



Multivariate injury risk criteria and injury probability scores for fractures to the distal radius

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ABSTRACT

The purpose of this study was to develop a multivariate distal radius injury risk prediction model that incorporates dynamic loading variables in multiple directions, and interpret the distal radius failure data in order to establish injury probability thresholds.

Repeated impacts with increasing intensity were applied to the distal third of eight human cadaveric radius specimens (mean (SD) age = 61.9 (9.7)) until injury occurred. Crack (non-propagating damage) and fracture (specimen separated into at least two fragments) injury events were recorded. Best subsets analysis was performed to find the best multivariate injury risk model. Force-only risk models were also determined for comparison. Cumulative distribution functions were developed from the parameters of a Weibull analysis and the forces and risk scores (*i.e.*, values calculated from the injury risk models) from 10% to 90% probability were calculated.

According to the adjusted R^2 , variance inflation factor and p -values, the model that best predicted the crack event included medial/lateral impulse, F_z load rate, impact velocity and the natural logarithm of F_z (Adj. R^2 = 0.698), while the best predictive model of the fracture event included medial/lateral impulse, impact velocity and peak F_z (Adj. R^2 = 0.845). The multivariate models predicted injury risk better than both the F_z -only crack (Adj. R^2 = 0.551) and fracture (Adj. R^2 = 0.293) models. Risk scores of 0.5 and 0.6 corresponded to 10% failure probability for the crack and fracture events, respectively.

The inclusion of medial/lateral impulse and impact velocity in both crack and fracture models, and F_z load rate in the crack model, underscores the dynamic nature of these events. This study presents a method capable of developing a set of distal radius fracture prediction models that can be used in the assessment and development of distal radius injury prevention interventions.

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1. Introduction

Fractures to the forearm have been estimated to comprise almost 20% of all reported fractures worldwide, with the distal radius being the most commonly injured site (Johnell and Kannis, 2006). While distal radius fractures have numerous etiologies, over 90% of distal forearm fractures result from a forward fall (Nevitt and Cummings, 1993). Numerous studies have attempted to determine the forces and mechanisms associated with these types of fractures (Augat et al., 1996; Duma et al., 2003; Frykman, 1967; Lubhan et al., 2005; Meyers et al., 1991); however, the loading protocols utilized may limit applicability. For example, some researchers have used a quasi-static loading protocol (Augat et al., 1996; Meyers et al., 1991), which is not indicative of the dynamic loading that occurs to the radius during a fall. Of those

studies that have made use of dynamic loading protocols (Frykman, 1967; Lubhan et al., 2005), there has been little control over the applied loads, which have often been excessively high in magnitude and have consequently created damage to many of the surrounding structures. This can make it difficult to accurately identify the true fracture forces and relevant fracture patterns.

Duma et al. (2003) systematically applied impacts to the distal forearm to determine the wrist fracture forces and, based on their results, developed an injury risk criterion or model for wrist fractures. They considered variables such as bone mineral density, donor age and height, but only measured the axial (F_z) force component (*i.e.*, off-axis forces and moments were not measured) and did not measure the dynamic variables associated with impact such as velocity and impulse. This resulted in an injury risk criterion based on the F_z force component only. Given the visco-elastic and anisotropic behavior of bone, this may be considered a limitation of the Duma et al. (2003) model when it comes to assessing injury risk. Accurate failure probability models are needed for the assessment of the effectiveness of injury

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prevention strategies, such as wrist guards, protective flooring and fall prevention training. For example, although Burkhart and Andrews (2010) found that wrist guards were capable of reducing off-axis wrist accelerations during simulated forward fall arrest, it is unclear whether these reductions are sufficient to lower the overall risk of injury to a significant proportion of the population. Developing a multivariate injury prediction model, such as the one described herein, will improve such estimates and provide a basis by which different intervention strategies can be assessed.

