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Complementing subjective with objective data in analysing expertise: A machine-learning approach applied to badminton

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ABSTRACT

This study aimed to assess which combination of subjective and empirical data might help to identify the expertise level. A group of 10 expert coaches classified 40 participants in 5 different expertise groups based on the video footage of the rallies. The expertise levels were determined using a typology based on a continuum of 5 conative stages: (1) structural, (2) functional, (3) technical, (4) contextual, and (5) expertise. The video allowed empirical measurement of the duration of the rallies, and tri-axial accelerometers measured the intensity of the player's involvement. A principal component analysis showed that two dimensions explained 54.9% of the total variance in the data and that conative stage and empirical parameters during rallies (duration, intensity of the game) were correlated with axis 1, whereas duration and acceleration data between rallies were correlated with axis 2. A random forest algorithm showed that among the parameters considered, acceleration, duration of the rallies, and time between rallies could predict conative stages with a prediction accuracy above possibility.

This study suggests that performance analysis benefits from the confrontation of subjective and objective data in order to design training plans according to the expertise level of the participants.

ARTICLE HISTORY

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KEYWORDS

Performance analysis; data mining; accelerometry; conative

Introduction

According to Seifert et al. (2013), expertise can be considered the relevant ongoing co-adaptation of an individual's behaviours to dynamically changing, interacting constraints, individually perceived and encountered. It is therefore essential to understand how underpinning performance parameters interact with skill level to constrain performance. Understanding expertise (or skilful behaviour) means that the analyst should be able to outline not only the system's components, but also the interrelations that are significant to performance in order to guide learners to new adaptation according to their expertise level. Identifying the key properties of expert movement is crucial in sport coaching or teaching. Both empirical and subjective methods have been developed in a sporting context for this purpose.

With regards to subjective methods, the capacity to recognise a behavioural pattern is a general requirement of human performance in various domains, such as sports science and performance analysis (Mather & West, 1993). For example, it has been suggested that the ability to extract higher order predicates (e.g., tactical information) from positional data and temporal relationships between individuals on field is an important part of skilled motion perception (Smeeton et al., 2004). Observation grids, used to establish typologies (Bailey, 1994), have proven particularly useful in identifying different levels of skilful behaviour (Cools et al., 2009; Williams et al., 2006). These typologies can be observed in racquet games (M. Hughes, 1998) such as tennis (Taylor & Hughes, 1998) and badminton

(M. Blomqvist et al., 1998; M. T. Blomqvist et al., 2000; Wang & Liu, 2012; Wang et al., 2009; Wang & Moffit, 2009). These methods tend to evaluate the type of behaviour exhibited but fail to specify on the underlying strategy which guides the actions performed by the player.

The conative educational approach developed by Bui-Xuân (1993) in the field of sports (J. Vanhelst, Béghin, Duhamel et al., 2012) offers interesting perspectives on setting expertise-based typologies, especially sports in which strategy is paramount (Dieu et al., 2014).

Conation has been used to explore what encourages people to act and goes beyond cognition (Gerdes & Stromwall, 2008; Gholar & Riggs, 2004). The conative framework suggests that each individual has his/her personal conative style, i.e. a preferred method of putting thought into action and interacting with the environment (Lorgnier et al., 2018; Mikulovic et al., 2002; Vanhelst et al., 2013). In the field of sports, the purpose of the conative model is to identify what gives an athlete meaning and makes them want to act (Bui-Xuân & Récopé, 2006).

This framework is based on the hypothesis that progress in sports is not solely a question of greater efficacy (Hastie et al., 2009), but relies also on a shift in the conative domain, i.e., a shift in the player's tactical and strategical focus (Bui-Xuân, 1993). Depending on their level of experience (i.e., "conative stage"), players may focus on the game's structural (e.g., physical abilities), functional (e.g., tactical) or technical aspects (e.g., technical skills). This model identifies different forms of impulse, or *impetus*, which guide actions. The impetus is

