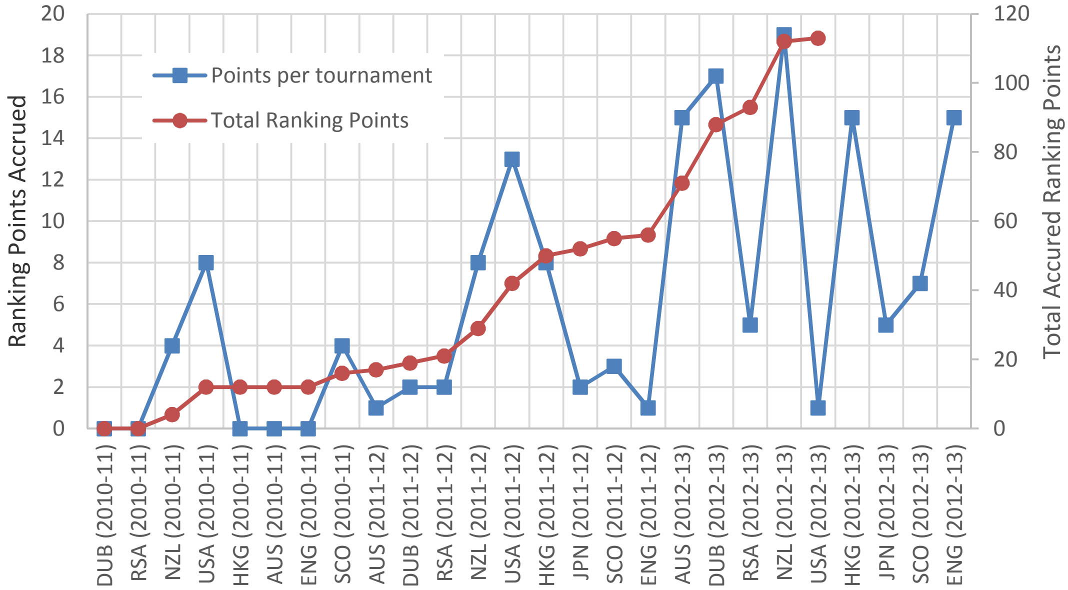

Figure 8 – Kenya's points accrual during the RWC Sevens qualification period.

Discussion

Of all the independent variables examined in the initial research, only the relative strength of the teams showed any significant correlation with the points difference of between two sides.

The lack of correlation between travel effects and points difference appears to cast doubt over the assumption that there are significant travel effects in sport, and is in part supported by other attempts to identify correlations between performance and travel (Forbes-Robertson, *et al.,* 2012; Youngstedt *et al.,* 1999). However, very little is known about how well the estimated travel variables used in the current study reflect the actual environmental and logistical circumstances of the associated performances. In order to properly determine sensitivity to travel effects, detailed travel plans of the teams involved would be required, coupled with verified measurements of the environmental conditions either side of the journey.

While the performance impact of trans-meridian air travel can be expected to be proportional to the number of time zones crossed, its ongoing impact is thought to diminish with the passage of time. Therefore in order to test for sensitivity, it would be preferable to couple the UTC offset with the number of days between arrival and performance, so that both effects can be examined.

Sensitivity of performance to travel time was examined using data from Skyscanner, in an attempt to test the shortest practical travel time between venues, rather than the straight line distance which is often used in studies of this nature, though no improvement was observed. However, any effect would again have been clouded by uncertainty around the amount of recovery time between arrival and the start of the performance, and any other entrainment strategies employed by competing teams. Further uncertainty is presented by the reality that the funding for all teams is not equal, and certain lower ranked nations may be forced to opt for longer, less convenient flight routes, where the need to minimise costs may take precedence over travel disruption (e.g.: Friday, 2013).

Furthermore, the study gave no consideration to the format of the IRB Sevens series, which typically features pairs of tournaments played on successive weekends. In these cases, it is likely that most teams would opt to travel directly to the venue of the second tournament rather than returning home in the intervening week, in order to minimize costs and travelling time. Given that this might typically be the case for up to four of the nine events in a given year, it would be sensible to remove such tournaments from the data set in any follow up studies, which might in turn reveal a greater sensitivity.

