Adaptive velocity-based six degree of freedom load control for real-time unconstrained biomechanical testing

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Abstract

Robotic biomechanics is a powerful tool for further developing our understanding of biological joints, tissues and their repair. Both velocity-based and hybrid force control methods have been applied to biomechanics but the complex and non-linear properties of joints has limited these to slow or stepwise loading, which may not capture the real-time behaviour of joints. This paper presents a novel force control scheme combining stiffness and velocity based methods aimed at achieving six degree of freedom unconstrained force control at physiological loading rates.

Keywords: spine, biomechanics, load control, adaptive stiffness matrix, hexapod robot

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1. Introduction

Robots have great potential to further the field of biomechanics. They present the capacity for more advanced and more physiological testing of whole joints, bones, soft tissues and implants than previously possible (Fujie et al., 1993; Walker and Dickey, 2007; Goertzen et al., 2004; Gilbertson et al., 2000; Bell et al., 2013; Kelly and Bennett, 2013). Parallel robots are particularly well suited to biomechanical testing due to their high stiffness, precision and force capacity (Ding et al., 2011). Furthermore, robotic methods in general enable advanced, integrated testing techniques such as the reproduction of recorded in vivo kinematics, closed loop position and force feedback control, four dimensional vectoring and broad biomechanical applicability.

The utility of in vitro testing is highly dependent on the physiological relevance of the testing methodology. With particular respect to the spine but regardless of testing platform, the prevalent stepwise or quasi-static methods do not capture the dynamics of human movement and have been shown to produce differing results (Goertzen et al., 2004). Despite contention and a bias toward the flexibility protocol in the literature (Goel et al., 1995; Wilke et al., 1998; Panjabi, 2000, 2007a,b; Crawford, 2007), we recognise that the stiffness, flexibility and hybrid protocols are each situationally appropriate. All three protocols can be achieved with robots, however system compliance has a large influence on the performance (Walker and Dickey, 2007). Confounded by the unknown, nonlinear, biphasic, viscoelastic and anisotropic material properties of biomechanical applications, deployment of the load control algorithms required for dynamic flexibility and hybrid protocols remains limited and has yet to be optimized.

Goertzen and Kawchuk (2009) introduced velocity-based load control for biomechanical testing with an approach that does not account for specimen stiffness. In this method the magnitude of the difference between the force command and force feedback (force er-
ror) is used to linearly regulate a velocity in position control within a predefined force error window. Outside this window, a maximum velocity threshold is set which ensures stability and minimises overshoot. If this threshold is low enough to guarantee stability, the velocity can be independent of specimen stiffness, which is advantageous for biomechanical testing. This method is broadly applicable to any robot with a jog function, however the limitation of this approach is the very slow realisation of force targets and restriction to step inputs. These limitations are also encountered with hybrid position-load control (Walker and Dickey, 2007; Fujie et al., 1993; Tian and Gilbertson, 2004; Bell et al., 2013; Gilbertson et al., 2000), wherein a stepwise method calculates the stiffness matrix of the previous motion step and predicts the displacement required in the next iteration to achieve the desired force. This method is computationally expensive and has been restricted to stepwise quasi-static loading.

The overall objective to which this work contributes is to enable more physiologic, dynamic in vitro biomechanical joint and tissue testing. This study specifically aims to build on the work of Goertzen and Kawchuk (2009) and develop an adaptive stiffness velocity-based six degree of freedom (6DOF) unconstrained load control method in an effort to increase the loading rate and command complexity of dynamic testing beyond that which has previously been possible. The algorithm is applied to a hexapod robot (Ding et al., 2011) (Figure 1, Table 1) but is similarly applicable to other parallel or serial robots.

