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Visualisation of Fundamental Movement Skills (FMS):

An Iterative Process Using an Overarm Throw

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ABSTRACT

Fundamental Movement Skills (FMS) are precursor gross motor skills to more complex or specialised skills and are recognised as important indicators of physical competence, a key component of physical literacy. FMS are predominantly assessed using pre-defined manual methodologies, most commonly the various iterations of the Test of Gross Motor Development. However, such assessments are time-consuming and often require a minimum basic level of training to conduct. Therefore, the overall aim of this thesis was to utilise accelerometry to develop a visualisation concept as part of a feasibility study to support the learning and assessment of FMS, by reducing subjectivity and the overall time taken to conduct a gross motor skill assessment. The overarm throw, an important fundamental movement skill, was specifically selected for the visualisation development as it is an acyclic movement with a distinct initiation and conclusion. Thirteen children (14.8 ± 0.3 years; 9 boys) wore an ActiGraph GT9X Link Inertial Measurement Unit device on the dominant wrist whilst performing a series of overarm throws. This thesis illustrates how the visualisation concept was developed using raw accelerometer data, which was processed and manipulated using MATLAB 2019b software to obtain and depict key throw performance data, including the trajectory and velocity of the wrist during the throw. Overall, this thesis found that the developed visualisation concept can provide strong indicators of throw competency based on the shape of the throw trajectory. Future research should seek to utilise a larger, more diverse, population, and incorporate machine learning. Finally, further work is required to translate this concept to other gross motor skills.

DECLARATIONS AND STATEMENTS

DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated. Where correction services have been used, the extent and nature of the correction is clearly marked in a footnote(s).

Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

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Contents

LIST OF FIGURES

LIST OF TABLES

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ACRONYMS AND ABBREVIATIONS

3D	Three-Dimensional
ANCOVA	Analysis of Covariance
BOT-2	Bruininks-Oseretsky Test – Second Edition
CBA	Cost-Benefit Analysis
COG	Centre of Gravity
DFT	Discrete Fourier Transform
FFT	Fast Fourier Transform
FL	Florida
FMS	Fundamental Movement Skills
IFFT	Inverse Fast Fourier Transform
IMU	Inertial Measurement Unit
KP	Knowledge of Performance
KR	Knowledge of Results
LLC	Limited Liable Company
MA	Massachusetts
MABC-2	Movement Assessment Battery for Children – Second Edition
MVPA	Moderate to Vigorous Physical Activity
PA	Physical Activity
PC	Physical Competence
PDMS-2	Peabody Developmental Motor Scales – Second Edition
PE	Physical Education
PL	Physical Literacy
SKIP	Successful Kinesthetic Instruction for Pre-schoolers
TGMD	Test of Gross Motor Development
TGMD-2	Test of Gross Motor Development – Second Edition
TGMD-3	Test of Gross Motor Development – Third Edition
UK	United Kingdom
USA	United States of America
VARK	Visual, Auditory, Reading/Writing, Kinaesthetic

CHAPTER 1: INTRODUCTION

1.1. Context

Fundamental Movement Skills (FMS) are precursor gross motor skills to more complex or specialised skills often required in sports and games (Hands, 2012). While there are many FMS described in the literature, each fundamental movement skill can typically be categorised in to one of two categories: locomotor or object control (Walkley et al., 1996), with some sources suggesting that a third category – balance skills – may also be considered (DeMont, 2017; Rudd et al., 2015). Congruent with the findings of Clark (2007), Kirk (2005), Lubans et al. (2010) and Macdonald et al. (2016), FMS are recognised as important indicators of physical competence (PC), subsequently influencing overall physical literacy (PL), which has been defined by Whitehead (2019, p8) as

"the motivation, confidence, physical competence, knowledge and understanding to value and take responsibility for engaging in physical activities for life"

Improving PC has a substantial influence on other components of PL (Whitehead, 2010), creating the potential for future physical successes, and academic and societal development throughout the lifecourse (Kirk, 2005; Macdonald et al., 2016; Pagani & Messier, 2012).

A vast array of research has identified that FMS, and indeed PC as a whole, are best learnt prior to adolescence (Lubans et al., 2010). As such, it is important that FMS are suitably practiced and assessed during childhood. Indeed, physical education (PE) lessons during school hours and extra-curricular activities outside of school are essential to educating and refining gross motor skills such as FMS (Barnett et al., 2016; Foweather et al., 2015). However, the overall level of FMS competency in the United Kingdom (UK) is low, particularly in more deprived areas and those where access to adequate facilities is limited (Foulkes et al., 2015). This is often due to the insufficient training of some educators to adequately teach and assess FMS (K. Kirk, 2012), the demands placed on teachers to prioritise other school subjects over PE (Gehris et al., 2015), and the addition of factors such as cost and facility restrictions (Dallinga et al., 2017; Mayagoitia, Nene, & Veltink, 2002). Furthermore, the available assessments used to evaluate gross motor skill competency, such as those identified by Griffiths et al. (2018), while effective, are manually conducted and therefore time demanding to complete (Valentini et al., 2018). Moreover, there is often a demand for additional training such that the chosen assessment method can be suitably conducted (Griffiths et al., 2018). Consequently, there exists an opportunity for the learning and assessment processes associated with FMS to be improved to reduce or eradicate the existing limitations.

To date, there has been a large amount of research conducted into the use of technology for assessing physical activity (PA), though this has predominantly focused on the volume of activity (Capio et al., 2012; Capio et al., 2015; Mackintosh et al., 2016). Conversely, there is limited research into the assessment of gross motor skill competency, particularly the competency of FMS, using affordable technologies, despite the potential for commercialisation and mass application. Currently, where technology has been applied for the assessment of gross motor skills, research has favoured optical technologies, such as marker-based motion capture and markerless motion capture utilising video cameras and infrared depth sensors (Kim & Lee, 2013; van Diest et al., 2014), though these tools are costly to implement and have greater facility demands (Mayagoitia et al., 2002). Therefore, using non-optical measurement devices, such as accelerometers is warranted for the assessment of FMS, where the associated cost and facility requirements are substantially less (Mayagoitia et al., 2002). There have been studies which evaluated the use of accelerometers for assessing gross motor skills, including FMS, such as that presented by Lander et al. (2020) and Grimpampi et al. (2016). However, studies such as Lander et al. (2020) typically utilise multiple sensors for tracking movement which is theorised to have greater cost implications and less transferability to real-world applications. A reduction in the quantity of sensors used for measuring FMS is therefore preferred, providing the effectiveness and validity of assessments are not hampered. By adopting affordable non-optical measuring devices in lieu of expensive optical or multi-sensor alternatives, the application of technology for gross motor skill assessments in environments such as schools and sports clubs becomes more feasible (Lander et al., 2020). The introduction of technology to assess gross motor skills, specifically FMS, can substantially benefit practitioners, where assessments can be performed with feedback delivered almost instantly (Bisi et al., 2017), thereby being more time-efficient and less subjective. Moreover, using ingrained algorithms and machine learning may enable the reduction, or indeed elimination, of the need for specialist training to be able to conduct a valid assessment of FMS (Bisi et al., 2017). Implementing technology to improve FMS, an indicator of physical competence (PC), can be integrated within a holistic approach to support the complete development of PL (Whitehead, 2010), in turn enhancing the likelihood of later athletic and academic successes, and social opportunities.

Furthermore, there are numerous educational possibilities that accompany the implementation of technology, benefitting both the learner, through increased participation and a desire to learn (Lindberg, Seo, & Laine, 2016), and the educator, by saving time (Lander et al., 2020; Sgrò et al., 2017) and improving on the delivery of feedback (Zhang et al., 2019).

Consistent with the findings of Schmidt and Wrisberg (2008) who promote the use of extrinsic feedback, the delivery of feedback to aid the learning of motor skills may be most effective by means of a visual representation on a remote device. Indeed, whilst visual aids have been used in PA applications, these have typically been to indicate movement quantity, rather than quality (Crossley, McNarry, Rosenberg, et al., 2019; Fan, Forlizzi, & Dey, 2012). Metrics focusing on movement quantity, i.e. the total amount of movement an individual performs, are commonly used for assessing PA, such as total number of steps taken (McIntyre, 2009), calories consumed, and distance travelled (Kaewkannate & Kim, 2016), all of which are indicative of energy expenditure (C. C. T. Clark et al., 2016). While a lack of total activity has been linked to various comorbidities (World Health Organization, 2018), highlighting the benefits of quantity-based metrics, total energy expenditure only provides part of a comprehensive PA assessment. Measuring movement quality, i.e. how well an individual moves while conducting activity, offers additional important information relating to PA, with movement quality characteristics able to provide specific and contextualised feedback (C. C. T. Clark et al., 2016), in turn reducing injury risk (Andrews & Fleisig, 1998; Lyman et al., 2002; Young, 2009) and encouraging participation in sports and other recreational activities (Whitehead, 2010). A range of visualisation approaches, including abstract imagery (Williams et al., 2017) and graphical illustrations (Crossley, McNarry, Rosenberg, et al., 2019) have been used to assess movement quantity. It is therefore important to transfer the application of visual aids to assess movement quality to ensure all components of movement can be accurately assessed, and feedback provided. Considering the target audience – educators and children – it is imperative that information presented through visualisations can be easily interpreted, with the use of vibrant colours, which are hypothesised to support the interpretation of the data while making the learning experience more appealing to children (Dzulkifli & Mustafar, 2013). Given that it is likely that the process of developing simple visualisations will not only take time, but will require different accelerometer placements depending on the skill, it is important to develop a process rather than a specific outcome. It is speculated that a single fundamental movement skill, such as the overarm throw, would enable the development and refinement of the concept, prior to application of other FMS, or indeed accelerometer placements. Specifically, the overarm throw is a common skill featuring whole-body movement with clear phases (Ulrich, 1985, 2000, 2016; Whiteley, 2007; Young, 2009), ultimately enabling ease of transferability to other FMS. Moreover, the overarm throw is an acyclic movement, thereby aiding the identification of the starting and concluding points of the throw and reducing the risk of influence from movement 'noise' sometimes observed in cyclic movements, such as locomotor skills (Pfau, Witte, & Wilson, 2005). Such 'noise' in the current context would be considered to be a lack of signal clarity which may be produced by cyclic movements due overlapping phases of the movement pattern during certain locomotor skills (Mentis, 2013). Notably, the overarm throw has a distinct focal limb when executing the skill, with the movement of the throwing arm ultimately delivering the outcome. The overarm throw is essential in many sports, including track and field (Ogiolda, 1993), baseball (Seroyer et al., 2010) and handball (Wagner et al., 2014), hence mastery of this particular movement is often necessary for sporting success.

One of the most common ways to assess gross motor skill proficiency is to use a manual assessment method, such as the Test of Gross Motor Development – Third Edition (TGMD-3; Ulrich, 2016). Nonetheless, manual assessments are inherently limited by subjectivity (Bardid et al., 2019; Giblin, Collins, & Button, 2014; Masci et al., 2012), while also being time consuming, a luxury that often cannot be afforded to educators (Hardman, 2008). Recent research has highlighted opportunities to overcome these limitations by providing an accelerated assessment process with clear and interpretable outputs, in addition to supplementary metrics which are not readily available to the target population at this time, but are imperative to the competent performance of certain gross motor skills. One such example is the provision of velocity data, where research has shown that ball velocity is associated with the level of development in the overarm throw (Logan et al., 2018; Stodden et al., 2008), with the complete and correct sequencing of the movement being shown to apply greater velocities to the ball (Wagner et al., 2014).

1.2. Thesis Aims

The aim of this thesis was to ascertain whether a single Inertial Measurement Unit (IMU) device could be used to develop a visualisation of the overarm throw. Moreover, the thesis sought to identify whether such a visualisation aid could not only assess the competency of an overarm throw but could be further developed to provide feedback to support the learning of the overarm throw. Following a comprehensive review of the available literature in Chapter 2, which provides the basis for this study, Chapter 3 provides the method used to develop a visualisation tool concept with preliminary results indicating the effectiveness of the concept. The method describes the iterative process by which a visualisation tool concept was developed to support the testing and learning of FMS, commencing with the necessary pre-processing of raw IMU data, followed by the development and subsequent refinement of the visualisations, including detail of the key decisions made to obtain the final aesthetic characteristics and the derivation of the performance metrics used. Given the iterative process, Chapter 3 incorporates preliminary results which are indicative of the effectiveness of the concept. The thesis concludes in Chapter 4, which presents a discussion around the visualisation concept, as well as the strengths and limitations. Finally, Chapter 4 highlights the opportunities for further development and feedback provided.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction and Context

The purpose of this chapter is to review the literature concerning Fundamental Movement Skills (FMS) and their importance to childhood development and lifelong activity. This chapter will consider the current state of the education regarding FMS and the methods by which FMS are taught and tested. The effectiveness of these methods and their limitations will be explored, with the use of technology and its potential to improve FMS learning considered in detail. Specifically, effective methods by which data can be captured using technology and visually represented in a manner that is readily interpretable by individuals without prior training in gross motor skill assessment will be reviewed.

2.1.1. Physical Literacy

Physical literacy (PL) is a multifaceted concept applicable to various situations due the range of attributes the term encompasses. Specifically, PL has been defined by Whitehead (2019, p8) as

"the motivation, confidence, physical competence, knowledge and understanding to value and take responsibility for engaging in physical activities for life".

This overarching statement highlights the inherent inter-relationships between attributes, as demonstrated in Figure 2.1, with changes in one attribute directly and indirectly affecting the other. Individuals that demonstrate high levels of a certain attribute will typically also express high levels of the other attributes.

A. Motivation
B. Confidence and physical competence
C. Interaction with the environment
D. Sense of self and self-confidence
E. Self-expression and communication with others
F. Knowledge and understanding

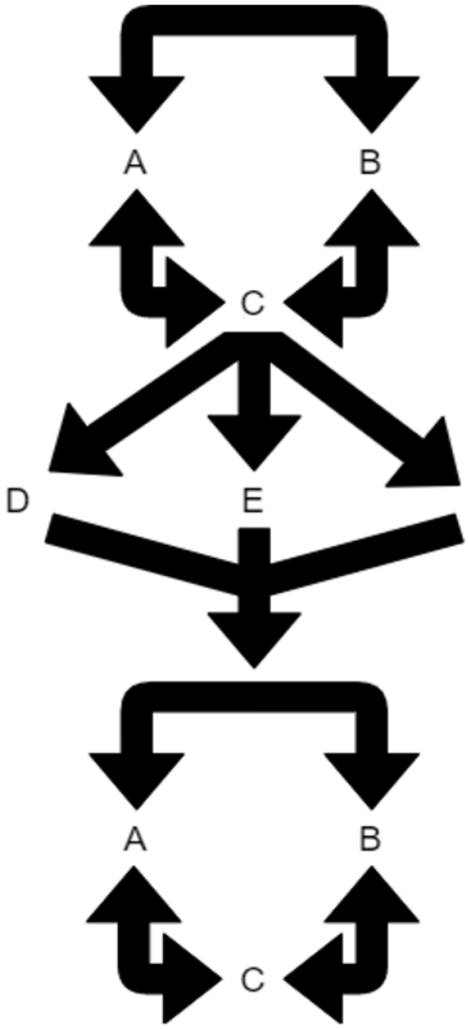


Figure 2.1 – The relationship between all the attributes of physical literacy (adapted from Whitehead, 2010)

Developing PL from an early age is imperative, as it becomes increasingly difficult to develop PL (Loitz, 2013). As such, early stage development of PL is critical in creating opportunities later in life. There is evidence that indicates early stage development of both fine (e.g. drawing, tracing, manipulating small objects) and gross (e.g. throwing, catching, kicking) motor skills (Macdonald et al., 2016) can create opportunities in the short- (Macdonald et al., 2016) and long-term (Kirk, 2005). It has also been suggested that early development of PL can have a profound influence on later athletic and academic success, positive social behaviours and lifelong PA (Becker et al. 2014; Kirk, 2005; Loitz, 2013; Macdonald et al., 2016; Pagani & Messier, 2012).

Figure 2.1 shows that each attribute of PL influences the others but it is generally accepted that physical competency is the most easily developed attribute of PL (Giblin et al., 2014; Rainer & Davies, 2013). Furthermore, Giblin, Collins and Button (2014), and Rainer and Davies (2013) highlighted the importance of fundamental movement competence in developing other attributes of PL in children, including an increase in confidence and environmental interaction. There is therefore a need to integrate motor skill development into the curriculum through physical education (PE; Basoglu, 2018; Kirk, 2005), and sporting practices (Delaney et al., 2008; Valentini et al., 2018) to ensure that there are opportunities to apply the learned PL through both sport and play (Hands, 2012). Given the reciprocal benefits of promoting physical competence (PC) for motivation, confidence and environmental interactions (Whitehead, 2010), and the greater accessibility of motor skills as a teachable construct, further emphasis on the development of motor skills is warranted.

2.1.2. Fundamental Movement Skills

PC is described as a lifelong attribute of PL (Loitz, 2013; Whitehead, 2010). FMS, however, are largely developed in the early years of human development, with Lubans et al. (2010) highlighting the importance of learning such skills prior to adolescence, at an age when children are at an optimal stage for the development of motor skills. FMS are defined by Hands, (2012, p11) as

“the basic building blocks or precursor patterns of the more specialised, complex skills used in organised and non- organised games, sports and recreational activities”.

FMS are essential to many factors associated with PL, contributing to lifelong PC and PA. FMS are learned, voluntary, gross motor skills, fundamentally differing to those developed through the first year of life which are either ‘reflexive’ or ‘preadapted’ (J. Clark, 2007). More specifically, FMS can take the form of locomotor (e.g., running, jumping, hopping) or object-control skills (e.g., catching, throwing, kicking) as detailed in Walkley et al. (1996). However, recent research has suggested the inclusion of stability-based FMS, or balance skills (e.g. log roll, rock, back support), in which the body remains stationary but moves about its horizontal and/or vertical axes (DeMont, 2017; Rudd et al., 2015). The development, and indeed refinement of FMS provides a gateway to more complex applications of gross motor skills, such as sports in which the learned movements are contextualised (J. Clark, 2007; Ulrich, 2000). Table 2.1 presents the stages of development relative to age according to Ulrich (2000), with Stage 3 suggested as the age category during which FMS are predominantly developed. Similarly, Altunsöz and Goodway (2016) emphasise this period as the most optimal for the development of FMS, suggesting that the best time to instruct FMS is the early childhood years (2–7 years).

Table 2.1 – Sequential periods reflecting qualitative differences in motor behaviours (adapted from Ulrich, 2000)

Time Interval	Stage	Major Periods
Neonatal (first 2-3 months)	1	Reflexive and spontaneous movements
First 12-14 months	2	Preadapted behaviour repertoire
Nursery and primary school years	3	Fundamental gross motor behaviours
Secondary school through adulthood	4	Sport and context-specific movements

While the number of FMS is often disputed, twelve specific skills are generally cited within the literature (Foweather et al., 2015; Valentini et al., 2018), which align with the Test of Gross Motor Development (TGMD) introduced by Ulrich (1985), and the subsequent Test of Gross Motor Development – Second Edition (TGMD-2; Ulrich, 2000). The twelve skills are presented in Table 2.2, categorised as *locomotor* or *object-control*. Whilst balance skills, as described by DeMont (2017) and Rudd et al. (2015), are important for future considerations, given the lack of consistency with which they currently appear in literature, they will not be considered as part of this thesis.

Table 2.2 – List of twelve commonly cited FMS

Locomotor Skills	Object Control Skills
Running	Striking a Stationary Ball
Galloping	Stationary Dribble
Leap	Kick
Horizontal Jump	Catch
Hopping	Overarm Throw
Slide	Underhand Roll

2.2. Existing Methods for the Education and Development of Fundamental Movement Skills

The role that FMS play in lifelong human development and continued PA is substantial. Considering the importance of FMS and the resulting future applications that can arise through mastery of these skills (Hands, 2012; Lubans et al., 2010), there is a need for effective education in the development of FMS and effective testing of FMS in children.

2.2.1. Teaching Fundamental Movement Skills

The role of educators is crucial for the development of motor competency during childhood. The term ‘educator’, in this instance, largely refers to teachers, both generalists and PE specialists, but may also encompass sports coaches, all of whom are influential in developing motor competence in a formalised setting (Foweather, 2010; Rainer & Davies, 2013). Whilst parents and other prominent adults are also likely to play a key role in the development of childhood motor competency (Foweather et al., 2015), this typically comes without the same degree of structure as PE classes or planned sporting activities. It is acknowledged that teachers and sports coaches receive contrasting volumes of training to support the development of gross motor skills, with specialist PE teachers expected to be far more effective when delivering such training and conducting relevant assessments given their expertise (K. Kirk, 2012). Comparably, in accord with K. Kirk (2012), many sports coaches will also have a firm understanding of gross motor skill training and development, albeit with a lower level of formal training than PE teachers. By comparison, generalist teachers, commonplace within primary schools to teach an array of subjects, often lack sufficient PE training to suitably support the development of gross motor skills (Hardman et al., 2014; K. Kirk, 2012).

The development of FMS through education is important given that, while these may be developed naturally to a certain extent, FMS are best refined through instruction and practice (Breslin et al., 2008). There have been numerous approaches to the development of FMS including, but not limited to: focused learning (Breslin et al., 2008), deliberate practice (Breslin et al., 2008; Burns et al., 2017), and practice through play (Breslin et al., 2008; Burns et al., 2017). Focused learning and deliberate practice of FMS improves PA and lifelong participation in sport (Giblin et al., 2014), though by contrast, being physically active does not necessarily contribute to the improvement of FMS as a by-product without dedicated training (Breslin et al., 2008; Burns et al., 2017). However, once FMS are developed to a competent standard through focused learning and deliberate practice, continued practice through participation in sport can sustain and indeed further enhance the performance of FMS (Breslin et al., 2008; Burns et al., 2017).Studies by Robinson et al. (2012) and Robinson and Goodway (2012) promoted the use of a Mastery Motivational Climate centred around TARGET (Task, Authority, Recognition, Grouping, Evaluation, and Time) to support the initial learning of FMS. More specifically, a learning environment is created to provide an instructional approach which offers developmentally appropriate instruction in a success-oriented environment (Robinson et al., 2012). In a mastery climate, a successful completion of a specific task would be the child’s focus, with overall improvement in personal performance of the task being the ultimate goal (Ohlert & Zepp, 2016). Indeed, participation in a mastery climate has been shown to improve FMS in young children as well as to enable a higher retention of motor skill learning (Robinson et al., 2012). Papaioannou (1998) also encouraged the use of a mastery climate in PE, highlighting that a performance-oriented climate, where ego is often present, can hinder progress due to, at least in part, the addition of undue pressures. It would be preferable, therefore, to ensure that ego is not a contributing factor in the learning process of FMS, instead ensuring that the learning of new motor skills occurs within a familiar practice environment and with a familiar teaching process to which learners are more receptive to instruction and feel more comfortable communicating with educators (Schmidt & Wrisberg, 2008). Beyond the environment within which FMS are learned, the specific method by which motor skills are taught, the amount of time spent focusing on the development of FMS, and other foundational gross motor skills, must also be considered.