Another likely source of error in the sample data is that while capital cities were used as reference points for teams, whereas in larger countries the teams may be based in a different time zone to the capital city. For example, it is known that the USA have a centralized residential training camp is in Chula Vista, California (UTC -8) (www.usarugby.com, 2012), which is three time zones from the capital city, Washington DC (UTC -5). Clearly any evidence of a travel effect is likely to be obscured by systematic sources of error of this kind, with attempts to compare altitude and typical seasonal temperature suffering similarly.

The circadian disruption model adopted in this study was only loosely academically founded, and further research may allow the adoption of a more sophisticated model which may better reflect the circadian rhythms in athletes. However unless the actual travel plans of teams can be examined, it is impossible to conduct a rigorous analysis, regardless of model sophistication.

The availability of such data would allow a much more reliable analysis of travel effects, and also allow characterization and evaluation of any entrainment strategies employed. However, the importance of entrainment strategies is highlighted in both academic literature (Forbes-Robertson, *et al.,* 2012) and anecdotal coaching discussions (Friday, 2013; www.irbsevens.com, 2013), and so it is likely that competing nations would consider their travel plans to be part of the pursuit for competitive advantage, and as such be reluctant to allow its use for publication and research. Furthermore, the practicalities of obtaining such data would limit sample size such that the "whole database" approach attempted here would not be possible. In this case it might be better to embark on a long term, longitudinal study focusing on a limited number of teams of similar standing, where it may be possible to negotiate access to travel documentation from individual National Governing Bodies.

In summary then, while there was no obvious travel effect observed in this study, it may be that this is due to a lack of accurate travel data in the study, rather than a lack of effect, highlighting the need to pursue accuracy in data over quantity of sample size when studying travel effects.

In spite of the limitations described above, much can be learned about Sevens Rugby as a result of this study. Initial analysis revealed that the likely result between two teams in a given match was far more likely to be predicted by the two teams' respective performances over the last 25 tournaments than in the most recent, which lends support not only to the RWC seeding strategy. Further, the curve of data presented appears asymptotic, with only a marginal improvement in shown in model sensitivity when 25 tournaments are used rather than 20, predicating the need to include yet more tournaments. This is reinforced by the fact that the actual overall RWC standings were largely as predicted by the model.

However, the suspicion is that performance is related to a combined effect of both form and sustained quality. The "Whole Database" approach has been criticised as inflexible and insensitive to form (Hughes *et al.,* 2001; Reed, *et al.,* 2005), and this is supported by the regression model's inability to react to Kenya's surge in pre-tournament form, which was followed by the team's strong showing in the RWC. This could be tested in future research via the application of a weighted approach, to determine whether more recent tournaments held more or less influence on the model's ability to predict points difference between teams. Equally, the size of the data set may have been responsible for the lack of kurtosis or skewness in the data set, in contrast to other comprehensive tournament studies which nevertheless involved fewer data, due to the number of matches played (O'Donoghue, 2013, unpub.). Similarly, outliers could be removed without particularly diminishing the sample size.

The predicted upset frequency of the RWC Sevens from the model is in keeping with the source data set, where analysis of the input dataset revealed an upset frequency of 24.7%, As an aside, this presents an opportunity to position International Rugby Sevens relative to other similar "Invasion games" (Hughes *et al.*, 2008), in terms of competitiveness. Though the frequency is distinctly lower when compared to other sports, such as English Premier League Football (45.2%), NBA Basketball (36.5%) and NFL American Football (36.4%) (Ben-Naim, *et al.,* 2005), it is certainly much higher than its parent sport, Rugby Union., which "is dominated by a small number of very strong teams" (Reed et al., 2005). The 2011 Rugby World Cup produced only 3 upsets (based on pre-tournament ranking, IRB 2011 [online]) in the 48 games played (6.25%), all of which occurred in the group stage (IRB Match Analysis, 2012). While on the one hand Sevens is shown to be an inherently more variable sport than Rugby Union, it is still the case that relatively few competing nations have a meaningful chance of winning, with only 5% of simulated victories coming from outside the top five pre-tournament seeds, and 1% coming from outside the top eight. However, according to the model in the current study, the incumbent champions, Wales, had only a 1.2% chance of retaining their title, underlining their achievement in 2009. The number of draws which occurred was also similar to the prediction. Meanwhile it was predicted that 2.4% of knock out stage matches would go to extra time, but it is not known how this compares to the source data set within Rugby Sevens.