Choosing the correct statistical distribution is critical to developing the most accurate injury prediction models. While logistic regression is a powerful statistical tool for this purpose, it requires a large number of samples (Peduzzi et al., 1996) to produce valid results. Large samples are not always possible or economically feasible in *in-vitro* testing, particularly with human specimens. A Weibull analysis is an alternate method that was designed specifically for the assessment of failure and survival data (Abernathy, 2006). This method provides graphical, easily interpretable results that can offer direct evidence of the underlying failure mechanism (Abernathy, 2006). This type of analysis is also robust (accurate) to small sample sizes, which makes it an ideal method for analyzing failure data of human specimens (Sullivan and Lauzon, 1986; Wu and Vollertsen, 2002; Abernathy, 2006).

Therefore, the purpose of the current study was two-fold. The first was to systematically produce distal radius fractures to cadaveric human radii, with the aim of developing a multivariate distal radius injury risk prediction model that incorporates dynamic loading variables in multiple directions. It is anticipated that including such variables will provide more robust injury risk prediction models compared to those currently available. The second purpose was to utilize the Weibull distribution to interpret the failure data and establish distal radius injury probability thresholds.

2. Methods

The methodology described in Burkhart et al. (2012) was utilized to test eight (4 male, 4 female; 5 left, 3 right; mean (SD) age 61.0 (9.7) years) fresh-frozen human cadaveric radius specimens. Specimens were screened to ensure that they were free of metabolic bone diseases, metastatic cancers, diabetes renal failure and pre-existing trauma. The articular surface of the distal radius was kept intact, while the remainder was cleaned of all soft tissues. Specimens were cemented into sections of 8.89 cm (3.5 in.) diameter PVC tubing (distal third of radius exposed), and were arranged to mimic the position of the radius *in-vivo*, during a forward fall (i.e., specimens were potted at a 75° angle in the sagittal plane (Fig. 1) (Greenwald et al., 1998) with no frontal plane tilt (Staebler et al., 1999), and oriented with the dorsal surface facing down (Burkhart et al., 2012)). To isolate injury to the distal radius and to avoid potential lunate and scaphoid fractures,

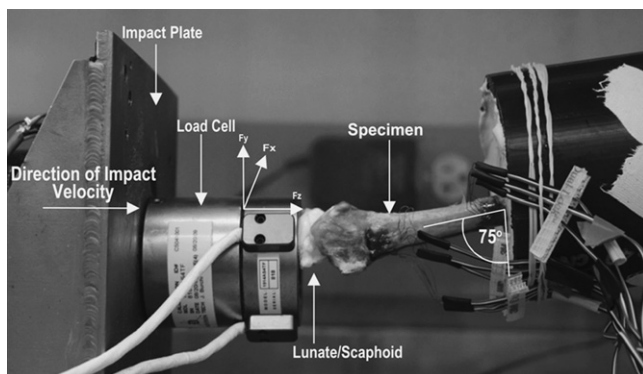


Fig. 1. Experimental set-up showing the position of the radius specimen in contact with the model lunate/scaphoid. The impactor strikes the impact plate, transferring the load through the lunate and scaphoid onto the distal articular surface of the radius.

which also commonly occur after forward falls (Leslie and Dickson, 1981), a high density polyethylene scaphoid and lunate model (SawBones®, Pacific Research Laboratories Inc., Vashon, Washington) was used to impact the articular surface of the distal radius (Fig. 1). The model was attached to a load cell, which in turn was attached to the impact plate of a pneumatic impact system (Fig. 1) (described below). To accommodate the *in-vivo* 45° wrist extension angle during a fall (Troy and Grabiner, 2007), the radio–carpal angle was set at approximately 42° using a custom potting jig. This was in accordance with the findings of Werner et al. (1997), who found that the mean angle between the radius and proximal row of carpals is approximately 93% of the global wrist angle.

