

INTRODUCTION

The use of data from wearable sensors to identify human activity is a staple of wearable computer research (Bulling et al., 2014). A core challenge arises from the need to partition these data into segments which can be used to label repetitions of discrete events which correlate with specific actions. Such an approach draws on signal processing techniques developed to work in the frequency domain and can, through stochastic processes, be used to recognise sequences of events. As Hammerla et al. (?) note “[t]herefore information about *what* subjects are doing is readily available, rendering activity segmentation a straight-forward followup task”. Identifying how well the action is performed is more challenging. When it comes to studying skilled or dextrous performance, recognition of sequences of events might not be sufficient. The reason for this is that dexterity is seldom a matter of performing events faster or even of sequencing the events in the same manner as the novice. Rather, the expert segues actions into smooth sequences which, through their overlapping and intertwining, become difficult for event-based approaches. An alternative is to apply time-series techniques to such data. The focus of this paper is on the use of a specific time-series technique to explore a specific aspect of dextrous performance. However, the approach can be easily applied to other data and domains. Before explaining the approach, the paper begins with a short discussion of dexterity in human performance.

DEXTERITY IN HUMAN PERFORMANCE AND HUMAN ACTIVITY RECOGNITION

Studies of skilled psychomotor performance indicate the expertise is not simply a matter of performing actions in a more consistent manner than novices. Often the expert is able to produce different but contextually appropriate actions in a manner that the novice is unable to perform. This highlights a paradox in human motor control: in order to act consistently, people need to produce stable patterns of movement which can be repeated efficiently, but these movements also need to exhibit sufficient variability to cope with changes in contextual demand. Biomechanics research explains this control of movement in two broad approaches: a common approach is to assume that movement is specified in a hierarchy of commands, with a high-level description of a movement goal defined in terms of location of end-point for a movement, from which is possible to calculate optimal paths for movement; or, less commonly, in terms of parameter optimisation. For these approaches, consistency is explained through the definition of ‘motor schema’ which specify the neural commands required to enervate the musculoskeletal system to perform a specific action. In such a system, variability in movement arises from noise and interference in the translation of motor command to the performance of the movement. This means that variability is seen as something which needs to be either ignored or dismissed. For Human Activity Recognition, the motor schema view of variability could lead to the assumption that it is beneficial to either filter out such ‘noise’ or to define averaged patterns which capture the underlying consistency in movement and recognise activity against these patterns.

An alternative approach sees variability in human movement as defined by the originating system. Yamamoto and Gohara (2000) define dexterity as “...the capacity of goal-directed movement to adapt itself to changes in the external environment...” An action involves the coordination of muscles and joints in an efficient manner and this raises the ‘degrees of freedom’, or ‘motor equivalence’, problem (Bernstein, 1967). The motor equivalence problem notes that each joint in the human body has several degrees of freedom in the postural angles that it can adopt, and that combining several joint angles in a given movement can result in a great many alternative postures, particularly when actions are performed dynamically. While people might appear to be making consistent motions in repetitive actions, there is sufficient variability to make it difficult to define a single solution to the motor equivalence problem. The challenge here is to reconstruct the originating system in such a way as to allow us to predict the parameters which are being optimised in the performance of the movement. From this perspective, dexterity, or expert performance, could arise from the use of specific parameters in the control of movement and the assumption is that experts seek to optimise different parameters to novices. Viewing human motor control in terms of dynamical systems allows researchers to consider how expert performance capitalises on the inherent ‘noisiness’ of the human movement system. This approach has been particularly fruitful in the field of skill in sports (Davids et al., 2003) and we believe that it offers an interesting perspective for activity recognition. Applying this assumption to Human Activity Recognition, the goal would be to identify the parameters that are being optimised in a data stream that is produced when activity is performed, rather than in identifying discrete events within that data stream.

RECOGNISING EXPERTISE IN DANCE

As Miura et al. (2015) point out “...how the human motor system produces dance movements is still poorly understood.” A key issue concerns the manner in which experienced dancers solve the degrees of freedom problem in the face of changing contextual demands. Miura et al. (2013) measured muscle activation using electromyography (EMG) collected from muscles in the lower limb, for a task requiring participants to bounce up and down in time to a metronome beat. They demonstrated that experienced dancers show much better precision in synchronizing movements to beat than non-dancers, i.e., dancers maintained much lower standard deviation in temporal deviation against the beat than non-dancers. This result is consistent with work which shows that, compared with inexperienced- or non-dancers, trained ballet dancers exhibit superior postural stability (Crofts et al., 1996), and show superior ability in position matching of upper limbs (Ramsey and Riddoch, 2001). This suggests that one dimension of dexterity in postural

control lies in the manner in which posture is managed and controlled. In addition to dexterity relating to posture, the work on Miura et al. (2013) indicates a further dimension, in the manner in which the timing of actions is managed.

Capturing dance activity through sensors has tended to rely on motion capture (Alexiadis and Daras, 2014) or sensors mounted on the person (Lynch et al., 2005) or in their shoes (Paradiso and Hu, 1997) or from their smartphones (Wei et al., 2014). Much of this work has been concerned with using the dancers' motion to work with multimedia presentations that augment and complement the dance (Griffith and Fernstrom, 1998; Park et al., 2006) or as interfacing to a game (Chu et al., 2012) or commercial games, such as *Dance Dance Revolution*. While the range of sensing technology used in these papers is diverse and the result of the activity recognition is varied, it is fair to say that few of the papers have considered variation in how well dance is performed. In their work, Aristidou et al. (2014) have considered the manner in which dance steps conform to a set of defined templates that describe steps in terms of three-dimensional rotation (described using quaternions). The implication is that a goodness-of-fit can be ascertained to determine how well a dancer performs a step, and how any deviation from 'good' can be modified through practice.

For this paper, we are interested in the question of how time-series techniques can provide insight into the dexterity of dancers. To this end, we consider the performance of a set of steps from Latin dance and compare untrained, inexperienced and non-dancers in one cohort with experienced dancers on another.

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