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A Novel Walking Cane with Haptic Biofeedback Reduces Degenerative Loading in the Arthritic Knee

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Abstract

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Knee osteoarthritis is the most common joint disorder and a leading cause of ambulatory disability in adults. Conservative treatments of osteoarthritis are lacking and the most commonly prescribed mobility aid, the walking cane, is often misused and therefore fails to provide symptomatic relief. For this study, a novel walking cane with haptic biofeedback was designed to improve the partial weight-bearing techniques used for transferring bodyweight from an affected leg to a mobility aid. Proper transfer of bodyweight from an arthritic limb to a walking cane has shown to reduce joint loading associated with symptomatic pain and disease progression. The novel cane was designed to be intuitive to use and conducive to use outside of a controlled laboratory environment. Improving the design and usability of common mobility aids serves the

aging, injured, and disabled communities by providing tools for independent disease maintenance thus reducing reliance on reactionary treatments to worsening symptoms.

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Chapter 1. INTRODUCTION

1.1 BACKGROUND ON KNEE OSTEOARTHRITIS

Osteoarthritis (OA) is the most common joint disorder and the leading cause of ambulatory disability in adults [1], [2]. Approximately 50 million Americans suffer from OA [3]–[5] and numerous independent studies estimate that knee OA affects at least 35% of adults over the age of 65 across the globe [3], [6], [7]. The number of people above the age of 60 is expected to increase globally to 22% by 2050 [8]. As the world's population ages knee OA prevalence is expected to increase [9].

OA is a degenerative disease, meaning its symptoms - destruction of healthy cartilage, subchondral bone thickening, and development of bone osteophytes (Figure 1-1, reproduced from [10]) are cumulative and non-reversible [1]. These symptoms are often innocuous and difficult to diagnose in the early-stages of the disease but become increasingly painful and debilitating over time, thus limiting preventative treatments. This lacking in effective conservative treatments forces those living with osteoarthritis to rely on reactionary measures in response to worsening symptoms.

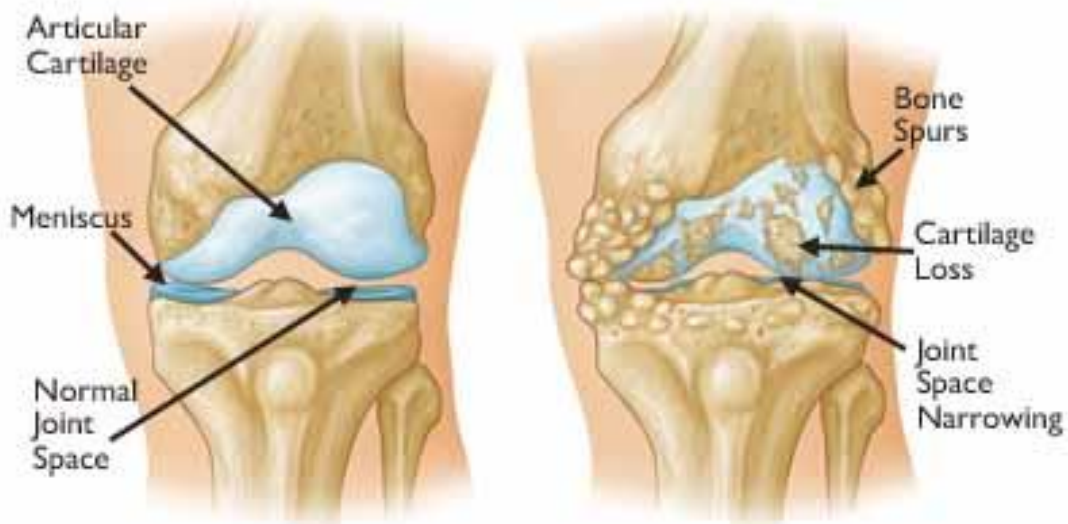


Figure 1-1. Representative comparison of Left) a healthy knee joint and Right) a knee joint exhibiting symptoms of progressed knee OA [12].