determined by the player's progress throughout the three components of the model (structural, functional, and technical). These three components constitute the guiding principle which organises each conative stage. Five conative stages are proposed for the classification of players, from novice to expert: (1) structural, (2) functional, (3) technical, (4) contextual, and (5) expertise. All these stages are characterized by a combination of the abovementioned components (physical, technical, tactical), but in each stage one of the components dominates the other, as described by Bui-Xuân (1993). The criterion of the conative classification has been applied to athletic activity to classify participants (Vanhelst et al., 2012) and more recently in badminton (Dieu et al., 2014). In badminton, on Stage 1 (structural), the player's intent is to send back the shuttlecock, therefore physical abilities are mobilised first. Once the player has solved the problem of returning the shuttlecock, he/she begins playing in the game space, with the aim of forcing the opponent to move. At this point, the player is already in a "tactical" or functional stage (Stage 2), even if the techniques for handling the shuttlecock are basic. On Stage 3 (technical), the player loses in functionality what he/she gains in technical efficiency, given that this stage concerns the stabilisation of the driving skill. It is not until the next level (Stage 4) that the player is able to "contextualise" his/her technique in a sequence of strokes, therefore this stage is again tactical. The highest or expert stage (Stage 5) is characterised by the optimal mobilisation of structural, functional, and technical abilities in order to form the player's style of play. Conative classification that modelizes five foci (or intended goals) makes it possible to think of expertise within the framework of the complex systems approach (Ibáñez-Gijón et al., 2017; Seifert et al., 2013). The latter adopts a more integrated approach to qualitative descriptions of the changes in the physical activity from novice to expert. The conative stage is therefore a subjective way of characterizing expertise based on a classification that reflects not only the mechanical aspect of expertise (technical skills, tactical indicators or physical variables), but also the specific relationship between mechanical and functional aspects of expertise (the focus that guides players).

Typologies are therefore a highly useful tool to identify complex behaviours. However, typologies have received some criticism (Bailey, 1994) for three reasons: they are often based on somewhat arbitrary criteria, they are essentially static, and they can pose significant reliability challenges. Such classification based on human perceptions and judgements which may limit their use in scientific studies (Knudson, 2013). Developing a strong strategy to analyse performance in such sporting contexts requires complementing these subjective assessments with more objective methods as notational (M. Hughes & Franks, 2004), kinematic (Hamill & Selbie, 2004) and kinetic methods (Caldwell et al., 2004). Performance analysis is a complex task which relies on a wide array of indicators. Qualitative methods offer interesting perspectives to outline skill level, but present issues of reliability and validity (Bailey, 1994). Quantitative methods, on the other hand, provide an insight on the kind of tactic used with notational analysis, as well as providing a precise description of how a movement is performed (kinematic and kinetic analysis). However, when used in isolation, these methods fall short in characterising

skilful performance. Finding out how qualitative and quantitative data relate to one another is therefore essential to sport analysis (M. D. Hughes & Bartlett, 2002). In badminton, few studies have attempted to establish an analysis framework that encompasses both forms of analysis. Many authors (Abian-Vicen et al., 2013; Cabello et al., 2004; Cabello Manrique, 2003; H.-L. Chen & Chen, 2008; Faude et al., 2007; Ming et al., 2008) used notational analysis, but the scope of those studies was limited to a description of high-level play according to age, sex or a change in scoring rules. Other authors examined how kinetic data, assessed by accelerometry, could be used as a non-invasive method to account for tactic used throughout the play in a real-game conditions (Dieu, 2012; Dieu et al., 2014; Silva et al., 2015), but a link with a more subjective component of skilful behaviour was not established. This accelerometry measurement appears to be particularly relevant in a 3-dimensional sport characterized by continual changes in movement direction and a high frequency of "stop and go" manoeuvres (M. Phomsoupha & Dor, 2015). This method provides access to physical activity quantification and temporal data (rally time, match duration) reflecting the tactical aspect of match management (M. Phomsoupha & Laffaye, 2015).

These approaches point to the fact that novices and experts differ not only in their physical characteristics and skillsets, but also their typical focus during games, which is born from the interactions between all these characteristics. The original nature of this data collection is that it relies on both empirical and subjective data, which requires the use of a specific data analysis method. Machine learning methods offer an interesting perspective to bridging this gap. These computational methods use a different set of algorithms to make predictions based on data (Kohavi & Provost, 1998), and have proven useful in sporting contexts for their ability to objectify typologies by connecting physiological and biomechanical data with subjective assessments from experts during safety swim tasks (Schnitzler et al., 2014). In this respect, these unconventional methods (as compared to linear ones) could be useful for two reasons. First, because they allow for feature selection, thereby ensuring that potentially unnecessary variables (or features) are not present in the final model. Second, machine learning algorithms are capable of fitting non-linear data, as is often the case in studies on expertise (Seifert et al., 2017). Lastly, these procedures split the dataset and perform the analysis on independent sub-settings of the data, which helps minimize overfitting.

Therefore, the aim of this study is to examine the relationship between the judgement of expertise levels and objective measurement in order to understand the complexity of performance and progression in badminton using machine learning.

Materials and methods

Participants

Forty French participants took part in this study. Their characteristics are summarised in Table 1. Participants were fully informed before providing written and informed consent. The University Ethics Committee approved all experimental procedures.

Table 1. Characteristics of participants.

Participants	Total	Males	Females
N	40	31	9
Age (years)	22 [17–37]	22 [17–37]	21 [18–26]
Height (cm)	176 [160–195]	178 [160–195]	168 [162–176]
Weight (kg)	70.0 [52.0–100.0]	73.0[53.0–100.0]	59.4 [52.0–70.0]

Continuous data are presented as mean [range].