2. Methods

Briefly, the hexapod robot was based on the concept of the Stewart Platform and employs six servo-controlled ball screw driven actuators that precisely position a mobile upper plate with respect to a fixed base plate (Figure 1). Specimens are bolted between the fixed base and the mobile upper plate. Displacements and rotations of the speci-
Table 1: Hexapod Specifications (from Ding et al. (2011))

<table>
<thead>
<tr>
<th>Axis</th>
<th>Hexapod Capacity</th>
<th>Hexapod Accuracy</th>
<th>Load Cell Capacity</th>
<th>Load Cell Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axial</td>
<td>20 kN</td>
<td>±0.02 mm</td>
<td>4450 N</td>
<td>±0.4 N</td>
</tr>
<tr>
<td>Bending</td>
<td>2 kN m</td>
<td>±0.02°</td>
<td>113 N m</td>
<td>±0.01 N m</td>
</tr>
<tr>
<td>Torsion</td>
<td>1.5 kN m</td>
<td>±0.02°</td>
<td>56.5 N m</td>
<td>±0.01 N m</td>
</tr>
<tr>
<td>Shear</td>
<td>6 kN</td>
<td>±0.003 mm</td>
<td>2225 N</td>
<td>±0.04 N</td>
</tr>
</tbody>
</table>

Men were directly measured by six linear optical encoders with a resolution of 0.5 µm (B366784180185 LDM54, MicroE Systems, USA) that were positioned independently to the loading frame and load cell. This configuration eliminated system compliance from the measurement of specimen behaviour, as detailed in Ding et al. (2011). Forces and moments were measured by a six axis load cell (MC3A-6-1000, AMTI, USA) having a maximum axial compressive force capacity of 4450 N and 56.5 N m of axial torque. The displacement measurements were independently validated prior to this study to NATA standards (ISO 10360-2, 2009) and the load accuracies were based on NATA calibrations provided by AMTI (Table 1).

Dynamic stiffness based velocity control was developed by relating the velocity to force error through an adaptive gain representative of the system stiffness. Since it is very difficult to know the 6 x 6 stiffness matrix of a biological specimen, six decoupled adaptive gains were introduced that account for the 6DOF anisotropic, non-linear modulus:
\[ K_{g}^{-1} = \begin{pmatrix} k_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & k_6 \end{pmatrix} \] (1)

where \( K_{g}^{-1} \) is the decoupled time-varying stiffness matrix having non-zero diagonal terms only and \( k_i (i = 1 : 6) \) is the gain representative of the specimen stiffness in each of the six degrees of freedom. The scheme (Figure 2) applies an upper level force feedback controller running at 100 Hz to calculate the desired velocities of the specimen \( v^s_d \), which is then integrated to obtain the required specimen displacements \( d^s_d \) for the robot’s lower-level position control stage, which has been implemented on two field-programmable gate array (FPGA) boards at 10 kHz. Each gain in the decoupled stiffness matrix is optimized based on the force tracking performance in the corresponding DOF. This implicitly allows the force controller to adapt to unknown system non-linearities, specimen coupling and robot dynamics.

The adaptive gain algorithm monitors the command and feedback load signals from the previous second and decides to increase, decrease or maintain the gain based on the root mean square (RMS) error, oscillation frequency and time-weighted average of the feedback with respect to the command (Figure 3).

System stability and performance were improved by reducing the sensitivity of the velocity response to signal noise. Relating velocity to force errors by a hyperbolic sine function below a tunable threshold reduces both noise sensitivity and overshoot by ensuring steep but smooth and continuous deceleration as the force error converges to the noise floor of the load cell (Figure 4, Equation 2).
\[
\mathbf{v}_f = \begin{cases} 
\varphi, & k_j e_c \geq \varphi \\
-\varphi, & k_j e_c \leq -\varphi \\
k_j e_c, & k_j \delta \leq |k_j e_c| < \varphi \\
\sinh(\text{asinh}(k_j \delta)\frac{e_c}{\delta}), |e_c| < \delta 
\end{cases}
\]  

It has been demonstrated that both the inclusion and method of application of compressive preload affects the stiffness of the spine (Cripton et al., 2000; Patwardhan et al., 2003; Gardner-Morse and Stokes, 2004). Similarly to Bennett and Kelly (2013), the load control algorithm was used to develop a decoupled preload vectored perpendicular to the mid-transverse plane of the disc. The preload is decoupled in the sense that it is independent of the applied test commands and is thus constant throughout all dynamic tests and recovery periods (Figure 2).