1.2 KNEE LOADING AND OSTEOARTHRITIS PROGRESSION

It is widely accepted that medial contact forces (MCFs), i.e. joint contact loads in the medial compartment of the knee, increase the rate of cartilage degeneration and exacerbate symptoms of knee OA [2], [3], [11]–[13]. Since MCFs are difficult to measure *in vivo*, the external frontal-plane knee torque, also known as the knee adduction moment (KAM), is often used as a surrogate - with the peak knee adduction moment (PKAM) and the knee adduction angular impulse (KAAI), representative of the force-time integral, as primary predictors of MCFs [14]–[22].

The KAM is a frontal plane, adduction torque, the magnitude of which is predominantly determined by the ground reaction force and the length of the moment arm from the force vector, directed from the foot's center of pressure to the body's center of mass, and the knee joint center (Figure 1-2, reproduced from [23]). A longer moment arm shifts the force vector medially causing increased medial compartment loading [17], [22], [24], [25]. It is thought that chronically higher medial compartment loading due to over expressed KAM, also known as varus knee alignment, is

thought to be related to bone surface malalignment, changes in bone mineral density, and progression of knee OA [22], [24], [26], [27].

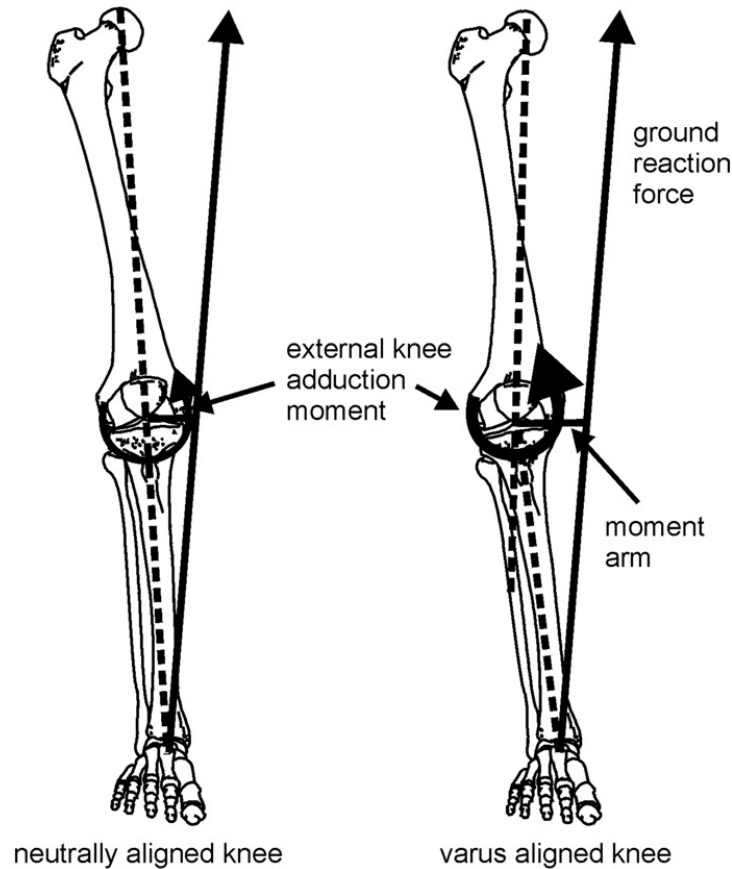


Figure 1-2. Moment arm comparison of a Left) neutrally aligned knee and Right) varus aligned knee. The greater distance of the varus knee's joint center from the foot's center of pressure creates a larger moment arm and higher than normal KAM [1].

Although most research agrees that MCFs are a primary indicator of the progression and severity of OA, there exists some debate regarding the degree to which KAM can approximate MCFs [11], [27], [28]. It is important to note that these studies do not claim that the KAM is without merit in estimating joint loading and characterizing OA, but rather that it is not solely sufficient as a correlator to dynamic loading in the medial compartment. A number of other factors, such as the mechanical axis of the knee joint [27], gait type [11], foot angle [17], and placement of the mobility

aid relative to the affected limb [18], [29] have been suggested as other predictors of MCFs. In this regard, the exclusion criteria of our study, described in Section 2.1 Subject Demographics, was implemented in part to account for dramatic deviations in mechanical axis of the knee joint or foot/ankle and instructions were given in non-control trials to ensure adequate form, described in detail in Section 2.3 Data Collection. Gait was normalized by use of a maintained walking speed during testing and no gait alterations were implemented as this would convolute results and the impact of gait modifications on KAM is unclear [11], [30], [31]. For these reasons, in addition to the vast amount of research supporting KAM as a proxy for MCFs, we are confident that our focus on changes in the peak value and force-time integral effects of the arthritic knee's adduction moment are sufficient for the scope of this investigation.