The respective curricula for PE within Wales, set by the Department for Children, Education, Lifelong Learning and Skills (DCELLS, 2018), and England, implemented by the Department for Education (DfE, 2013), necessitates that foundational gross motor skills, including a number of FMS, are taught during school hours. Furthermore, Hardman et al. (2014) reported, in a study on the state of PE globally, that the development of motor skills is prioritised over other themes in primary schools (Table 2.3), with an average of 24% of PE lesson time in Europe being allocated to motor skill development (Hardman, 2008).

Table 2.3 – Physical education curriculum themes ranking: primary schools area (adapted from Hardman et al., 2014)

Area	Motor Skills	Active Lifestyle	Personal/Social Development
Global	1	2	3
Africa	1	2	3
Asia	1	2	3
Europe	1	2	3
Latin America/Caribbean	1	2	3
Middle East	1	2	3
North America	2	1	3
Oceania	1	-	2

Rankings are on a scale of 1-3, where 1 is the highest priority and 3 is the lowest priority.

While the focus in PE on motor skill development is encouraging, Hardman et al. (2014) also found a decline in the allocated time for PE from a global mean of 116 to 97 minutes per week in the year 2000 and 2013 respectively. Such a decrease was postulated to be due to the emphasis being placed on other ‘academic’ subjects (Norris et al., 2017). This is particularly concerning given that current PA guidelines in the United Kingdom (UK) promote a minimum 60 minutes of PA per day in 5-18 year olds (Chief Medical Officers, 2019), resulting in the need for additional PA to be achieved through other means, such as extracurricular sports and active travel. This, therefore, suggests that while gross motor skill development is prioritised during PE lessons, there is insufficient time allocated to PE to effectively educate children to competently perform gross motor skills. In addition, Hardman (2008) and Hardman et al. (2014) propose that most gross motor skill learning in primary schools occurs through games and play. While it is necessary for children to enjoy PA, the lack of evidence to indicate focused learning of gross motor skills through direct instruction, particularly FMS, is alarming, given the need for specific instruction and practice (Clark, 2007; Logan et al., 2018).

In addition to an insufficient amount of time being spent providing formal motor skill education, it is also concerning that a global average of 79% of PE was found to be taught to primary school children by generalist teachers rather than specialists (Hardman et al., 2014), signifying that PE lessons are often delivered by educators insufficiently trained to support the proper development of gross motor skills and PL as a whole. This belief is shared by the early years teacher community in the United States, who also recognise that there are a number of challenges that exist in early years education when trying to include PA and motor skill learning as part of the school day (Gehris et al., 2015). Indeed, while Gehris et al. (2015), found that early years teachers fully acknowledged and understood the benefits of PA and learning motor skills, often implementing movement within the classroom to support the learning of other subjects, the teachers cited the pressure of academic demands as restrictive when trying to focus on the inclusion of movement, as well as identifying a lack of formalised training in educating movement as a limitation.

Robinson and Goodway (2012) described an effective intervention for teaching gross motor skills within a student-centred Mastery Motivational Climate, which involved children completing an instructed session for learning Object Control FMS twice per week, for nine weeks. Robinson and Goodway (2012) also demonstrated the effectiveness of a low-autonomy approach for teaching FMS, where children are taught in a teacher-centred manner and therefore follow the guidance and directions of the instructor. However, the low-autonomy approach was shown to be marginally less effective than a Mastery Motivational Climate, with improvements in the mean TGMD-2 object control skill raw score of 48.6% compared to 52.2% respectively. Each session for both the Mastery

Motivational Climate and the low-autonomy approach had a duration of 30 minutes and consisted of a 2-3 minute warm up activity, 24 minutes of motor skill instruction and a 2-3 minute closure activity. Robinson and Goodway (2012) revealed the importance of instruction when learning FMS relative to a non-instructed approach, where despite participation in PA of equal duration with access to the same equipment as the intervention groups, no significant progression in FMS competency was identified with the absence of instructions.

Various methods of educating individuals to correctly perform gross motor skills have been acknowledged, though written communication, while potentially effective for teaching gross motor skills to more literate individuals (Singer, 1972), is inappropriate for most learners of FMS given their typical ages. Taking influence from the VARK (Visual, Auditory, Reading/Writing, Kinaesthetic) model, originating from Fleming and Mills (1992), it is proposed that children can learn via a number of learning styles. Using VARK enables educators to identify and utilise a single-modal approach appropriate to each individual learner, though other studies by O'Rourke (2005) and Yelland, Lee, O'Rourke, and Harrison (2008) suggest that early years learners also have the capability to learn using more than one mode, particularly given the prominence of technology in the upbringing of the modern day child, which often readily combines multimodal learning into a single package. Given that early years learners are unlikely to have developed proficiency in reading and writing (Copple, Bredekamp, & Neuman, 1998), it is hypothesised that the optimal approach for instructing gross motor skills will include a combination of visual, auditory and kinaesthetic features.

2.2.2. Testing Fundamental Movement Skills

Studies have demonstrated the effectiveness of many manual methods by which gross motor skills are assessed. Specifically, a recent systematic review by Griffiths et al. (2018) identified seven tools for assessing gross motor skills, with four tools, the Bruininks-Oseretsky Test – Second Edition (BOT-2; Bruininks & Bruininks, 2005), the Movement Assessment Battery for Children – Second Edition (MABC-2; Henderson, Sugden, & Barnett, 2007), the Peabody Developmental Motor Scales – Second Edition (PDMS-2;

Folio & Fewell, 2000) and the Test of Gross Motor Development – Second Edition (TGMD-2; Ulrich, 2000), found to be the most reliable assessments for children aged 2 to 12-years-old (Griffiths et al., 2018). However, whilst Griffiths et al. (2018) summarised the associated training demands for assessors and administration times for each tool, no consideration was given to the time demands beyond the initial assessment (i.e. analysing time). For example, Valentini et al. (2018) stated that an additional 30 minutes was required to 'code' using the scoring system in the TGMD-2 manual (Ulrich, 2000) upon conclusion of the assessment. Whilst Valentini et al. (2018) sought to develop and refine a short form of the TGMD-2 (Ulrich, 2000), the overall time taken was reduced through the omission of the constituent FMS, rather than by rationalising the time taken to assess each skill *per se*.

The TGMD-2 (Ulrich, 2000), which superseded the original Test of Gross Motor Development (TGMD; Ulrich, 1985), is currently the most utilised tool for assessing gross motor patterns. Indeed, the TGMD-2 (Ulrich, 2000), has been utilised effectively in several studies, such as Sgrò et al. (2013), who assessed FMS to identify correlates with other physical performance markers, and Burns et al. (2017), where FMS assessments were conducted to assess motor skill competency in children with contrasting socio-economic backgrounds. Most recently, the TGMD-2 (Ulrich, 2000) has been superseded by the Test of Gross Motor Development – Third Edition (TGMD-3; Ulrich, 2016), though much validation work remains to be conducted. Contrary to other assessments of gross motor skills, the various iterations of the TGMD (Ulrich, 1985, 2000, 2016) consider movements in isolation. While for many applications this can be problematic or restrictive, isolation can be advantageous when assessing the quality of FMS, as the removal of complexity allows a greater depth of assessment of each fundamental movement. Specifically, this isolation facilitates the opportunity to use technology to decrease the time to conduct a FMS assessment and reduce, or eliminate, any training requirements.

The variations of the TGMD (Ulrich, 1985, 2000, 2016) use the binary numeral system to assess FMS proficiency, where '1' is used to indicate proficiency in a given behavioural component of the specific FMS and '0' indicates a lack of competency. Ulrich (2000) emphasised that a fractional value between these two integers is unacceptable due to the way in which the TGMD (Ulrich, 1985, 2000, 2016) scoring system operates to obtain a definitive score. However, this presents a problem, as the degree of the non-competency is not defined. A range of individuals could obtain the same or similar test results, but the quality of movement may differ substantially. As such, each behavioural component should be considered, and ultimately assessed, across a continuous spectrum. It is hypothesised that using such a spectrum would enable the easier identification of inadequacies and therefore the necessary interventions to enhance movement. Such an approach would provide a more accurate summary of a child's competence across specific skills. Furthermore, it is recognised that the available manual methods for assessing gross motor skills fail to eradicate human error, with Kezić, Šimunović and Kalinski (2020) commenting on the reliance upon PE teachers and coaches to appropriately administer such tests, risking the influence of bias on the results. The binary numeral system used for scoring movement in the TGMD (Ulrich, 1985, 2000, 2016), for example, may present difficulties in distinguishing whether a movement is competent or non-competent when the shortcomings of a behavioural component are not discernible through observation alone.

2.2.3. Fundamental Movement Skills Retention and Feedback

The cycle of instructing, practicing and testing FMS is necessary for the effective development of motor skills. However, between such sessions and beyond the age of formal PE, methods by which FMS competency can be retained must be maximised. Robinson et al. (2012) indicated that the use of a mastery climate for learning FMS also has a positive impact on FMS retention. It is theorised that this may be due to improved motor skill competence and the perception of PC, increasing motivation to engage in behaviours that contribute to a maintenance of performance levels over time (Valentini & Rudisill, 2004). In other words, children who learn within a mastery climate will be more inclined to practice the learned FMS outside of a formal education setting, such as during free-play sessions or while participating in extra-curricular activities.

The effectiveness of the Successful Kinesthetic Instruction for Pre-schoolers (SKIP) intervention (Altunsöz & Goodway, 2016) has been demonstrated for the development of

FMS, but it is also suggested that this approach could be effective for FMS retention. Altunsöz and Goodway (2016) reported improvements in FMS competency across an eight-week period using a low autonomy instructional approach, but also showed that FMS competence was largely retained one month after intervention cessation. This is somewhat contradictory to the findings of Valentini and Rudisill (2004), who suggested that low autonomy approaches, such as that used in the SKIP programme (Altunsöz & Goodway, 2016), were not as effective for gross motor skill retention as a mastery climate approach. However, while the retention of FMS in Altunsöz and Goodway's (2016) study was ultimately a positive finding, testing for FMS retention at a one month follow-up is still considered relatively short-term. Therefore, the findings of Valentini and Rudisill (2004) may yet be applicable given that the retention test in this study took place six months post-intervention. Further research investigating the long-term implications of interventions aligned to enhancing FMS are therefore warranted, particularly from a low autonomy approach.

It is hypothesised that there would be a decline in overall FMS competence over an extended period without appropriate interventions to retain FMS proficiency. Indeed, while there is a dearth of studies monitoring the long-term decline of FMS in children after the conclusion of instruction-based interventions, Savion-Lemieux and Penhune (2005) provided evidence from young adults (aged 18 to 35 years) to support the notion that motor skill competency can decline over longer periods without practicing the learned skills. In addition, Valentini and Rudisill (2004) and Altunsöz and Goodway (2016) targeted populations where the children were part of a school system where it is highly likely that the children would have had the opportunity to practice the learned skills through PE classes and free play; the level of skill retention could therefore be largely attributable to this. In contrast, the population assessed by Savion-Lemieux and Penhune (2005) would likely have had fewer, if any, opportunities to practice learned skills due to time restrictions that often occur during adulthood (e.g. jobs, chores, family commitments). Thus, the decline in motor skill competency was likely more significant.

In addition to the opportunity to practice, the type of practice can also have a bearing on motor skill retention. Schmidt and Wrisberg (2008) compared the effects of *blocked practice* and *random practice* on motor skill retention. Blocked practice, often also referred to as 'constant practice', where a task is performed repeatedly before moving on to another task, was shown to be highly effective in learning a new motor skill, but less effective for skill retention (Schmidt & Wrisberg, 2008). In contrast, random practice, where tasks are learned without long periods of focus on each, has been shown to be effective for motor skill learning under practice conditions, but less so than blocked learning (Schmidt & Wrisberg, 2008). However, random practice is suggested to be significantly better for skill retention, with Schmidt and Wrisberg (2008) demonstrating that populations who learned under random practice conditions performed the learned skills better ten days after the initial practice session. Schmidt and Wrisberg (2008) explained that random practice is better for motor skill retention as it drives the learner to forget short-term solutions, meaning that the solution must be rediscovered the next time the skill is performed. Random practice has been shown to provide the learner with clearer and more interpretable memories of the numerous tasks, increasing memory capabilities and reducing confusion (Schmidt, 1991). It is therefore theorised that interventions seeking to enhance FMS should capitalise on a rotation of the learned movements throughout each session and each programme.

Schmidt and Wrisberg (2008) also promoted the use of feedback during practice sessions to increase the retention of motor skill competency. However, whilst the use of feedback has been utilised in numerous other studies (e.g. Eather et al., 2018; Lubans et al., 2010; Robinson et al., 2012), the method and frequency of feedback has varied as have the consequent results. Schmidt and Wrisberg (2008), for example, promoted the use of *summary feedback*. This concept functions by withholding feedback until a number of repetitions are performed (Schmidt & Wrisberg, 2008). The number of repetitions can vary using this approach, with no consensus as to the optimal number of repetitions. However, Schmidt and Lee (2012) suggested that the optimal number of repetitions prior to feedback is dependent on the complexity of the motor skill performed; the retention of *simple* motor skills increased as the number of repetitions prior to feedback was increased (Schmidt &

Lee, 2012). Nonetheless, it remains unclear whether there is an upper limit before a plateau or decline occurs, as the trial was limited to a maximum of fifteen repetitions. In contrast, Schmidt and Lee (2012) provided evidence that indicated one's ability to competently perform *complex* motor skills degrades as the number of repetitions prior to the delivery of feedback increased, suggesting that an increased feedback frequency when learning complex tasks may promote a desire to persist with practice. This is congruent with the findings of Schmidt and Wrisberg (2008) who postulated a relationship between task complexity and optimal number of repetitions in summary feedback (Figure 2.2). It is hypothesised that the higher levels of retention through an increase in repetitions prior to feedback, for the simple motor skills, is due to the allowance of the trial population to attempt to find a solution to the task at hand, hence enhancing the potential for learning (Schmidt & Wrisberg, 2008). Moreover, it is intuitive that an increased number of repetitions prior to the delivery of feedback would enable the instructor to identify the consistent failures in the demonstration of a movement. Single repetitions can often be poorly performed in one-off instances, therefore judging movement competency based on a single repetition would be unreasonable.

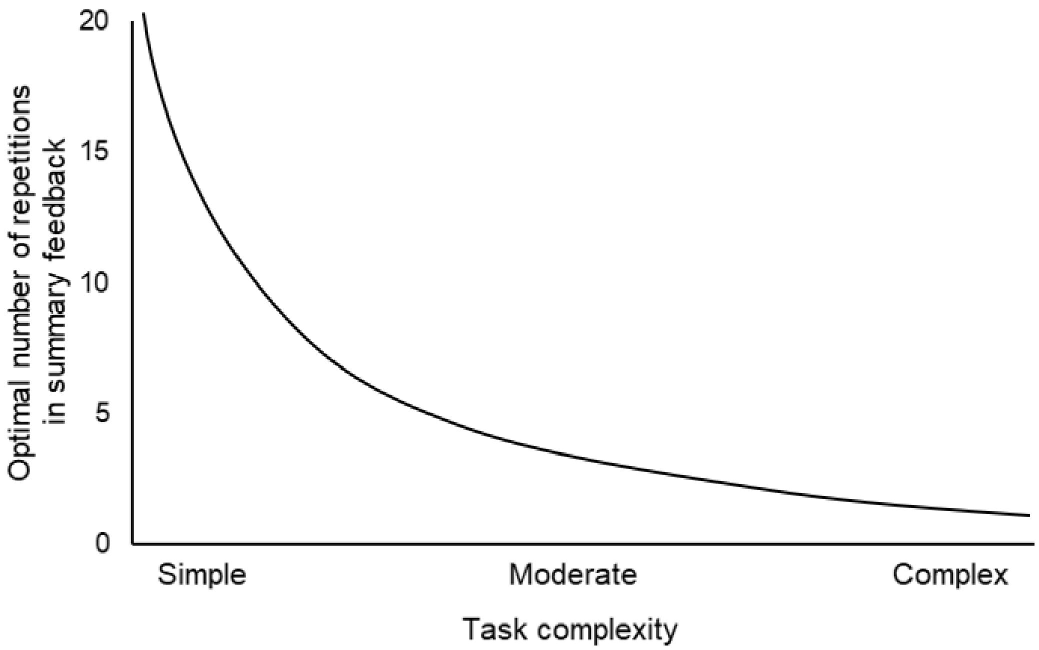


Figure 2.2 – The probable relationship between task complexity and optimal number of repetitions in summary feedback (adapted from Schmidt and Wrisberg, 2008)

FMS are inherently simplistic by nature. Therefore, it seems reasonable to suggest that there must be allowance for numerous repetitions to occur prior to delivering feedback when teaching FMS in order to optimise skill retention. However, the use of the word ‘simplistic’ to describe FMS is relative. Populations learning FMS will predominately be children, ideally aged 2-7 years (Altunsöz & Goodway, 2016). Hence, learning of FMS can be construed as more complex to the learner population than initially perceived, given their premature stages of overall development. The concept of *task difficulty* may apply in this instance (Guadagnoll & Lee, 2004; Sanli & Lee, 2015). Sanli and Lee (2015) described the two variants of task difficulty, defining *nominal task difficulty* as the “absolute constraints of the task” (p. 219), and *functional task difficulty* as “the challenge presented by a task relative to the conditions in which the task is performed and the skill level of the learner” (p. 219). The performance of FMS by children is hypothesised, therefore, to be strongly dictated by functional difficulty, where children will find the task significantly easier as they become more educated and rehearsed in the given movement. Overall, the frequency of feedback is largely dependent on the specific movement skill being learned and the stage of development of the individual learning the skill.

Further to the frequency of feedback, the type of feedback provided when instructing FMS also appears to be important, not least for maximising motor skill retention. There are two main categories of feedback recognised in the literature: intrinsic and extrinsic (Schmidt & Wrisberg, 2008). Intrinsic feedback is defined by Schmidt and Wrisberg (2008, p285) as “the sensory information that arises as a natural consequence of producing a movement.” Examples include the sound of kicking a football, or the feeling of torso rotation while striking a tennis ball. Extrinsic feedback, in contrast, is defined as “sensory information provided by an outside source” (Schmidt & Wrisberg, 2008, p286). The instructions of a teacher, or feedback delivered by a device are examples of extrinsic feedback. Figure 2.3 was constructed to assist in the identification of the optimal feedback mode for each unique circumstance. As previously identified, FMS performance relative to the expected learner population comes with a degree of complexity. Figure 2.3 has been modified from the original presented by Schmidt and Wrisberg (2008) to highlight the optimal feedback considerations for maximal skill retention based on these prior findings. These parameters suggest that extrinsic is the best mechanism for delivering feedback for optimising FMS learning.

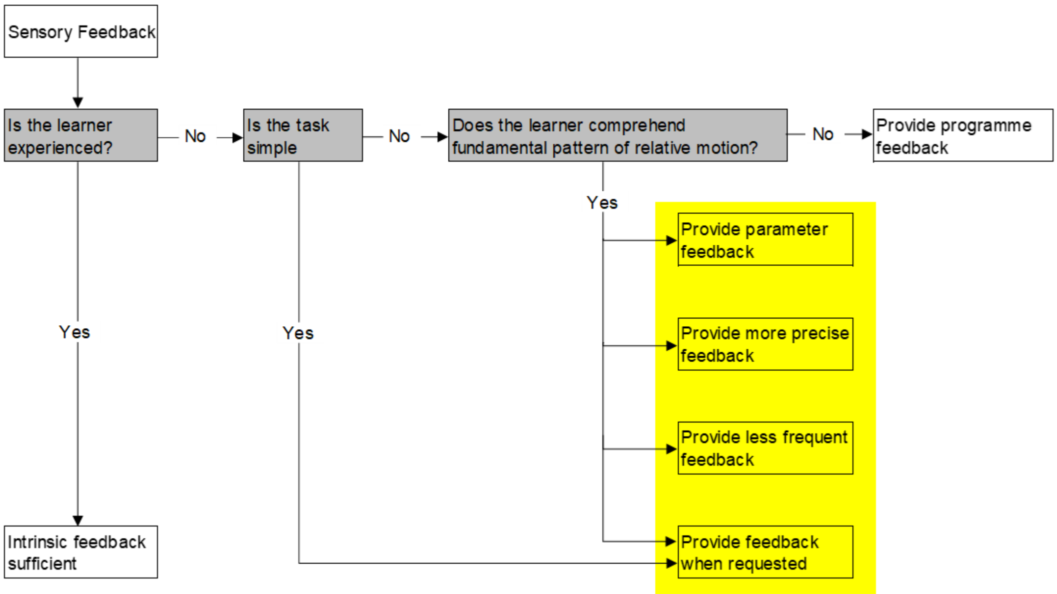


Figure 2.3 – A flowchart for determining the provision of instructional feedback with key feedback modes for FMS retention in children highlighted (adapted from Schmidt and Wrisberg, 2008)

Two sub-categories of extrinsic feedback that are commonly discussed in the literature are *Knowledge of Results* (KR) and *Knowledge of Performance* (KP; Abbas & North, 2018; Schmidt & Wrisberg, 2008; Sharma et al., 2016). These two methods for feedback delivery have both been used effectively in the learning of gross motor skills (Sharma et al., 2016). In the case of motor learning, KR offers the learner information about the degree to which they achieved the desired movement outcome (Schmidt & Wrisberg, 2008). Moreover, KR is commonly used in applications for measuring movement quantity, with the current marketplace saturated with a range of fitness trackers that count steps, measure distance travelled, as well as other output metrics (MacDermott et al., 2019; Tully et al., 2014). KR may also be used in learning of FMS (e.g. providing the learner with their results of the various TGMD; Ulrich, 1985, 2000, 2016) as well as being valuable in the learning of gross motor skills to enable learners to use the results to identify improvements in their performance (Sharma et al., 2016). Learners can also use KR as motivation to continue practicing (Sharma et al., 2016). However, in order to enhance motor skill proficiency, the learner needs to be provided specific feedback on why and how to correct deficiencies in the performed fundamental movement skill. As such, KP feedback is beneficial, as it provides information regarding the quality of movement (Schmidt & Wrisberg, 2008) and where the learner can therefore make the necessary corrections to their performance. It is theorised that a combination of KR and KP feedback will optimise FMS instruction (Schmidt & Wrisberg, 2008; Sharma et al., 2016) and retention (Abbas & North, 2018; Schmidt & Wrisberg, 2008), though the quality of the feedback provided is essential to maximising both of these elements (Abbas & North, 2018; Schmidt & Wrisberg, 2008).

