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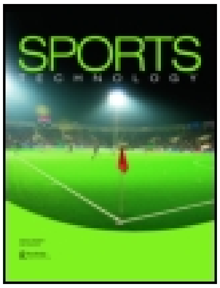

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RESEARCH ARTICLE

Visualization of wearable sensor data during swimming for performance analysis

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Abstract
Sensor-based biomechanical monitoring of sporting activity requires the interpretation of large data-sets of time series data-sets. Visualization techniques are a powerful method for displaying these data in a meaningful way to assist in understanding the complex interrelationships of the data and biomechanics. In particular, repetitive actions such as seen in many sports, including swimming can benefit from such analysis where overlay and visual comparison of multiple strokes can be advantageous. Many other disciplines, such as medicine visualize repetitive data and are translational opportunities for the investigation of biomechanical data, such as swimming. This paper presents a case study in which inertial sensor time series data from an elite and sub-elite swimmer were compared using visualization techniques to highlight differences in their action and performance. In particular, the metrics of body roll velocity was captured from the gyroscope sensor and was used as the key time series data to be visualized. Visualization techniques investigated were time-series overlay, phase space portraits, ribbon plot overlay, and wavelet scalograms. The phase space portraits, ribbon plots, and wavelet scalograms demonstrated clearly self-consistency of the swimmer's action. As a cross-comparison tool, these techniques showed clear difference between the elite swimmer, who had lower variability and thus a more consistent action than the sub-elite swimmer. This paper has demonstrated that there is merit in further examination of these techniques as a tool for feedback. It was found that all the methods presented unique views of stroke biomechanics in a nontechnical yet intuitive way for clearer communication.

Keywords: *visualization, swimming, inertial sensor, biomechanics, performance analysis*

Introduction

Visualization involves using a graphical representation to aid in the understanding of complex interactions and concepts and has been applied to the medical fields to aid in the understanding of complex electrophysiology where traditional methods are difficult to diagnose particular abnormality (Cooper, Rowlands, James, & Cutmore, 2005; Diery, Rowlands, James, & Cutmore, 2003; Page & Moere, 2006). More recently, visual methods have been applied to the sporting domain as an aid to understanding and presenting complex dynamics such as ball spin and aerodynamics (Fuss, Lythgo, Smith, Benson, & Gordon, 2011; Fuss & Smith, 2011). Swimming can also be considered as a complex system since the movement is based upon a complex and interrelated set of biomechanical actions (James et al., 2012; Lee et al., 2012) and is the focus of this paper.

It has been shown that from the early stages of learning to swim through to elite athletes, information given to swimmers is critical for continued improvement (Maglischo, 2003). Typically, the information provided would usually result in an increased level of skill. The more skilled an athlete becomes, the less reliance there is on having to think about what they have to do (Andersen, 1982). Therefore, performance becomes a product of efficient swimming.

Visual feedback is one of the most commonly employed methods in sport and can provide immense benefits when learning a new skill or improving an

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existing skill (Wulf, McNevin, & Shea, 2001). Providing external feedback has been shown to benefit athletic performance (Shea & Wulf, 1999). This means that feedback that highlights the outcome, rather than the action results in better performance outcomes.

Over recent years, sporting endeavors have been assessed using inertial sensors (Harding & James, 2010; Lee, James, Ohgi, & Yamanaka, 2012; Neville, Rowlands, Wixted, & James, 2012; Rowlands, James, & Thiel, 2009). Within these endeavors, swimming parameters have been the focus when using inertial sensor technologies (Davey, Anderson, & James, 2008; LeSage et al., 2011; Ohgi, Ichikawa, Homma, & Miyaji, 2003). In this case, swimming performance monitored by sensors can be used to provide feedback that coaches and athletes can understand. However, to date the feedback has been predominately technical in nature, requiring high technical literacy in athletes and coaches.

The inertial sensor data are typically streamed or stored in a time series format which shows the evolution of the signal over time. These data can be sampled at a high rate and therefore can generate a large amount of data that makes it difficult for the sport's professional to analyze. This time series data are useful but can be very difficult to discern trends or variations in the data due to volume of data that is typically produced. For example, a typical monitoring unit based upon inertial sensors will stream six channels of data at 100 Hz for the duration of activity. It appears that it would be useful to apply different visualization techniques to time series data in order for the data to be displayed on the one graph for ease of understanding.