1.3 CURRENT KNEE OSTEOARTHRITIS TREATMENT METHODS

Diagnosis techniques have vastly improved over the past decade [2], [32]–[35] but as OA is progressive, early-identification is only as good as the preventative measures available. Prophylaxis usually takes the form of mobility aids: walking canes, specialized shoe insoles, four-legged walkers, and wheelchairs [36]–[41]. Physical therapy may also be combined with use of mobility aids but lack of reliable diagnosis techniques and continued disagreement regarding the etiology of the disease [11], [17], [28], [42] have made providing adequate patient-specific care difficult [1], [14], [43], [44]. Walkers and wheelchairs are usually only suggested for progressed cases, as they require greater reliance, limit self-sufficient mobility, and often coincide with reactionary treatments, prescribed once independent disease maintenance and/or physical therapy are no longer adequate. Reactionary treatments are defined in this report to include the prescription of opioids or non-steroidal anti-inflammatory drugs (NSAIDs) and/or surgical intervention. Surgical intervention is usually conducted to identify/remove damaged cartilage or replace the

joint entirely. Surgery is often frightening to individuals [45] and can lead to stiffness, reduced range of motion in the joint, and other problematic side-effects [46]. NSAIDs address symptomatic pain, however, often individuals are hesitant to use NSAIDs because of allergies, unwanted side-effects, or proclivity to addiction [36], [37].

There is evidence that walking canes provide better symptom relief when used regularly [47], [48] and that moderate exercise with proper use of mobility aids leads to improved physical functioning and decreased pain in patients with knee OA [49]. Unfortunately, the tendency of patients to delay doctor visits [37] and physicians' inability to accurately diagnose and relay useful case-specific information [43] leaves many of those with knee OA unsure of what constitutes healthy activity levels and pain management techniques for their condition [50]. This failure in communication also results in patients who are uncertain of when and how to use an assistive mobility device [37]–[39], [41], [43], [50].

1.4 PRIOR ATTEMPTS TO IMPROVE CANE TECHNIQUES

Mobility devices require proper technique to be effective at treating the symptoms of OA and reducing the loading associated with disease progression [1], [18], [29], [37]. This is especially true for walking canes used for off-loading of an injured or disabled leg. While cane use may seem straight-forward, one of the most important aspects for knee OA patients – applying enough load to the cane in order off-load the arthritic joint – is patient-specific, and often underestimated [18], [19]. Failure to apply sufficient axial load to the walking cane, in turn, does little to relieve the arthritic leg of undue stress and symptomatic pain. When used correctly (contralaterally to the affected leg, with sufficient transfer of bodyweight), walking canes have shown to be effective at decreasing measures of joint loading commonly associated with joint degeneration and disease progression [18]–[20], [29], [38], [51]–[55].

Many of those with knee OA who use canes are unaware that they are insufficiently loading their canes and even for those who are conscious of the correct technique, estimating and regulating the amount of weight being applied to a cane during walking is an extremely challenging task to accomplish without additional tools or extensive training. In response to these troubles, attempts have been made to quantify and improve upon conventional walking aids' usefulness at ameliorating the symptoms of knee OA [47], [48], [56]. Studies comparing various methods used to improve subjects' adherence to partial-weight loading instructions found that biofeedback based on an applied load, as a percentage of the user's bodyweight (%BW), was the best method to improve patients' use of walking aids [19], [55]–[57].