2.3. Existing Technologies for Gross Motor Skill Data Collection and Analysis

To date, movement quality has been assessed using visual methods, often with technological support. Specifically, the real-time observation with a review of the video footage, as per the variations of the TGMD (Ulrich, 1985, 2000, 2016), is a simple example of this, or optical motion capture tools, as presented by Kim and Lee (2013) and van Diest et al. (2014). However, these methods are time-consuming to implement (Valentini et al., 2018), and/or require costly equipment (Mayagoitia et al., 2002). In addition, there may be facility demands for the use of video and motion capture tools, often restricting the use of such equipment to laboratories or larger physical spaces, as highlighted by Dallinga et al. (2017) and Post et al. (2016). Furthermore, the use of video capture can be sensitive, particularly when working with children, and therefore introduces additional restrictions regarding the usage and management of such data (Bardid et al., 2019). Due to these limitations, there is growing interest in the use of non-optical motion capture devices featuring accelerometers, gyroscopes and magnetometers, often in a combined unit known as an Inertial Measurement Unit (IMU; (Bisi et al., 2017). Whilst these tools, particularly accelerometers, are frequently used for measuring movement, they are typically used for measuring the quantity, rather than the quality, of movement (Capio et al., 2012; Capio et al., 2015; Mackintosh et al., 2016). Nevertheless, there is growing evidence to suggest that such devices could be valuable in evaluating movement quality. Indeed, research utilising multiple accelerometers on a variety of body locations has shown positive outcomes (Grimpampi et al., 2016; Tiesel & Loviscach, 2006), in a laboratory setting. However, given the decreased adherence and increased cost of multiple sensors, a reduction in the quantity of worn devices is desirable for 'real-world' applications.

Of the available manual test methods for assessing FMS, the variations of the TGMD (Ulrich, 1985, 2000, 2016) are renowned for being reliable options (Kezić et al., 2020; Sanders & Kidman, 1998; Webster, Martin, & Staiano, 2019). Nevertheless, Kezić et al. (2020) and Bisi et al. (2017) recognised limitations with the TGMD variations (Ulrich, 1985, 2000, 2016), with the latter commenting on the need for multiple trained assessors to ensure reliable results. Subsequently, Bisi et al. (2017) successfully employed IMUs in conjunction with the TGMD-2 (Ulrich, 2000), overcoming subjectivity by eliminating the need for trained assessors and greatly reducing assessment time via algorithms uniquely produced for each behavioural component of the assessed skills. Each algorithm was developed to detect specific signal features obtained through the use of IMUs. The recognition or absence of such features dictated the scoring which was adopted from the TGMD-2. The approach provided by Bisi et al. (2017) has limitations however, not least the use of multiple sensors, which, in turn, significantly increase set-up time. In addition, while the instrumented test offered by Bisi et al. (2017) is suggested to provide reliable results, there is no support provided to the assessor in recognising how to correct a movement when assessed as non-competent, particularly given the removal of any form of visual aid.

FMS are generally systemic and therefore have the potential to use minimal devices at body locations perceived to be not directly associated with the specific movement (Kim & Lee, 2013). For example, a wrist-worn device in jumping, kicking and hopping could potentially be used, as there is distinct upper body movement, including the arms. For non-systemic movements, such as cycling, a wrist-worn accelerometer would be unsuitable due to the lack of upper body movement. As FMS are systemic, and therefore have certain complexities, it is yet to be identified whether it will be possible to accurately assess all FMS using a single measurement device. However, it is noteworthy that the validity of some FMS has been questioned (Barnett et al., 2016), with the number of skills required for valid testing reduced from earlier research. As such, there is a decreased need to assess a large array of movements as part of the same test. While it would be desirable to have a concept that can be easily transferred to other FMS, there is evidence to suggest that motor behaviour can be assessed to the same standard using smaller selections of

FMS if the selection is intelligently made (Valentini et al., 2018). Only four FMS were used in McIntyre (2009): one explosive locomotor skill (standing broad jump), a continuous locomotor skill (50m run), an object control skill (overarm throw), and a body management skill (line walk). It is hypothesised that, as a minimum, the selection of FMS for use in conjunction with an IMU-based visualisation concept should include both locomotive skills and object-control skills, with the addition of stability-based FMS if found to be necessary. If, therefore, technological options can be applied to the development of a non-optical visualisation concept, the range of assessed FMS within the capabilities of the tool need not be exhaustive.

2.4. Visualisation

The term ‘visualisation’ is ambiguous. An opportunity has been identified for the generation of a visual aid to be delivered using technology in support of FMS learning, to be presented via a colour electronic visual display, such as a computer monitor or smart watch face, having found limited evidence of such concepts in the available literature. Extrinsic feedback, such as that provided by a device, enhances gross motor skill retention (Schmidt & Wrisberg, 2008) and is therefore promoted for use in the instruction of FMS. Furthermore, as multimodal learning has been shown to be effective for learning FMS (O’Rourke, 2005; Yelland et al., 2008), visualisations can contribute to the optimal learning experience. To date, many studies have been conducted to consider visualisations for the quantity, rather than the quality, of PA. Some studies, such as Fan, Forlizzi and Dey (2012), have placed an emphasis on the artistic nature of the visual aid, where colours and abstract imagery are prioritised. In contrast, other research has utilised more graphical visual aids (Crossley, McNarry, Rosenberg, et al., 2019); Figure 2.4), with others combining both artistic and graphical elements (e.g., Williams et al., 2017; Figure 2.5). However, there is a lack of visual aids considering movement quality. There is therefore an opportunity for movement quality visualisations to be produced not only to assess FMS, but to teach them and provide individualised feedback.

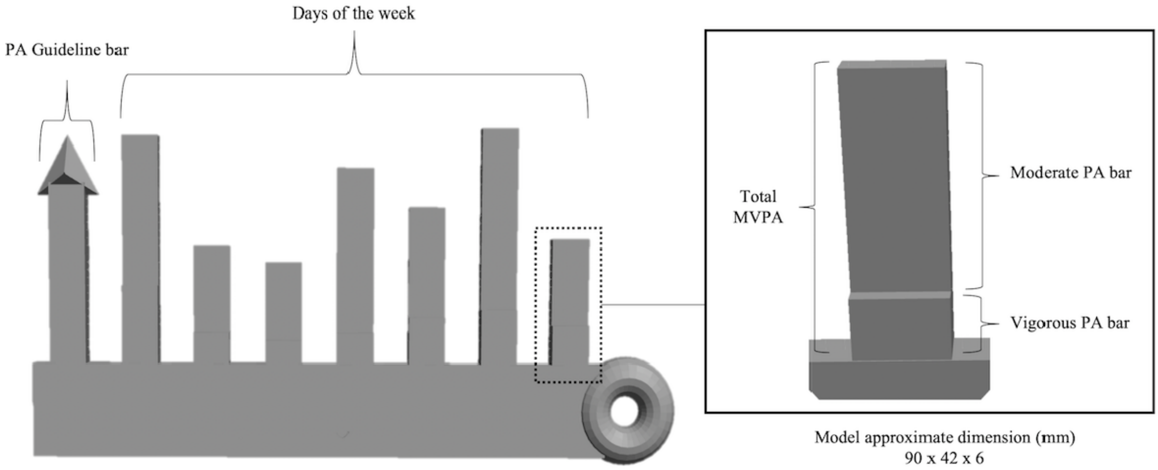


Figure 2.4 – Adolescents' bar chart 3D model by Crossley, McNarry, Rosenberg, et al. (2019) used under the terms of the Creative Commons Attribution License (https://creativecommons.org/licenses/by/4.0/)

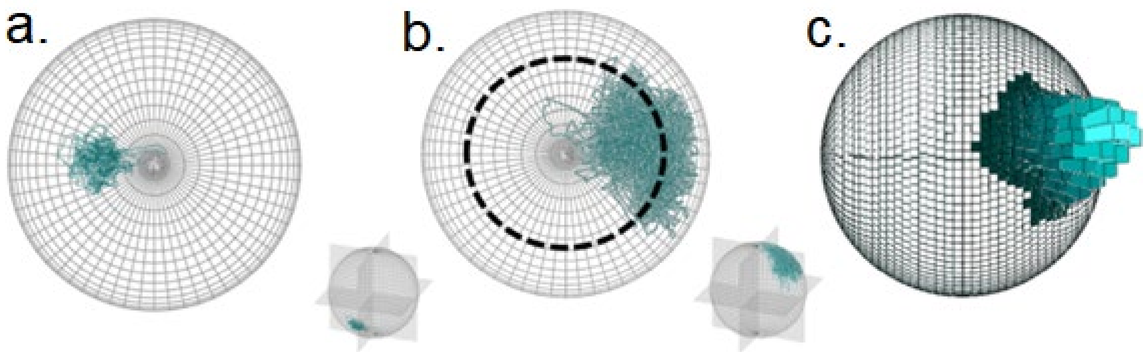


Figure 2.5 – a) Tri-axial plots of 10 min of 40 Hz acceleration data, b and c) TriMag data from an active European badger equipped with a collar, by Williams et al. (2017) used under the terms of the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/) / cropped and adapted from original

Future concepts should feature simplistic visual aids that can be easily interpreted by an individual lacking in formal movement assessment training. With an absence of specialist PE teachers in early years learning for many children (Hardman et al., 2014), there is a reliance upon generalist educators to teach children how to competently perform FMS. Unfortunately, due to the lack of formal PE training provided to generalist teachers (Kirk, 2012), there is a risk that children will learn FMS incorrectly. In addition, Kirk (2012) suggested that primary schools should seek to employ specialist PE teachers to support the generalist teachers, though the associated costs with employment of an additional staff member are likely to deter schools from pursuing this avenue.

By introducing a cost-effective tool that can produce interpretable results for untrained educators, particularly primary school teachers, there can be an increased quality in the instruction of FMS through a more economically viable option. It is hypothesised that by pursuing a simplistic visual outcome, the learning and assessment processes will be easier to implement and will be more time-efficient. It has been shown that the varying age groups will prefer different visualisations (Crossley, McNarry, Hudson, et al., 2019), where children favoured abstract visualisations and adolescents tended towards graphical representations. Crossley, McNarry, Hudson, et al. (2019) commented on the visual representations of data and advised that abstract visualisations allow users to be more inquisitive about the data presented, compared with graphical representations, which provide more direct representations of data. The graphical approach is also described to be better suited to information recall, while the abstract concepts are better for engagement and support (Crossley, McNarry, Hudson, et al., 2019). As the expected end-users of an FMS visualisation tool will be of adult age (i.e. teachers and coaches), bias will lean towards a more direct data representation approach to enable effective feedback from the educator to the child, meaning that the visualisation must be interpretable to the adult educator first and foremost, with any visual aids directed towards the child being provided to assist in explanations from the educator to reinforce feedback.

2.5. Fundamental Movement Skill Selection

Whilst there are 12 FMS used in the TGMD (Ulrich, 1985) and subsequently TGMD-2 (Ulrich, 2000), the selection of one skill was important to identify a suitable process and foundation for skill visualisation, prior to applying to other FMS. To maximise transferability, it was important to select a fundamental movement skill which is a systemic movement with distinct behaviour components.

Valentini et al. (2018) generated a reliable short form of the TGMD-2 (Ulrich, 2000) reducing the number of skills from 12 to six. The final six skills included three locomotor skills (run, gallop, hop) and three object control skills (strike, kick and overarm throw). More specifically, the object control skills incorporated in Valentini et al. (2018) are performed in isolation as acyclic movements, with integrated rest periods, whereas locomotor skills are performed in a cyclic manner, as described by Mentis (2013), who also highlighted the potential for overlapping phases of the movement pattern during certain locomotor skills. Lukášek and Vychodilová (2016) graphically depicted the complexity of cyclic movements, while the acyclic movements presented were relatively simplistic by comparison. The complexity of the cyclic movements, therefore, may be problematic when using non-optical motion capture tools, with the initiation and completion of object control movements being easily distinguishable (Song et al., 2005). It could therefore be postulated that object control skills would be better aligned for initial visualisation concept development.

Research has highlighted that gross motor skills can be reliably assessed using wrist-worn accelerometers (Kim & Lee, 2013). Indeed, Kim and Lee (2013) concluded that the benefits of wearing accelerometers on the wrists to assess movement outweigh the benefits of wearing such devices on other parts of the body, where it is stated "in many human activities, the hands have the utmost functional and semantic importance among all the human body parts, and the lower body only assists the hands to reach the target points" (p. 329). It is hypothesised that a wrist-worn accelerometer will be more effective in detecting motion in the torso than one worn on the leg or foot, congruent with other research using IMUs to assess the overarm throw (Grimpampi et al., 2016). By comparison, the influence of torso movement on the legs is theorised to be less significant, particularly in movements where both feet are in contact with the ground for much of the movement. According to FMS literature (Ulrich, 2000), the arms appear to move as a direct result of torso movement due to unavoidable displacement of the shoulders, whereas most movement of the legs is voluntary, typically to accommodate a change in position of the centre of gravity (COG), or to prepare for any succeeding movement. Specifically, while torso movement does not always necessitate a change in leg position, movement of the legs is usually concurrent with movement of the torso given the need to retain a stable base of support (Patla, 2003). Therefore, it is hypothesised that a wrist positioned measuring device will be better placed to detect lower body movement than a leg or foot positioned measuring device would be in the detection of upper body movement.

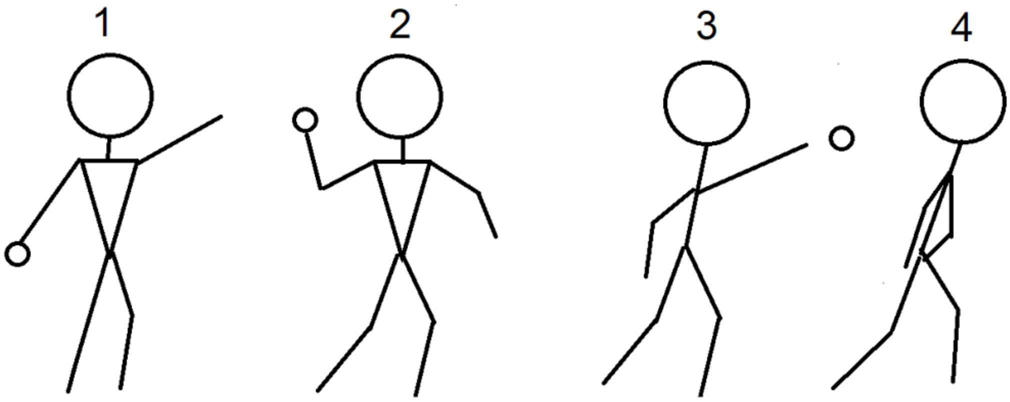
In the selection of an appropriate FMS for the generation of a visualisation concept, utilising a wrist-worn placement, it would be intuitive to utilise a movement whereby the arm is the focal limb. Therefore, both striking and overarm throwing meet this criterion, according to the short-form TGMD-2 (Valentini et al., 2018). This is not to suggest that movements where the focal limb is one or both legs, such as in kicking, cannot be analysed when using a wrist-worn device, however.

When competently demonstrated, striking and overarm throwing have similarities. Young (2009) utilised an overhead strike (i.e., tennis serve), where similarities with the overarm throw were emphasised. It is noted that the overhead strike used by Young (2009) was discordant with the striking movement defined in the TGMD-2 manual (Ulrich, 2000), where the striking implement follows a rotational path around the body. However, regardless of the striking movement applied, there are key elements which apply to both striking and throwing, including the rotation of the shoulders and hips, and the weight transfer between feet, initiating the movement with a transfer of weight over the back foot and concluding the movement with weight over the front foot (Ulrich, 2000). These commonalities should, in theory, result in similar traces when obtaining data using wrist placed measurement devices, assuming the skills are performed competently.

As Young (2009) identified, striking is seldom studied, and therefore a lack of useable data is available for the skill. Conversely, overarm throwing has been rigorously assessed and is therefore better suited to support the initial development phase of a visualisation concept, given the greater availability of data relating to optimal and suboptimal movement. It is theorised that as the concept is progressed using overarm throwing, it will be relatively straightforward to transfer across to striking, subject to the generation of applicable data. However, based on current available resource, it has been determined that of the available FMS, overarm throwing is best placed for the initial development of a visualisation concept.

2.5.1. Overarm Throw

The overarm throw, is one of the key object control skills (Fisher et al., 2005; Gimenez et al., 2012; Grimpampi et al., 2016; Luz et al., 2019), integral to numerous sports, such as baseball, cricket, track and field, and handball. Nonethless, the overarm throw is often performed differently across various sports, largely dependent on the shape, size and mass of the object thrown, or by rules and regulations (Wagner et al., 2014). However, the performance of the overarm throw as a fundamental movement skill is largely standardised throughout the literature (Gimenez et al., 2012; Ulrich, 2000; Young, 2009) with the following common phases identified: wind-up, rotation, weight transfer, and follow-through. Descriptions and illustrations for these phases are provided in Figure 2.6.



Phase	Description	Phase	Description
1	Windup is initiated with downward movement of hand/arm	3	Weight transferred by stepping with the foot opposite the throwing hand
2	Rotates hip and shoulders to a point where the nonthrowing side faces the wall	4	Follow-through beyond ball release diagonally across the body toward the

Figure 2.6 – Overarm throw object control subtest phases (adapted from Ulrich, 2000)

Due to the prevalence of the overarm throw in sport, it is essential that movement competency is achieved early to maximise performance and minimise the risk of injury (Andrews & Fleisig, 1998; Lyman et al., 2002; Young, 2009). Although girls are slower to develop and reach competency in the overarm throw (Eather et al., 2018; Goodway, Robinson, & Crowe, 2010; Young, 2009), the process of development for the overarm throw is relatively consistent. Young (2009) suggested that early years children first developing the overarm throw use a simple arm movement only, with a forward-facing torso. As the children mature, this leads to the introduction of rotation and a weight shift, first without, then with a stepping motion (Young, 2009). In addition, the arm movements become more complex as the children develop, leading to a fully competent demonstration of the windup, and horizontal adduction and elbow extension during the release of the projectile (Young, 2009). However, Young (2009) noted that girls may not develop the same complex arm movements as boys before stagnating, or even regressing, and there are no guarantees that boys will achieve full competency either. It is therefore important to introduce appropriate interventions to maximise competency of the overarm throw (Eather et al., 2018; Foweather, 2010).

2.6. Summary

Education and learning of FMS is a key focus and a prominent theme within research to date. While effective teaching and testing methodologies exist and are frequently implemented, recent advancements in technology have increased the opportunity by which gross motor skills can be learned effectively and efficiently, not least due to significant time reduction by which movement skills can be assessed and feedback delivered. In addition, many of the education and test requirements place specific training demands on the individuals providing instruction and conducting tests, so technology can also be used to reduce or eliminate these demands.

Technological support in the learning of gross motor skills is currently achieved primarily using video analysis, motion capture and other costly visual analysis tools typically reserved for use in elite sport and medical services. Therefore, there is a need to provide a method, or methods, by which gross motor skill analyses can be conducted effectively by populations where more stringent budget restrictions are present. Equally, there is a strong requirement for education and analysis of gross motor skills to be conducted in a broader range of environments. Given that video-based tools often require specific facilities, the utilisation of wearable sensors eliminates these restrictions, thereby increasing the opportunity for application in other environments, such as playgrounds and schools. Indeed, utilising technology, and associated outcomes, for use within such environments is paramount to the successful application of future concepts, not just the implementation of FMS in children. Whilst research has provided promising evidence for the use of tools such as accelerometers, magnetometers and gyroscopes for effective assessment of gross motor skills, a clear consensus remains to be elucidated. Nonetheless, IMUs are commercially available tools which encompass all three of these devices within a single unit, such that data can be simultaneously sampled for the performed skill.

This thesis sought to focus on the use of cost-effective IMUs to develop a visualisation concept to support the effective delivery of both KR and KP feedback to children in the learning of FMS. Therefore, the primary aim of this feasibility study was to assess the quality of the overarm throw, which is an important fundamental movement skill with many sporting crossovers (Barnett et al., 2016). A secondary, but no less important, aim, was to utilise IMUs to reduce the subjectivity of FMS assessment and provide the foundations of an easily interpretable visual tool to enable child-specific feedback in a more efficient manner which not only reduces educator training requirements but enhances learning.

CHAPTER 3: METHODS AND RESULTS

The method by which the raw Inertial Measurement Unit (IMU) data was utilised to generate a visualisation concept for the overarm throw is described in this chapter. Furthermore, some preliminary results are provided as an initial indicator of the efficacy of the concept. The development was conducted using a sequential process as the timeline in Figure 3.1 indicates. Using a linear, iterative approach, it was possible to trail and refine a number of approaches to optimise the outcome each phase of the development.

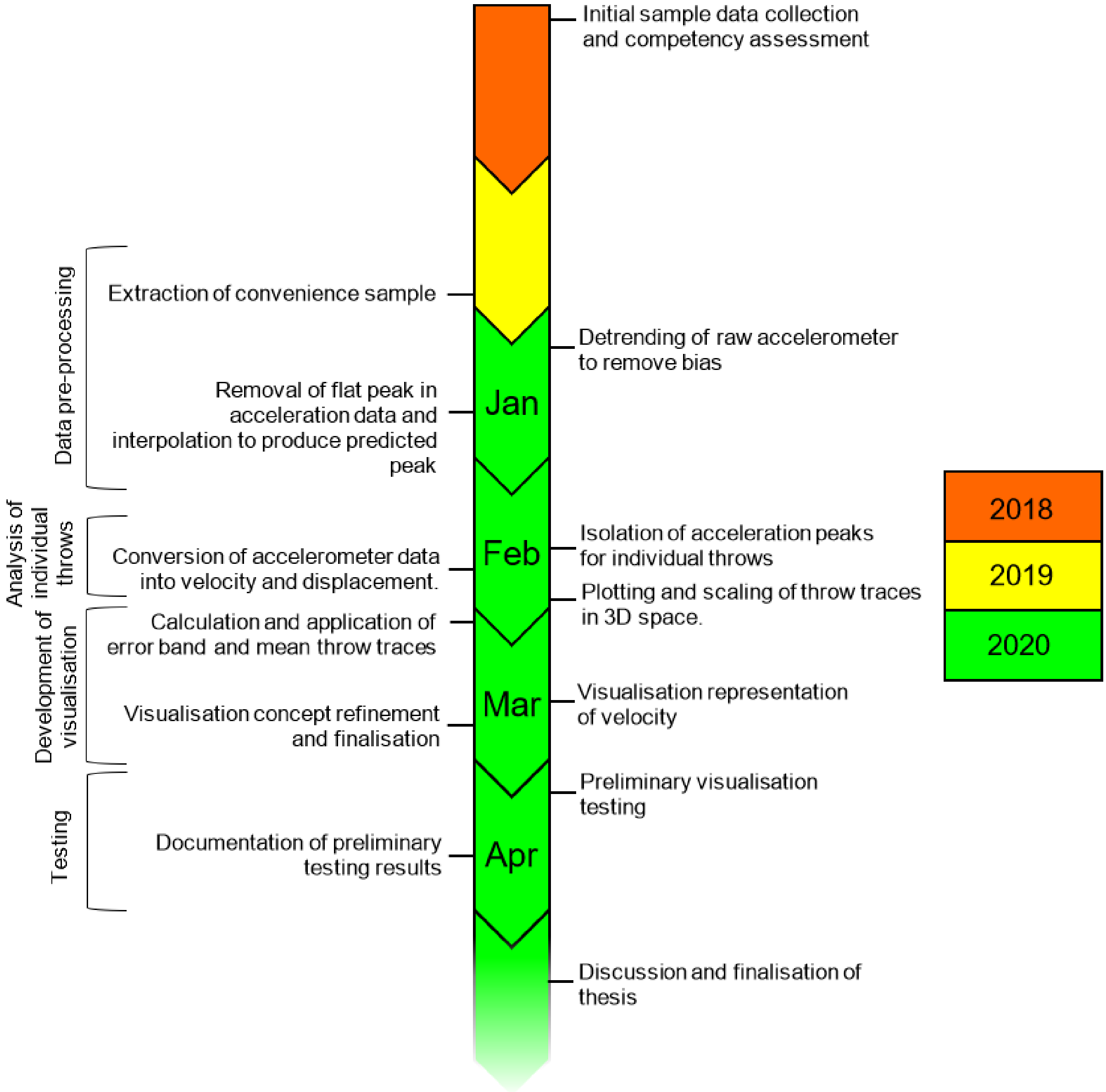


Figure 3.1 – A timeline to show the sequential process used in the generation of a visualisation concept for assessing the overarm throw

3.1. Data Collection

From an overall sample of 214 participants, a convenience sample of 13 youth (14.8 ± 0.3 years; 9 boys) was obtained for this analysis. A small sample size is typical for this area of research (Lander et al., 2020) and was appropriate given that the primary focus of this study was the development of a concept as part of a feasibility study. This study was approved by the institutional research ethics committee (PG2018-065) and was conducted according to the Declaration of Helsinki. Following written informed consent and assent from parents/guardians and the adolescents, respectively, participants completed the Test of Gross Motor Development-3 (TGMD-3; Ulrich, 2016). The TGMD-3 is a process-orientated assessment designed to assess the gross motor performance of children (Webster & Ulrich, 2017). The assessment includes a selection of locomotor and ball skills that represent fundamental movement skills (FMS) that are commonly taught in Physical Education curriculums (Allen et al., 2017). From this range of skills, data from the overarm throw were used for the subsequent analyses. Participants repeated each skill 2-3 times, resulting in a total of 34 overarm throws in the current thesis. Of the 34 throws, 21 were initially assessed as competent against the criteria of the TGMD-3, all of which were performed by boys. Of the 13 throws assessed as non-competent, three were performed by boys and 10 were performed by girls.

