Reducing Human Fall Injuries using a Mobile Manipulator

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***Abstract*— Falls among elderly persons are both common and have significant negative impacts on their immediate and long-term health. In this paper, we consider whether current mobile manipulators could reduce the severity of injuries caused by human falls, and we focus on developing simple strategies toward this purpose. We present a simulation of a fall scenario that includes a humanoid and a mobile manipulator that can manipulate the humanoid at one or more points. Using metrics, we estimate the severity of injury to a human from a fall, and then we evaluate these metrics across four scenarios for interactions between the robot and the humanoid. We conduct experiments with a PR2 robot and a 20 degree-of-freedom humanoid. We parameterize the humanoid with human biometric data including mass distributions, link lengths, joint ranges of motion, and link centers of mass to approximate human fall behavior. Utilizing the full, but limited, force of its arms, the robot was able to reduce the median injury to the human as assessed by the metrics. However, scenarios where the robot's intervention exacerbated injuries did occur, which indicates that algorithms to reduce fall damage must be carefully designed and applied to avoid worsening fall injuries.**

I. INTRODUCTION

Using robots to help care for our elderly has been a longstanding goal of the robotics community. Preventing falls is a critical task in elderly care due to the sheer number of injuries from falls: in the United States, *one-third of adults aged 65 years and older fall every year.* These falls are the leading cause of injury-related death for this age group [25]. Most fractures among older adults are caused by falls [31] and falls are the most common cause of traumatic brain injuries [35]. Approximately one-third of falls results in significant injuries including lacerations, hip fractures and head trauma [35], [1]. Among the elderly, falls are one of the greatest causes of long-term disability and death [36]. A fall often leads to a fear of a future fall [5], which may cause an elderly person to reduce physical activity. This reduction can result in diminished mobility and physical fitness, which can then increase the person's actual fall risk [42]. The economic costs incurred due to falls are also immense. In 1995, the cost per fall was $4,692 and the total costs of fall injuries across all age cohorts was $64.41 billion. These costs are estimated to increase by 2020 to $85.37 billion (in 1994 dollars) [8].

Furthermore, mobility is a key factor in maintaining health [38] and independence in the elderly. One recent medical study found that regaining functionality (the ability to perform basic tasks such as walking, dressing, and bathing) after acute illness was independently correlated with a reduction in long-term mortality [4]. In addition, surveys of elderly persons have found that "independence, control over life, freedom" are key indicators of quality of life [6].

A. Robotic fall prevention

We envision a mobile manipulator providing more effective fall prevention than current assistive devices (described below) without altering a patient's gait. One option for patients who are at high risk of fall would be for the robot to walk or move with the patient throughout the patient's daily routine. When the robot detects a fall it could quickly grasp the patient and attempt to prevent or mitigate the fall. While a robot assistant may not necessarily perform this fall-prevention task more effectively than a dedicated human nurse, the robot could free human caregivers to perform other, more critical tasks. Robots could also perform this task safely for massive individuals and without being frustrated by a patient's pace.

B. Current assistive devices

A wide array of assistive devices such as walking canes, passive walkers, active (motorized) walkers, and electric wheel-chairs have been proposed as solutions or partial solutions to mobility challenges. One survey found 58% of residents at assisted care facilities depended on these types of walking aids [3]. However, these existing solutions present some significant negative side effects:

- Many devices (including robotic canes and passive walkers) significantly alter gait biomechanics, which can lead to injuries including carpal tunnel [43], [37], median neuropathy [39], stress fractures [24], and risk of upper limb pain [20].
- Non-robotic assistive devices are not completely effective. One recent study of falls in nursing homes found that 21% of falls occurred when the person was using either a walker or a cane [29]. 29% of falls were due to the person's foot catching on various equipment, including mobility devices [29]. While one study found that passive assistive devices were indeed helpful [40], no studies have quantified the change in fall risk. Additionally, one study found that the use of such devices is associated with lower physical functioning and health [2].
- At least in the case of robotic devices, these solutions require special purpose, often expensive hardware and regular maintenance. Mobile manipulators would not be exempt from this problem, but conceivably could act as a general purpose tool in assisting the elderly and infirm by helping with other tasks including bed

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transfers [27], medication reminders [28], bathing [18], and dressing [18].

II. RELATED WORK

Roboticists have researched the potential for robots to assist in elderly care over the last two decades and have published several investigations of it. These include Pineau et al. [28], who developed a prototype robot Pearl that was tested in a nursing home while delivering food, providing reminders, and guiding patients; the Care-O-Bot, which was designed to assist elderly patients by delivering meals and water, acting as a walk-aid, and communicating with physicians [32], [11], [12], [13]; and Nursebot, which focused on providing social interaction, remote telemedicine, safeguarding and acting as "cognitive prosthesis" for the elderly [30]. None of these robots focused on fall prevention and mitigation during walking.