Subjective assessment of the skill level of participants

Participants were classified into five groups according to their performance levels. Every participant had to play one set of 21 points against an opponent from the same performance level group. To avoid a significant imbalance between players, each set in which the loser's score was below 11 points was rejected from the analysis. All players were videotaped and classified into one of five conative stages: (1) structural, (2) functional, (3) technical, (4) contextual, and (5) expertise, using the conative criteria developed for curriculum by Dieu et al. (2014). This conative curriculum is described in Table 2.

This theoretical conative classification grid was certified by a video testing of the ten badminton specialists on the 2011 national committee, in charge of recruiting physical education teachers (Dieu, 2015). For the present study, two expert analysts classified the players according to the conative stages of each player independently. Chronbach's alpha was considered excellent ($\alpha = 0.91$). But when a disagreement occurred between the analysts, the video was viewed again conjointly. If a consensus couldn't be reached, the participant was discarded from the analysis. This was the case for 2 participants. In total, 50 sets between the 40 players of equivalent performance level were selected for this analysis, which provided 1806 rallies (Table 3).

Notational analysis

Video recordings of each game were used to investigate the duration of each rally, which were categorised as short (<4 s), medium (4–7 s), long (8–11 s) or very long (>11 s) (Table 3). We also measured the duration of rallies and the duration between

rallies and calculated a ratio: time of rallies/time between rallies (T_{ratio}) to quantify the percentage of playing time during a game (H.-L. Chen & Chen, 2008).

Kinetic variables

Each participant wore an accelerometer while playing one set of badminton (a 21- point "tie breaker" without over-time). The only instruction given was "play like you're in a real game". Accelerometer was attached to an elastic belt at the base of the spine. The GT3X[®] accelerometry monitor (Pensacola, FL), measures magnitude vectors on three axes (VM_X: vertical, VM_Y: mediolateral, and VM_Z: anteroposterior). This technology was proven valid and reliable (Craig et al., 2003; De Jonge et al., 2007) to estimate energy expenditure (Chu et al., 2007; J. Vanhelst et al., 2010). Accelerometers allow subjects' physical activity to be evaluated on the basis of a mechanical measurement of movements (K. Y. Chen & Bassett, 2005); the frequency, duration and intensity of the physical effort were thus recorded. Results are expressed in "counts." The quantity of physical activity is calculated in terms of vector magnitude (VM), which is the square root of the sum of the squares of each axis (VM_X, VM_Y and VM_Z) of data (counts). We determined the magnitude vector during the rallies (VM_R), between rallies (VM_BR) and calculated the ratio VM_R/VM_BR (VM_ratio) as an indicator of the difference in activity between those parts of the game.

Statistical analysis

We used a typical machine learning procedure for this study, following the machine-learning examples provided by Lantz (2019). This statistical analysis consisted of five steps:

Step 1: An exploratory analysis first examined to what extent each variable related to the others. We used Spearman's correlation coefficient in order to examine the strength and the direction of the link between the conative stages and the other variables of interest. We then applied a Kaiser-Meyer-Olkin test (KMO) and a Bartlett test. The correlation matrix is fit to apply exploratory analysis when

Table 2. Description of conative classification criteria for badminton player according to Dieu et al. 2014.

Conative stages	Behaviour description	Classifying indicators
Stage 1 Criterion: structural Conation = returning the shuttle-cock	The player is the returner. He/she will return the shuttlecock to the other side of the net regardless of where it lands. The shuttlecock is seen as an obstacle.	Long sending back-central axis. No status differentiation between opponent and defender. Only concern: to send shuttlecock the other side of the net.
Stage 2 Criterion: functional Conation = directing the shuttlecock	The player is a dispatcher, seeking for free space to send the shuttlecock.	Trajectory variations. It forces the opponent to run after the shuttlecock.
Stage 3 Criterion: technical Conation = making a winning stroke	Technical application. The player seeks to find himself in a favourable position for smashing the shuttlecock but does not re-position him/herself after hitting.	Smash or drop-in attack. Pause in re-positioning to observe the result of action.
Stage 4 Criterion: contextual Conation = tactical sequence	Technical-tactical sequence. The player develops tactical plans, strategies of attack and defence that combines the search for free space and opportunities to spike the shuttlecock powerfully.	Re-positioning directed after hitting (sequence). Playing in interception.
Stage 5 Criterion: expertise Conation = force your game on the opponent	In addition, players at this stage are capable of adapting their game-power balance and the playing style of their opponent.	Mobilises his/her own structure and techniques according to his/her own playing style.

Table 3. Number and distribution of rallies played per conative stage.