Data was collected using a wrist-worn ActiGraph GT9X Link (ActiGraph, Pensacola, Florida [FL], United States of America [USA]) wearable IMU. The ActiGraph GT9X Link device is a commercially available IMU device that is widely used in physical activity tracking applications. The device features a solid state 3-axis micro electro-mechanical system (MEMS) accelerometer, a gyroscope and a magnetometer. The device was worn by participants on the dominant throwing hand: the right-hand for all participants. The literature has highlighted the reliability of assessing the quality of gross motor skills using wrist-worn sensors (Kim & Lee, 2013) while also indicating the benefits of doing so when assessing the overarm throw specifically (Grimpampi et al., 2016). The sampling rate of the IMU was set to 100 Hz. Anthropometric data were also collected from the participants but was not intended for use as part of this sub-study. As such, the anthropometric data was insufficient to contribute to the development of the visualisation, though future work should seek to obtain the necessary anthropometric data to support visualisation refinement.

Prior to the analysis of the data obtained by the IMUs, video footage of each participant was reviewed to assess overarm throw competency based on the criteria of TGMD-3 (Ulrich, 2016). Prior identification of throw competency was essential for the development of the visualisation as it enabled a baseline competency standard to be set.

3.2. Pre-processing of ActiGraph Data

Data collected using the ActiGraph GT9X Link device were uploaded to the ActiLife v6.13.3 software. The raw accelerometer data was subsequently exported to Microsoft Excel in a tabular form. The data was labelled dichotomously as competent or non-competent based on the review and assessment of the video footage. The data file for each participant contained both accelerometer and gyroscope data, but unfortunately the magnetometer was not used due to inconsistency of environmental conditions within which the data was collected. Furthermore, as the data was cropped from a longer recording, the initial starting position of the IMU was unknown. Therefore, the gyroscope data was not utilised for this study as it was not possible to use reliably without information relating to the starting position of the overarm throw movement. While gyroscope data has promise for application in the development of future visualisations, particularly when used in conjunction with magnetometry for presenting orientation information, this study focused on the accelerometer data. Accelerometer data has already been shown to be effective at determining position (Kim & Lee, 2013) and velocity (Lukášek & Vychodilová, 2016) when analysing human movement and as such was an appropriate dataset for developing a visualisation concept for overarm throwing.

3.2.1. Error Reduction of Each Acceleration Dataset

For the data analysis, MATLAB R2019b (MathWorks, Natick, Massachusetts [MA], USA) software was utilised. The inherent nature of IMUs allows for errors to often occur and, despite the use of proprietary filtering algorithms within ActiGraph IMU devices to reduce noise, the raw accelerometer output data still showed the presence of error. Indeed, trendlines were applied to a typical acceleration trace in the x-, y- and z-directions relative to the casing of the ActiGraph GT9X Link device as depicted in Daniels (2018) during three overarm throws, identifiable as distinct peaks in acceleration, to demonstrate this (Figure 3.1). Specifically, the error was most evident in the x-direction, where the data appeared to distort over time, as evidenced by the trendline progressively tending away from zero acceleration. Failure to omit this error could have influenced the results when trying to accurately determine velocity and displacement due to integration drift (Kok, Hol, & Schön, 2017). While not possible to confirm the specific cause of this error, Figure 3.2 indicates a tendency for the accelerometer data to settle further from zero acceleration on conclusion of each throw. One hypothesis for this issue is that the true acceleration experienced by the device exceeded the peak recordable acceleration and deceleration limits of the accelerometer, stated by the manufacturer as ±16g (±156.96 m·s^{-2}).

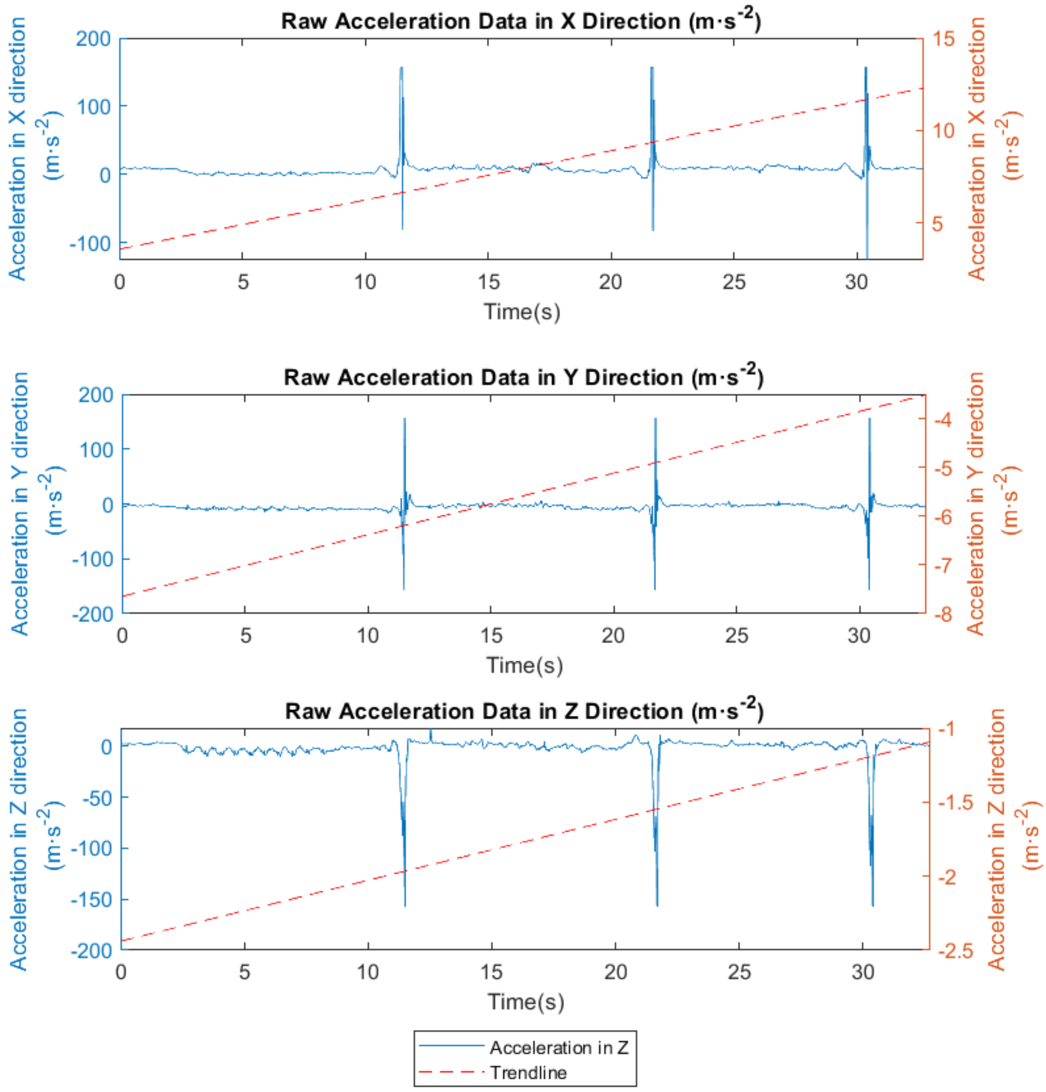


Figure 3.2 – Typical accelerometer overarm throw data output with trendlines in x-, y- and z-directions

Due to evidence of error, or 'bias', it was necessary to detrend the data such that the initiation and conclusion of each throw was consistent, a common method to combat such occurrences in accelerometer data (Ali, Sandhu, & Usman, 2019; Pan et al., 2016). The trend was removed by subtracting the mean from the data, culminating in an overall mean acceleration of 0 m·s^{-2}. The detrended acceleration data in the x-, y- and z-directions is presented in Figure 3.3, with the initial trendline plotted alongside the detrended line to depict the shift.

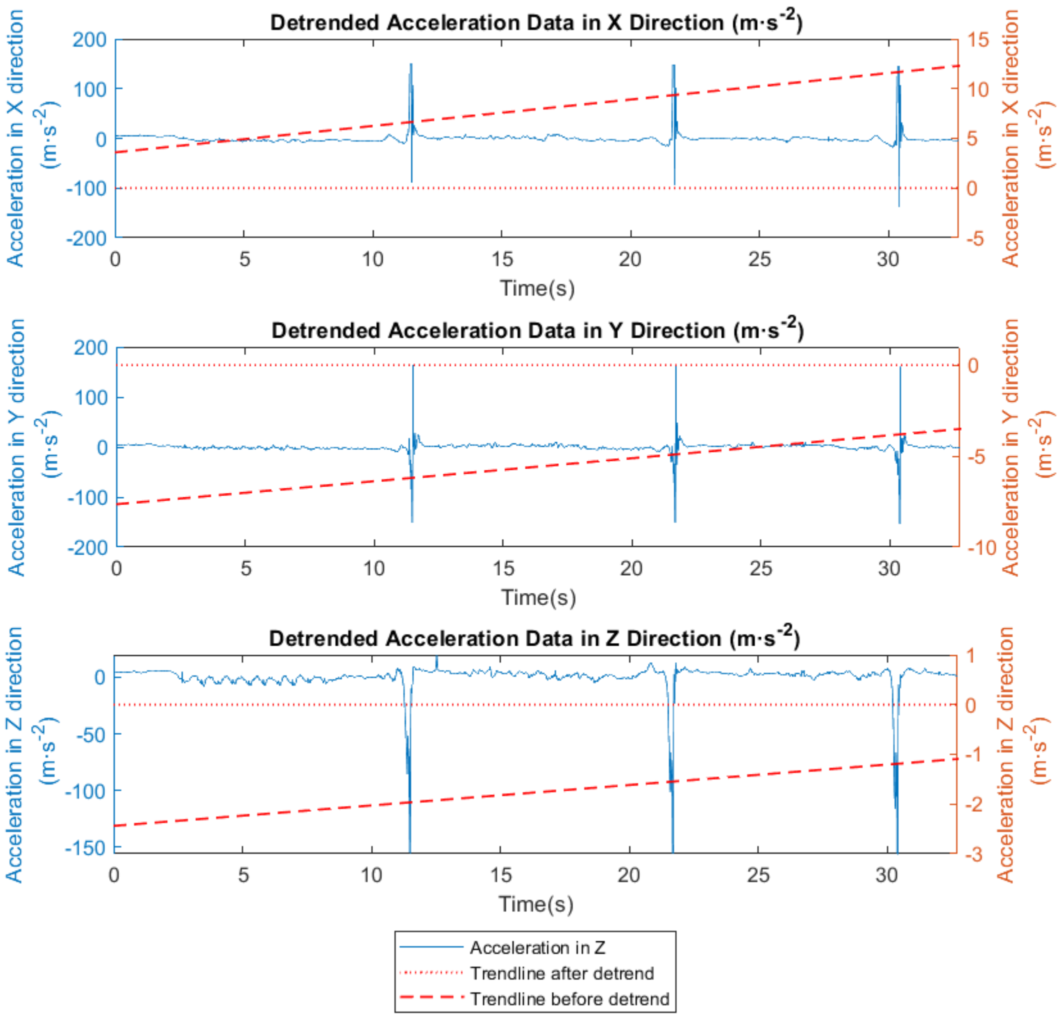


Figure 3.3 – Typical accelerometer overarm throw data output after detrending in x-, y- and z directions with trendlines pre- and post-detrending

3.2.2. Overcoming the Range Acceleration Limits

Due to the limitations of the ActiGraph GT9X Link, acceleration cannot be recorded beyond the range of ±16g (±156.96 m·s^{-2}). As the typical wrist acceleration and deceleration extremes identified in the data exceeded these limits during overarm throwing, many acceleration traces for the data obtained produced flattened peaks (Figure 3.4), erroneously suggesting a brief period of constant acceleration. This false representation could have produced unreliable results when attempting to determine velocity and/or position, so the data was manipulated to predict the actual peak acceleration and deceleration.

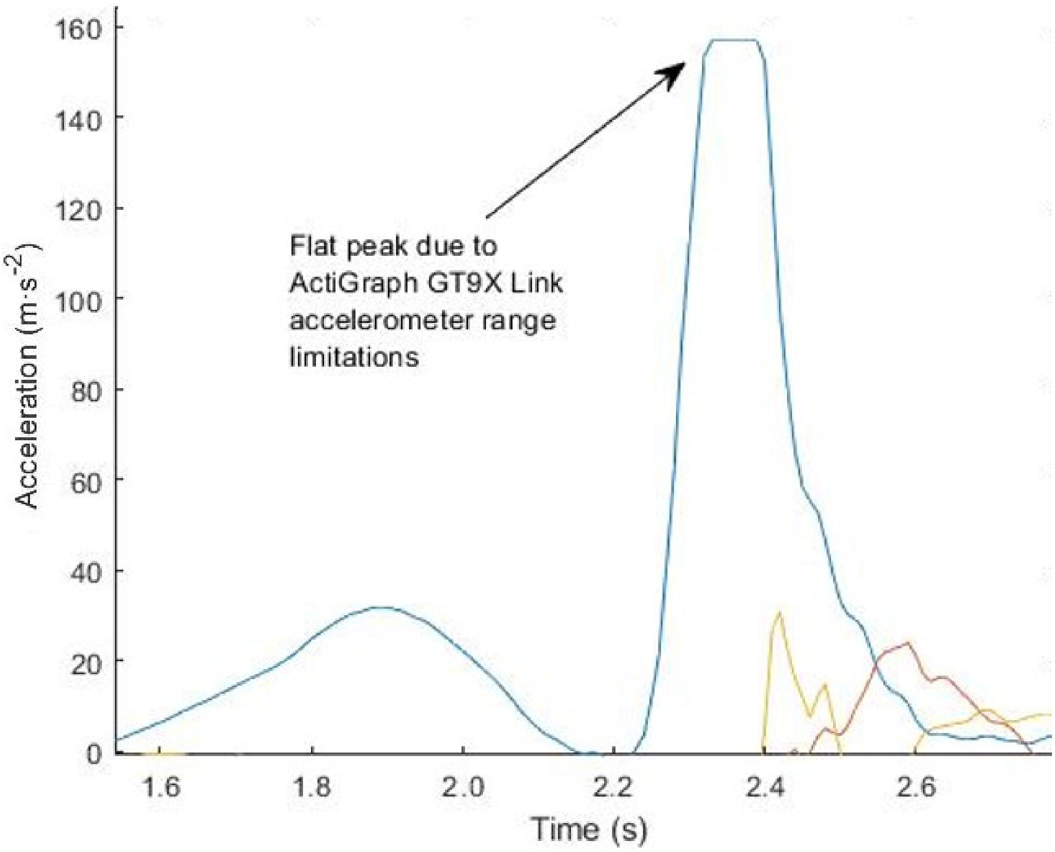


Figure 3.4 – Flat Acceleration Peak due to ActiGraph GT9X Link accelerometer range limitations

The acceleration and deceleration peaks for each individual throw were manually identified using MATLAB. A flat peak was observed where the peak acceleration or deceleration was sustained beyond the limits of the accelerometer for a period long enough to extend across a minimum of two time-points. As the accelerometer sampling rate was set to 100Hz, the maximum capability of the ActiGraph GT9X Link device, a minimum of 0.02s of sustained acceleration beyond the upper or lower limits could generate such a feature. As the flat peaks were the result of constant acceleration output values, they were easily identified within the data when displayed in a tabular or matrix format and were subsequently omitted, creating a series of gaps along the plotted line (Figure 3.5). A MATLAB interpolation function called ‘makima’, a modified version of Akima (1969) interpolation, was then applied to estimate the true acceleration peaks (Figure 3.6). The Akima (1969) interpolation method was selected through the trial and error of a number of polynomial interpolation methods and was preferred to the alternatives readily available on the MATLAB R2019b software, such as ‘spline’ and ‘pchip’, as it produced the most natural peak when directly compared to the other methods, reinforced by the findings of Akima (1970). When implementing other interpolation methods, undesirable features were observed, typically producing either flattened peaks or irregular shapes due to the inability of certain functions to adapt to the asymmetry. The modified version of Akima (1969) interpolation in MATLAB was used as it was more accomodating for the connecting of slopes with different asymmetrical gradients either side of the peak, as is the case with the acceleration and deceleration phases of the overarm throw. The modification gives priority to the side of the throw acceleration peak with the less steep gradient to avoid overshoot.

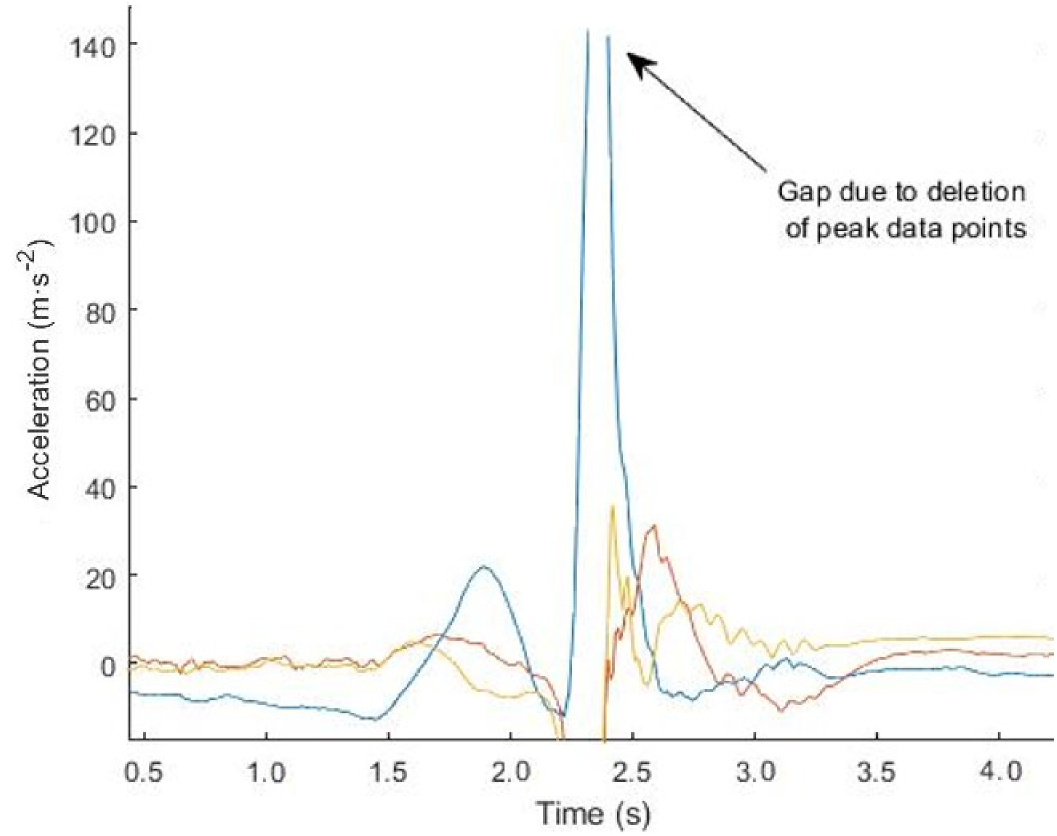


Figure 3.5 – Deletion of acceleration data points to remove the flat peaks

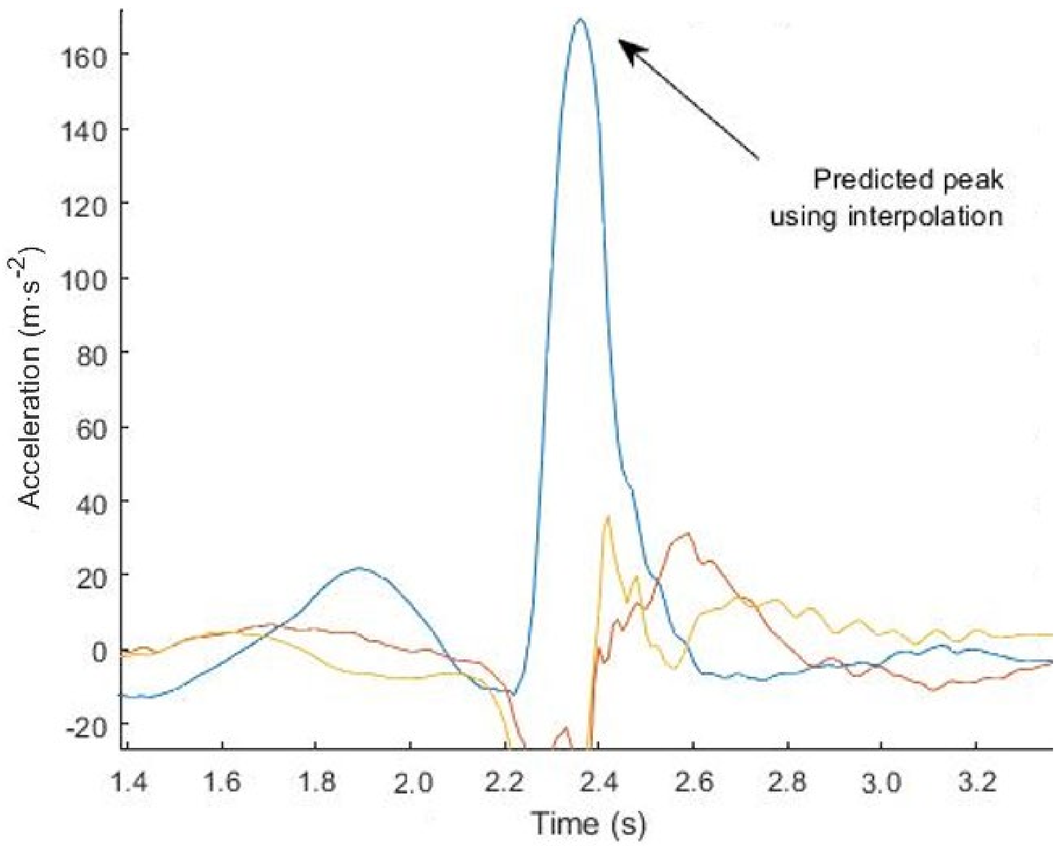


Figure 3.6 – Predicted acceleration peak

3.3. Analysis of Each Individual Throw

This subsection describes the process taken to convert the pre-processed accelerometer data into data that can be effectively visualised to advance our understanding and the learning of FMS. This was achieved through the isolation of each individual throw within the complete dataset and subsequent manipulation of the data to determine values for velocity and displacement.