Several research teams have also developed robots capable of lifting or transporting humans, including [26] and [17], but these focused on carrying humans with no contact between the human and the ground, not preventing falls. Another active area of research has been intelligent walkers, which do attempt to prevent falls. These intelligent walkers include the passive walker developed by Hirata et al. [14], [16], [15], and a modified mobile manipulator developed by Graf [10]. Also, recently robotic gait rehabilitation systems such as CORBYS have been proposed [33]. While these systems attempt to prevent falls, they do not attempt to mitigate falls once they occur.

III. APPROACH AND METRICS

Due to the inherent danger of physical experiments with human subjects, particularly elderly subjects, we have pursued this research initially in simulation. We selected the PR2 robot for the mobile manipulator as its capabilities are representative of the capabilities currently available in general purpose mobile manipulation platforms, a simulation model for the robot is readily available, and we can conduct physical experiments with the robot when we are ready. In addition, it has passively compliant arms, which are desirable for safety when directly interacting with humans. For the human component of the simulation, we developed a humanoid model that closely models key physical attributes of humans—link lengths, mass distributions across links, joint ranges of motion, link centers of mass, and inertial properties—towards realistically modeling human fall and how humans would react to the forces applied by the robot. We limited the complexity of the model to maintain reasonable simulation performance (our current Gazebo-based simulation runs at approximately 20% of real time). We then evaluated the behavior of these models using several metrics.

A. Metrics

Drawing from research in elderly care and automobile safety, we argue that effective fall prevention should focus on two primary goals, in descending order of priority: (1) minimizing collision forces on the head/neck link and (2) minimizing collision forces on all other links. This choice is based on medical research showing that head injuries (specifically subdural hematomas) are the most common cause of death after a fall [36]. The primary metrics we use are not informative in absolute terms, as there is little research that correlates impact forces to injuries, but the metrics allow us to assess alternative strategies relatively. In addition we calculate a common measure used in the car industry, the Head Impact Criterion (HIC), which allows us to estimate the likelihood a collision will result in a concussion. We sample each metric at 1ms intervals in simulation. These measures are not easily combined, and fall mitigation strategies may improve one metric while worsening another; consequently, we report all three metrics in our results. We elaborate upon these metrics below.

1) Maximum Head Collision Force: Among fall injuries, head injuries are the type of injury most likely to cause death, which led us to select a measure to assess the impact forces on the head/neck link of the biped during the fall. This metric seeks to measure the most forceful impact on the head/neck link of the biped at any point during the fall. This collision may be between the biped and the ground or the biped and the robot. If the contact force on the head/neck link at time t is $F_{head}(t)$ and the fall occurs over T seconds, then the Maximum Head Collision Force (MHCF) is:

$$MHCF = \max_{t \in T} F_{head}(t) \tag{1}$$

2) Maximum Link Collision Force: The Maximum Link Collision Force (MLCF) metric is defined as the maximum of the collision forces applied to any link. We selected this measure to determine whether collision forces were increasing on other links, such as the chest, pelvis, or extremities, as a result of the fall prevention strategy. If the set of all links on the biped is L, and the contact force on link ℓ at time t is $F_\ell(t)$ and the fall occurs over T seconds, this metric is:

$$MLCF = \max_{\ell \in L, t \in T} F_\ell(t) \tag{2}$$

3) Head Impact Criterion: The Head Impact Criterion (HIC) was developed in 1971 by the U.S. National Highway Traffic Safety Administration (NHTSA) to assess head injuries in crash test dummies [23]. It based on the observation that the severity of a head injury is a function of both the acceleration and duration of the impulse. Various studies have validated the HIC as a predictor for brain injuries and skull fractures at specific levels on the Abbreviated Injury Scale (AIS) [9]. The duration of the impact measured is generally limited to a specific range, specifically 36ms or 15ms, which are known as HIC_{36} and HIC_{15}, respectively. We use the HIC_{15} measure for this study, which is the current NHTSA standard. If the acceleration of the head at the center of mass is given by a_t, the impact occurs over T seconds, t_1 and t_2 are any times within T, Δt_{min} is 3ms, and Δt_{max} is 15ms, then HIC is defined as:

$$HIC = \max_{t_1 \in t, t_2 \in t} \left\{ [\frac{1}{(t_2 - t_1)} \int_{t_1}^{t_2} a(t)\,\mathrm{d}t]^{2.5} (t_2 - t_1) \right\},$$

subject to $\Delta t_{min} \leq t_2 - t_1 \leq \Delta t_{max}$

IV. EXPERIMENTS

We designed a simulation environment and a series of scenarios to investigate how varying the robot's actions would change the humanoid's fall, as assessed by the metrics described above. We now proceed to describe the simulation environment (Section IV-A), four tested scenarios (Section IV-B), and the experimental setup (Section IV-C). We will conclude this section with our findings (Section IV-D).

