Assessment 2- Literature Review of Spatiotemporal Data

Many data collection tools are common in Rugby Union such as notational analysis, accelerometers, and GPS tracking. While computer modelling, machine learning and statistical models are providing ongoing insights into Rugby gameplay. Can these modern data collection tools and processing techniques help inform defensive strategies in Rugby Union?

In field-based sports, technologies such as GPS tracking, and accelerometers can be used to physically track player movements during a game. Along with this, manual coding can be undertaken to plot events as they happen, this type of analysis involves filming a game and entering observations into software to provide details of what, how and when certain events took place during a game (Colomer et al., 2020). Time motion analysis can be performed by filming and then digitising players to provide detailed coordinate data. This data can then be used to understand the movement of players throughout a game via their energy pathways (Deutsch et al., 2007) or how they react to the information they’re receiving (Correia et al., 2011). Machine learning and data science are becoming increasingly common tools in all sports. There have been minimal studies involving Rugby to date, but the enlarging pool of data and the improvement in Artificial Neural Networks has made it easier to model this complex, non-linear sport (Watson et al., 2020).

A study by Howe et al., (2020) described GPS tracking as an important tool for tracking the movement of players during games, GPS units can provide information about velocity, distance travelled and position. This information allows coaching teams to prescribe conditioning, load management and inform substitution choices. They found that GPS has poor sensitivity when measuring movement during Rugby Union match play, with the maximum mean movement varying by ~11% between measurements. To lower this level of noise to an acceptable level approximately 16 games worth of repeated measurements would need to take place to ensure adequate precision. In addition to this, they found that the reliability of mean movement data was low for within-match, between-half measures and between-match, within-half measures and that reliability of team sport movement measurements decreases with increases in the speed of the movement. Muñoz-López et al., (2017) noted how difficult it is to test GPS reliability for speed as this would require athletes to run circuits at the same speed numerous times. However, they found good inter and intra-unit reliability for total distance, average speed, and high-speed sprints.

Time motion analysis can be used to quantify the physical demands of a field-based game to further improve the information for training and conditioning sessions. Information is typically collected via video or computer-based methods. Video-based involves analysing the vision of players post-match manually or by using software. Computer-based involves markers and reference points that generate coordinates from a calibrated playing field. This method of data capture is non-invasive but can be labour-intensive in terms of processing the data post-match. A study by Doğramac et al., (2011) looked to compare time-motion analysis and GPS tracking to assess athlete movement patterns in a simulated futsal course. In terms of validity, they found that there was a significant difference between the values found in total distance, with GPS tracking being lower than the criterion and time analysis data, while the time-motion analysis had a larger standard deviation (GPS distance 1,101.9 ± 52.6 m, criterion distance 1,260.5 ± 61.6 m, and time-motion distance 1,265.4 ± 64.5 m). A significant difference was also seen when assessing the total number of events, with the GPS calculating the highest number compared to criterion and time-motion (criterion value 128.0 ± 6.32; GPS value 189.0 ± 19.2; and time-motion value 133.9 ± 8.97).

Machine Learning via Artificial Neural Networks (ANN) can be employed to predict outcomes of sequences of play depending on the order certain actions occur and where on the field they happen. These models can then be used to provide coaches with support around tactical decision-making. Watson et al., (2020) state that most performance analysis studies are based on KPIs and the overall outcomes of a game with few examining within-game outcomes. Some studies have looked at using multiplayer perceptrons to predict the outcomes of sporting events (McCabe et al., 2008) or to model the on-field dynamics between players (Passos et al., 2006). Combining data science and Operational Research has become an important research avenue given the increase in datasets available. Watson et al., (2020) used manually coded data from European Rugby to assess five different types of ANN. Models that involve a mechanism to remember the sequence of data performed better than those without, while those that considered location information performed the best. Further to this, data can be used to understand how information from a player’s in-game environmental interactions is guiding the decisions on how best to negotiate certain scenarios such as the distance between them and a defender when choosing what to do with the ball. Correia et al., (2011) conducted a study using the approach variable Tau for the gap between the first receiver and the approaching defensive line. They found the initial Tau value (the instant the player receives the ball) from the rate of the change of distance of defenders informs of the time remaining before the collision and whether that will allow him to perform a specific pass.

The collection tools available provide varying levels of data to sports analysts and coaches. With GPS tracking and time-motion analysis, there can be varying levels of validity and reliability variance with data. However, subsequent testing of players across many events can limit the effect of these variances. Machine Learning and statistical models are becoming increasingly common due to the large amounts of emerging data. When considering Rugby using an ecological framework from these techniques, defensive strategies are sure to be improved if the information can be visualised in a manner that coaches can glean meaningful and implementable strategies.

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