Any neutral zone of a biological joint can cause poor performance in load control. Very low stiffness in the neutral zone creates a situation wherein even a small force error causes the robot to displace to the edge of the neutral zone because the force error cannot converge until the specimen exhibits a tangible stiffness. This condition is difficult to predict and is highly dependant on the specimen, test type and loading rate. Longer duration shear, compression and recovery preload conditions are likely to experience slow but unrecoverable bending rotations in 6DOF force control. In this work the neutral zone was managed by constraining the affected bending axis in position control for long recovery periods and slower shear tests that experienced large rotations to the edge of the neutral zone (Table 3). Together with the constant presence of the preload, this constraint established a reproducible datum from which to begin each test and dynamic tests remained correctly aligned with the anatomical axes.

An ovine functional spinal unit (FSU) was tested to demonstrate this algorithm in a
biomechanical context due to its ready availability and similarity to human lumbar spine (Wilke et al., 1997). A fresh-frozen ovine lumbar spine was flensed of all non-ligamentous soft tissue and an FSU was dissected by cutting through the vertebral bodies parallel to the mid-transverse plane of the intervertebral disc (IVD). Wood’s Metal (LW4, AMAC Alloys, Australia), due to its increased stiffness over polymethyl methacrylate (PMMA) and dental stone (Kim et al., 2006), was used to pot the FSU in alignment with the hexapod coordinate system. During testing, the FSU was submerged in a protease inhibited phosphate buffered saline (PBS) bath kept at 37°C to simulate a physiologic environment, since the testing environment has been shown to affect results (Costi et al., 2002; Race et al., 2000). Further, a compressive preload directed normal to the disc mid-transverse plane and acting through the specimen centre of rotation (COR) generating a typical 0.2 MPa intradiscal pressure (Sasaki et al., 2001; Wilke et al., 1999; Edwards et al., 2001) was applied to most closely mimic in vivo loading conditions. It was concluded that the unconstrained algorithm would converge to rotating about the specimen’s COR, however the preload and moment transformations required an initial estimate of the COR which was calculated by the Pearcy and Bogduk (1988) method, which assumes symmetry about the sagittal plane and is fixed. Isolated directions were tested via haversine command waveforms, due to the highly anisotropic nature of the IVD (Costi et al., 2008). Force targets were designed to explore the nonlinearity of the specimen without causing damage. The algorithm was demonstrated in each primary axis - compression, flexion/extension, lateral bending, axial rotation, posterior and lateral shear. The limits of the algorithm were tested by increasing the loading rate from a baseline of 0.01 Hz until tracking performance monitored in real-time was subjectively deemed to have substantially deteriorated. 6DOF RMS force errors were calculated and grouped into force and moment axes for each test. The RMS tracking error provides a sense of the overall ability of the system to achieve the desired force-target waveform on the primary axis at the prescribed frequency.
The adaptive algorithm is designed to be self-tuning, however its region of operation must be bound by system-specific user-defined parameters to protect the specimen and prevent system instability. These parameters are fine-tuned by trial and error from their physical representations, balancing the inversely proportional stability and responsiveness characteristics of the system (Table 2). The boundary parameters should be retuned when the joint type or system changes, but are intended to remain constant between specimens of the same joint.

3. Results

Results of the boundary parameter tune for this system are presented in Table 2. Once the trial and error tuning process produced subjectively satisfactory results, these parameters were set for the duration of the study. The use of a hyperbolic sine drastically reduced noise sensitivity and oscillation due to overshoot compared to a linear velocity-force error relationship, although it also decreased system responsiveness.

Example load versus time and stiffness plots are illustrated in Figures 5 - 6. Test parameters and RMS force errors are summarised in Table 3. Force and moment errors across all primary axes were restricted to twice the noise floor (±5 N, ±0.3 N m) of the load cell signal, with the exception of the shear axes in axial rotation at 0.3 Hz (11.7 N) and bending axes in posterior shear (0.61 N m) and compression (0.67 N m). In flexion, the tracking error increased by 134 % (0.40 to 0.93 N m) with an order of magnitude increase in test frequency (0.01 to 0.1 Hz), although the increase in RMS force and moment errors was less pronounced (94 and 28 %, respectively). The tracking error fell by 41 % between 0.01 and 0.1 Hz in axial rotation, but increased by 160 % at 0.3 Hz. Increasing the force target from 200 to 300 N at 0.01 Hz in compression reduced tracking error (10 %) and RMS force error (18 %) but the constrained bending axis caused a 416 % increase in RMS moment error (Table 3).
4. Discussion