A. The Simulation Environment

Due to the difficulties of conducting in situ experiments on human subjects with respect to this problem, we employed a robotic simulation environment designed to mimic the key components of the falling problem: the human, the robot, and contact between the two. We used the `Gazebo v5.1` robotic simulation environment [19] to physically model a PR2 robot. The simulation ran approximately 5 times slower than real-time. Details of our simulation environment follow.

The PR2 is a mobile manipulator equipped with a wheeled omni-directional base, two 7-DOF arms, LIDAR, camera, and Kinect sensors. Both sensors and dynamics (using rigid body models) are simulated.

We required a virtual human that is computationally fast to simulate (eliminating approaches that would, for example, model skin deformation), but would approximate human falling behavior. We developed a rigid body model based on Dempster's research on human body anthropometry [7]. That study provides effective link lengths, 3-DOF joint limits, relative masses, and center-of-mass positions for links. We utilized Dempster's data for a median male adult, and supplemented the data with additional information from other researchers for joint limits in the neck [22].

The model is a 20 degree of freedom (DOF) multi-rigid body; each link is modeled as a cylinder. The virtual human is shown in Figure 1. Each joint is either a 1-DOF revolute joint or a 2-DOF universal joint. We modeled the 3-DOF human joints (the shoulders, hips, and neck) as 2-DOF universal joints because `Gazebo v5.1` cannot currently enforce joint limits for 3-DOF joints. We eliminated the DOF for the most constrained axes. We did not model the human spine due to its kinematic complexity. Instead, the spine link is attached to transverse links at the hips and shoulders with fixed joints. The head and neck are modeled as a single rigid link attached to the spine with a 2-DOF universal joint. The inertia matrices for each link are set such that the center of mass matches the data from Dempster [7].

Because the humanoid links and the ground are modeled as rigid bodies the physics engine de-accelerates the links very rapidly upon collision with the ground. This causes contact forces over short time periods with higher absolute values (as much as three orders of magnitude higher) than would be expected for human falls. However, this factor should apply equally to all scenarios and should not significantly affect relative results across scenarios.

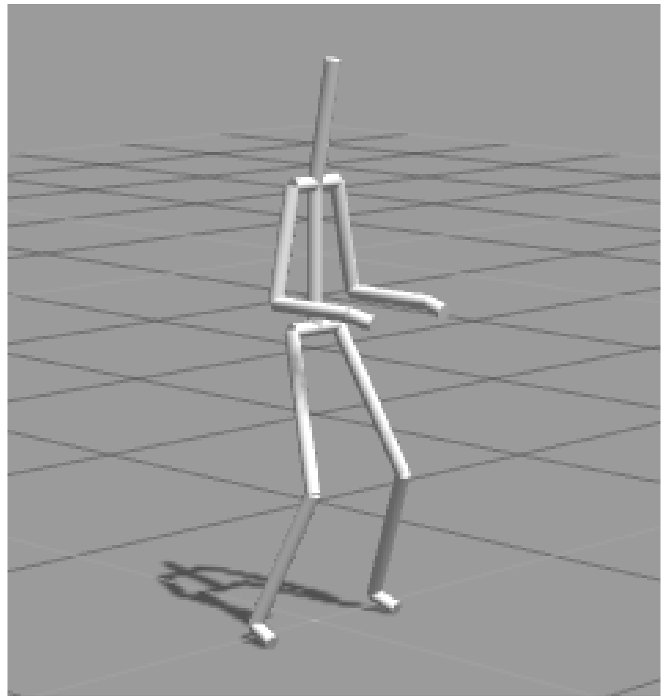

Fig. 1: *The above graphic shows the humanoid in a standing configuration selected to show the joint locations and degrees of freedom.*

B. Scenarios

We developed four scenarios to assess the ability of the robot to decrease the impact forces on the human due to falling. The scenarios are as follows:

1) Human Only: This is the experimental control scenario where the human falls with no support from the robot.