Researchers have previously attempted to implement such biofeedback into conventional walking canes in order to provide the OA community with a more effective and intuitive solution to their ailments [53], [56]. A study conducted by Simic *et al*, evaluating the effect of cane load on KAM, found a dose-response relationship between the applied load and KAM during stance. Their study varied cane loadings from 10% to 20%, based on preliminary research regarding the minimum and maximum loads cane-users felt comfortable applying. However, Simic's cane study used visual feedback on a projector (Figure 1-3, reproduced from [18]) and therefore could not reasonably be taken out of a lab environment. Despite the substantial research into walking cane usage, its effect on the symptoms of knee OA, and ways to potentially improve devices, little has been done to implement these findings in a practical device that can leave the constraints of a lab and be used in a longitudinal study or the “real-world.”

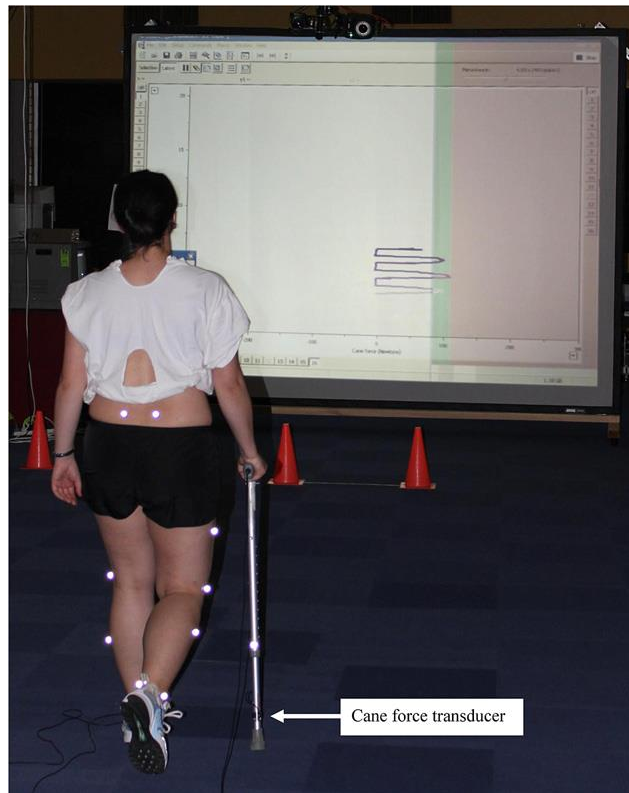


Figure 1-3. Participant in Simic's cane study using visual feedback to encourage better cane loading, reproduced from [18].

1.5 STUDY PURPOSE

The purpose of this study was to determine the short-term efficacy of a novel walking cane that uses haptic biofeedback to encourage proper cane loading. Visual [18] and audio [53], [56] biofeedback have previously shown to allow participants to achieve a target cane load which reduced their knee loading. However, such systems cannot be taken out of the laboratory. Here we have developed a novel walking cane that provides a vibratory tactile sensation in the handle when proper cane loading is reached. We hypothesized that haptic biofeedback would increase cane loading (H1) and decrease knee loading (PKAM (H2.1) and KAAI (H2.2)) when compared to naïve cane use. We also compared the haptic biofeedback cane to use of a traditional cane with verbal instruction and scale training and explored short term retention and performance of partial

weight-bearing after a 5-minute break. By developing a cane that can be easily brought out of the lab and into the hands of the OA community, we hope to delay the need for surgical intervention, reduce injury recovery times, and slow the progression of diseases such as osteoarthritis.

1.6 HYPOTHESES

We developed two measures of interest by which to evaluate our novel cane's ability to lower degenerative loading in the arthritic knee during walking. The following outcome measures were analyzed across trial conditions for each subject.

Specific Aim 1: Demonstrate that cane loading is greater when walking with a cane with haptic biofeedback as compared to walking with a conventional cane. *Hypothesis 1: Mean peak cane load when using a cane with haptic biofeedback is greater than mean peak cane load when using a conventional cane. (H1)*

Specific Aim 2: Demonstrate that the KAM is reduced when walking with a cane with haptic biofeedback as compared to walking with a conventional cane. *Hypothesis 2.1 & 2.2: Mean peak KAM (H2.1) and mean KAAI (H2.2) when using a cane with haptic biofeedback are less than mean peak KAM and mean KAAI when using a conventional cane.*

The following sections detail the methodology of our data collection, processing, and analysis, from participant recruitment and model creation to statistical analyses of loading metrics.