Many sports contain repetitive actions that can be used to help in the visualization of the data. Varied visualization techniques based upon repetitive data have been applied to great effect in other disciplines such as in health (Cooper et al., 2005; Diery et al., 2003). Since swimming also consists of repetitive actions, many of these techniques can be applied to the activity. However, it is important that these techniques add extra to the understanding of the action, otherwise there are no benefits to using the techniques. Therefore, these techniques need to be investigated to determine whether any new opportunities for swimming or sport in general can be utilized.

This paper presents a case-based approach in which inertial sensor time series data from an elite and sub-elite swimmer was visualized in different forms to determine whether any merit existed warranting further examination. The visualization techniques that were investigated were time-series overlay, phase space portraits (two different methods), ribbon plots, and wavelet scalograms.

Experimental

This section gives the experiment methods used in this paper. It outlines the methodology employed to obtain the body roll data for the pilot study and then outlines the method used to create the visualization from the body roll data.

Data collection

Two competent swimmers (one elite and one sub-elite) freely consented to participate in this pilot study. The elite swimmer, a former Olympian, and the sub-elite swimmer had competed at State Swimming and National Age Championships. After reading the research information sheet, they signed the institution's ethical informed consent. Ethical approval (ENG/02/13/HREC) was guided by the Australian Code for the Responsible Conduct of Research and in line with the Helsinki Declaration.

A single sport specific designed inertial sensor was used for data capture (James et al., 2012). Sampling frequency of the sensor was 100 Hz and gyroscopic rate was 1500 rad s^{-1}. Data were collected from a sensor placed on the skin in alignment with S1 of the sacra. Sensor alignment was to the swimmer's orthogonal planes with X aligned to the longitudinal plane (swimming direction), Y to the transverse plane (mediolaterally) and direction of body roll, and Z perpendicular to the other two planes (anteroposterior orientation) (Figure 1). The gyroscopic data were the focus of this pilot investigation due to these being the cleanest signal and being a more true measure of the rotation as well as the fact that they are reasonably robust to small changes in orientation. This paper is mainly concerned with gyroscope rotation about the X-axis which corresponds to the body roll velocity.

Distance swum in each capture was two laps of a 25 m pool. The two participants commenced swims from an in-water standing position with a push off the wall signifying the start. Both participants were instructed to swim at their self-selected pace as if swimming for 400 m. The first lap was ignored to

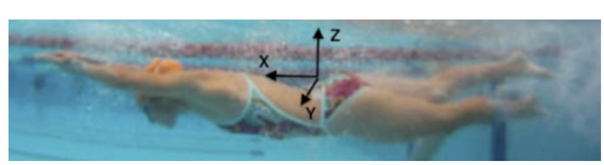

Figure 1. Sensor orientation. X: longitudinal (direction of travel); Y: mediolateral; and Z: anteroposterior.

allow for settling into the participant's typical technique. Data were taken from the second lap.

All the channels were preprocessed using a low-pass third-order Butterworth filter at a 2 Hz cutoff frequency to identify the peaks arising from the gross swimming action and to eliminate both the noise and faster moving artifacts. The body roll around the longitudinal axis due to the stroke action was examined in this study; hence, this pilot study focused upon the rotation velocity obtained from the gyroscope sensor. The gyroscope X channel corresponded to the rotation velocity of the body roll and the positive peaks indicated each stroke in the swimming action starting from the "catch" phase. The gyroscope Y channel corresponded to the rotational velocity associated with the tumble turn and indicated the end of a lap. Therefore, individual laps could be extracted and the individual strokes in that lap could also be extracted for visualization.

Visualization

The six visualizations detailed in this section were programmed in Matlab and six plots were produced. The six visualizations consisted of a time series plot, a time series overlay plot, two phase space plots built with two different methodologies, a ribbon plot, and a wavelet scalogram. In this paper, a single lap was chosen to see the effectiveness of the visualizations and to have enough repetitive data. The single lap was representative of the larger data-set.

The major steps involved in the visualization of the body roll for each swimmer were:

1. Filter X & Y channels using a low-pass third-order Butterworth Filter with cutoff at 2 Hz.
2. Find peaks in the Y channel. This corresponded to the tumble turns signifying the end of the lap.
3. Extract each individual lap data which is the X channel data between the peaks found in step 2.
4. Find the peaks in the lap data. This corresponded to the catch phase of each stroke.
5. Extract each individual stroke which is the lap data between the peaks found in step 4.
6. Plot the data using the required visualization technique.
7. Repeat step 6 for the six different visualization techniques.

