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Short communication

# Application of a symbolic motion structure representation algorithm to identify upper extremity kinematic changes during a repetitive task

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Efficient and holistic identification of fatigue-induced movement strategies can be limited by large between-subject variability in descriptors of joint angle data. One promising alternative to traditional, or computationally intensive methods is the symbolic motion structure representation algorithm (SMSR), which identifies the basic spatial-temporal structure of joint angle data using string descriptors of temporal joint angle trajectories. This study attempted to use the SMSR to identify changes in upper extremity time series joint angle data during a repetitive goal directed task causing muscle fatigue. Twenty-eight participants (15 M, 13 F) performed a seated repetitive task until fatigued. Upper extremity joint angles were extracted from motion capture for representative task cycles. SMSRs, averages and ranges of several joint angles were compared at the start and end of the repetitive task to identify kinematic changes with fatigue. At the group level, significant increases in the range of all joint angle data existed with large between-subject variability that posed a challenge to the interpretation of these fatigue-related changes. However, changes in the SMSRs across participants effectively summarized the adoption of adaptive movement strategies. This establishes SMSR as a viable, logical, and sensitive method of fatigue identification via kinematic changes, with novel application and pragmatism for visual assessment of fatigue development.



## 1. Introduction

The intricate relationship between upper extremity kinematics, task repetition, and tissue demands prioritizes identifying kinematic changes. Repeated efforts can cause shoulder muscle fatigue, leading to local kinematic changes including those that reduce the size of the subacromial space and increase injury likelihood (Chopp et al., 2010b). Currently, systematic identification and interpretation of within-subject kinematic changes during repetitive tasks is challenging due to large between-subject variability in upper extremity joint angle data descriptors (mean, range) (Frost et al., 2015; Tse et al., 2016). Thus, an alternative method to systematically identify within-subject kinematic changes is essential.

Approaches that concurrently consider the spatial and temporal aspects of joint angle motion may offer insight beyond consideration of means or ranges of joint angle data. The symbolic motion structure representation algorithm (SMSR) pioneered by Park et al. (2005) summarizes the basic spatial-temporal structure of joint angle data. SMSR identifies elemental motion segments and classifies them using symbols to reflect changes in joint angle magnitudes over the segment: (1) increasing (U), (2) decreasing (D), or (3) stationary (S). Time-ordered combination of these symbols creates an interpretable character string reflective of directional motion segments. Evidence that upper extremity joint movement strategies change during repetitive tasks (Fuller et al., 2011; Gates and Dingwell, 2008; Lomond and Côté, 2011) highlights the potential of SMSR as a method, to simplify identification of within-subject kinematic changes in repetitive tasks. This study investigated the utility of SMSR for identifying these changes.

## 2. Methodology

### 2.1. Subjects

Twenty-eight right handed participants (15 M, 13 F; 23.8 ± 3.9 years) free of upper extremity injury provided informed consent and completed the experiment. The study was approved by the university office of research ethics.

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*2.2. Instrumentation*

Participants were instrumented with 9 reflective markers and rigid clusters on the torso, humerus and forearm segments (Table 1). Reflective markers were placed on task-specific targets and the manipulated hand load (bottle). The 3D position data of these markers were recorded at 50 Hz using 8 Vicon MX20+ cameras (Vicon Motion Systems, Oxford, UK).

Muscle fatigue was quantified as a decrease in maximal force generating capacity following the repetitive task (Vøllestad et al., 1997). Force data were recorded during external rotation maximal voluntary isometric contractions (ER-MVIC), at rest and immediately following the repetitive task, using an AMTI 6 degree-of-freedom force transducer (MC3A, AMTI, MA, USA). Participants were seated with their right arm in 0° thoracohumeral elevation, 45° thoracohumeral external rotation, 90° elbow flexion and the dorsal hand against the force transducer. Participants gradually produced external rotation force to maximum and then gradually returned to rest (Brookham et al., 2010a; Kelly et al., 1996). At baseline 3 ER-MVICs were performed, each separated by 2 min of rest (Chopp et al., 2010a; Ludewig and Cook, 2000). A single ER-MVIC was performed following the repetitive task. Multiple ER-MVIC efforts after the repetitive task were not performed due to likely fatigue recovery contamination of the estimate. Force data were amplified (1000×), sampled at 150 Hz, and converted to a digital signal using a 12 bit A/D card and Vicon Nexus software.

*2.3. Protocol*

Participants performed a seated repetitive task consisting of transferring a weighted bottle, set to 40% of their baseline maximum ER-MVIC, between 2 targets at a 1 Hz frequency paced via metronome. Audible bottle placement was synchronized with the audible metronome beep (Bosch et al., 2012; Cantú et al., 2014; Fuller et al., 2013). To mitigate potential anthropometric effects, the targets were positioned at set azimuth angles from the principal body planes and at distances scaled to participants' reach lengths (Fig. 1). Kinematic data were recorded every other minute, referred to as an "epoch". The task was terminated if any of the following criteria occurred: (1) rating of perceived discomfort or fatigue ≥ 8/10, (2) verbal request to stop, or (3) 60 min.