2) Zero-Force: The robot is attached to the human (as if by grasping), but does not apply any forces via its actuators (except those in the wheels). We developed this scenario to assess the effect of only grasping the humanoid on fall impacts. The primary mechanism of modifying the fall is the limitation of the human's freedom of movement. Due to limitations in the robot's range of motion and the end-effectors' attachments to the human, the human cannot move beyond a certain range. This scenario also allows us to investigate possible impacts between robot and human.

3) Normal-Force: The robot is attached to the human (again, as if by grasping) and applies forces up to the maxima of the PR2 model. These limits are 30N for all links on the arm (shoulder joints, upper arm roll joint, elbow joint and forearm roll joint) except for the wrist (roll and flex joints), which are 10N. The specifications for the PR2 state that the maximum payload for the robot arm when fully outstretched is 1.8kg; we found that with these force limits, the maximum payload in simulation is approximately 4kg. Both limits are far below the weight of the virtual human. In this scenario, the robot attempts to maintain its initial joint angles of the arms using PID controllers for each joint. PID gains were tuned using the Ziegler-Nichols method [45].

4) Locked-Arms: This scenario sets the joints to be nearly fixed using extremely high joint friction values (we did not use fixed joints because they seemed to cause instability in `Gazebo v5.1`). This scenario is not physically feasible with the PR2 and it would be very difficult to interact with a human using fully non-compliant arms. Using such a strategy could also be dangerous, as the fixed robot arm would act as a lever. Weight applied during the fall to the robot arm could cause the robot to tip over and injure the human. Indeed, we saw this nearly occur several times in simulation. We modeled this scenario to act as an approximate upper-bound on the performance of a robot reducing falls using this type of strategy.

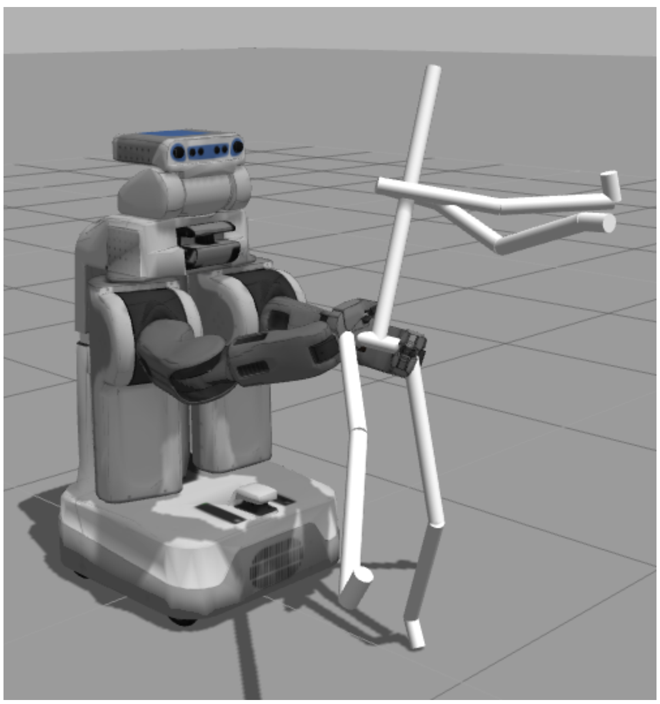

Fig. 2: *A depiction of the initial conditions prior to an experimental run. One can see the humanoid's left leg is in contact with the ground. The remaining joints are set to random positions, and the orientation of the trunk link is random. The robot's end effectors are connected to the humanoid's upper-leg links near the hips.*

C. Experimental setup

We executed each strategy with 100 randomly initialized configurations of the humanoid. The configurations were generated with a pseudo-random number generator, so that we were able to run each strategy with identical configurations. The process for initializing the configuration of the robot and human for each trial in the simulator was as follows:

1) Select a random leg L, with $p(left) = p(right) = 0.5$, to be the support leg. Let the foot, lower-leg, and upper-leg comprising L be considered the support leg chain.
2) Let $upper_j$ be the upper limit of motion of joint j according to the kinematic model and similarly let $lower_j$ be the lower limit. Set the angle a_j for each joint, excluding the support leg chain, to a uniformly selected random angle where $lower_j \leq a_j \leq upper_j$.
3) Set the yaw of the trunk equal to a random angle ϕ, where $-\pi \leq \phi \leq \pi$.
4) Set the pitch of the trunk equal to a random angle θ where $-\pi/4 \leq \theta \leq \pi/4$. The limits on pitch and roll were selected to avoid infeasible configurations.
5) Set the roll of the trunk equal to a random angle ψ where $-\pi/4 \leq \psi \leq \pi/4$.
6) Find an inverse-kinematics (IK) solution such that the tip of the foot of the support leg is in contact with the ground. This solution does not restrict the orientation of the foot. The KDL library was used to perform the inverse-kinematics [34].
7) If an IK solution does not exist, restart from 1).
8) Perform IK for each robot arm such that each of the end-effectors of the robot are in contact with the nearest hip joint of the human. These solutions do not restrict the orientation of the end-effectors.
9) If IK solutions for both end-effectors cannot be found, restart the process at 1). If solutions for either or both arms are found, proceed.
10) Position the links for each robot arm for which IK was successful to the solved joint angles found above. Planning and arm motion is not required as this step is prior to the start of the trial.
11) Compute bounding boxes for all links of robot and human.
12) Detect collisions between:
    - Any two links l_a and l_b of the human where l_a is not a direct child in the kinematic chain of l_b and vice versa.
    - Any link on the human l_h and the robot l_r where l_r is not part of either end-effector of the robot.
    - Any link on the human l_h and the ground where l_h is not the foot link of the support leg.
13) Restart the process at 1) if there are any geometric intersections.
14) Construct a virtual joint between each of the attached robot-end effectors and the nearest hip of the human. The virtual joint is defined as a ball joint (3-DOF) with very high friction such that it acts nearly like a fixed joint. This method was chosen because `Gazebo v5.1` does not provide fixed joints.
15) Apply a random velocity v to each link of the humanoid along all linear and rotational axes where $-1m/s \leq v \leq 1m/s$.

The human model is not controlled, so when the simulation begins, the human falls. We assume the robot is able to immediately detect the human's fall and take action.

This assumption has a basis in human cognition: anecdotally, humans are able to rapidly detect falls in other people. To assess whether reaction time significantly impacts these results, we re-ran this experiment with a 200ms delay prior to the robot applying force.[1] We found that this delay increased the median impact force by less than 1% in the Normal-Force scenario. It had no effect on the Zero-Force scenario because no reaction by the robot is required in that control strategy.

By applying no forces at the human's joints, we simulate the human falling in a fainting manner. We chose this fall type, among the many possible types of human falls, due to its simplicity and the difficulty of modeling human fall and fall response accurately (which are open problems [44], [41]). Example initial conditions for one scenario are shown in Figure 2.

D. Results

Quantitative results are compiled in Table I. Using the Normal-Force strategy to maintain the initial position of the robots' arms causes a marked decrease in the median peak impact force compared to both the experimental control strategy and the Zero-Force strategy. However, even the Zero-Force strategy shows a significant decrease in the median peak impact force over the control strategy. The peak median head impact force and HIC are also reduced. The Normal-Force strategy yields a 32% improvement in the HIC over the Zero-Force strategy. We can visually observe these results in Figure 6. The gray line in those charts displays for each scenario the average velocity across all trials. The variance is depicted using a red gradient, which shows the area one standard deviation surrounding the mean. These plots show that both robot fall mitigation strategies reduce both the peak negative vertical velocity and the magnitude of bounce after the human impacts the ground. The plots of the horizontal velocities show that the variance is also reduced for those axes, particularly in the direction toward the robot. Qualitative results from a single random trial of the Normal-Force control strategy are depicted in Figure 5.

Scenario	Med. Peak Impact Force(N)	Med. Peak Head Impact Force(N)	Med. HIC(s)
Human Only	42,211	29,663	356
Zero-Force	28,889	22,580	235
Normal-Force	25,198	17,314	159
Locked-Arms	9,990	1,063	116

TABLE I: *Values for the three metrics evaluated across the scenarios. The number shown is the median of the metric across all trials ($N = 100$). One can see that all three metrics decrease as additional force is applied by the robot.*

However, there are several characteristics of the fall that may become worse as the robot applies controls. Table IV-D shows that 23% of the Zero-Force trials and 18% of the Normal-Force trials had higher peak impact forces than the human-only baseline. The average increases in peak impact forces were 15,347N and 12,573N respectively. Additionally, the maximum increases were a factor of three higher. Figure 3 also shows that the proportion of trials where the peak impact force is due to a collision with the robot increases in scenarios where the robot applies more control. Observing the link on the human that is impacted (graphed in Figure 4), head collisions become more frequent in the Zero-Force and Normal-Force scenarios as compared to the human-only baseline. Visual analysis of trials where the human's head impacts the ground shows that the placement of the robot's end-effectors on the human's hips allows the robot to prevent the human's pelvis from contacting the ground. This is because the PR2's kinematics do not allow its end-effectors to reach the ground. However, the robot is unable to control the human's torso, which rotates into the ground when the velocity of the pelvis is arrested. Overall, the median head impact force and HIC were still lower in scenarios where the robot applied controls.