The time series overlay plot consisted of plotting each individual stroke on the same plot which overlays the strokes allowing direct comparison. It was chosen since it appears to be an effective method to highlight any variations and identify any outliers in the data. This was performed using the Matlab plot() command applied to the stroke data. The plot for each stroke was overlaid on the previous plot.

The phase space portraits are parametric plots with one plot employing the derivative technique and the other plot employing an embedded delay technique (Zhenzhou, Xinbao, Yu, & Du, 2000). The derivative technique involved plotting the signal versus the first time derivative of itself ($\omega(t)$ vs. $\mathrm{d}\omega(t)/\mathrm{d}t$). The second method involved plotting the signal against a delayed version of another signal or itself ($\omega(t)$ vs. $\omega(t+\delta)$ where δ is a delay factor). As these plots are parametric, each repetitive stroke will form a loop or orbit on the plot. Multiple strokes in a lap will form multiple loops on the plot. Phase space was chosen because it is ideal for highlighting the consistency of the action. The phase space portraits were performed using the Matlab plot() command applied to the individual strokes in a lap. For the derivative method, the derivative of the stroke data was determined and a plot of each stroke versus its derivative was plotted. The plot for each stroke was overlaid on the previous plot. For the delay method, a plot of each stroke versus itself delayed by five samples was performed. The plot for each stroke was overlaid on the previous plot.

The ribbon plot was a three-dimensional plot that showed each individual stroke as a ribbon clearly delineating each stroke. The ribbon plot was chosen since it could give information about the consistency of the strokes. This was performed by using the Matlab ribbon() function.

The continuous Mexican Hat wavelet transform (Mallat, 2008) was applied to an entire lap to produce a 2D scalogram. The wavelet method was chosen because it has distinctive frequency and time localization (Mallat, 2008), thereby highlighting both consistency and variation. This was performed using the cwt() function from Matlab's wavelet toolbox.

Results

Figures 2 and 3 show visualizations of the swimming stroke cycle in six different formats for an elite (Figure 2) and sub-elite (Figure 3) athlete where the differences are visually clear. All plots were created from the second lap of a swim in a 25-m pool to allow for the athlete to settle into their natural action. The data analyzed in the two figures are based upon a single channel from the gyroscope inertial sensor corresponding to the angular velocity around the longitudinal axis (body roll velocity).

Typical data from inertial sensors can be displayed in the form of a continuous time series as shown in Figures 2(a) and 3(a). Each stroke cycle can be clearly seen and the repetitive nature of the stroke cycle with time can be seen.

Figures 2(b) and 3(b) show the time series data separated into individual stroke cycles and overlaid on