**Table 1**
Locations of the passive kinematic markers placed on the participants, grouped according to body segments. The 3D position of markers placed overtop of boney landmarks on the humerus and forearm were recorded during a calibration trial to develop an anatomical calibration matrix describing the position of the anatomical landmarks on the humerus and forearm within the respective cluster coordinate systems. During the repetitive task, the marker clusters were used recorded and used in conjunction with the anatomical calibration matrix to construct the joint coordinate systems.

| | Kinematic markers | |
|---|---|---|
| Body segment | Boney landmarks | Marker cluster |
| Thorax | Xiphoid Process<br>Suprasternal Notch<br>Cervical Vertebrae 7<br>Thoracic Vertebrae 8<br>Acromion Process | N/A |
| Humerus | Medial Epicondyle<br>Lateral Epicondyle | Humerus Marker Cluster |
| Forearm | Radial Styloid<br>Ulnar Styloid | Forearm Marker Cluster |

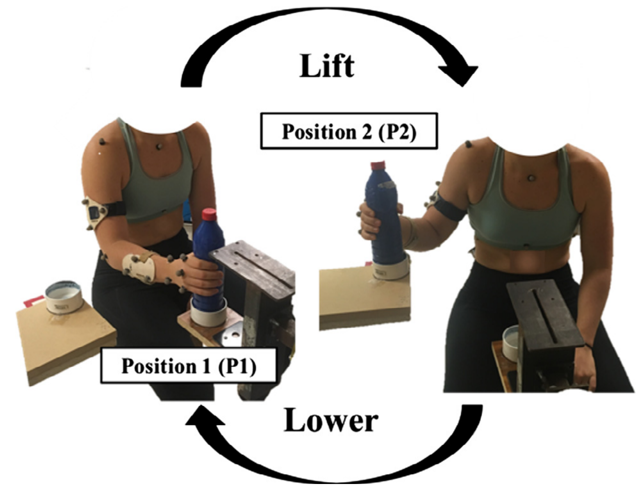


**Fig. 1.** A schematic representation of the repetitive task performed during this study. Participants lifted and lowered a weighted bottle (40% MVC) at a 1 Hz frequency between 2 positions (referred to as targets). The locations of the targets were scaled to participants reach length. Position 1 was directly in front of participants' right shoulder, and position two was aligned with the scapular plane (40° anterior to frontal plane).

*2.4. Data analysis*

Kinematic data were digitally bandpass filtered using a dual pass 2nd order Butterworth filter (fc = 5 Hz) and lift motions were identified using the position and velocity of the bottle. The bottle was considered at rest when its vertical velocity was between ±10 mm/s for ≥40 ms (Burkitt et al., 2015).

The last 5/15 lifts in an epoch were analyzed, coincident with prior characterization of fatigued upper limb kinematics (Fuller et al., 2011, 2009; Lomond and Côté, 2011). Thoracohumeral and forearm joint angles were computed using the 3D position of the cluster markers and an anatomical calibration matrix representing the relationship between the cluster and body segment coordinate systems (Winter, 2009) (Table 1). Torso to global and elbow joint angles were computed using a Z-X-Y rotation sequence (Wu et al., 2005) while an X-Z-Y sequence was used for thoracohumeral angles (Phadke et al., 2011).

*2.4.1. Symbolic motion representation algorithm (SMSR)*

The SMSR algorithm (Park et al., 2005) consisted of 4 steps to characterize joint angle time series data as a string sequence of shape-centric symbols. First, data points were classified as landmarks according to criteria: (1) the first or last point in the time series data, (2) a local maxima or minima, (3) the start or end of a stationary segment; a point at time t in which the derivative at either t − 1 or t + 1 (not both) was greater than the user specified threshold "*elsope*". Next, close proximity (within a minimum segment duration, '*etime*') landmarks were combined. Remaining landmarks were considered boundary points. Third, the "*e-angle*" of angular displacement determined whether each segment, encompassed by successive boundary points, was stationary (***S***), increasing (***U***), or decreasing (***D***). Park et al. (2005) recommended physiologically-derived user defined thresholds of *eslope* of 1°/min (Clark et al., 1985, 1986), *etime* of 1/6s (Wikens, 1986), *and e-angle* of 1° were applied. Finally, consecutive duplicate strings (i.e. SS becomes S) were removed. Remaining symbols were concatenated into string representations. Strings computed for each of the 5 lifts per epoch were collapsed and, when multiple strings existed in an epoch, the most common across the 5 lifts was selected. At the participant level, for each joint angle, strings