The accuracy of the model could potentially be improved by examining temporal issues within and between tournaments. It is reasonable to hypothesise that certain teams may perform differently in knock out stages than in pool stages due to fatigue. Information gleaned on this could not only be used to improve the predictions of the models, but could also be used to characterise the relative strengths of teams and give further routes to explain performance differences, as implied by Reed *et al* (2005). Similarly the effect of varying recovery times between matches may be explored.

Conclusions

The actual winners of the 2013 Rugby World Cup were identified as the most likely to win (New Zealand), with a 95% chance that the tournament will be won by one of the top five seeds. Scotland and Georgia were shown to be most likely to win the Plate and Bowl competitions respectively, though both teams were eliminated in the respective semi-finals. The number of tournaments used to generate the seeds for the RWC Sevens was validated and is shown to be better able to predict relative strength of two teams than when fewer tournaments were included in the model, and with little further improvement when more are used. Overall correlation between the simulation results and actual tournament were strong, with half of all standings between +/- 1sd of the prediction, and twenty of the twenty four teams placed within +/- 3sd of their prediction. Around one in four matches of International Rugby Sevens can be expected to produce an upset. This allowed the sport of Rugby Sevens to be characterised as more unpredictable than its closest comparative sport, Rugby Union, yet less so than other invasion games such as American Football, Basketball and Association Football.

In line with other texts surveying the impact of air travel (trans-meridian or otherwise) on other sports, there was no correlation between performance in International Rugby Sevens and jet lag or other travel variables, although limitations arising from the assumptions and subsequent treatment of the source data were acknowledged.

Avenues for future research were identified as examination of the weighted effect of recent form and overall quality, various temporal effects such as the changing nature of the sport over time, the difference between individual teams' performances in knock out stages compared to group stages, and if possible, an in depth review of actual travel details and correlation to performance and fatigue.

References

Ben-Naim, E., Vazquez, F., & Redner, S. (2005). What is the most competitive sport?. *arXiv preprint physics/0512143*.

Berthelot, G., Thibault, V., Tafflet, M., Escolano, S., El Helou, N., Jouven, X., & Toussaint, J. F. (2008). The citius end: world records progression announces the completion of a brief ultra-physiological quest. *PloS One, 3(2), e1552. doi:10.1371/journal.pone.0001552*

Forbes-Robertson, S., Dudley, E., Vadgama, P., Cook, C., Drawer, S., & Kilduff, L. (2012). Circadian Disruption and Remedial Interventions. *Sports Medicine, 42(3),* 185-208.

Fordyce, T (2013). Olympic status sees rugby sevens comes of age [onlne]. Availanle from http://www.bbc.co.uk/sport/0/rugby-union/22451264 Accessed 10th May, 2013.

Friday, M. (2013). Inside Kenya Sevens: Travel, Hotels, Decisions, Winning, Losing and that final in Wellington [Online]. Available from http://ur7s.com/news/2342/mike_friday_inside_kenya_sevens_travel_hotels_decisions_winning_losing_and_that_final_in_wellington (accessed 12th May 2013).

Heazlewood, T. (2006). Prediction versus reality: The use of mathematical models to predict elite performance in swimming and athletics at the Olympic Games. *Journal of sports science and Medicine, 5(4),* 541-547.

Hughes, M., Evans, S., & Wells, J. (2001). Establishing normative profiles in performance analysis. *International Journal of Performance Analysis in Sport*, *1*(1), 1-26.