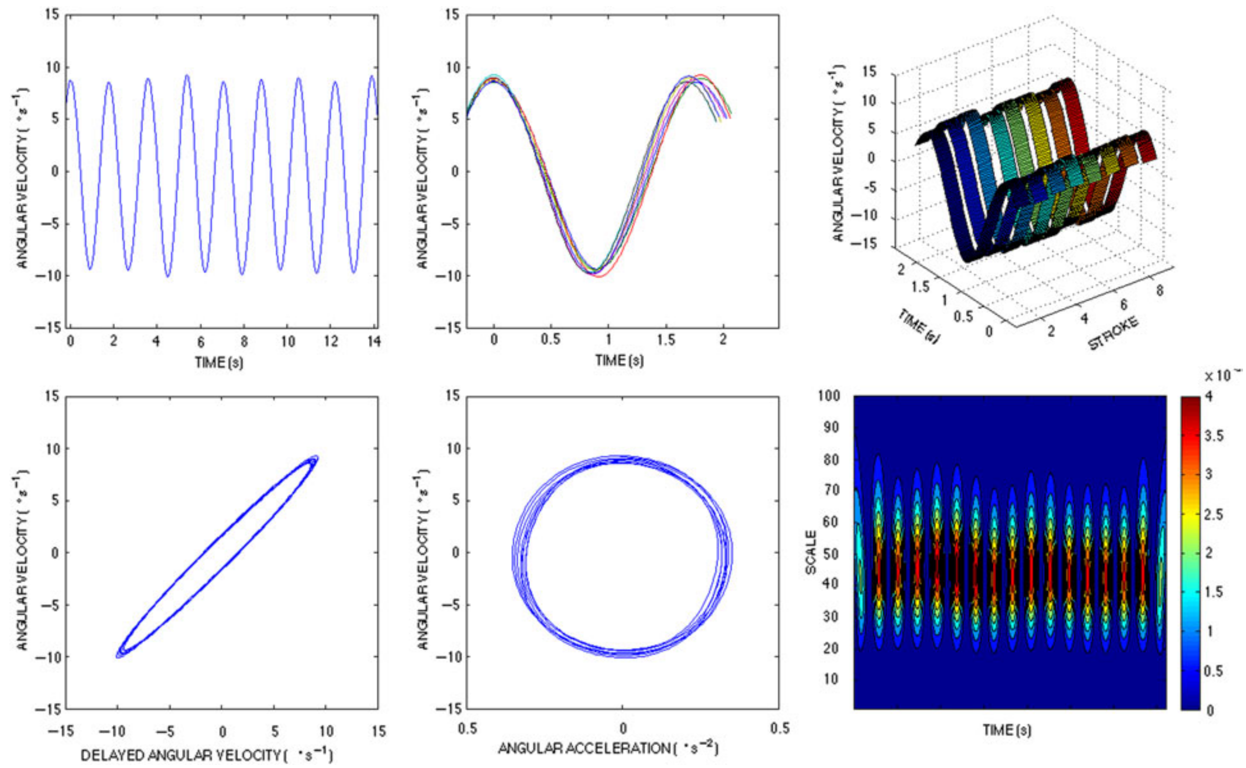

Figure 2. Six displays of body roll during one 25 m lap of freestyle swimming by an elite athlete. Starting top left to right. (a) Time series; (b) time series overlay; (c) ribbon plot; (d) phase space portrait (embedded delay method); (e) phase space portrait (derivative method); and (f) wavelet scalogram.