Scenario	Trials with increase	Mean increase (N)	Max. Increase (N)
Zero-Force	23%	15,347	50,818
Normal-Force	18 %	12,573	39,411
Locked-Arms	10%	6,487	20,022

TABLE II: *Percentage of trials for each scenario where the impact force is greater than the human falling unassisted. The mean magnitude of this increase is relatively low, but outlying trials exist with large increases.*

V. DISCUSSION

Initially, we were concerned that the low force limits of the PR2's arms would limit the robot's ability to reduce peak impact forces from the fall. However, when the robot's arms were connected to the human without applying any force, median peak impact forces were reduced by 32%. From visual analysis, we believe this is primarily due to the restrictions on the range of movement of the human caused by the joint limits of the robot. The joint limits often prevent the human's torso from hitting the ground by catching the human's hips at the lower vertical limits of the PR2's arms (above the ground). The median head impact force and HIC were similarly reduced by 24% and 34% respectively. In rare cases, the robot was in able to completely prevent the

[1] Various studies have found human reaction time to be between 160 and 400ms depending primarily on the complexity of the recognition task [21].

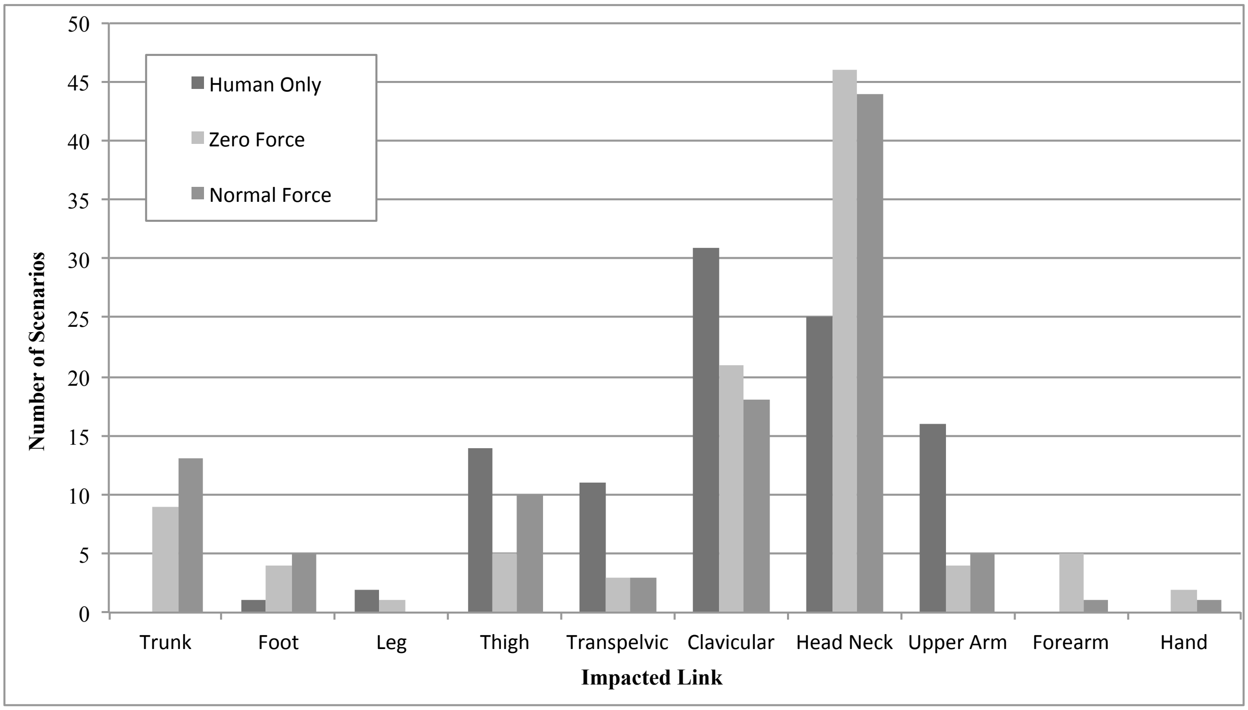

Fig. 4: *The human link that received the peak collision force. We can see that while the magnitude of the impacts were reduced by the robot control strategies, the frequency of head impacts increased over the baseline.*