Conative stages	Sets	Males	Females	Rallies (N)	Short (<4 s)	Medium (4–7 s)	Long (8–11 s)	Very long (>11 s)
Structural	10	4	6	372	105	161	62	44
Functional	10	10	0	373	89	208	65	11
Technical	10	6	4	347	50	233	52	12
Contextual	10	10	0	372	61	209	66	36
Expert	10	10	0	342	41	125	90	86

KMO>0.5 and if the Bartlett test was statistically significant ($p < .05$). We used a corrplot toolbox in R software for this part of the analysis

Step 2: A principal component analysis was performed to examine the dimensionality of the data. For this analysis, we considered vector magnitude during rallies (VM_R) and vector magnitude between rallies (VM_BR) as supplementary variables, being a linear combination of the other accelerometric variables. We used FactoMiner in R software for this part of the analysis.

Step 3: We used a Random Forest Supervised Learning algorithm (Breiman, 2001) with conative stages as a dependent variable to examine to which extent an algorithm can predict the conative stage solely on the basis of notational and kinetic variables. For this purpose, a feature selection through a wrapper algorithm was performed to determine which of the variables are relevant to classifying the conative stages. We used the Random Forest toolbox in R software for this part of the analysis.

Step 4: As normality of the residual's distribution (Jarque-Bera test) and homoscedasticity (Levene Test) were not met in the considered parameters, we used the Kruskal-Wallis test to outline, among the quantitative variables of interest, which one changed significantly as a function of the conative stage. The difference among the conative stages was more specifically examined using a pairwise Wilcoxon test. The difference was considered significant when $p < 0.05$. We computed eta-squared (η^2) effect sizes which were labelled as small [0.02–0.12], medium [0.13–0.25], and large [0.26 and above] (Cohen, 1988). We used R software for this part of the analysis.

Step 5. We tested how 22 classifiers algorithms could predict the conative stage based on these selected variables. We used a 5-fold cross validation method to avoid overfitting (Moore & Lee, 1994), and used the "classification learner" Matlab toolbox. The algorithm presenting the best percentage of overall classification was selected. This algorithm aims to show to which extent quantitative data are related to the subjective judgement of the conative stages. Using the confusion matrix, the classifier was considered successful in complementing subjective assessment if it performed better than chance, that is, over 20% correct classification (given that there are 5 conative stages).

Results

Step 1

The data seem to be fit for multiple correlation analysis, since KMO = 0.7 (considered as acceptable), and Bartlett test was significant ($p < .05$). Table 4 shows that conative stages are correlated

Table 4. Spearman coefficients of correlation between conative stages and quantitative variables of the study.

	Conative stages
Duration of the rallies (s): T_R	0.19*
VM rallies: VM_R	0.65*
VM_X (rallies): X_R	0.60*
VM_Y (rallies): Y_R	0.52*
VM_Z (rallies): Z_R	0.54*
Between-rallies duration (s): T_BR	0.23*
VM between rallies: VM_BR	-0.25*
VM_X (between rallies): X_BR	-0.25*
VM_Y (between rallies): Y_BR	-0.19*
VM_Z (between rallies): Z_BR	-0.18*
Duration Ratio: T_ratio	NS
VM Ratio: VM_ratio	0.59*

* significantly correlated with $p < .05$

positively with VM during rallies ($R = 0.65$, $p < .05$), in all plans. Conversely, it is negatively correlated with VM between rallies.

Step 2: principal component analysis (PCA)

The PCA showed that dimension 1 and 2 explained 54.9% of the total variance (respectively 32.6% for dimension 1 and 22.3% for dimension 2). The plotted representation on factors 1 and 2 (Figure 1) also suggested that parameters of acceleration during rallies and conative stage were well projected on axis 1, whereas parameters of acceleration between rallies were better projected on axis 2.

Step 3. Supervised learning

As can be seen in Figure 2 and Table 5, all features did contribute to predicting the subjective conative stage, but not with the same significance. The wrapper method for feature selection shows that this is VM_ratio which, by far, contributes the most to the classification, followed by kinetic parameters during the rallies (VM_R), the duration of the rallies, then all variables related to non-game (kinetic and duration). Table 5 shows that T_ratio contribution to determine the conative stage is more than the contribution that would have been made by a random variable, even if its contribution is low. For this reason, we kept it in the next stage to build the prediction model.

Step 4. Main descriptors of conative stages

Results from the Kruskal-Wallis test show that all selected parameters differed as a function of the conative stage.