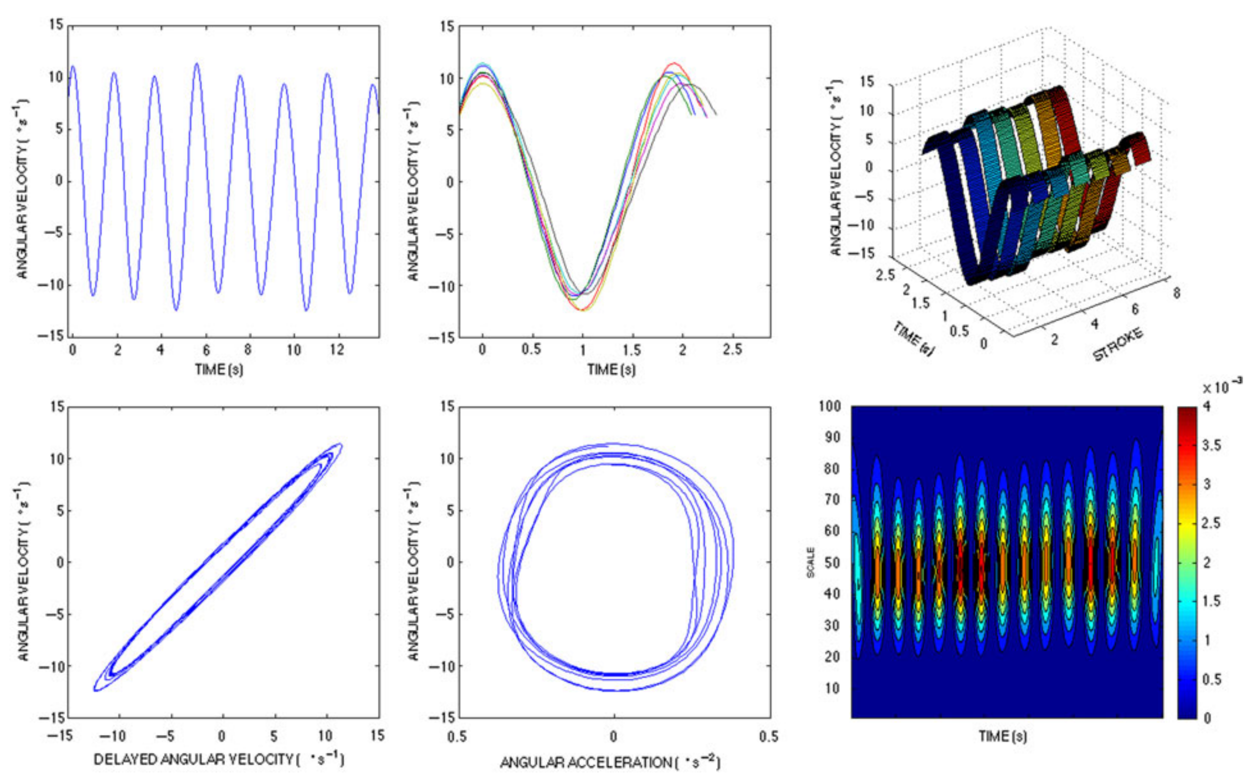

Figure 3. Six displays of body roll during one 25 m lap of freestyle swimming by a sub-elite athlete. The displays are the same as Figure 2.

top of each other. This plot displays the repeatability of body roll velocity during arm stroke cycles. The variation between the stroke cycles is clearly visible. The difference in consistency of the stroke cycles between the elite and the sub-elite is also apparent. There is a greater stroke consistency of the elite swimmer compared to the sub-elite swimmer. Through visual inspection, it is possible for a coach to determine whether the swimmer's breathing strokes affect subsequent non-breathing strokes.

A 3D ribbon plot based upon the individual stroke cycles is shown in Figures 2(c) and 3(c). Each ribbon corresponds to a single stroke cycle, so a pair of strokes would correspond to a left-hand side stroke and right-hand side stroke or vice versa. It is postulated that the higher peaks (clearest in Figure 3(c)) are due to the breathing stroke. Hence, it may be possible to identify breathing stroke information during the lap.

The phase space portrait created using the embedded delay method is shown in Figures 2(d) and 3(d). From these figures, the consistency in the stroke action can be seen as the tightness of the banding. The apexes of the ellipse correspond to the positive and negative peaks shown in the time series data. The asymmetry at the peaks can also be clearly seen as a spread in the banding at these points. This phase space portrait visualization also demonstrates greater variability in the stroke of the sub-elite swimmer's output (Figure 3(d)) compared to the elite swimmer (Figure 2(d)).

The phase space portrait created using the derivative method is shown in Figures 2(e) and 3 (e). From these figures, the consistency in the stroke action can be seen as the tightness of the banding. This phase space portrait can clearly show technique differences between swimmers such as the body roll velocity and how fast that changes during a stroke cycle. Any lag or lead will become apparent as a less circular trajectory. Comparing the graphs between the elite swimmer (Figure 2(e)) and the sub-elite swimmer (Figure 3(e)) indicates that each stroke cycle tends to be more consistent with the more experienced swimmer and that the body roll velocity and the body roll acceleration tend to track each other more consistently throughout the stroke.

The color in the wavelet scalograms in Figures 2(f) and 3(f) shows the amount of energy contained in a given scale at a given time (Diery et al., 2003) and the contours show the regions of equal energy. Each individual stroke can be clearly seen on the scalogram. The highest energy peaks for each stroke is contained in a band between scales 30 and 60 in both Figures 2(f) and 3(f). The shape of the strokes and the peak energy of the strokes can indicate the consistency of the stroke cycle. The elite swimmer's scalogram shows a consistent color range across all strokes (Figure 2(f)), whereas in the sub-elite swimmer's scalogram (Figure 3(f)), there is a variation in the color. This indicates that the elite swimmer's stroke cycle is more consistent than the sub-elite swimmer's stroke cycle.

Discussion

Swimming technique is difficult to monitor by traditional means; video is a clear tool though more recently the use of inertial sensor data has proven to be a valuable addition (Lee, Ohgi, & James, 2012). Visualization techniques can be applied to help the coach and swimmer understand the complex signals from these sensors and interactions involved in the swimming action. However, all performance assessment using any of these visualization methods needs to be effective for athlete feedback. If not, there is little benefit for swimmers or coaches. The purpose of this case study has been to examine novel visualization techniques applied to swimming in order to determine their merit for further investigation. In this study, two swimmers who were visually similar showed differing actions in the raw sensor data, though this was difficult to communicate in a nontechnical way. The aim was to explore visualizations that could benefit all parties involved in performance assessment through highlighting such differences. The paper presents six different possibilities of visualization of the same data. The correct options could be dependent on what may be analyzed for performance improvement.