An adaptive velocity-based load control algorithm was implemented on a parallel robot (Ding et al., 2011) and demonstrated on an ovine FSU. This algorithm builds upon the velocity-based methods of Goertzen and Kawchuk (2009) and improves upon previous implementations of load control (Goertzen and Kawchuk, 2009; Walker and Dickey, 2007; Bell et al., 2013; Bennett and Kelly, 2013), particularly in its ability to test at physiological rates. This work demonstrates average loading rates between 19 and 578 times faster than that presented on rabbit lumbar spine by Goertzen and Kawchuk (2009), with a corresponding 12 to 32 fold increase in RMS errors. With a well conditioned signal and by manually tuning their cascaded force over position control loops, Kelly and Bennett (2013) demonstrated excellent accuracy (mean tracking errors across all tests and DOF (< 0.81 ± 0.68 N and 0.18 ± 0.19 N m) at an effective 0.02 Hz in 6DOF tests on human lumbar spine in their custom machine.

By adapting to system stiffness in real-time this routine is platform independent, however the characteristics of the hardware, particularly system compliance and temporal, positional and load-cell resolution dictate the method’s performance, as experienced by Walker and Dickey (2007). With a retuning of the boundary parameters the adaptive algorithm is applicable to any joint or tissue. The parameters tuned for this work (Table 2) may serve as a starting point for deployment to other joints and systems. Multi-segment spines could be tested with this method, however measurement of intersegmental motions and forces would require external measurement systems and sacrifice of the temperature controlled bath.

The maximum loading rate achievable by the adaptive algorithm is in principle limited by the maximum speed of the end effector. In practice, biomechanical joints are highly complex and the maximum achievable testing frequency is determined by system stability.
and the tracking and off-axis RMS force errors considered acceptable in the context of the tests being performed.

6DOF load control performance, especially oscillatory stability (Figures 5-6, top, middle), was observed to be highly direction dependent due to complex axis coupling and anisotropic material properties (Figures 5-6, bottom). Control performance was best in axial rotation, in which facet joint engagement linearises FSU stiffness and limits hysteresis compared to bending tests such as flexion, in which the spine’s stiffness is highly non-linear and significant hysteresis is observed due to the bi-phasic and viscoelastic IVD (Costi et al., 2008). Control system stability, FSU mechanical properties and coupling are also loading rate dependant. These attributes demand, but have until now prevented, unconstrained protocols from being performed at rates representative of dynamic in vivo motions. This algorithm has enabled real-time testing and demonstrated continuous loading at rates up to 4.8 N m s$^{-1}$. This advance in real-time control over earlier methods represents a significant milestone in the pursuit of more relevant in vitro biomechanical testing and a deeper understanding of dynamic in vivo joint and tissue mechanics.

This method should be considered in the context of its limitations. Since the algorithm is velocity controlled, large or rapid changes in force error, due mainly to inconsistent specimen stiffness, will cause rapid changes in the velocity prescribed to the system. Although the average velocity is describing a smooth, continuous waveform, the inter-loop accelerations may be much higher and oscillatory, which may not represent the way the spine experiences changes in force in vivo. Any lever arm between the load cell and specimen COR will generate a moment at the load cell and corresponding corrective rotation in response to shear experienced by the specimen. While we minimised the distance between the specimen and load cell, this condition was exacerbated by the substantial neutral zone and restricted the unconstrained testing of shear to 5DOF. The noisy load cell signal severely limited control stability and hampered efforts to reduce tracking errors on all
axes. The sensitivity of the algorithm was tuned to reduce the influence of noise on the system response, however this also caused increased delay and decreased precision due to the increased magnitude of the force error required to elicit a significant change in velocity. Minimisation of the noise floor by hardware upgrades is expected to increase the responsiveness of the load control algorithm and significantly improve tracking performance on all axes. Incorporating an adaptive COR algorithm such as described by Bell et al. (2013) should see further improvements in high speed performance and physiological relevance.