Pairwise Wilcoxon shows accelerometric parameters during the game, and also the ratio magnitude vector during rallies/magnitude vector between rallies (VM_ratio)

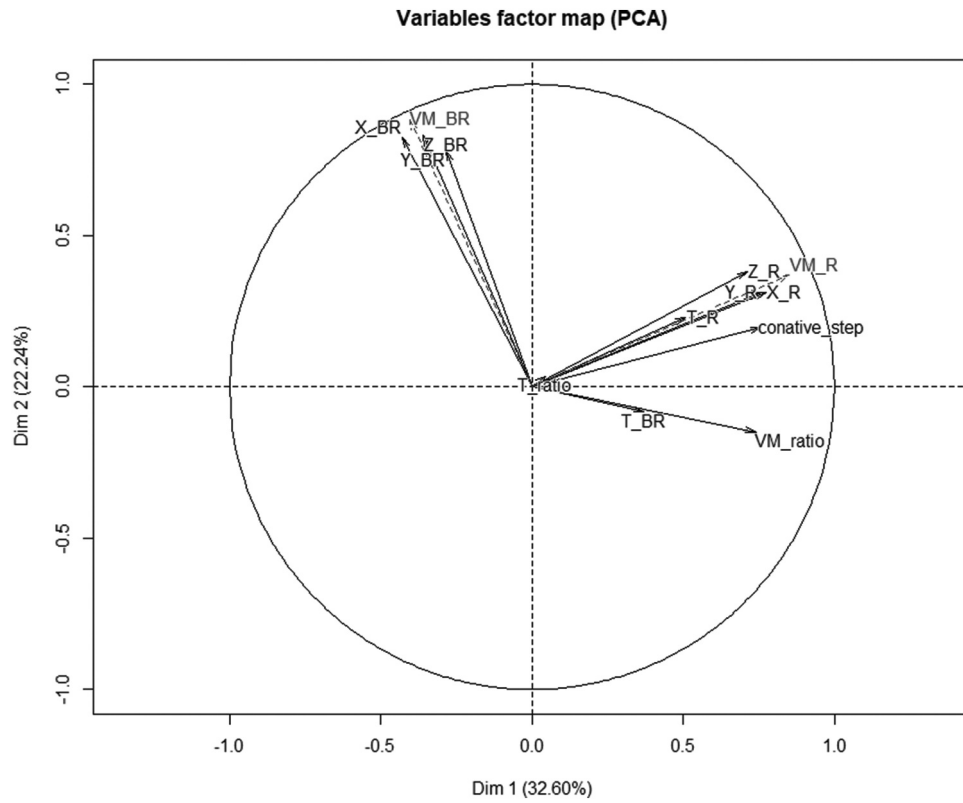


Figure 1. Organisation of the variables on the first factorial plan.

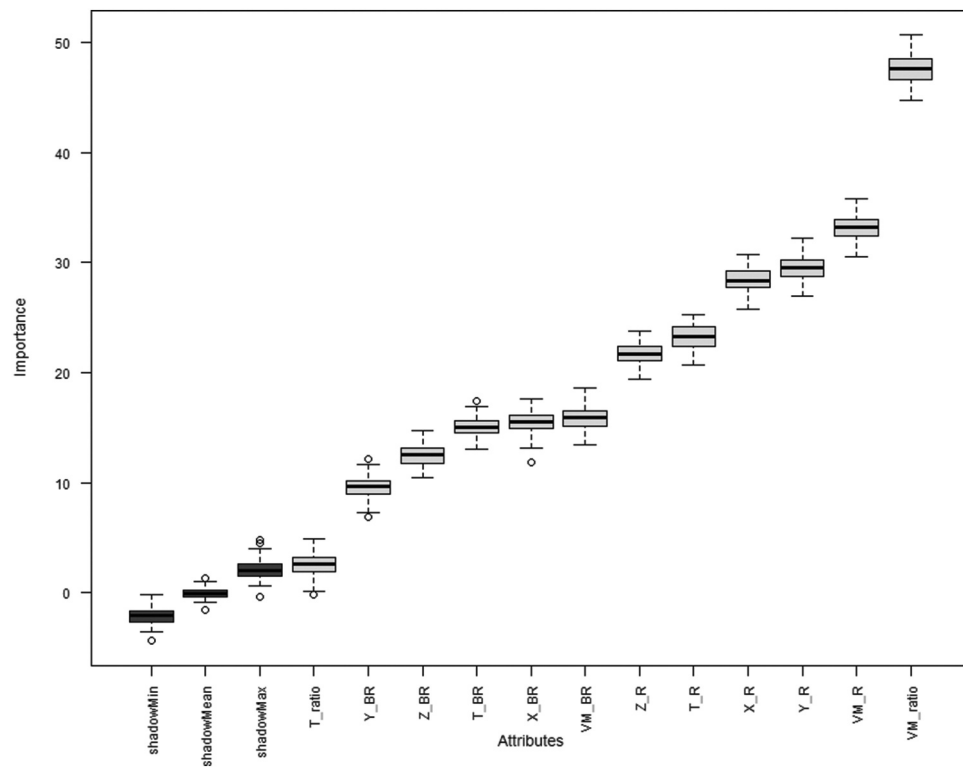


Figure 2. Importance of the different parameters in explaining the conative stage (from random tree analysis).

increased from stage to stage and had large effect sizes. As can be seen in Table 7, the duration of the rally increases and acceleration between rallies in X, Y, Z decreases but

only in stage 5 (expert), with small effect sizes. Ratio time (T_ratio) (small effect) and between rallies duration have a bell-shaped curve (medium effect).