3.3.1. Throw Isolation

On conclusion of data pre-processing, it was necessary to isolate the individual throws. Despite best efforts to eradicate the influence of error through pre-processing, it was not possible to guarantee total omission of error from the complete dataset obtained from each participant. Therefore, rather than assessing the movements as part of a complete dataset, it was advantageous to isolate each throw. Failure to do so would have resulted in the visualisation of all captured movement within the recorded time period, not just the throws, as a single continuous line. Isolation of each overarm throw reduces the effects of integration error when determining velocity and displacement. Further, isolation enables an easier and clearer assessment of each throw without additional unnecessary information, while also adding the ability to set a common origin for each throw to aid comparisons.

Due to specific data limitations, such as a lack of anthropometric data, in addition to the requirement for consistency, the identification of an appropriate time interval was required within which the data for each throw could be contained. This was essential such that each throw could be fully captured without pre- and post-throw noise and undesirable motion detection also contributing to the results. Through an iterative process of manually expanding and reducing the time interval, a period of 1.00 s was identified as suitable for this purpose, though the iterative process taken to determine optimal duration suggested that the effect of incorporating a small amount of time prior to the throw initiation and/or following the throw conclusion was not significant. The throw peak acceleration value was used as a central reference point for all throws for comparative purposes given that alternative reference points, namely the throw initiation and throw conclusion, were difficult to pinpoint accurately without the availability of additional data. Given that the sampling rate was 100 Hz and the initial data point was at time-point 0.00 s, 101 data points were encompassed within the 1.00 s time interval.

3.3.2. Obtaining Velocity and Displacement Data

Kinematic principles dictate that acceleration must be integrated once to obtain the velocity data, with a second integration performed to determine displacement. Initial attempts to determine the velocity and displacement were conducted in the time domain using trapezoidal integration. However, this generated dissatisfactory results as the visual output did not resemble that of an overarm throw. This largely agrees with the findings of Brandt and Brincker (2014), and Han (2003, 2010), who identified that such approaches are often suboptimal and may be heavily influenced by the presence of error, particularly when dealing with higher frequencies, instead promoting a conversion within the frequency domain. Therefore, the pre-processed accelerometer data was converted into the frequency domain using the Fast Fourier Transform (FFT), an efficient algorithm used to calculate the Discrete Fourier Transform (DFT) to extract the frequency content of a signal (Heideman, Johnson, & Burrus, 1984). Within the frequency domain, the accelerometer data was converted as required using the Omega Arithmetic method (Mercer, 2006), a process which was automated using the MATLAB function 'iomega', before using the Inverse Fast Fourier Transform (IFFT) to convert back into the time domain, subsequently obtaining the velocity and displacement values.

3.4. Visualisation Development

3.4.1. Plotting Throws in Three-Dimensional Space

Once the position and velocity data for each throw was obtained, it became possible to commence the development of the desired visualisation tool. Due to the nature of an overarm throw taking place in a three-dimensional (3D) space, a visual aid representing the data in three-dimensions was preferred to provide overarm throw feedback. As a preliminary concept test, each throw was plotted in 3D space, a selection of which is shown in Figure 3.7. For this example, the number of throws shown was restricted to four, each from a different participant. Using this plot, it is evident that each throw differs in both shape and size, though it was the shape of the throw that offered the greatest value for assessing throw competency with the available data. The size could indeed be valuable for contributing to the assessment of throw competency, though additional anthropometric data would be required to incorporate this into a visualisation. Moreover, the origin of each throw was not common for all throws in Figure 3.6, so it was also necessary to resolve this issue for consistent comparisons between and within individuals.

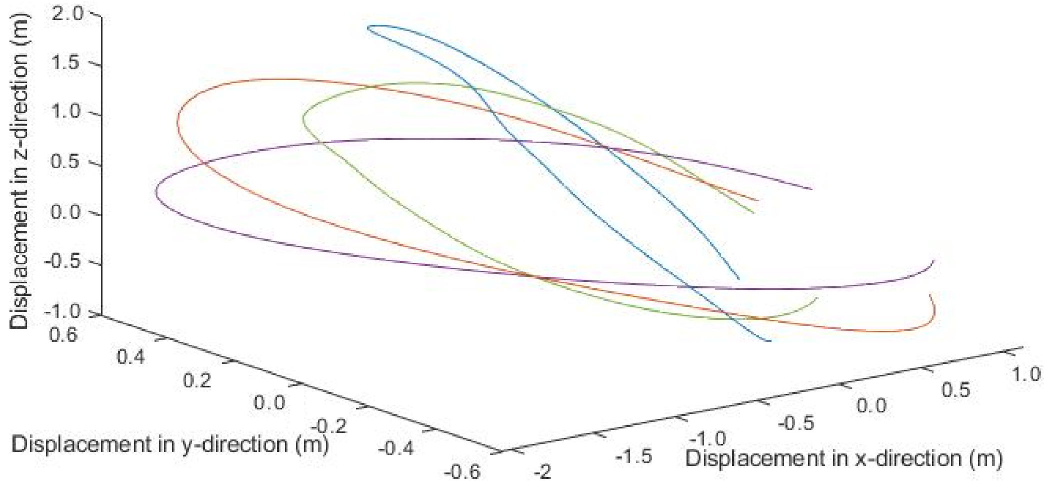


Figure 3.7 – Selection of overarm throw position plots to demonstrate throw size differences

The isolated throw traces were translated such that a common origin of (0,0,0) was set by subtracting the initial position in the x-, y- and z-directions from each data point, such that:

$$x - x_0 = x_T$$

$$y - y_0 = y_T$$

$$z - z_0 = z_T$$

Where:

x, y and z are the initial coordinates of the throw trace

x_0, y_0 and z_0 are the coordinates of the origin of the original trace prior to translation

x_T, y_T and z_T are the translated coordinates of the throw trace

Using the same throws as in Figure 3.7, the traces were plotted again following translation, as shown in Figure 3.8, where all throws share a common origin. This enabled a more representative comparison of the throws.

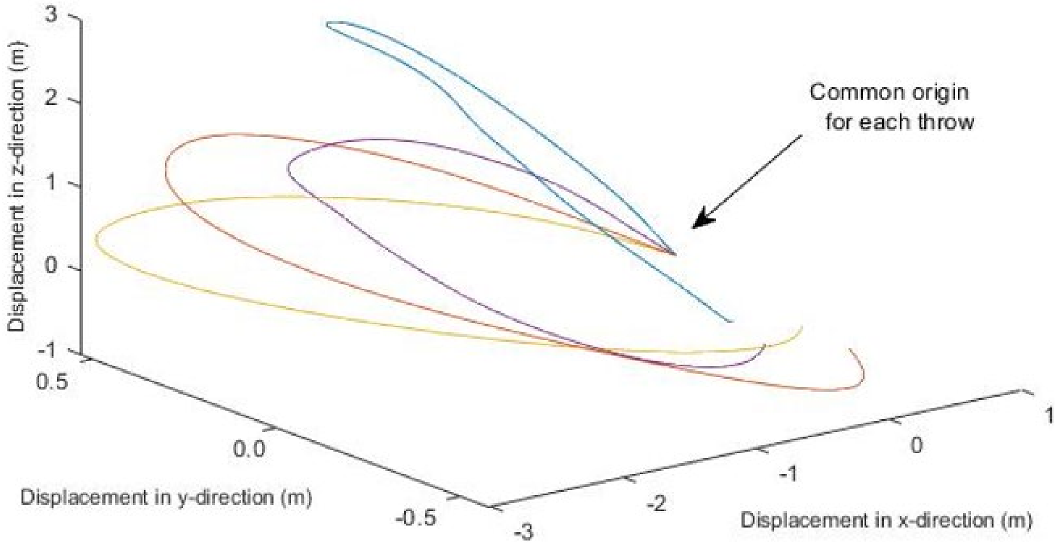


Figure 3.8 – Selection of overarm throw position plots with common origin

3.4.2. Normalisation of Data and Identification of Optimal Throw Trace

Due to the size differences of each throw, it was necessary to scale, or normalise, the data, so a valid comparison could be conducted. While anthropometric data was collected for the sample population, a greater selection of anthropometric data, such as arm length and the length between limb joints, would ideally be available for each participant such that an appropriate scale could have been determined using this information as a basis, hence the dimensions of each throw trace could have possibly contributed to the assessment of competency. As an example, it would be expected that an individual conducting an overarm throw without torso rotation and weight transfer would produce a throw trace with significantly less displacement than an individual demonstrating both torso rotation and weight transfer. Nevertheless, Z-score normalisation was applied, given that when a distribution of points is transformed into Z-scores, the distribution is rescaled while retaining the original shape (Abdi, 2007). As all distributions, in this instance the positions in Euclidean space at each timepoint, were subject to Z-score normalisation, each trace was captured on the same scale while still showing the true shape of the wrist trace during each overarm throw; an essential feature for the development of the visualisation concept. Having all throw traces plotted on the same scale crucially enabled the next stage of analysis and visualisation formation to take place, such as the identification of a suitable margin of error within which throw competency could be assessed. Despite the absence of data relating to certain anthropometrics, normalisation of the throw data still enabled an assessment of competency to be conducted, with more emphasis placed predominantly on the shape of each throw trace to contribute to the assessment of competency.

The normalisation was applied to all throws, irrespective of competence, as part of a complete matrix within MATLAB to ensure that all throw traces were normalised to the same scale. Figure 3.9 provides the traces of all throws assessed as competent, with an additional curve to show the mean of the competent throws (thicker green line). The mean was produced in order to set a gold standard for a competent throw. It should be noted that the axes on Figure 3.9 indicate the normalised values, not the true positional values, though the relative shapes of the traces remain consistent. Therefore, the values displayed on the axes are arbitrary in this context and add no value to the visualisation. Consequently, the axes were omitted for any future visualisations utilising the normalised values.

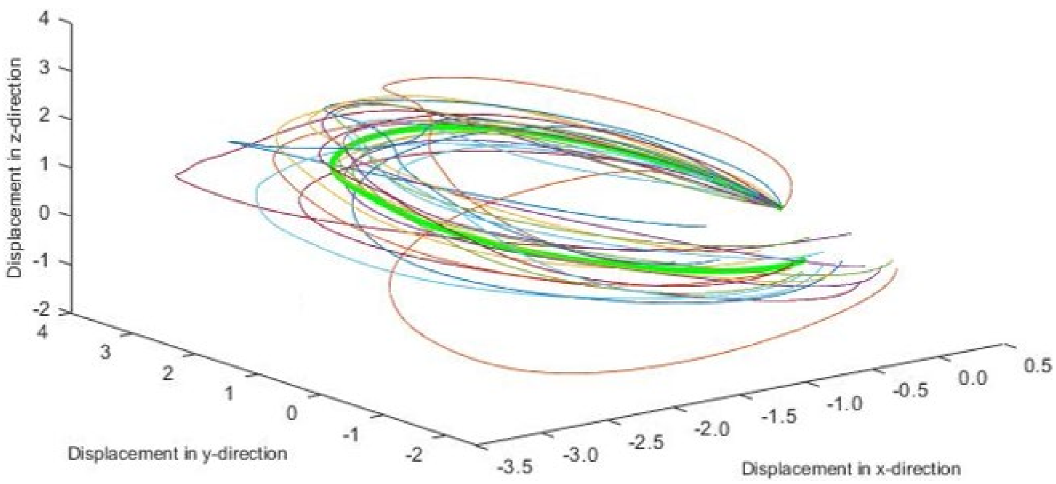


Figure 3.9 – All competent overarm throw traces compared against the mean competent throw trace, identifiable as the thick green line

While the curves of the competent throws in Figure 3.9 appear to follow a similar profile, there are curves that noticeably appear to deviate from the others. The initial assessment of competency using the TGMD-3 (Ulrich, 2016) was based on a series of overarm throws performed consecutively by each participant, rather than each throw individually. Therefore, it was possible that some of the throws were categorised as competent when they were perhaps not. As there was a risk that outliers may have been present when generating the mean competent throw trace, its use as a gold standard without further assessment could be brought into question. As such, the video footage from the initial competency assessment was reviewed to determine if there were, indeed, incorrectly assessed throws included in the generation of the mean competent throw trace. However, while some throws were dubious, the subjective binary criteria of the TGMD-3 (Ulrich, 2016), that is the participant is classified as meeting the criteria or not, meant it was not possible to state with certainty that the throws were incorrectly classified. Therefore, statistical analysis was instead applied to determine whether any of the competent throw traces were outliers. The approach taken for this was to group the x-, y- and z-values for each throw in individual rows, then compile each row within a matrix, such that there existed one matrix for the x-values, another for the y-values, and a third for the z-values. The individual outliers of each column were then detected, where each outlier identified related to a single data point coordinate. Following the identification of the outliers, the quantity of outliers for each row of the matrices was calculated. Consideration was given to what constituted an outlier in this instance, given that the full throw trace was being assessed rather than any single data point. It was easy to detect an outlier throw trace when a large quantity of outlier data points was identified within a single row of the matrices, however, there were also traces that contained a smaller number of outliers, often in isolation along the row of the particular matrix. In these instances, it was difficult to omit all rows that produced an outlier, or a small quantity of outliers, given the prevalence of outliers throughout the matrices. Therefore, justification was made as to whether the curves could be omitted based on the location along the curve that the outliers were identified. Specifically, a small quantity of outliers localised to the start of a trace could be deemed acceptable given that the common origin leads to a less significant deviation between the data point's initial phases. With a smaller deviance, it was more likely to find outliers at the start of a trace. It was not considered necessary, therefore, to exclude the complete traces in such circumstances. Through analysis and review of the outlier quantities and locations, the number of competent throws included in the generation of the mean competent throw trace was reduced from 21 to 17. The mean competent throw trace was reproduced following the omission of the outliers and was compared against the original mean competent throw trace prior to removal of the identified outliers, plotted and presented isometrically in Figure 3.10a and in the x-y plane in Figure 3.10b for clarity. The two traces differ, albeit slightly, justifying the need to consider and omit the outliers.

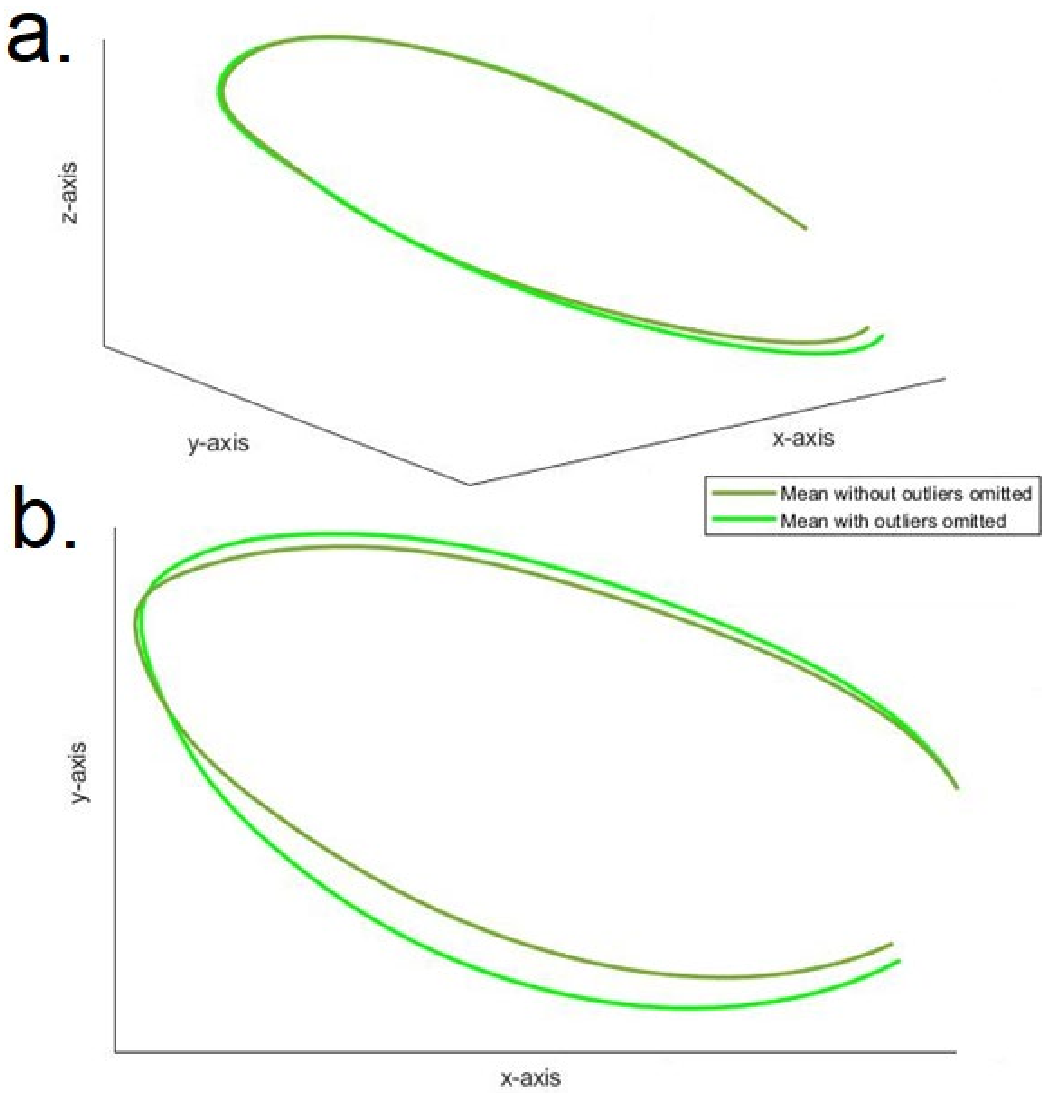


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Figure 3.10 – a) mean with outliers and b) mean without outliers

3.4.3. Application of an Error Band to Help Identify Competent Throws

Following the generation of a gold standard competent throw, the next phase of the development identified a tolerance within which a throw could still be considered competent. A typical approach for setting a tolerance for error is to utilise the standard deviation (Dallinga et al., 2017; Knight et al., 2007). The standard deviation for each data point in the x-, y- and z-direction was calculated using the mean competent throw trace as a baseline. Subsequently, an error band could be constructed using the standard deviation values to define the limits. It is noted that the non-competent throws were also analysed, with a mean trace for the non-competent throws also generated for comparative purposes, though the error band was based exclusively on the competent throws. Given the typical shape of the mean competent throw curve, both the upper and lower vertical tolerance limits, were defined consistently with the standard deviation at each point in the z-direction. However, due to the U-shape of the mean competent throw trace and the need to rotate the error band such that it stayed consistently normal to the curve, the width of the error band was either defined using the standard deviation in the x- or y-direction depending on the position on the curve when applied. The maximum value from the x- and y-values at each data point was used to set the lateral tolerance limits. Typically, the standard deviation was greater in the x-direction than the y-direction during the backward and forward motions of the wrist. However, the standard deviation was greater in the y-direction as the wrist direction changed, particularly where the rotation of the torso had an influence, as this phase is the only segment of the overarm throw that has a larger displacement in the y-direction than the x-direction.

To create a visual error band, it was necessary to determine the direction of normal to the curve in the x-y plane at each point and the associated angle of rotation about the z-axis. This was achieved by first identifying the gradient, or tangent, at each point. Specifically, in this instance, the change in displacement in the y-direction against the change in displacement in the x-direction. Knowing that the product of the gradient of the tangent and normal line is -1, the normal was calculated by dividing the gradient by -1. On finding the normal at each data point, the application of trigonometry enabled the angle of rotation about the z-axis to be calculated for each data point, as shown in Figure 3.11.

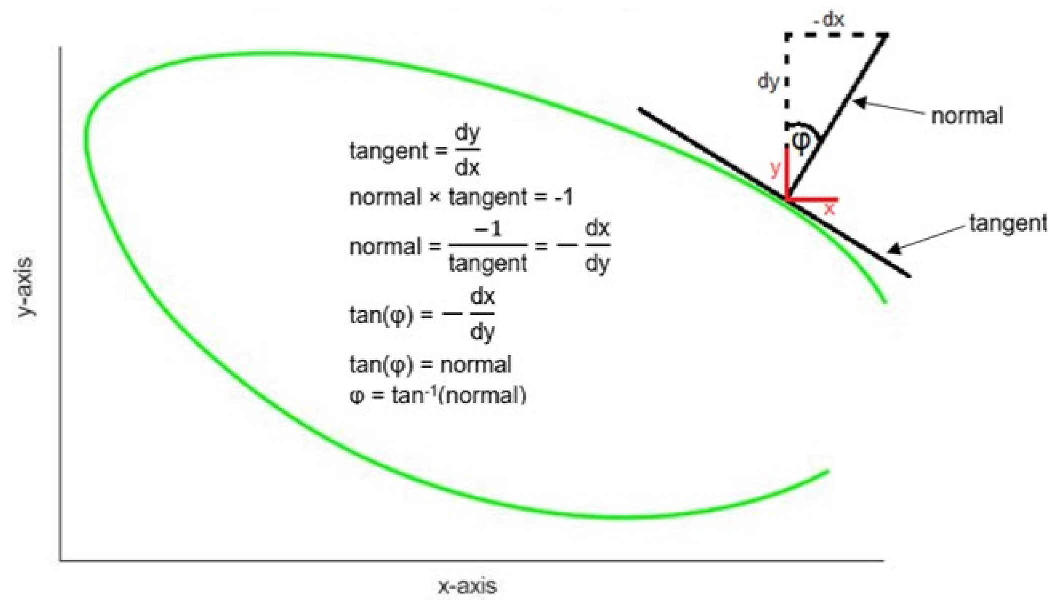

Figure 3.11 – Calculation of normal and angle of rotation about the z-axis on the mean competent overarm throw trace

With the knowledge of the angle of rotation about the z-axis, an error band could be plotted with the limits set by the standard deviation values. The limits of the error band were set normal to the curve at each data point and rotated along the curve about the z-axis such that the error band limits were consistently maintained at the furthest point from the centre. The error band used for the visualisation was plotted as a rectangular sweep (Figure 3.12). While other shapes, an ellipse for example, were also considered due to their aesthetic qualities, the rectangular shaped band was the only shape that correctly displayed the defined limits.

