Towards Dynamic Visualisation: Interactive Analysis via the Cloud

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ABSTRACT

Inertial sensor technologies are quickly becoming more affordable, unobtrusive and ubiquitous, leading to an influx of data from multi-sensor configurations. By improving existing methods of analysis, the process of identifying and extracting useful patterns from this data can be facilitated. Extracted patterns may be used as direct feedback for athletes, or as input for dynamic visualisation systems [1].

Within the Centre for Wireless Monitoring and Applications (CWMA) at Griffith University, sporting data is often analysed via MATLAB, a numerical computation engine that allows users to design algorithms in the form of scripts, and visualise their output using table-, plot-, graph- and surface-based data representation templates. Depending on the nature of the data, these algorithms can require significant guesswork and estimation in the design process [2], while also demanding large amounts of storage space and processing time to execute them [3].

Through the use of modern server and web technologies, it is possible to delegate this type of data analysis to a cloud-based online system. The entire process, from data import to pattern extraction, can be performed by a centralised but internally distributed network of server computers. Ancillary client software can subsequently provide the user with a discrete, customisable interface for manipulating and refining algorithms interactively [1][4].

MATLAB-centric data analysis within the CWMA tends to follow a rather consistent pattern: (1) develop a script to produce visual output from the data (tables, plots, graphs and/or surfaces) by estimation, thresholding and regression; (2) run the script and review the generated visual representations; (3) adjust assumptions and refine the script to suit; and (4) repeat steps 2 and 3 frequently, and perform major revisions occasionally. Alternatively, in the proposed environment, the developer would avoid

estimation in step 1, and instead flag regions of uncertainty to be adjusted and refined in step 2. The user may still choose to perform steps 3 and 4, but will also have the ability to manipulate the script interactively through auto-generated instruments. These instruments, beginning with sliders, buttons and viewing tools, will apply minor changes to the script and re-execute it, thereby allowing visual representations to appear dynamic from the user's perspective. It is expected that the use of these instruments could replace direct manipulation of script code in some circumstances.

As an example of use, consider a supervised training session in which a freestyle swimmer has one triaxial gyroscope attached to each wrist during their time in the pool. Each gyroscope records 100 samples per second of angular rotation (Coriolis force component), and there are no specific reference points indicating the beginning or end of each lap. The sampled waveforms are likely to be affected by background noise, cumulative zero drift, variance in technique and fatigue levels. The supervisor uploads the data for analysis, and can visually observe groups (laps) of somewhat cyclic motions (strokes) within it. They decide to generate a 'wave-of-best-fit' for each lap by approximating known influences and including different types of unknown influence quantities. All contributing factors are adjustable, and can be overlaid onto the recorded data for fine-tuning. If successful, these waveforms can be standardised across multiple sessions and/or athletes, and provide a quantitative metric for perceiving long-term change.

While it is difficult to predict the efficacy of this technique in its early stages, the importance of developing next-generation tools can be seen by our dependence on those that exist today. It is hoped that the development of these new techniques will eventually facilitate a better understanding of the characteristics and patterns that influence sporting performance.

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