Table 5. Importance of the various quantitative indicators in explaining the conative stage.

Variable	Mean importance	Decision
VM_ratio	47.7	Confirmed
VM_R	33.2	Confirmed
Y_R	29.5	Confirmed
X_R	28.4	Confirmed
T_R	23.2	Confirmed
Z_R	21.7	Confirmed
VM_BR	15.9	Confirmed
X_BR	15.4	Confirmed
T_BR	15.0	Confirmed
Z_BR	12.5	Confirmed
Y_BR	9.5	Confirmed
T_ratio	2.5	Confirmed

Step 5. Prediction of the conative stage based on the 12 best predictors

According to the previous results, all variables were included to calculate the predictive model. The 22 classifiers trained had a range of 45.1% to 57.7% of correct classification of subjective conative stages. The quadratic support vector machine algorithm performed best and was therefore chosen for the confusion matrix.

All classes were predicted with a true positive rate superior to chance (in this case, 20% given that there are 5 conative stages).

The rate of true positive varied among classes, proving more reliable for class 5 (72% of true positive) and less for class 3 (25% positive rate).

It is also interesting to note that most of the cases of misclassification could be found in the immediate neighbourhood of the true class. For example, class 3 has a misclassification rate of 76%, but when adding its two neighbours, this rate fell to 44%. This shows that the classifier performs rather fairly.

Discussion

The objective of this study was to examine to which extent selected notational and kinetic variables could relate to conative stages obtained using a more subjective but holistic approach. The main results show that VM_ratio is the most powerful predictor of the conative stage, but that both accelerometric and notational data are important in differentiating among conative stages. More specifically, using all twelve parameters helped to classify the conative stage with an accuracy above chance, ranging from 24% for “technical” stage to 75% for “expertise” stage.

Badminton is a complex sport, in that many parameters such as physical, physiological, psychological, tactical and affective variables might influence performance level. Our data show an excellent overall reliability level among observers in the use of the conative stage observation grid. However, this result does not reveal much about how observation relates to empirical data, which is why these relationships were analysed. Our first set of analysis-based correlations show that acceleration and notational data during rallies are positively correlated with the conative stage, whereas this correlation is negative between rallies. This result is in accordance with previous studies

showing that (1) experts exhibited a higher intensity of acceleration vector (M. Blomqvist et al., 2000); and (2) management of resting time relates to expertise level (O'Donoghue & Ingram, 2001; M. Phomsoupha & Laffaye, 2015). On the other hand, the principal component analysis showed that during rallies, parameters (acceleration and time) are more related to expertise than between-rallies parameters. This apparent orthogonality between within- and between-rallies parameters questioned the relevancy of keeping all these 12 parameters in a performance analysis. To examine this specific point, we decided to use Supervised Learning procedures to (1) see if those quantitative data could be considered as features of the conative stage, using the Random Forest feature selection algorithm, (2) to examine how empirical data changed as a function of conative stage, and (3) to examine to which extent machine learning algorithms could predict the conative stage based on those quantitative measurements, bearing in mind that those data were collected separately.

Feature selection showed that both within and between rallies parameters are related to the conative stage. Accelerometric data seem to be the most important predictor of the conative stage. Our results indicate that, the better the conative stage, the higher the overall VM_R. More specifically, it seems that the activity is higher in the three planes of motion: X_R accounts for the acceleration in the vertical plane, Y_R in the medio-lateral plane accounting for side stepping (very specific in badminton), and Z_R in antero-posterior plan. This shows that players in higher conative stages tend to take advantage of all three planes in space to play faster and break the game of the opponent. Interestingly, the predictor with the highest load was the VM_ratio which increased significantly from stage to stage. As it showed that imbalance between VM during rallies and VM between rallies increased, we considered that as an indicator of game management. Those results confirmed past literature which showed that apart from technical repertoire, the capacity to generate large acceleration in the three planes of motion (Jaworski et al., 2017; Lieshout & Lombard, 2003; Raman & Nageswaran, 2013; Tiwari et al., 2011), and the ability to manage energy resources (Fahimi & Vaezmousavi, 2011; M. Phomsoupha & Laffaye, 2015) explain skill level in badminton, “one of the fastest and most demanding racket sports” (Lees, 2003; Reilly, 1990). Interestingly, as can be seen from the feature selection, notational parameters such rally time (T_ratio, T_BR, T_R) also contributed to the overall explanation of the conative stage, but its relationship with the conative stage seems more complex and non-linear.