The outputs displayed in various forms in Figures 2 and 3 indicate identifiable differences of body roll velocity. This is more apparent in some of the visualization processes than others.

Figures 2(a) and 3(a) are common time series plots. For a professional such as a sports scientist experienced in sensor use, the data at this stage can easily be taken for further analysis. To an untrained person, this direct output data would most likely mean little. However, information such as consistency or variation between the stroke cycles can be hard to see in the time series even when comparing the elite with the sub-elite. Hence, different visualization techniques may yield more information and hence were explored in this paper.

The time series overlay of strokes (Figures 2(b) and 3(b)) offered a different perspective on continuous time series. The width of the band of the overlays shows the consistency between each stroke cycle. The narrower the width, the more consistent the whole swim. Again, this will be of minimal benefit because there is no indication where any variation occurs in the swim, e.g. the change in consistency due to fatigue which occurs toward the end of the swim. A ribbon plot (Figures 2(c) and 3 (c)) may provide at what stage a change in the body roll velocity occurs.

The clear difference in skill level between an elite and sub-elite swimmer can be seen in the phase space portraits (Figures 2(d), 2(e), 3(d) and 3(e)). From this, a coach could get a sense of the consistency of a swimmer. The swimmer not as skilled had an output that displayed wider plot banding during the whole body roll cycle, and hence was less consistent in action. Furthermore, in Figures 2(e) and 3(e), the output was less circular in pattern indicating greater variances in the body roll acceleration. Differences in left to right symmetry of the strokes may be detectable with both styles of phase space portraits (Figures 2(d) and 3(d) and Figures 2(e) and 3(e)).

Symmetrical pattern changes may identify where a coach may have to target a swimmer's training. However, this may not be effective enough. It may have to be considered that viewing multiple visualization styles is needed for effective performance analysis. In such a plot, the coach may be able to identify which strokes might be affected during the course of a swim. A phase space portrait can identify a loss of consistency, and a 3D ribbon plot can be used to determine at what time in the swim the change started to occur. For example, it may be determined that the athlete may have to undergo a higher level of conditioning, or alternatively to teach the athlete to hold their technique once in a fatigued state. The blending of this with other developed research (James et al., 2012; Ride, James, Lee, & Rowlands, 2012; Rowlands, Laakso, McNab, & James, 2012) may result in effective real time feedback. Athletes receiving feedback promptly results in better performance improvement (Wulf et al., 2001). This will enable different feedback options to athletes and coaches.

The wavelet scalogram visualization also indicated consistency from the elite swimmer compared to the sub-elite swimmer. At this stage, what may be taken from this is that changes can be seen for each stroke which allowed determining at what point in time during the course of the swim a change occurred or whether the swimmer was inconsistent throughout the swim. Once it is known where the swimmer changes style, then this can be targeted by the coaches for improvement.

More investigation is required to ascertain the full potential and meaning of the data in the pilot study of visualization techniques presented in this paper. Additionally, the optimal visualization method or combinations of methods for each desired outcome need to be confirmed in order to achieve the best feedback tool for an athlete's focus. Since visualization is not the exact image of the athlete's action, the feedback would be considered an external focus. External focus methods of performance feedback have been shown to be more effective for skill improvement (Shea & Wulf, 1999). The outcome provides a focus on an effect rather than actual body movements. Therefore, feedback in the nature of understandable plots, such as the visualization plots produced in this paper, instead of video alone would most likely be more efficient in aiding performance improvement.

Conclusion

This paper presented a case study in which inertial sensor time series data from an elite and sub-elite swimmer were visualized in different forms to determine whether any merit existed warranting further examination. The repetitive nature of the swim stroke cycle allowed techniques from other disciplines to be applied to the repeating stroke cycles. The body roll velocity was captured from the gyroscopic sensor and was used as the time series data to be visualized. The visualization techniques that were investigated were time series overlay, phase space portraits (two different methods), ribbon plots, and wavelet scalograms. Obvious differences were observable in all the visualization methods. It was found that all the methods were able to give useful information about the consistency of the stroke cycle. Each of the visualization techniques also showed that the consistency was higher in the elite swimmer than the sub-elite swimmer which was expected. Therefore, these techniques do show merit due to the extra information that can be provided about the swimming action.

Future investigations will involve a deeper analysis of each of the visualization techniques to a larger number of swimmers to develop a better understanding of their outputs.

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