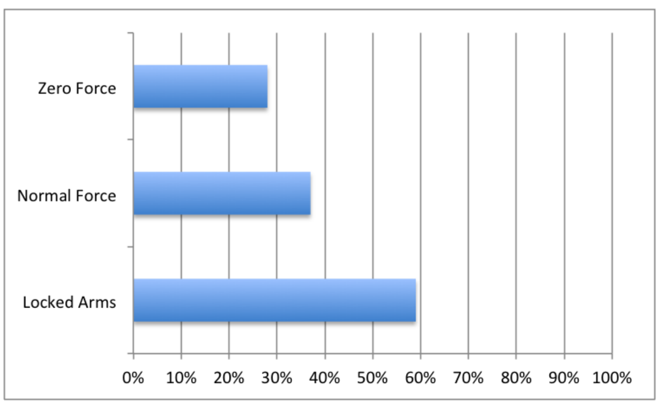

Fig. 3: *Percentage of trials where the peak collision was between the human and the robot. This occurs more frequently as larger forces are applied by the robot's control strategies.*

human's torso and head from impacting the ground, but this was usually due to the human impacting the robot's base instead.

Building on the above strategy by applying forces up to the limits of the robot only caused a median decrease in peak impact forces of 13%. The median head impact force was reduced by 23%. This improvement was limited due to the force limits of the robot that are very low relative to the weight of the human. However, the median HIC value was reduced by 32%. This implies that the limited force applied by the arms reduced the acceleration of the head during the impact or increased the duration of the de-acceleration. This metric is predictive of certain types of head injuries, so this result demonstrates the potential for existing robots with limited force arm motors to be used to limit head injuries from falls.

VI. FUTURE WORK

Experiments in simulation indicated that simple control strategies for a robot with limited strength would generally be able to reduce collision forces on a falling human. These control strategies performed significantly worse than our estimated upper bound on performance (demonstrated by the Locked-Arms strategy). We expect that more sophisticated control strategies could improve performance significantly. For example, an "oracle" macro-controller that always selects the ideal strategy from the three strategies (Human-Only, Zero-Force, Normal-Force) decreases collision forces by 18% over any single strategy.

In addition, while simulation is necessary due to the complexity and safety issues with experiments involving humans, there may be significant gaps between the results in simulation and in situ. We are in the process of implementing similar experiments in situ using a PR2 and a weighted and instrumented mannequin. We plan to use this data to provide insight into and improve upon the simulation.

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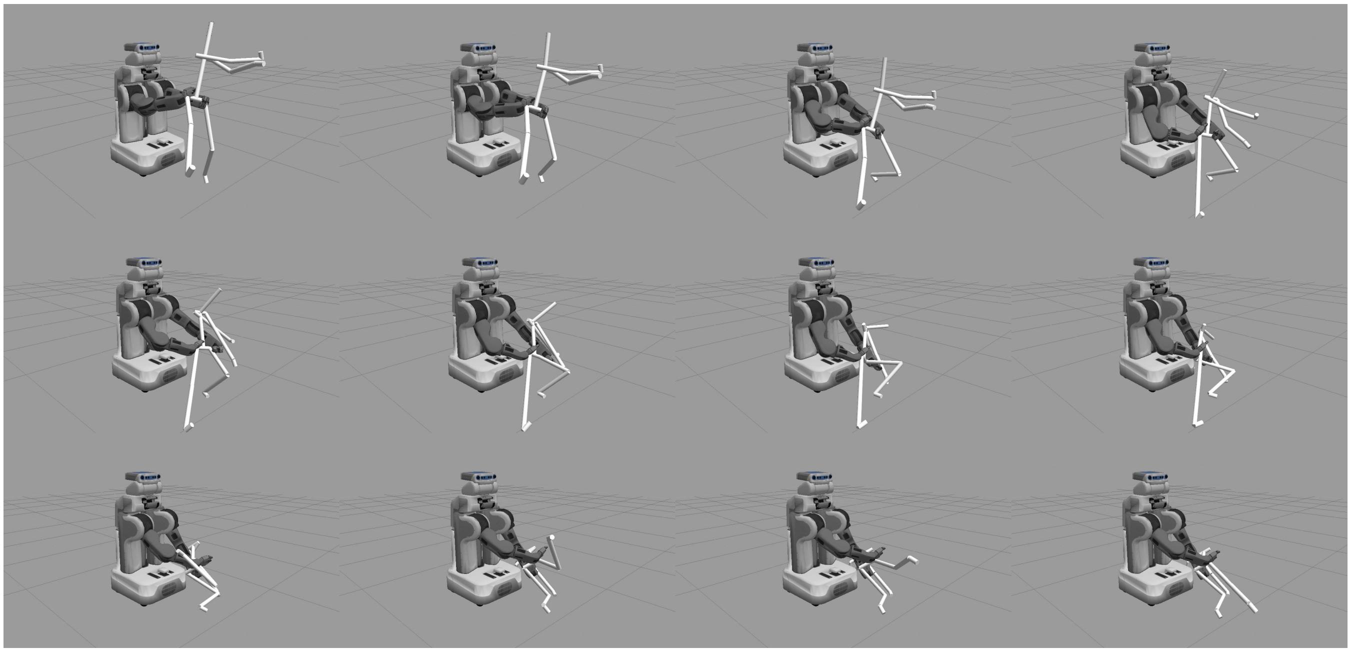