This work has demonstrated the adaptive algorithm’s ability to apply a real-time load waveform at physiological rates in 1DOF while maintaining a constant force target in 5DOF and a three dimensional preload vector. With the addition of this load control method to the intrinsically position controlled robot, the stiffness, flexibility and hybrid protocols can be applied as appropriate. Furthermore, new protocols combining position and load control can be explored. Future work includes extending the algorithm to super-impose multi-DOF waveforms and replicate recorded in vivo kinetics.

5. Acknowledgements

The authors wish to thank Mr Richard Stanley for manufacturing the tooling required for this work.

6. Conflict of interest statement

The authors have no personal or financial relationships that could inappropriately influence this work.
7. References


Figure 1: Hexapod robot. The specimen is fixed to the central pillar and manipulated by the end effector, which is connected to the actuators only through the load cell, decoupling the sensing and loading frames.
Figure 2: Block diagram showing the adaptive velocity-based force control scheme. Subscripts \( d \) and \( r \) represent the desired and real value, superscript \( s \) is the value at the specimen centre of rotation (COR). \( \{Sp\} \) is the specimen coordinate system with origin at the COR. The load cell loads \( W^l_r \) in the load cell coordinate system \( \{Lp\} \) are transformed to the loads \( W^s_r \) in \( \{Sp\} \). \( W^s_r \) is the superposition of the six axis commands \( W^u_d \) and the preload \( W^p_d \). Saturation and hyperbolic functions in the feedback controller ensure stability.
Figure 3: Block diagram of the adaptive gain logic at each discrete time $t_j$ (100 Hz). A load error vector $e_f = [e_1...e_{10}]$ is sampled from the previous second. The RMS value of $e_f$ is calculated and compared to a defined threshold $a$. $e_{rms} \leq a$ means the force tracking error is controlled within the acceptable range by the current control gain $k_{j-1}$, thus $k_j = k_{j-1}$. If $e_{rms} > a$, the current gain is inadequate. An index $n = \sum_{i=1}^{9} \text{XOR}(\text{sign}(e_i) > 0, \text{sign}(e_{i+1}) > 0)$ counts the number of sign changes (NSC) in $e_f$. $n \geq 3$ means the error is oscillating and the system is likely unstable; thus, the gain is decreased by a defined constant $b$ to increase stability. If $n = 2$ the gain is reduced by $b/2$ to discourage a tendency toward oscillation. If $n \leq 1$, the error is due to tracking lag and the gain is increased proportionally to the weighted average of $e_f$, $e_{wa} = \frac{1}{1023} \sum_{i=1}^{10} 2^{i-1} e_i$. Finally, $k_j$ is bound by user-defined $k_{max}$ and $k_{min}$ to tune system stability and responsiveness.
Figure 4: General form of the relationship between velocity $v_f$ and force error $e_c$. $\varphi$ is the saturation threshold that controls maximum robot velocity. The slope of the linear region $k_j$ is the current value of the adaptive gain for that axis. The reaction of $v_f$ to $e_c$ with a low signal-to-noise ratio is damped by the sinh function between the tunable force error threshold $\pm \delta$. 
Table 2: System specific user-defined algorithm boundary parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Related to</th>
<th>6DOF Vector</th>
<th>Units</th>
<th>Increase for</th>
<th>Decrease for</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_{\text{max}}$</td>
<td>Inverse of approximate</td>
<td>[50 50 20 900 900 900]</td>
<td>$N=\text{N m as appropriate}$</td>
<td>Responsiveness</td>
<td>Stability</td>
</tr>
<tr>
<td>$k_{\text{min}}$</td>
<td>specimen stiffness range</td>
<td>[1 1 0.2 20 20 20]</td>
<td>$10^{-3} \text{ mm s}^{-1} \text{ N}^{-1}$</td>
<td>Responsiveness</td>
<td>Stability</td>
</tr>
<tr>
<td>$a$</td>
<td>Acceptable RMS error</td>
<td>[5 5 0.3 0.3 0.3]</td>
<td>$N$</td>
<td>Stability</td>
<td>Tracking</td>
</tr>
<tr>
<td>$b$</td>
<td>Highest anticipated rate</td>
<td>[0.1 0.1 0.05 2 2 2]</td>
<td>$10^{-3} \text{ mm s}^{-1} \text{ N}^{-1}$</td>
<td>Stability</td>
<td>Responsiveness</td>
</tr>
<tr>
<td>$c$</td>
<td>of stiffness change</td>
<td>[0.02 0.02 0.01 2 2 2]</td>
<td>$10^{-3} \text{ mm s}^{-1} \text{ N}^{-1}$</td>
<td>Responsiveness</td>
<td>Disturbance rejection</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Noise floor</td>
<td>[5 5 0.3 0.3]</td>
<td>$N$</td>
<td>Noise rejection</td>
<td>Responsiveness</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Maximum allowed velocity</td>
<td>[2 2 2 3 3 3]</td>
<td>$\text{mm s}^{-1}$ or $^\circ \text{s}^{-1}$</td>
<td>Tracking</td>
<td>Specimen protection</td>
</tr>
</tbody>
</table>
Table 3: Summary of results. Shear tests were constrained in the coupling bending axis to prevent excessive rotation due to the specimen’s neutral zone.