As all parameters were confirmed to relate to the conative stage, we sought to examine how expertise began to emerge as the learner progressed. The Pairwise Wilcoxon test results suggest that each conative stage may be characterised differently.

Players at stage1 are characterised as having the lowest acceleration rate during rallies and the lowest ratio VM rallies/VM between rallies. Low values for both these parameters suggest a low involvement in the game, which may explain the lack of need for game management.

Players at stage 2 and 3 are characterised by a higher vector magnitude during rallies, but also higher VM_ratio, and between rallies duration as compared to stage 1. Stage 3

Table 6. Notational and kinetic variables as a function of the conative stage.

	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Partial eta-squared
Duration of rallies	6.4 ± 4.3 ^e	5.5 ± 2.6 ^{d,e}	5.6 ± 2.5 ^e	6.3 ± 3.3 ^e	9.3 ± 6.7 a, b, c, d	0.06
T_R	148.6 ± 40.5 b, c, d, e	173.1 ± 45.9 a, d, e	176.2 ± 44.2 a, d, e	232.8 ± 52.7a, b, c, e	264.9 ± 52.6 a, b, c, d	small
VM rallies	92.5 ± 36.1 b, c, d, e	109.3 ± 35.3 a, d, e	114.4 ± 37.8 a, d, e	157.8 ± 43.3 a, b, c, e	167.8 ± 40.6 a, b, c, d	0.45
VM_X (rallies)	84.2 ± 22.7 c, d, e	83.7 ± 24.4 c, d, e	88.9 ± 26.3 a, b, d, e	109.6 ± 33.9 a, b, c, e	136.5 ± 31.1 a, b, c, d	0.38
X_R	65.8 ± 21.9 b, c, d, e	89.6 ± 31.7 a, c, d, e	81.7 ± 28.8 a, b, d, e	109.4 ± 35.3 a, b, c, e	129.6 ± 35.8 a, b, c, d	large
VM_Y (rallies)	7.2 ± 2.6 b, d, e	6.6 ± 1.8 ^{a, c, e}	6.9 ± 1.9 b, d, e	6.7 ± 2.4 ^{a, c, d, e}	11.3 ± 9.1 ^{a, b, c, d}	0.33
Y_R	93.8 ± 34.3 d, e	96.6 ± 34.0 d, e	94.6 ± 33.4 d, e	88.6 ± 36.3 a, b, c, e	81.7 ± 69.8 a, b, c, d	large
VM_Z (rallies)	51.4 ± 29.1 e	51.1 ± 29.9 e	49.1 ± 26.9 e	47.8 ± 29.7 ^e	35.7 ± 47.2 a, b, c, d	0.16
Z_R	48.1 ± 15.7 d, e	47.1 ± 13.1 e	46.4 ± 15.8 e	45.7 ± 17.8 a, e	45.6 ± 32.6 a, b, c, d	0.10
Between-rallies duration	50.1 ± 21.9 b, c, d, e	55.1 ± 23.3 a, d, e	54.7 ± 23.3 a, d, e	47.1 ± 22.3 a, b, c	47.1 ± 39.8 a, b, c, d	small
T_BR	0.94 ± 0.7 d	0.85 ± 0.4 ^d	0.88 ± 0.5 d	1.01 ± 0.5 ^{a, b, c, e}	0.91 ± 0.7 ^d	0.06
VM_BR	1.7 ± 0.8 b, c, d, e	2.0 ± 0.9 a, c, d, e	2.3 ± 1.4 a, d, e	3.1 ± 1.4 a, b, c, e	4.9 ± 1.8 a, b, c, d	0.37
X_BR						large
VM_X (between rallies)						
VM_Y (between rallies)						
VM_Z (between rallies)						
Duration Ratio						
T_ratio						
VM_ratio						

Table 6 shows significant difference with (a) stage 1; (b) stage 2, (c) stage 3, (d) stage 4, (e) stage 5.

Table 7. Confusion matrix: classification of subjective conative stages.

True conative stages	Predicted conative stages				
	1	2	3	4	5
1	55%	31%	10%	3%	1%
2	19%	53%	16%	11%	2%
3	22%	41%	24%	11%	2%
4	6%	21%	14%	45%	14%
5	5%	3%	4%	17%	72%

players differ from those of stage 2 due to the greater difference in acceleration rates between play and non-play, as VM_ratio increases significantly, although the difference is small (~300 ms). This suggests that energy involvement becomes more important, which implies the need for more recovery time. More specifically, Z_R (anteroposterior movement) increases significantly from stage 1 to stage 2, whereas Y_R (mediolateral), which accounts for side-stepping displacement, is significantly higher in stage 3. This interpretation remains speculative, however, and would require further studies to be confirmed.