Chapter 2. METHODS

2.1 SUBJECT DEMOGRAPHICS

Twenty-one individuals who had experience using a walking cane and reported clinically diagnosed knee OA attended data collection sessions for this IRB approved study. Equipment malfunction resulted in unusable data for two subjects, thus data from 19 participants (seventeen were male and two were female) was analyzed. Participants were excluded from the study if they had a knee replacement in the knee diagnosed with OA, had undergone knee surgery within the past year, could not perform cane walking continuously for 30 minutes, or exhibited other neurological and/or rheumatologic conditions that would impact gait. All subjects gave their informed consent to the IRB approved protocols. Biometrics, such as height, weight, and age were collected in addition to information about subjects' OA and cane use history (Table 1). Subjects were given the Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC) questionnaire, from which scores between 0 and 96 can be used to evaluate the impact of knee OA on the individual's quality of life [58], [59]. The average WOMAC score was 48.3 ± 19.7 . The average age was 60 ± 12.1 years, the average height was 1.79 ± 0.09 m, and the average weight was 99.9 ± 21.3 kg. Participants had an average of 12.5 ± 11.4 years with diagnosed knee OA and an average of 5.25 ± 7.4 years of experience with walking canes.

Table 2-1. Demographic data for study participants.

Subject	Sex	Age (yrs.)	Height (m)	Weight (kg)	Time since OA diagnosis (years)	Time using cane (years)
1	M	54	1.8	117	15	8
2	M	61	1.8	129	19	19
3	F	56	1.6	96	3-4	3.5
4	M	56	1.9	114	21	2
5	M	65	1.85	112	2	1
6	M	52	1.7	120	3.5	2
7	M	69	1.8	82.55	5	1
8	M	61	1.7	102	5-6	3.5
9	F	62	1.8	64	13	.25
10	M	53	1.8	74	9	2
11	M	55	1.8	88	34	27
12	M	45	1.7	110	16	2
13	M	57	1.9	94	5	3
14	M	41	1.83	117	13	20
15	M	60	1.75	113.5	2-3	1
16	M	33	1.88	125	10	6
17	M	87	1.68	77.6	6	.25
18	M	78	1.82	93.9	20	.25
19	M	69	1.62	59.6	47	2.5

WOMAC scores can be used to evaluate the impact of knee OA on the individual's quality of life. For our study, the WOMAC was used as an input in the statistical analysis to develop mixed-effects models, further explained in the Statistical Methods section of this chapter. Two of the 19 participants did not complete the WOMAC form during data collection and could not be contacted later to do so. Again, as this data was missing completely at random, rather than excluded due to performance, it should not bias the results.

2.2 GAIT LAB INSTRUMENTATION

Three-dimensional kinematics were collected using a camera 12 Vicon Nexus system (Vicon Motion Systems, Oxford, United Kingdom) with a sampling frequency of 120 Hz. Five force plates (AMTI) sampling at 1200 Hz were used for collection of ground reaction forces (GRFs) and

identification of gait events during walking trials. Two time-gates were placed 2-meters apart for measurement of walking speed, in order to maintain a consistent walking speed across trials.

A haptic biofeedback cane (Figure 2-1) was designed and manufactured to measure the user applied axial cane load, compare the load to the targeted 20% BW threshold, and then deliver a vibrotactile feedback in the cane handle when the loading was greater than the threshold. The cane data acquisition was temporally synchronized to the motion analysis system and recorded axial cane loads at 100 Hz for later analysis. The haptic biofeedback cane consisted of a conventional bariatric walking cane (Patterson Medical Ltd) with a loadcell (Measurement Specialties FC22-series) placed inside a 3D printed modular cane foot. A microcontroller (Sparkfun™ Pro Micro), SD disk storage (Sparkfun™ OpenLog), eccentric rotating mass vibration motor (Precision Microdrives Ltd), and USB communications port (used for file transfer), and battery completed the feedback system (Figure 1). A motor on/off switch was also implemented so the feedback mechanism could be disabled during conditions calling for a conventional cane, while still allowing for collection of cane-loading data. Before walking trials began, the cane height was adjusted to the participant's distal wrist crease [60]. Further information about the design process and functionality of the modified walking cane is in the *Device Development* section of this report.