In setting the error band limits, the number of standard deviations used was identified largely through trial and error, ultimately concluding that ±2.33 standard deviations was optimal. This threshold (Figure 3.12) estimated that 99% of all competently performed overarm throws would be contained within the limits of the error band. As the number of standard deviations increased, the error band limits expanded as the confidence level tended towards 100%. However, this also increases the likelihood of a non-competent throw also being fully captured within the error band. In addition, larger error bands tended to overlap, lowering the quality and clarity of the visualisation.

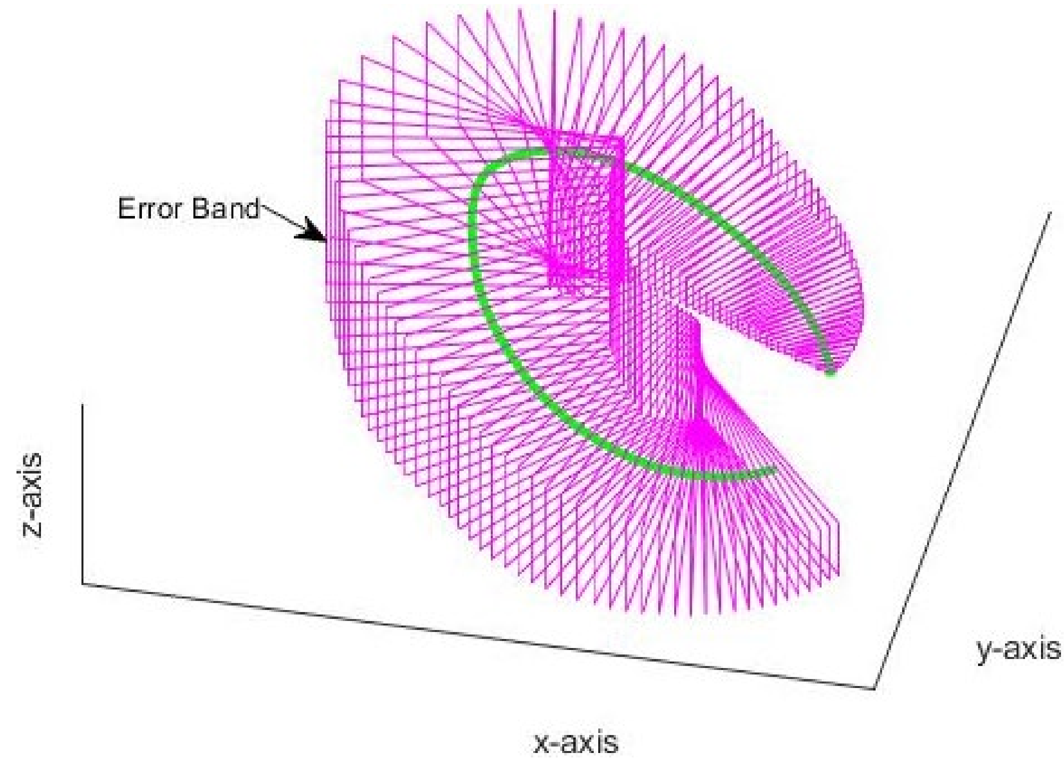

Figure 3.12 – Mean competent overarm throw with error band indicating 2.33 standard deviations at each 0.01s interval for the throw

3.4.4. Visually Representing Velocity Data

The last detail required for the visualisation was to present the velocity data of each throw. Each throw performed by the participants were maximum effort movements, rather than throwing for accuracy. Presenting the velocity of the throw enables the user of the tool to recognise that while a throw may be performed competently from a biomechanical standpoint, the performance of the throw may yet be substandard. Velocity is an essential component of overarm throwing when performed maximally (Ogiolda, 1993) and is an important attribute in many sporting applications, such as javelin (Ogiolda, 1993) and baseball (Seroyer et al., 2010). Overarm throws with poor technical proficiency have been shown to have reduced velocity, suggesting scope for improvement (Ogiolda, 1993;

Seroyer et al., 2010). However, while it is important to promote a forceful throw, the learner should be encouraged by the educator to prioritise technical proficiency, particularly outside of an assessment setting. Moreover, it may be advantageous for the educator to limit the provision of quantitative velocity data to the learner to prevent the unintentional introduction of a performance-oriented climate (Papaioannou, 1998) and to reduce the risk of technical regression in beginners due to a change in focus (Schmidt & Wrisberg, 2008), with the educator encouraged to instead provide less detailed qualitative feedback relating to velocity.

The velocity data was aligned with the associated position point of each throw. Each throw trace was plotted with the instantaneous velocity information depicted using colours linked to a ‘heat map’, as per Figure 3.13, which presents the overarm throw wrist traces for all competent throws, complete with velocity information. The greatest velocities were found along the sections of the curves indicating the wind-up and forward motion of the throws, with the initiation and conclusion of the movements showing the lowest velocities. It was also recognised that, typically, the velocity decreased at the point at which the direction of the arm direction changes. The upper limit for the velocity scale was defined by the maximum velocity identified within the dataset. It is noted, however, that this limit can be refined as necessary with additional data collection, assuming higher velocities are identified.

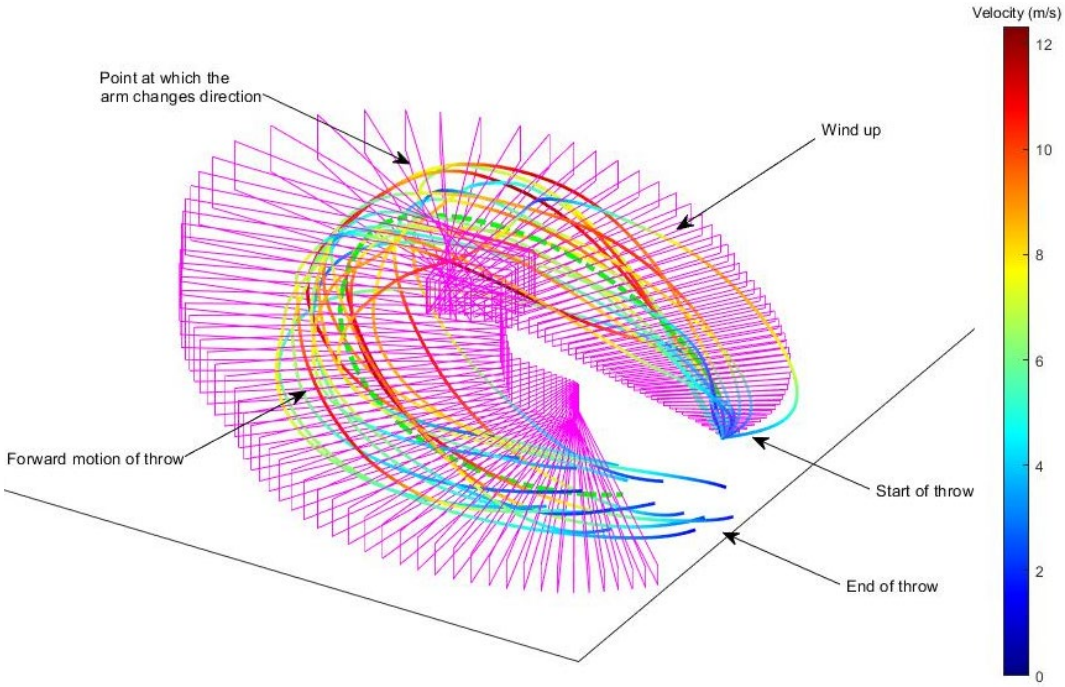

Figure 3.13 – Competent overarm throw traces with velocity data vs the mean competent overarm throw

3.4.5. Finalising the Visualisation Concept

For the development of the final concept, the appearance of the visualisation was considered. As the purpose of the visualisation is to assist in the education of FMS, namely the overarm throw, it was essential that the information offered by the visualisation was displayed clearly. One key factor deliberated was colour selection. Due to the need for clarity, vivid colours were utilised with care taken to select colours from a wide spectrum to prevent clashes. A black background was preferred to emphasise the vibrancy of the colours used in the primary elements of the visualisation, namely the velocity data and the error band. In presenting the mean competent overarm throw trace, bright green was used due to the positive connotations often linked to this colour (Kaya & Epps, 2004; Pravossoudovitch et al., 2014). In contrast, red was used to display the non-competent overarm throw mean due the generally negative associations (Pravossoudovitch et al., 2014). The use of magenta was chosen for the error band to prevent a colour clash with the velocity heat map colours while remaining visible. It was initially felt that the error band should be presented as a solid, semi-transparent tube. However, it was recognised that this hindered the clarity of the velocity data of the lines contained within. Therefore, a wireframe alternative was applied such that the error band remained identifiable without hindering the displayed velocity information. Furthermore, labels were added to indicate the start and the general direction of the throws to aid the user in conducting the assessment. The final concept developed for assessing a single overarm throw is illustrated in Figure 3.14. Subsequently, Figure 3.15 depicts three subplots: all overarm throws assessed as competent in the x-y plane, all overarm throws assessed as non-competent in the x-y plane, and the mean of all competent overarm throws plotted against the mean of all non-competent overarm throws. This facilitated a side-by-side comparison such that differences and patterns, or lack thereof in the case of the non-competent throws, could be shown.

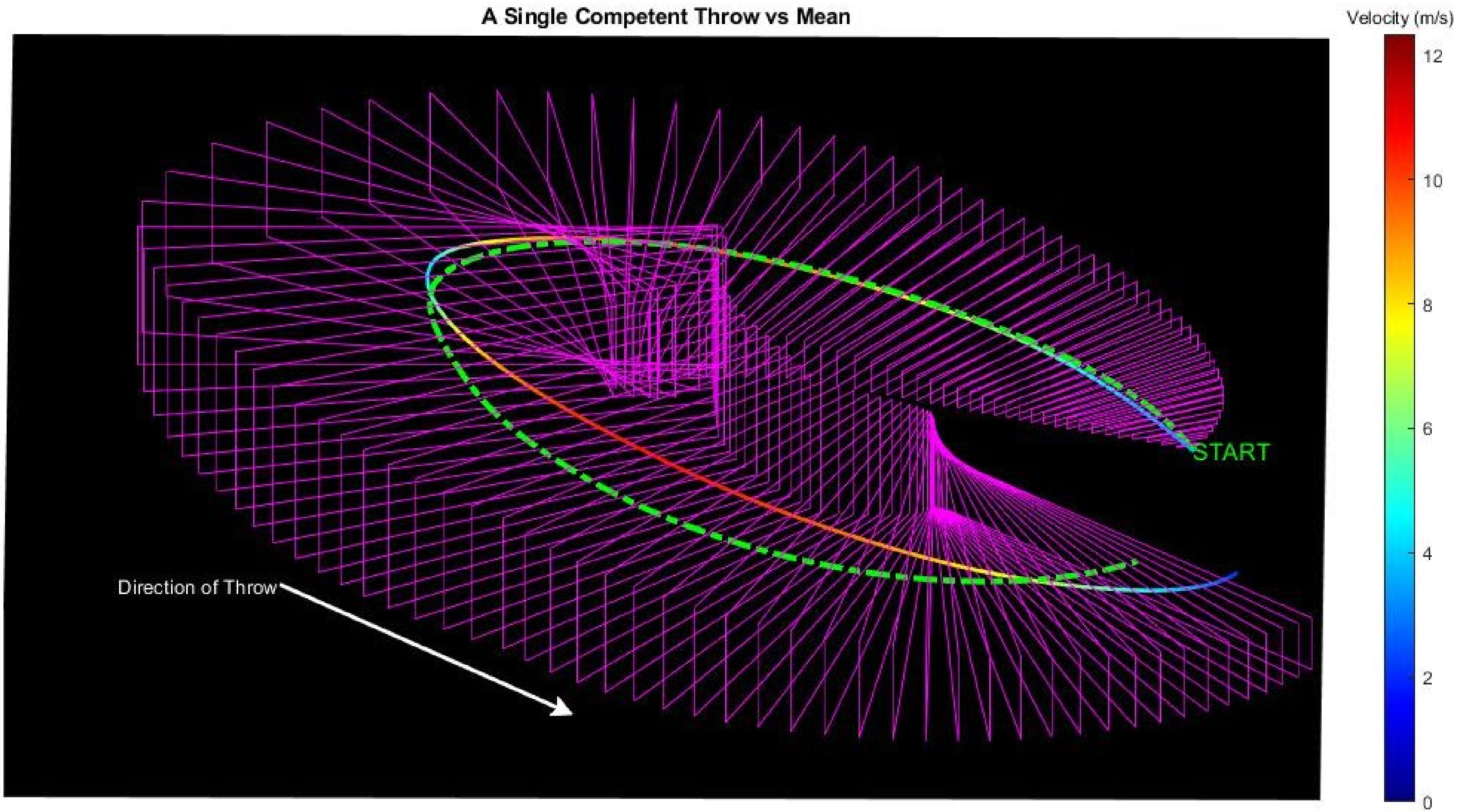

Figure 3.14 – Single overarm throw plotted against the mean using the final visualisation concept

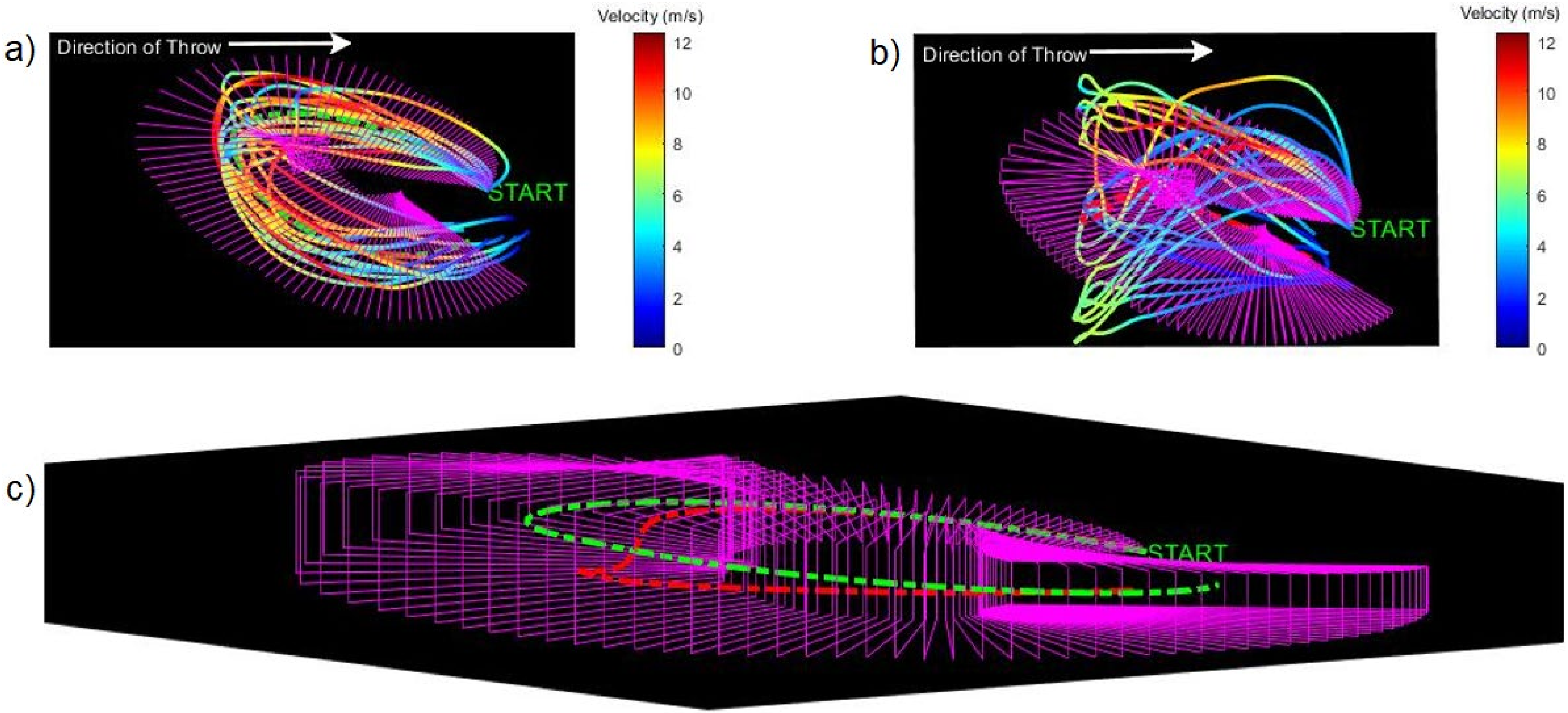

Figure 3.15 – Final visualisation concept used to present both competent and non-competent overarm throws. a) competent throws vs the mean of competent throws; b) non-competent throws vs the mean of non-competent throws; c) the mean of competent throws vs the mean of non-competent throws

3.5. Application of Visualisation Tool

3.5.1. Visualisation of Overarm Throws and Preliminary Results using the Visualisation Tool

While this thesis primarily centres around the development of a visualisation concept for assessing FMS as part of a feasibility study, it was beneficial to produce some preliminary results indicative of the efficacy of the concept. As the results are integral to the interactive development of the model, they have been incorporated into the same chapter as the methods to provide a coherent insight.

The visualisation tool delivers, by design, a simple and direct interpretation of data. When plotting traces of competent overarm throws, the traces for the most part share a similar shape. In nearly all cases, the traces are contained within the error band, though this is expected given the use of the same data in the generation of the current boundaries. The competent throws are depicted in Figure 3.16, which shows the throw traces in the x-y plane, the x-z plane and the y-z plane, in addition to an orthographic view to show the traces in three-dimensions. Specifically, Figure 3.16 demonstrates that only one out of the 17 overarm throws assessed as competent, following the omission of outliers, deviates beyond the boundaries of the error band, which is shown clearly in the x-y and x-z planes, giving a 94.1% success rate of the competent throws remaining within the boundaries of the error band for the entire movement. It is noted that even the single competent overarm throw trace that extends beyond the boundary only does so momentarily at the initiation of the throw, before returning to within the constraints for the remainder of the movement.

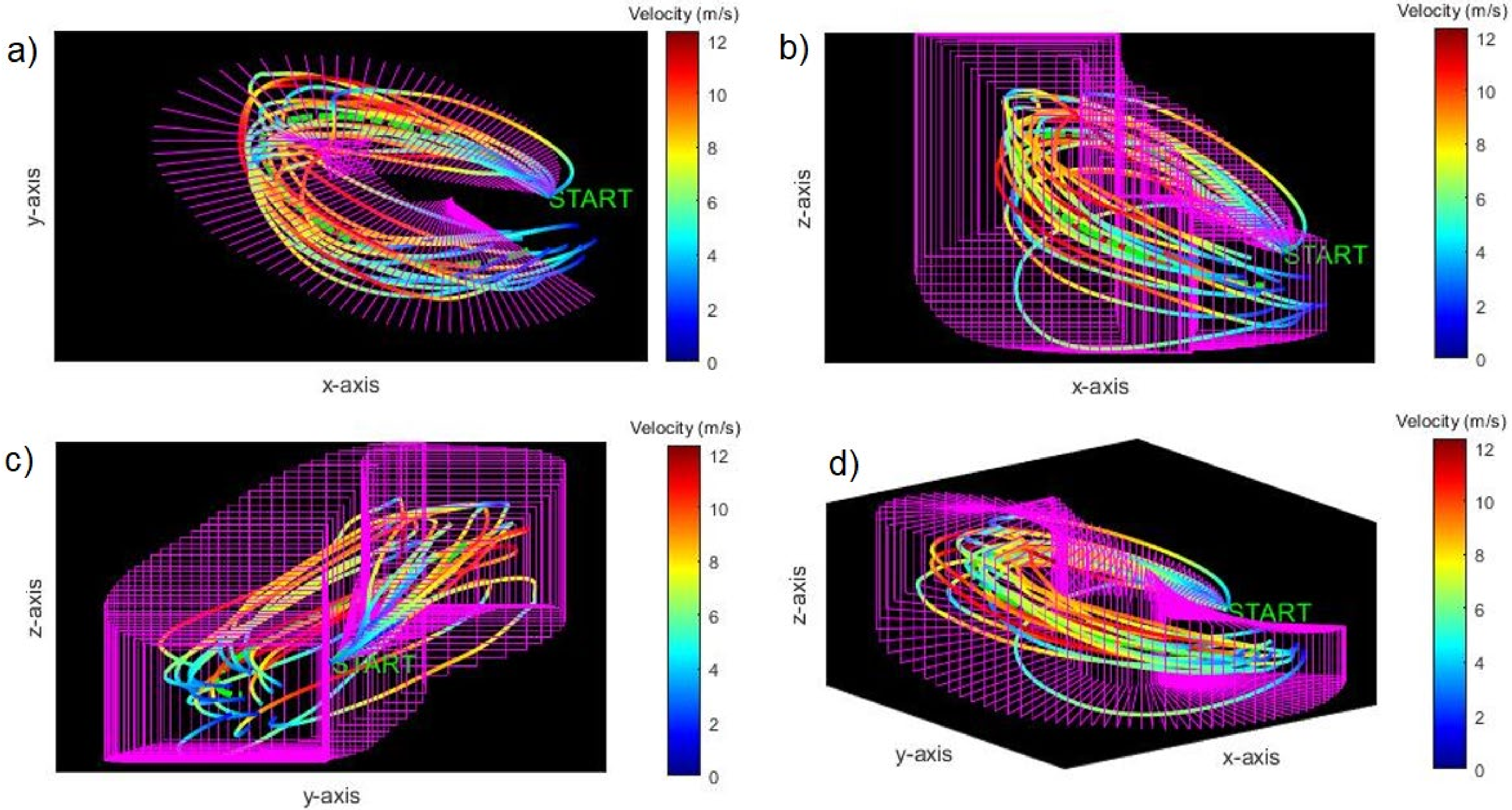

Figure 3.16 – Competent throws analysis. a) x-y projection; b) x-z projection; c) y-z projection; d) orthographic projection

Ideally, there would exist a straightforward assessment where the competent throws would all be fully contained within the error band, with non-competent throws deviating beyond these boundaries such that a lack of competency could be easily identified. However, this is not always the case, as more challenges arise when assessing the non-competent throws. As shown in Figure 3.17, the non-competent overarm throw traces are more sporadic and do not demonstrate a clear pattern. Indeed, this is due to incompetent throws resulting for various reasons, such as a failure to demonstrate competency in one or more of the common phases of the overarm throw: wind-up, rotation, weight transfer, and follow-through (Ulrich, 1985, 2000, 2016). To assist in the analysis of the non-competent throws, each of the traces initially assessed as non-competent was reviewed in isolation against the mean of the non-competent throws, as shown in Figure 3.18. It should be noted that the traces were assessed from all angles but have been presented in the x-y plane for clarity as deviations beyond the error band were found to be most clearly illustrated in this projection. Through observation of the traces in Figure 3.18, 11 out of 13 (84.6%) of the non-competent throw traces were shown to deviate beyond the constraints of the error band. Therefore, the remaining two throws (15.4%), Non-Competent Throw 4 and Non-Competent Throw 5 (Figure 3.18), were encased within the boundaries set by the error band.