Players at stage 4 differ from those of stage 3 due to both the greater difference in acceleration rates between play and non-play (VM_ratio increases significantly), and the shorter relative recoveries (T_ratio). At that stage, these data suggest that energy involvement might be the players' main feature, implying both a lower energy involvement between rallies and a more active behaviour, the aim of which is to put more temporal pressure on the opponent to win the match.

Players at stage 5 are characterised by having the longest rally durations, the greatest acceleration magnitude during rallies and the highest VM_ratio of all the players but the longest between rallies duration. Energy involvement is also very high, but those data suggest that game management becomes more important: those players are not only recovering exhibiting lower VM during recovery periods, but also using longer times between rallies.

The variable VM_ratio, which represents the ratio between acceleration during rallies and acceleration within rallies, is of particular interest as it has the highest, mean significance according to Table 4. Interestingly, it does not seem to evolve in a linear manner. It increases regularly from stage 1 to stage 3 (+0.3), and then increases dramatically at stage 4 (+0.8) and 5 (+1.8). The typology provided to the analyst to determine the conative stage stated that participants at stage 1 focus on means to return the shuttlecock into the field. This might explain why acceleration within and between rallies barely differs. Participants at a higher conative stage seem to be more oriented towards taking advantage of their opponent's lack of movement (functional stage), or by speeding up the exchange by using new techniques such as a "smash" (technical stage). At even higher conative stages (4 and 5), those data confirm the ability of the players to reposition themselves quickly, thus raising their ability to defend their playing field, as rally durations appear to increase.

All these results show how kinetic and spatio-temporal parameters relate to the conative stage and performance levels in badminton. But to which extent can those quantitative data predict the conative stage? To answer this question, we used

another set of machine learning algorithm. Our results indicate that the quadratic SVM classification algorithm can classify the data according to the conative stage with a better rate of classification than chance. This suggests that subjective video-based analysis could benefit from more objective measurement to classify the expertise level of badminton players according to conative levels. Thus, the accelerometer's objective data could complement a technical assessment provided by the coach.

However, there are some factors which limit the scope of this study. First, it was not possible to have all participants involved playing each other once again. This would have been the most objective way to classify our population according to performance level. However, there is no doubt that group 5 (expert), and group 4 (contextual), who were respectively national and regional level players, could be clearly hierarchised according to their ranking. Also, players in the first conative stage (structural) were real beginners, therefore of a performance level lower than all the other groups. We agree, however, that stage 2 and 3 were more difficult to determine according to the subjective grid. This factor might explain why these groups had such a bad classification rate on the confusion matrix (24% and 53% respectively). It is interesting, however, to note that if group 2 and 3 were amalgamated, the correct classification rate would climb to ~65-69%, as most of the players in this group were misclassified in the other conative stage. Further study should determine whether more specific indicators should be developed to account for these respective conative stages.

Second limitation: Technical parameters such as stroke positions of the shots were not included in the study. We believe that there is a major gap in this study, which, if addressed, could further characterise those conative stages. However, we decided to limit this study to the simple parameters of time and acceleration in order to demonstrate that subjective classification based on the conative stage had an empirical basis. We trust that the approach which we promoted, that is, using machine-learning techniques shows how various sets of variables, both qualitative and quantitative, can account for performance level, may be an interesting option for examining more parameters which could be included in this study, even on an individual level.

Third limitation: Population size might also be an obstacle to drawing general conclusions from the results. However, we compared groups with different expertise levels, which meant that we needed a balanced design between conative stage groups. Moreover, this number is typical for studies on motor expertise (Schnitzler et al., 2011; Seifert et al., 2018).

Fourth limitation: There was no distinction based on sex in this study, which potentially reduces the success rate of the confusion matrix. Although male participants have an advantage due to better physical abilities (Cabello et al., 2004), badminton remains a complex sport in which skill can compensate for physical differences. From a conceptual point of view, the conative stage model only differentiates people based on their expertise levels, which is why we decided to establish our group based solely on this factor and not on a competition that would have ranked players from the least to the most proficient performer.

Fifth limitation: Qualitative and quantitative data are related, but do not establish the direction of the link. For example, are

rhythm and acceleration consequences of the conative stage, or are they the parameters on which judgement on the conative stage is established? Such questions also call for further investigation. Nonetheless, the study provides an empirical means for identifying a player's conative stage, allowing for such investigation.

Conclusion

This study sought to establish a relationship between performance level and expertise level using a qualitative typology involving kinetic and notational indicators of performance. Our main findings were that quantifying acceleration is key to further objectifying the conative stages, and that qualitative and quantitative parameters actually complement one another. We also suggested a methodology for analysing expertise levels that could be relevant when designing performance analysis tools in sports with a high degree of uncertainty. We were able to show which parameters could be more specifically targeted as a function of a participant's conative stage. Overall, the study advocates designing performance analysis settings by complementing selected subjective observations with empirical data.

Disclosure statement

We declare no potential conflict of interest for this research.

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