<table>
<thead>
<tr>
<th>Primary Axis</th>
<th>DOF</th>
<th>Frequency (Hz)</th>
<th>Target Amplitude (N or Nm)</th>
<th>Tracking Error (N or Nm)</th>
<th>RMS Force Error (N)</th>
<th>RMS Moment Error (Nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posterior Shear (-Fy)</td>
<td>5</td>
<td>0.01</td>
<td>100</td>
<td>4.37</td>
<td>4.13</td>
<td>0.61</td>
</tr>
<tr>
<td>Lateral Shear (Fx)</td>
<td>5</td>
<td>0.01</td>
<td>100</td>
<td>4.23</td>
<td>4.95</td>
<td>0.20</td>
</tr>
<tr>
<td>Compression (-Fz)</td>
<td>6</td>
<td>0.01</td>
<td>200</td>
<td>5.14</td>
<td>4.24</td>
<td>0.13</td>
</tr>
<tr>
<td>Compression (-Fz)</td>
<td>5</td>
<td>0.01</td>
<td>300</td>
<td>4.63</td>
<td>3.46</td>
<td>0.67</td>
</tr>
<tr>
<td>Lateral bending (My)</td>
<td>6</td>
<td>0.01</td>
<td>8</td>
<td>0.35</td>
<td>6.82</td>
<td>0.32</td>
</tr>
<tr>
<td>Extension (Mx)</td>
<td>6</td>
<td>0.01</td>
<td>8</td>
<td>0.43</td>
<td>4.71</td>
<td>0.23</td>
</tr>
<tr>
<td>Flexion (-Mx)</td>
<td>6</td>
<td>0.01</td>
<td>8</td>
<td>0.40</td>
<td>5.07</td>
<td>0.23</td>
</tr>
<tr>
<td>Flexion (-Mx)</td>
<td>6</td>
<td>0.1</td>
<td>8</td>
<td>0.93</td>
<td>9.85</td>
<td>0.29</td>
</tr>
<tr>
<td>Axial Rotation (Mz)</td>
<td>5</td>
<td>0.01</td>
<td>8</td>
<td>0.23</td>
<td>5.94</td>
<td>0.25</td>
</tr>
<tr>
<td>Axial Rotation (Mz)</td>
<td>6</td>
<td>0.1</td>
<td>8</td>
<td>0.14</td>
<td>7.24</td>
<td>0.36</td>
</tr>
<tr>
<td>Axial Rotation (Mz)</td>
<td>6</td>
<td>0.3</td>
<td>8</td>
<td>0.36</td>
<td>11.7</td>
<td>0.43</td>
</tr>
</tbody>
</table>
Figure 5: 6DOF unconstrained load control results for flexion commanded to track an 8 Nm haversine at 0.01 Hz. Middle shows force axes errors and stiffness plot (bottom) demonstrates typical hysteresis curve.
Figure 6: 6DOF unconstrained load control results for axial rotation commanded to track an 8 Nm haversine at 0.3 Hz. The stiffness plot (bottom) demonstrates more linear stiffness in this axis, which improves control performance.