Impulsive impacts were applied with a custom designed pneumatic impact system (Burkhart et al., 2012; Quenneville et al., 2010) (Fig. 1), where a 6.8 kg projectile was propelled through an acceleration tube by pressurized air. The potted end of the specimen was attached to a bracket that moved freely along a linear rail and ball bearing system following impact. The mass of the specimen (with cement), bracket and potting jig (~7 kg) provided enough resistance to allow for adequate impulse duration of approximately 15–20 ms (Fig. 2) (Burkhart et al., 2012). Prior to testing, a pressure–velocity relationship was determined to allow fine control over the projectile's exit velocity. Impacts were energy-controlled; the projectile mass was kept constant and the velocity was incrementally increased. The impact plate was instrumented with a 6 degree of freedom strain gauge based load cell (Denton Femur load cell, Model # 1914A, Robert A. Denton Inc., Rochester Hills, MI; Natural frequency 6 kHz), and optical sensors (TCRT100 Vishay Semiconductors, Germany) to measure impact force, and velocity, respectively. Velocity and force data were acquired at 15 kHz (National Instruments NI-PXI 1050, and SCXI 1010) by a custom LabView (LabView 2008, National Instruments, Austin, TX) data collection program. Force data were filtered with a dual pass, fourth order Butterworth filter and the optimal cut-off frequencies were calculated via residual analysis (Burkhart et al., 2011).

Potted specimens were securely clamped into the testing system and positioned such that the carpals and radius were properly aligned. Pilot testing determined that initial target impact energy of 20 J was low enough not to cause any visible specimen damage; subsequent impacts occurred in 10 J increments until failure occurred. Failure was defined as specimens being fractured into two distinct segments. Specimens were visually inspected following each impact to determine if signs of external trauma were present and the energy at which the first crack event occurred was also recorded.

Force–time curves were used to calculate the peak force, impulse, impulse duration and load rate, for the three force components (F_x —medial/lateral; F_y —inferior/superior; F_z —anterior/posterior, and the resultant impact reaction force (IRF_r) defined in the load cell (global) coordinate system (Fig. 1). Data were classified into three impact events: (i) Pre-fracture (i.e., the first impact) at a 20 J target, (ii) the crack event, when damage was noted on the exterior surface of the radius but with no visual propagation beyond the surface and (iii) the fracture event, corresponding to the impact at which failure of the specimen occurred as described above.

Best subsets regression analyses (SigmaPlot 12.0, Systat Software Inc., Chicago, IL) were carried out to determine which combination of variables (and their associated coefficients) best predicted the injury event, providing an equation that could be solved to quantify a “risk score” (where the greater the risk score, the greater the probability that failure will occur). This was done separately for the crack and fracture events. A best subsets analysis produces a set (2^k ; where k is the number of variables) of prediction models, such that the adjusted R^2 values are used to identify the two best, one-variable models, followed by the two best, two variable models, and so on until the two best, $k-1$ variable models are produced.

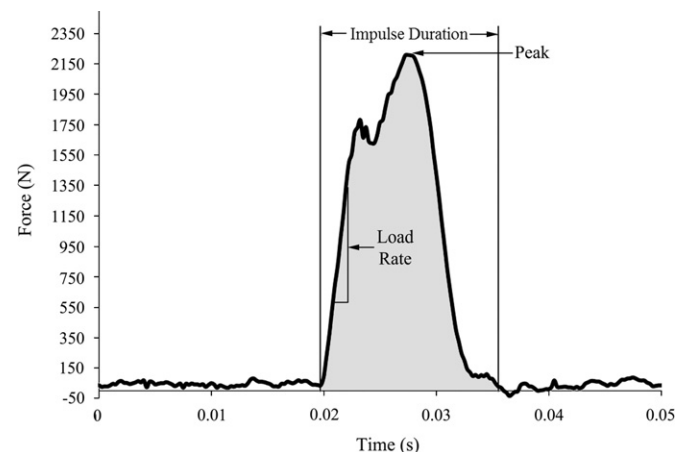


Fig. 2. Typical force–time curve for a fracture event. Shown are the force variables that were included in the regression analysis. The gray shaded area represents the impulse.

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