Fig. 5: *Screen captures of the simulation taken every 150ms while the human is falling and the robot is utilizing the Normal-Force control strategy. Screen captures are ordered left to right, top to bottom. The entire fall takes less than 2 seconds. One can see that the robot is able to prevent the humanoid's pelvis from impacting the ground in this trial.*

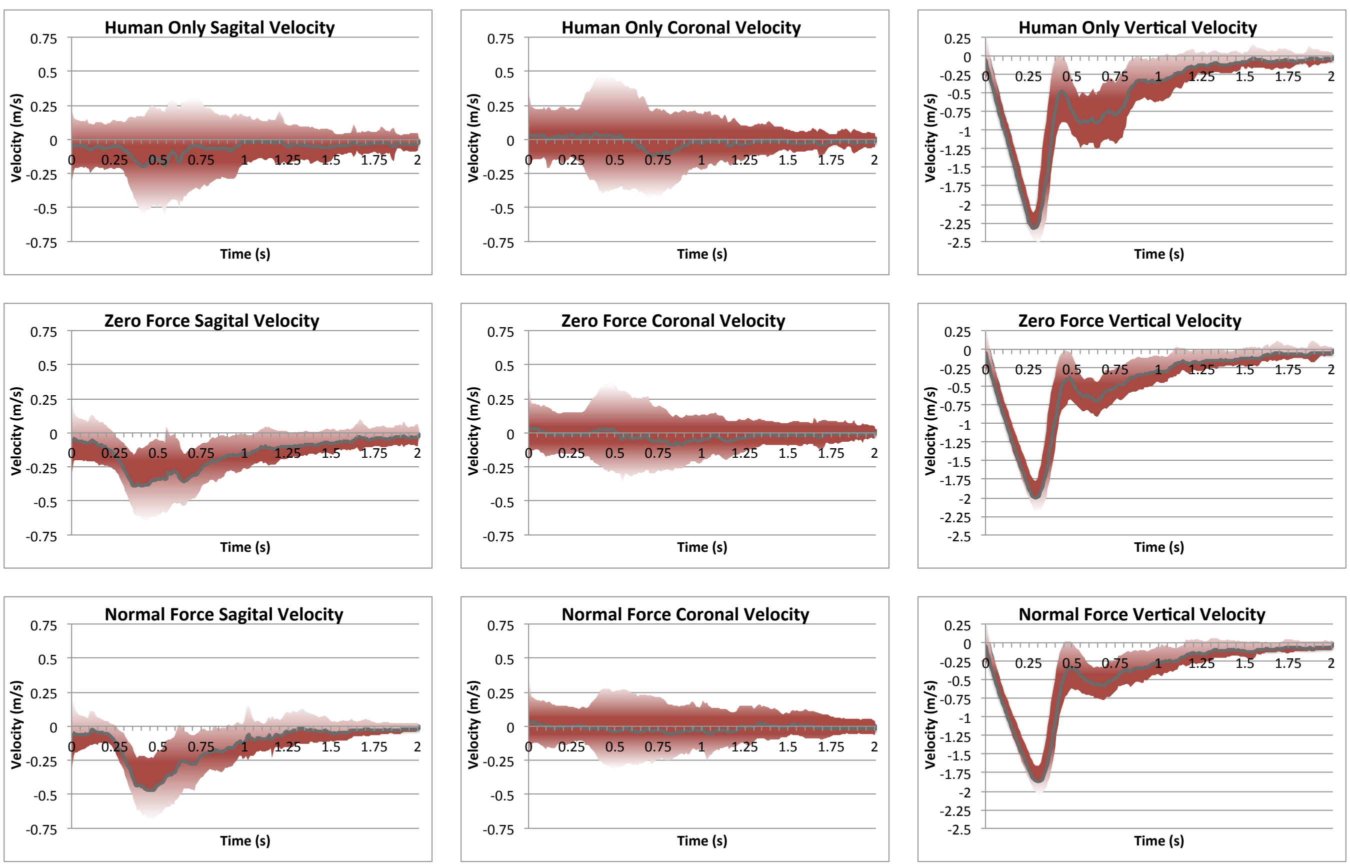

Fig. 6: *Average velocity and variance in horizontal and vertical axes across the robot-control strategies.*

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