Hughes, M. & Franks, I. (2008). The Essentials of Performance Analysis – An Introduction. Routledge

Hughes, M., & Jones, R. (2005). Patterns of play of successful and unsuccessful teams in men's 7-a-side rugby union. In *Science and football V: the proceedings of the Fifth World Congress on Science and Football* (p. 252). Routledge.

www.irb.com (2011). IRB World Rankings - 29 August 2011 [online]. Available from http://www.irb.com/rankings/archive/date=2011-08-29/histranking.html. Accessed 10th June 2013.

www.irbsevens.com(2013) Wales aiming high as Series climax approaches [online]. Available from http://www.irbsevens.com/destination/edition=10/news/newsid=2066313.html

IRB Match Analysis (2012). Rugby World Cup 2011 Statistical Review and Match Analysis [online]. Available from http://www.irb.com/mm/Document/NewsMedia/MediaZone/02/06/06/64/111026IRBGAMEANALYSIS2011IRBRugbyWorldCupStatisticalReview.pdf [Accessed 10th June 2013]

McGuckin, T. A., Sinclair, W. H., Sealey, R. M., & Bowman, P. (2012). The effects of air travel on performance measures of elite Australian rugby league players. *European Journal of Sport Science, (ahead-of-print)*, 1-7.

Ntoumanis, N. (2001). *A step-by-step guide to SPSS for sport and exercise studies*. Psychology Press.

O'Donoghue, P. (2009). Interacting performances theory. *International Journal of Performance Analysis in Sport*, *9*(1), 26-46.

O'Donoghue (2012). Statistics for Sports and Exercise Studies, Chapter 9. *Routledge, ISBN-13: 978-0415595575*

O'Donoghue, P. (2013). The Assumptoins Strike Back! A comparison of prediction models for the 2011 Rugby World Cup [unpub.]

O'Donoghue, P. (2013). Rare events in tennis. [Unpub].

O'Donoghue, P., & Cullinane, A. (2011). A regression-based approach to interpreting sports performance. *International Journal of Performance Analysis in Sport, 11(2)*, 295-307.

O'Donoghue, P., Dubitzky, W., Lopes, P., Berrar, D., Lagan, K., Hassan, D., ... & Darby, P. (2004). An evaluation of qualitative and quantitative methods of predicting the 2002 FIFA World Cup. *Journal of Sport Sciences*, *22*(6), 513-514.

O'Donoghue, P., & Williams, J. (2004). An evaluation of human and computer-based predictions of the 2003 Rugby Union World Cup. *International Journal of Computer Science in Sport*, *3*(1), 5-22.

Pengally, M. (2013) USA Sevens gives rugby a chance to shine on road to the Rio Olympics [online]. http://www.guardian.co.uk/sport/blog/2013/feb/07/usa-sevens-rugby-las-vegas-rio-olympics Accessed 28th May 2013.

du Preez, M., & Lambert, M. I. (2007). Travel fatigue and home ground advantage in South African Super 12 rugby teams. *South African Journal of Sports Medicine, 19(1)*, 20-22.

Reed, D., & O'Donoghue, P. (2005). Development and application of computer-based prediction methods. *International Journal of Performance Analysis in Sport*, *5*(3), 12-28.

www.rwcsevens.com (2013). England and NZ top of RWC Sevens seedings [online]. http://www.rwcsevens.com/home/news/newsid=2065240.html

Suarez-Arrones, L. J., Nuñez, F. J., Portillo, J., & Mendez-Villanueva, A. (2012). Running demands and heart rate responses in men rugby sevens. *The Journal of Strength & Conditioning Research*, *26*(11), 3155-3159.

Thibault, V., Guillaume, M., Berthelot, G., El Helou, N., Schaal, K., Quinquis, L., & Toussaint, J. F. (2010). Women and men in sport performance: the gender gap has not evolved since 1983. *J Sports Sci Med*, 9, 214-223.

www.usarugby.com (2012), Eagles announced for 2013 Residency Program [online]. Available from http://www.usarugby.org/womens-sevens-news/item/eagles-announced-for-2013-residency-program Accessed 16th June 2013.

van Rooyen, M. K., Lombard, C., & Noakes, T. D. (2008). Playing demands of sevens rugby during the 2005 Rugby World Cup Sevens Tournament. *International Journal of Performance Analysis in Sport*, *8*(2), 114-123.

Youngstedt, S. D., & O'Connor, P. J. (1999). The influence of air travel on athletic performance. *Sports Medicine*, *28*(3), 197-207.