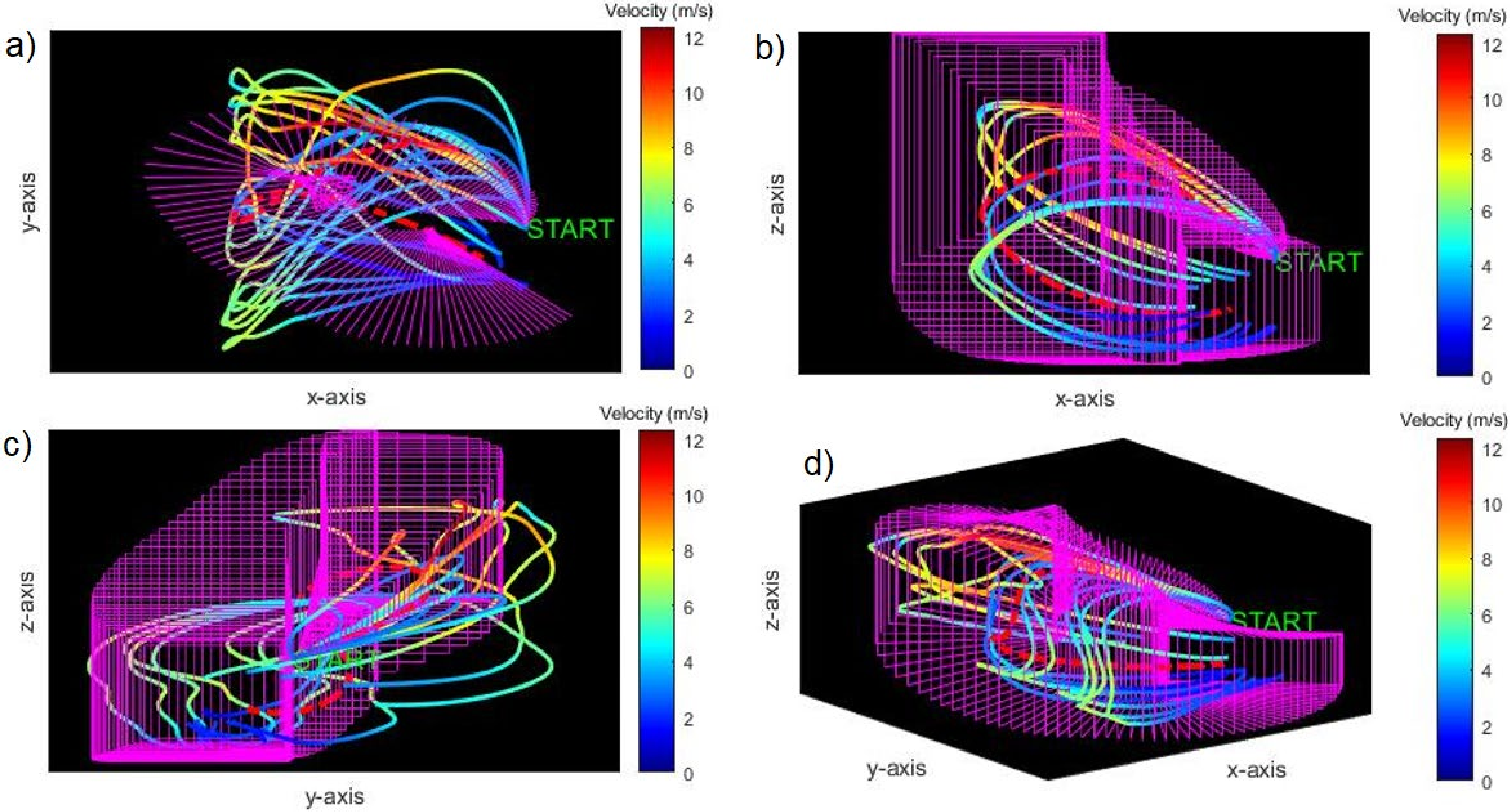

Figure 3.17 – Non-competent throws analysis. a) x-y projection; b) x-z projection; c) y-z projection; d) orthographic projection

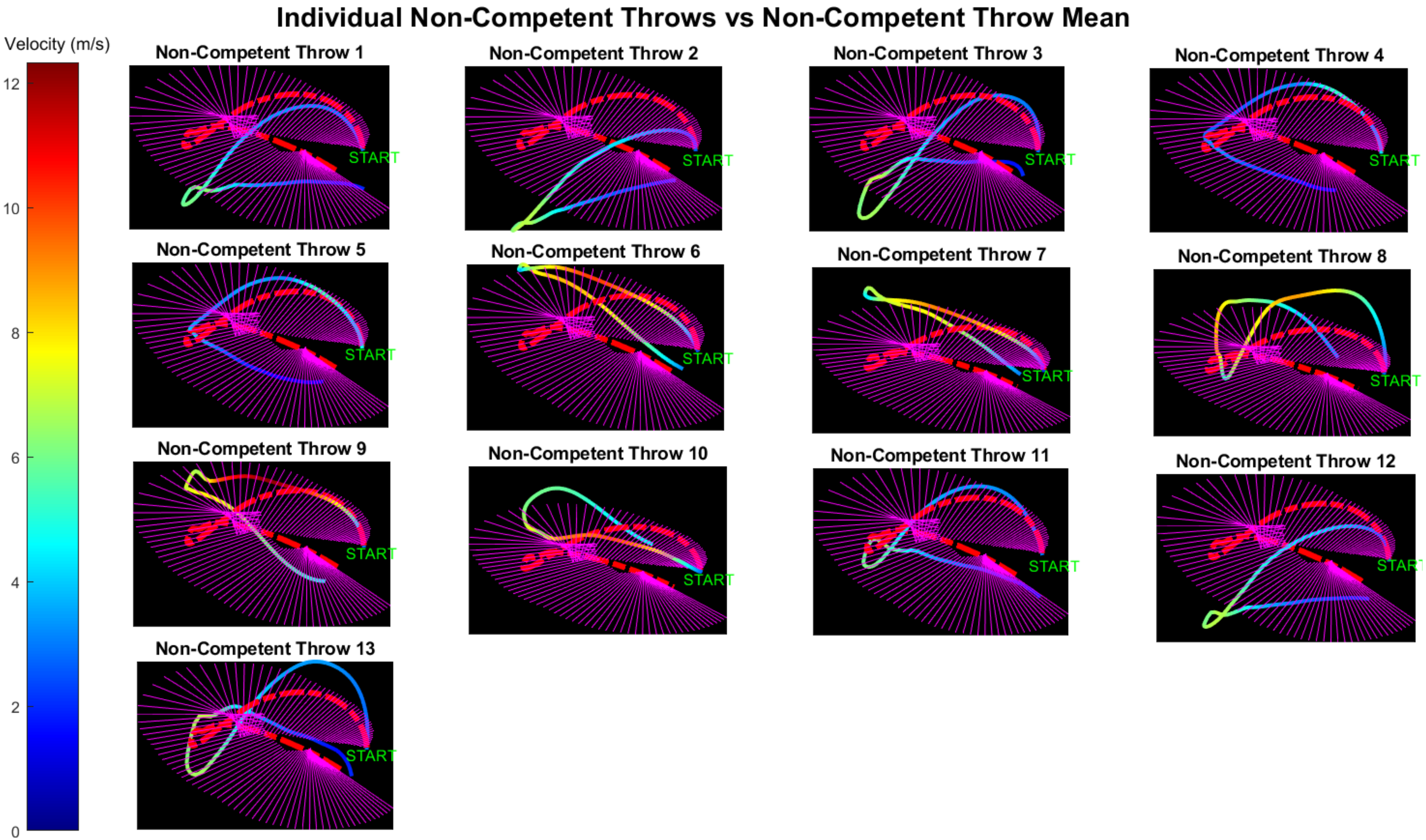

Figure 3.18 – Individual non-competent overarm throws vs non-competent overarm throw mean

The shape of the overarm throw traces is a potential indicator of competency, or lack thereof. With reference to the overarm throw object control subtest phases, described by Ulrich (2000), a failure to correctly execute any one of these phases can lead to a distinct feature as part of the throw trace. Figure 3.19 shows the mean of the competent throws against the mean of the non-competent throws using three different projections. The mean overarm throw trace for the competent throws presents a smooth U-shaped curve, which is consistent with the individual throw traces generated (Figure 3.20). However, the non-competent mean overarm throw trace (Figure 3.19) provides a far more irregular shape, where there is a clear and consistent change of position in the vertical direction at the end of the wind-up phase, a common trait on all overarm throws from the sample population initially assessed as non-competent (Figure 3.21). It is noted that the sudden change in vertical displacement is also often accompanied with lateral direction changes, though this is not always distinct, or indeed present. Furthermore, the two non-competent overarm throws where the change in vertical displacement is least obvious, Non-Competent Throw 4 and Non-Competent Throw 5 (Figure 3.21), are the same non-competent throws that were fully enclosed within the error band. For these two throws, both conducted by the same participant, it was recognised through re-assessing the videos against the criteria of TGMD-3 overarm throw object control subtest phases (Ulrich, 2016), that the incompetency was not as significant as demonstrated by other non-competent throwers, with the throws performed only narrowly failing to achieve the requirements of a competent throw. Indeed, the video footage suggests that only minor modifications to their technique would result in a competent overarm throw being performed.

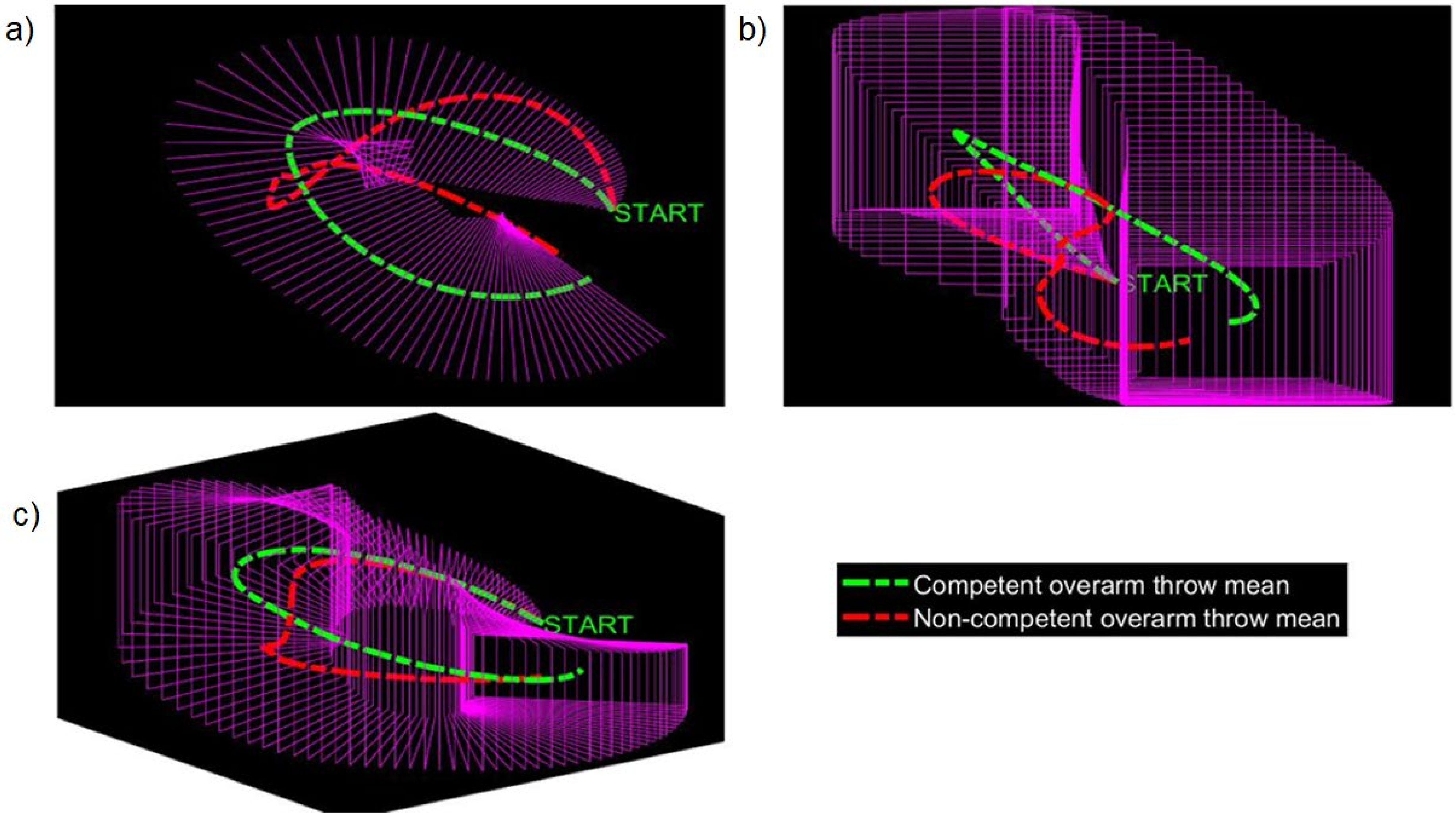

Figure 3.19 – Competent overarm throw mean vs non-competent overarm throw mean. a) x-y projection; b) x-z projection; c) orthographic projection

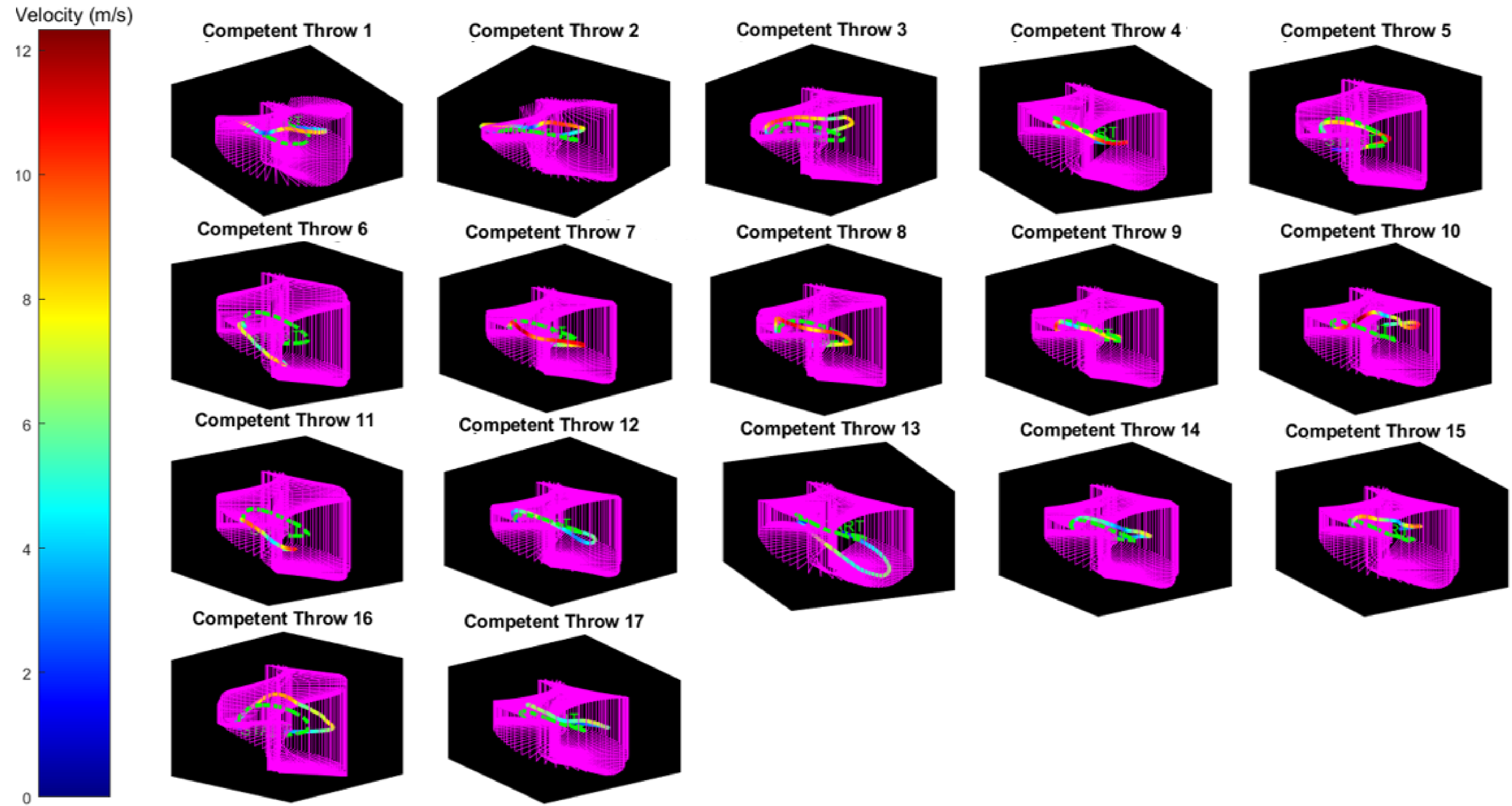

Figure 3.20 – Individual competent overarm throws vs competent overarm throw mean

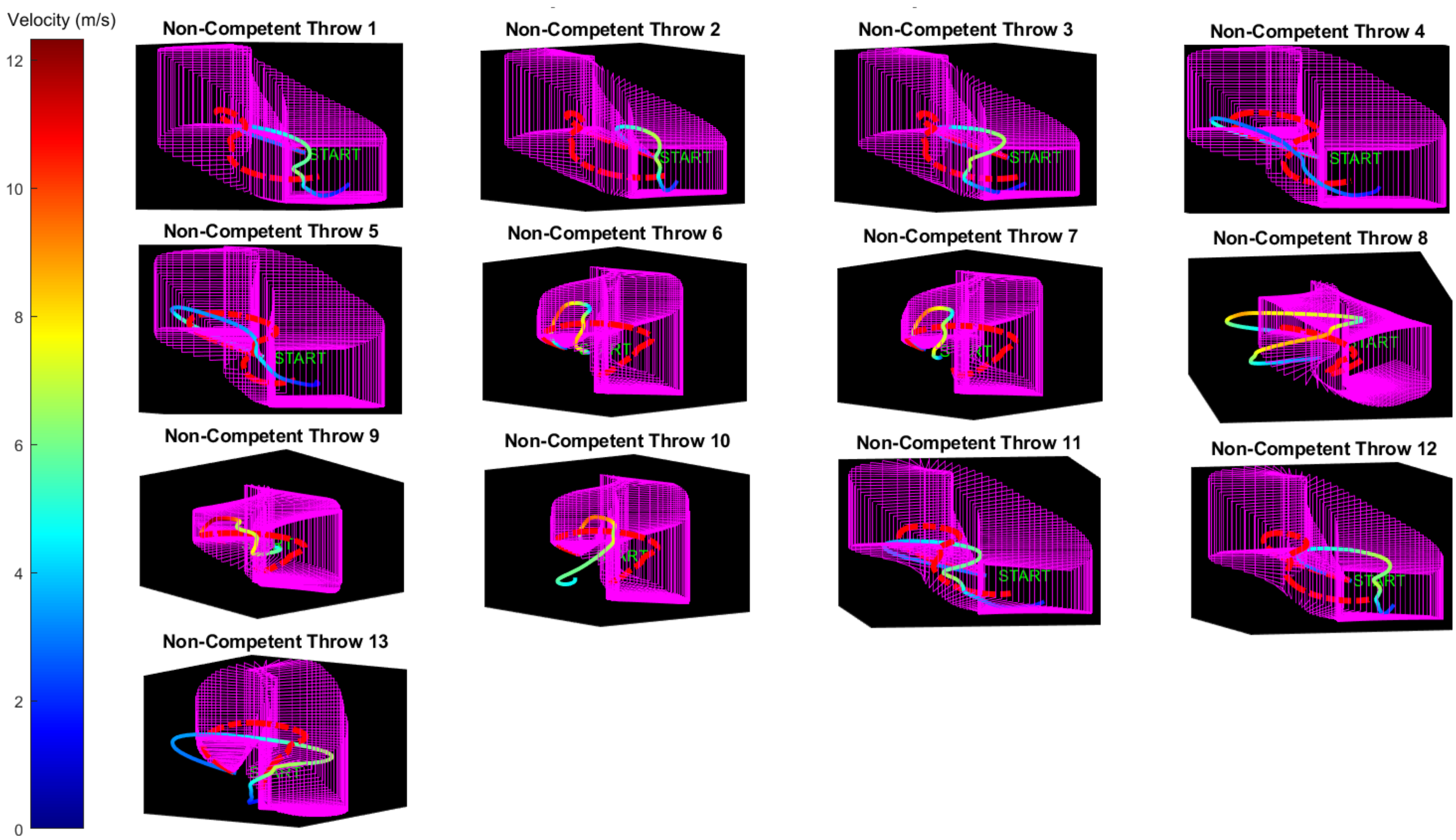

Figure 3.21 – Individual non-competent overarm throws vs non-competent overarm throw mean with optimal projection to view trace irregularity

Recognising that velocity is a strong product-based indicator of overarm throw performance, the availability of these visualisations can suggest whether a throw was performed to an acceptable standard. Indeed, while an overarm throw may appear competent due to the shape of the throw trace produced, an inadequate level of velocity is often indicative of a substandard throw, regardless of whether the necessary behavioural components of a competent overarm throw are successfully demonstrated. The visualisation provides the data for the wrist velocity during the throw, given that the IMU utilised for data collection was worn on the wrist, which is recognised as a good correlate of ball speed (Whiteley, 2007). Upon review of the throw traces, it was observed that the colours for the competent overarm throws were 'warmer' (Figure 3.16), indicating higher throw velocities, with the non-competent overarm throws exhibiting 'cooler' colours (Figure 3.17), signifying lower throw velocities. However, it was acknowledged that all 17 competent throws (outliers previously omitted), were performed by boys, with 10 of the 13 non-competent throws performed by girls. It was therefore hypothesised that the lower velocities may also be attributed to sex in addition to the competency of the throw. Indeed, an independent samples t-test found that when disregarding competency, the maximum wrist speeds of boys' overarm throws ($9.70 \pm 1.74\ m \cdot s^{-1}$) were significantly greater than girls ($7.09 \pm 1.52\ m \cdot s^{-1}$; $P<0.05$). Moreover, a Levene's test and normality checks confirmed assumptions were met for a subsequent ANCOVA to be conducted. The ANCOVA revealed that sex, the covariate, had a significant effect on maximum throw speed ($F(1, 27) = 7.93$, $p<0.05$). However, there was not significant influence of overarm throw competence on the maximum overarm throw speed after adjusting for sex ($F(1, 27)=0.351$, $p>0.05$), though there was an observed power of $1-\beta = 0.088$, estimating a 91.2% ($\beta = 0.912$) chance of a Type II error.

CHAPTER 4: DISCUSSION

The aim of this thesis was to demonstrate the feasibility of using commercially available and affordable technology, namely accelerometry, to i) assess the quality of an overarm throw; and ii) provide effective visual feedback. This would reduce subjectivity when conducting an assessment, while also reducing or eradicating educator training requirements, thereby potentially providing a useful tool to improve overarm throw performance. Overall, this thesis presents a visualisation concept developed for an overarm throw, which holds promise to be further developed and transferred across all Fundamental Movement Skills (FMS). The key features that the visualisation concept provides are the inclusion of an error band centred around a gold standard throw trace, generated using the mean of the competent throws, and the inclusion of velocity as a visual output. Preliminary results indicate that the visualisation tool not only provides a strong indication of overarm throw competence but is a much needed first step in the reduction of assessment subjectivity. However, further research is required to refine the process, and indeed visualisations to ensure reliability, validity and interpretability.

The ActiGraph GT9X Link, a commercially available and relatively affordable wearable device containing an Inertial Measurement Unit (IMU), was utilised as a cost effective, non-optical method by which the overarm throw could be assessed effectively. Hardman et al. (2014) recognised the advantages of such devices to support Physical Education (PE), an important development given the frequent absence of a trained PE specialist in primary education (K. Kirk, 2012). Furthermore, utilising IMUs to devise a visualisation method that can generate an effective visual aid using a single wearable device not only reduces environmental restrictions imposed by other methods, such as the requirement for space demonstrated by Dallinga et al. (2017), but also overall assessment time. While the manual methods of assessing FMS remain valuable, the proposed visualisation was developed to provide another viable option for evaluating gross motor competency, with the opportunity to use additional features to assist in the assessment.

Lander et al. (2020) presented comparable visualisations to those shown within this study, though they relied more heavily on the Test of Gross Motor Development – Third Edition (TGMD-3; Ulrich, 2016) for validation of the results, in addition to the participants wearing a larger number of IMU devices at different body locations. The novelty of the visualisation concept provided in this thesis is the use of a single sensor. Indeed, the current findings extend those of Lander et al. (2020), as the visualisation concept provided in this thesis aims to support the assessment of FMS as a standalone entity, rather than supplementing existing manual assessment methods, such as the TGMD-3 (Ulrich, 2016). A fundamental step in the present process is the inclusion of an error band, centred around the mean of the competent overarm throw trace used as the gold standard. It was shown that the majority of competent throws were encompassed within the error band boundaries, whereas non-competent throws deviated beyond the boundaries during some phase of the movement. Therefore, further research is warranted to explore the potential to automate this process, whereby a throw trace fully encased within the error band would be classified as competent. However, whilst the present research suggests this is possible, it will be important to cross-validate the data using a larger sample size to enable kappa co-efficients and/or percent agreement to be calculated (McHugh, 2012). Moreover, the inclusion of a larger, more diverse sample will enable the models to be further developed to increase the reliability. It is also noteworthy that the shape of the overarm throw trace could also provide an indicator of competency; a distinct change of position in the vertical direction at the end of the wind-up phase was evident for all non-competent throw traces (Figure 3.20). However, the non-competent throws exhibiting this profile less distinctly were visually closer to being competent than others. This therefore provides further evidence that competency should not be treated as dichotomous, with a key limitation of manual gross motor skill assessment methods such as the Test of Gross Motor Development – Third Edition (TGMD-3; Ulrich, 2016) being the binary scoring system. Using the TGMD-3 (Ulrich, 2016) scoring system alone would highlight the incompetency of a specific behavioural component of the overarm throw, but not the extent of the incompetency. For practitioners aiming to improve competency in FMS, this granularity of information is of vital importance. Future work should seek to refine the visualisation with a more definite indication of the degree to which an overarm throw is competent or incompetent utilising a continuum approach (Stodden et al., 2008). As such, the process outlined in this thesis may provide a step change in the conceptualisation of analysing FMS data.

The inclusion of velocity as a visual output is a key development on the visualisations presented by Lander et al. (2020). Velocity is a key component of many FMS, including locomotor skills, such as running (Masci et al., 2013), and object control skills, including overarm throwing (Hands, 2002), striking (Welch et al., 1995) and kicking (Logan et al., 2017). The present findings suggest that the inclusion of the velocity data could be beneficial in assessing overarm throw performance, a conclusion supported by Stodden et al. (2008) and which highlights an important omission from the manual methods of testing gross motor skills. Indeed, velocity has been frequently cited as an important indicator of overarm throw performance in many sporting applications (Barker, 2019; Wagner et al., 2014). It is hypothesised that a lack of throw competency correlates to a reduction in throw velocity, with both Stodden et al. (2008) and Wagner et al. (2014) providing indications that throw velocity may increase as an individual becomes more technically proficient. Research has frequently cited technical proficiency and velocity as performance predictors of a successful maximum effort throw (Calabrese, 2013; Roberton & Konczak, 2001; Whiteside et al., 2016), both of which appear to correlate with age and sex (Eather et al., 2018; Lorson et al., 2013). The results of the ANCOVA, however, failed to show the influence of overarm throw competency on the maximum overarm throw speed, likely due to a Type II error. A broader dataset is therefore necessary to further pursue this hypothesis. Additional research will help determine the true value of the velocity data when assessing movement quality, identifying whether velocity may indeed be an indicator of overarm throw competency. Furthermore, it may be feasible to demonstrate overall increases in throw velocity as an individual's performance approaches competent as an output of the visualisation.

The influence of sex may have skewed the results, given that all competent throws were conducted by boys and the majority (all but one) of the non-competent throws were performed by girls. Nonetheless, such findings are congruent with Eather et al., (2018), Goodway, Robinson and Crowe (2010), and Young (2009), who found that girls tend to lag behind boys in the development of the overarm throw, largely attributed to environmental and socio-cultural factors. The results show a difference between the maximum wrist velocity of girls and boys during the overarm throw, with boys producing greater velocities than girls. However, it cannot be determined whether this difference is attributable to sex specifically, or whether throw competence is a more influential factor, therefore warranting the collection of a broader dataset, to include sufficient data from competent throws performed by girls. Considering the anthropometric differences between girls and boys, boys in the sample population being taller (173.3 ± 8.9 cm) than girls (155.1 ± 8.9 cm) for example, it is noted that depite the normalisation of data aiming to the reduce the influence of these anthropometric differences, the gold standard competent throw was developed exclusively using data obtained from boys. Therefore, should a competent throw be performed by a girl, it is not possible at this time to rule out erroneous outputs. It is important to note that anthropometric differences between boys and girls may therefore necessitate separate visualisations. In sports featuring overarm throwing, anthropometrical differences have been shown to influence throwing performance, with research indicating that greater heights, limb length and body mass may have a correlation with increased ball velocity (Maki, 2013; van den Tillaar & Ettema, 2004). Indeed, van den Tillaar & Ettema (2004) provided evidence to suggest that the size differences between boys and girls are strongly influential to the sex disparity in overarm throw velocity. This is akin to observations in overhead striking (Söğüt, 2016), a movement in many ways analogous to the overarm throw (Young, 2009). To seemingly make up some of the deficit in performance relative to their male counterparts, girls will often introduce technical alterations, such as increased rotation of the hips and shoulders during the wind-up phase of a throw (Chu et al., 2009). It is noted, however, that the technical alterations displayed by girls relative to boys had no influence on the initial TGMD-3 competency assessment, as girls are still expected to display the same behavioural components as boys (Ulrich, 2016), albeit possibly with nuanced technique. Future research should seek to collect additional anthropometric data in order to facilitate alternative scaling methods which can be applied to the visualisation. It is theorised that introducing anthropometric constraints into the visualisation may assist in the recognition of each behavioural component of the overarm throw, or indeed the absence of a behavioural component. For example, a throw missing one or more key behavioural components would be expected to show a decreased range of motion during the throw (Roach & Lieberman, 2014). Additional anthropometric data should also expand on the age range incorporated in the present thesis such that future research should consider whether age- and/or sex-specific traces or error bands are required to enhance automated classification accuracy. It is recognised that boys and girls differ in maturation, with girls generally experiencing their first preadolescent growth spurts at around 9 years of age and boys experiencing theirs at around 11 years (Gallahue & Ozmun, 1998). There is also a divergent relationship between boys and girls in overarm throwing performance that occurs during puberty, with the maximum throw distance of girls typically plateauing at around 14 years in contrast to an accelerated performance increase in boys (Gallahue & Ozmun, 1998). Prior to puberty, the developmental trajectory of boys and girls is almost parallel (Gallahue & Ozmun, 1998). These factors are important for highlighting the need for additional research to be conducted in order to support the development of age- and/or sex-specific visualisations. Finally, all throws were performed by right-handed participants, so the visualisation tool is currently limited to right-hand throws only. Whilst it could be hypothesised that left-handed throwers would produce, and require, a mirrored visualisation, further research is required to verify this. Future research is therefore warranted with a larger, more diverse sample to provide more training datasets and enable cross-validation of the data (Stone, 1976; Vabalas et al., 2019), ensuring a child-specific visualisation is utilised for comparison.

Visualisations relating to physical activity (PA) have typically been generated for depicting movement quantity data (Crossley, McNarry, Rosenberg et al., 2019; Fan et al., 2012; Williams et al., 2017). Nevertheless, comparisons can be drawn between these visualisations and those generated in this thesis. The visualisation concept developed in this thesis was designed to provide information directly using a graphical approach, with the findings of Crossley, McNarry, Hudson, et al. (2019) indicating that age groups beyond childhood prefer the presentation of data in this manner. Indeed, a follow-up study (Crossley, McNarry, Rosenberg, et al., 2019) showed that adolescents were better able to interpret the data presented graphically than children. Given that the end-user population will be of adult age, i.e. teachers and coaches, it was postulated that a bias towards direct representations of data would be most appropriate, though it is recommended that this hypothesis is investigated when the visualisation tool is suitably mature. Fan et al., (2012) also comment on the benefits of graphical representations of data for providing specific information and trends, though they also observed the benefits of more artistic visualisations to encourage interest and interaction. Therefore, the visualisation tool also draws inspiration from the abstract visualisations shown by Fan et al. (2012), capitalising on the use of a black background, with vibrant colours overlaid to capture the interest of both educators and learners (Dzulkifli & Mustafar, 2013). It is theorised that the combination of a direct approach to delivering data combined with artistic elements, both of which were utilised in the current visualisation, will provide an optimal aid for supporting the assessment and learning of FMS.

The visualisation aims to provide Knowledge of Results (KR) feedback (Schmidt & Wrisberg, 2008), such as the containment of the throw trace within the error band and the provision of velocity data. Including these outputs can provide the educator and the learner with direct information relating to the success of the throw. In addition, Knowledge of Performance (KP) feedback (Schmidt & Wrisberg, 2008) is provided, such as the shape of the throw trace relative to the gold standard, which indicates to the educator and learner where the overarm throwing movement could be improved. Sharma et al., (2016) highlighted the benefits of both KR and KP feedback, both of which were shown to improve the outcome of a maximum distance throwing task. In particular, the KP feedback, delivered in the form of video replays and verbal cues, resulted in the largest progression. However, it would be interesting to expand on the study by Sharma et al. (2016) by introducing the current visualisation to supplement, or even replace, the KP feedback methods used, particularly as the visualisation provides additional outputs absent from the original study, such as velocity data and a gold standard throw against which comparisons can be made. It is acknowledged that there are opportunities for future refinement relating to the delivery of KR feedback to increase confidence in the results provided and further reduce, or indeed eliminate subjectivity, and for KP feedback by incorporating additional features that can offer direct instruction or indications as to what behavioural components are sub-standard and require focused attention. One such advantage of using IMUs to capture movement data is the presence of multiple sensors within one unit (Morrow et al., 2017), such that the visualisation could be refined through the use of other sensors often available within IMUs, namely gyroscopes and magnetometers, to provide information relating to orientation (Kok et al., 2017; Mayagoitia et al., 2002). In doing so, it is hypothesised that the detail of feedback provided via the visualisation could be enhanced further by offering recommendations for biomechanical refinement through process-oriented measures (Bardid et al., 2019), albeit in simplistic terms for easy interpretation by individuals lacking in formal motor skill assessment training. Including such information within the visualisation tool would extend the quality and detail of feedback beyond the current capabilities of the manual assessment methods, which provide only product-oriented measures relating to outcome (Bardid et al., 2019) and could lead to an expedited and higher quality learning experience, culminating in a substantial improvement in overarm throw performance. Moreover, having recognised the importance of practice (Breslin et al., 2008; Clark, 2007; Schmidt & Wrisberg, 2008), it is postulated that additional outputs and instantaneous feedback could assist in a more captivating learning experience and therefore encourage additional time spent refining the skill. The inclusion of magnetometer and gyroscope data may also enable the automatic identification of the exact throw initiation and conclusion points for each individual throw through recognition of orientation (Kok et al., 2017), resulting in the true isolation of the movement. Based on accelerometer data alone, as is the case with the current visualisation, it is challenging to accurately pinpoint the time-points for the true initiation and conclusion of the movement.

The ActiGraph GT9X Link device's acceleration limitations of ±16g (ActiGraph LLC, 2020) were largely overcome through interpolation. Utilising acceleration data without missing data points would remove the need for estimation and would subsequently reduce the risk of error. It is recognised that using even the most effective interpolation method for a given application, a small degree of error is still likely to exist (Long, 2015). However, the acceleration capabilities of the device did not directly result in innaccurate overarm throw traces as the peak accelerations experienced were not extensively beyond the capability of the device. As such, the interpolation was only required for the estimation of a small quantity of data points (Akima, 1969). An additional limitation of the ActiGraph GT9X Link is the sampling frequency, which is restricted to 100Hz. Recent research suggests that for seven day habitual research, 30Hz is optimal (Clevenger et al., 2019) with no clear benefit beyond this point (Twomey et al., 2018), with higher frequencies up to 100Hz being utilised for more specific activity recognition (Bayat, Pomplun, & Tran, 2014; Ravi et al., 2005). However, even greater sampling frequencies are advantageous for recording high speed movements, such as the vertical jump, with Rantalainen et al. (2018) using accelerometers with a 256Hz sampling frequency to determine jump height. Increased sampling frequencies accommodate a larger volume of data points captured through the duration of the movement, and in doing so may enable increased clarity in the velocity changes and a decrease in the influence of error throughout each throw trace given the reduction in the space between each data point. Nonetheless, an increased capability of accelerometers is often accompanied by an increase in unit cost, so a compromise may be necessary to identify the best sampling frequency while retaining affordability. It is advised that an investigation be conducted, perhaps applying a Cost-Benefit Analysis (CBA), such that the visualisation can be optimised by selecting an appropriate accelerometer without incurring unnecessary additional costs.

It is noted that the initial concept was developed for the overarm throw following a deliberate selection based on the reviewed literature. The overarm throw was chosen as the most suitable Fundamental Movement Skill for which an initial visualisation aid could be developed, thus presenting the opportunity for subsequent carry over to other movement skills. Indeed, the expectation exists for the concept to be applied to other FMS and possibly other gross motor skills, such as the ‘foundational skills’ described by Hulteen et al. (2018), to enable a complete assessment of motor skill competency and support effective learning and motor skill retention. The overarm throw was selected for the initial concept development as it is an acyclic movement (Ogiolda, 1993), where the single wearable IMU was worn on the main limb involved in the skill: the throwing arm. This resulted in the omission of certain complexities associated with cyclic movements, such as false detection (Anwary, Yu, & Vassallo, 2018; Meland, 2017), and movements where there is not a definitive primary limb to locate the IMU (Sgrò et al., 2017). Nevertheless, it is acknowledged that challenges exist in transferring the visualisation method to other skills where these complexities cannot be avoided. For example, Sgrò et al. (2017) demonstrated that a single IMU worn on the lower back indicated relatively low accuracy for assessing a standing long jump, suggesting that additional sensors may be required for assessing this movement and those of a similar nature, particularly other locomotor skills. Mackintosh et al. (2016) showed the effectiveness of a number of accelerometer placements for assessing energy expenditure, revealing that neither anatomical location nor the combination of multiple accelerometers significantly influenced the prediction of energy expenditure. However, when visualising movement, it may be necessary to select more specific sensor placements relative to the movement being assessed. Lander et al. (2020) were able to accurately assess movement quality while developing visualisations using just four sensors; one on each wrist and one on each foot, which was claimed to be the minimum required to test a battery of FMS, despite acknowledging that fewer sensors could be used for single skills. Congruent with these claims, both Sgrò et al. (2017) and Masci et al. (2012) have delivered effective assessments of a single fundamental movement skill using just one sensor, though visualisations were not produced to aid the assessment in both these cases. Conversely, this thesis, which also focuses on a just one fundamental movement skill, demonstrates the possibility of producing an effective visualisation with a single sensor. Nonetheless, it remains necessary to consider which gross motor skills the visualisation tool may be adapted to and what other modifications are required to accommodate those with greater complexities to overcome. Furthermore, this thesis recognised that the acyclic nature of the overarm throw resulted in the captured accelerometer data presenting distinct initiation and conclusion points for the movement, with unimportant motion detected either side of the throw, allowing for the approximation of a time interval within which each throw could be isolated. It is not yet clear whether this approximation will be suitable for other FMS, particularly cyclic movements, where an initiation and conclusion of the movement is unlikely to be well defined (Anwary et al., 2018). Therefore, future work should seek to introduce automatic identification of movement initiation and conclusion and observe whether there is a greater need for improved accuracy and precision when identifying these points for other FMS.

The visualisation tool was generated using MATLAB 2019b software and in the current format would require the user to have access to MATLAB software. Moreover, it necessitates that the user uploads the accelerometer data and performs numerous manual actions to obtain the desired visual output. As one primary aspiration is for a reduction in FMS assessment time (Bisi et al., 2017; Valentini et al., 2018), the process by which raw data is collected, processed and delivered to the user must be automated. In addition, there is a requirement for the tool to be transferred for use beyond MATLAB, so the data can be captured using the wearable device, with the visualisation immediately provided via a mobile phone application (Anderson et al., 2007), a computer monitor (Wyeld & Hobbs, 2016), or through the wearable device itself, as is possible using a smartwatch (Pizza et al., 2016). There is also the prospect of applying machine learning, a benefit of which includes the ability to support the continued development of the visualisation by providing continuous updates as data is applied (Halilaj et al., 2018), such that the gold standard throw profile, error band boundaries and velocity limits are optimised. Another theoretical benefit of machine learning is the ability for the visualisation tool to adapt to the user and provide real-time biomechanical feedback (Zhang et al., 2019) by recognising familiar patterns and detecting improvements by capturing such data as anthropometric measurements and increases in maximum velocity.

The directions for future work proposed throughout this discussion highlight the novelty of the visualisation concept in a rapidly developing area that is otherwise saturated with wearable devices providing only quantitative feedback (Siscoe, 2019). Indeed, while there are certainly benefits to obtaining such feedback (Kaewkannate & Kim, 2016), there is often little to no strategy provided to aid in the improvement of these metrics. Conversely, the visualisation presented in this thesis provides qualitative feedback, which has already been shown to support essential development in children (Altunsöz & Goodway, 2016; Sharma et al., 2016). However, it also expands on prior research by offering a time-efficient method with additional outputs that also offers affordability. The maturation of the visualisation through further research and development would improve FMS in children, an indicator of physical competence (PC), and will therefore also increase overall PA (Giblin et al., 2014; Lubans et al., 2010) and physical literacy (PL; Whitehead, 2010), all of which are key to influencing athletic and academic successes, and social stature in later life. Concerningly, radical approaches are necessary in order to meet current targets for a global decrease of physical inactivity by 15% before 2030 (World Health Organization, 2018). However, without the competency in FMS required to effectively participate in PA, these targets are unachievable, emphasising the importance of this research and the timely delivery of this thesis.

4.1. Implications

There are many implications of the work presented in this thesis, including, but not limited to:

- A significant reduction in assessment time subject to further refinement of the concept, a benefit which will afford educators more time to focus on teaching and learners more time to concentrate on improving their performance of FMS.
- A reduction in the subjectivity of assessments, with the longer-term goal of eradicating subjectivity entirely. The present work has already progressed from the existing manual methods for assessing gross motor skills by demonstrating a reduction in subjectivity of the overarm throw through the identification of throw trace characteristics and the novel use of an error band.
- The provision of meaningful feedback on movement quality for educators and coaches with the addition of novel features, such as the error band and the provision of velocity data. Coupled with the use of clear 3-dimensional (3D) imagery, the present work also provides a more captivating experience than the current manual methods available for assessing gross motor skills.
- The provision of a baseline from which more sophisticated models seeking to refine and enhance the current concept can be developed. This thesis provides a platform upon which the concept can be further refined for the overarm throw, though it also presents an opportunity for expansion to assess other FMS, or indeed other gross motor skills.

4.2. Future Research Directions

The present work highlights numerous potential future directions that warrant further investigation, including:

- The collection of additional anthropometric data accompanied with further IMU-captured data, focusing on an expanded participant age range and an increased quantity of data from both boys and girls. This additional information will enable the exploration of both sex- and/or age specific visualisations while also enhancing automated classification accuracy. Furthermore, the additional data will allow alternative scaling methods for the visualisation to be trialled. Indeed, it is hypothesised that the most relevant anthropometric characteristics will be dependent to some extent on the specific FMS being considered, as indicated by the findings of Silva, Petroski, and Gaya (2013) who studied an array of gross motor skills. It is therefore necessary to ascertain whether the number of anthropometric variables can be minimised while providing sufficient information regardless of the FMS considered to avoid overcomplicating the process.

- The collection of a larger, more diverse sample would provide additional training datasets to enable effective cross-validation of the data to better demonstrate the efficacy of the concept. An important factor moving forward is that any refined concepts are rigorously trialled prior to commercialisation to demonstrate the suitability of the visualisation for its intended purpose.
- The improvement of the delivery of feedback by further reducing subjectivity and by incorporating additional features that can offer direct instruction or indications as to how the performance of the overarm throw can be improved. Ideally, the assessment will become entirely objective, possibly through the application of machine learning, thereby eradicating the need for additional training that generalist teachers may lack (Bisi et al., 2017; K. Kirk, 2012). It is also recommended that educators as the intended end users are consulted and indeed contribute to future developments to optimise user-friendliness and therefore the delivery of feedback from the educator to the learner.
- The automatic identification of movement initiation and conclusion to instantly isolate each individual throw. It is theorised that the inclusion of magnetometer and gyroscope data and the subsequent recognition of orientation (Kok et al., 2017) will enable the true isolation of the throw (Bisi et al., 2017; Kok, Hol, & Schön, 2014). Furthermore, the additional data may be advantageous when expanding the concept to other FMS, especially locomotor skills where the complexities that accompany such cyclic movements (Mentis, 2013; Pfau et al., 2005) may be overcome.

4.3. Thesis Conclusions

It has been demonstrated through this study that affordable non-optical technologies can be utilised to generate visualisations for assessing FMS. Moreover, in line with the primary aim of the study, effective visualisations were developed for the assessment of the overarm throw using a single measurement device. Introducing gold standard throws for comparative purposes, with the inclusion of error bands, enabled visual assessments to be conducted to evaluate the competency of each throw, where several observations that could be indicative of competency were identified, such as the throw velocity, containment within the error band and the shape of each throw trace. It is important to recognise the significance of these findings in transforming the way that gross motor skills are learned, stepping towards a faster, less subjective and cheaper way of conducting assessments relative to the alternative options currently available, while also encouraging a more captivating and accelerated learning experience with greater improvements in performance.

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