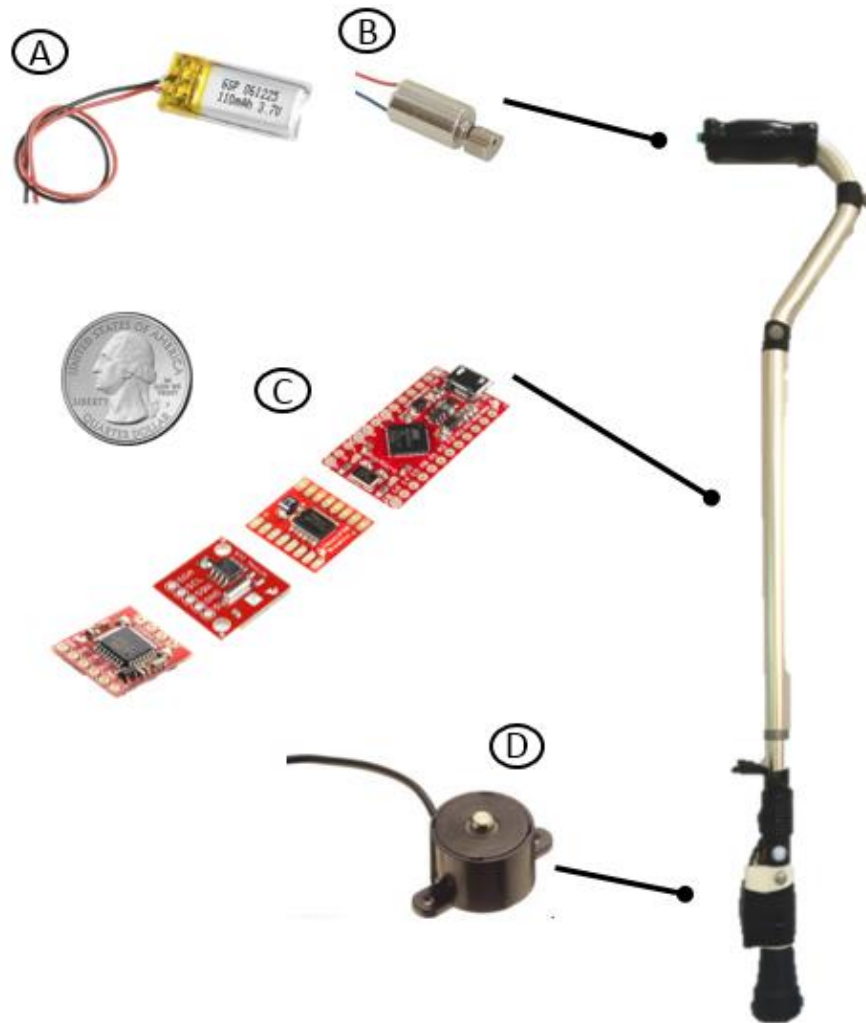


Figure 2-1. Components of the cane used for data collection comprised of A) battery power-source B) vibrational motor, C) electronics for feedback control and data logging, and D) a force sensor for cane load measurement.

2.3 DATA COLLECTION

Each participant attended a single laboratory data collection session for the acquisition of kinematic, kinetic, and biometric data. At the beginning of the session, participant consent was collected via signature through IRB approved paperwork. Next, the research team asked the participant a series of brief questions including but not limited to; years since OA diagnosis, how

many years they have used a cane for, which knee (left or right) was diagnosed with arthritis – if both, which was the most afflicting, and in which hand the cane was usually held.

First, the participant was asked to walk down an approximately 20-meter hospital hallway with a conventional cane to establish a self-selected walking speed (SSWS), which the participant was informed they would need to maintain during testing. After establishing a SSWS with a conventional cane, participants changed into motion capture conducive clothing and retro-reflective markers were placed using a modified Plug-In-Gait model with additional markers on the foot, thigh, and shank, via the Kadaba Model, for observation of the KAM during level ground walking [21], [61].

Additional markers were included on the following anatomical landmarks of both legs: lateral epicondyle, femoral-head, tibial tuberosity, the 1st and 5th metatarsals, and malleolus (Figure 2-1).

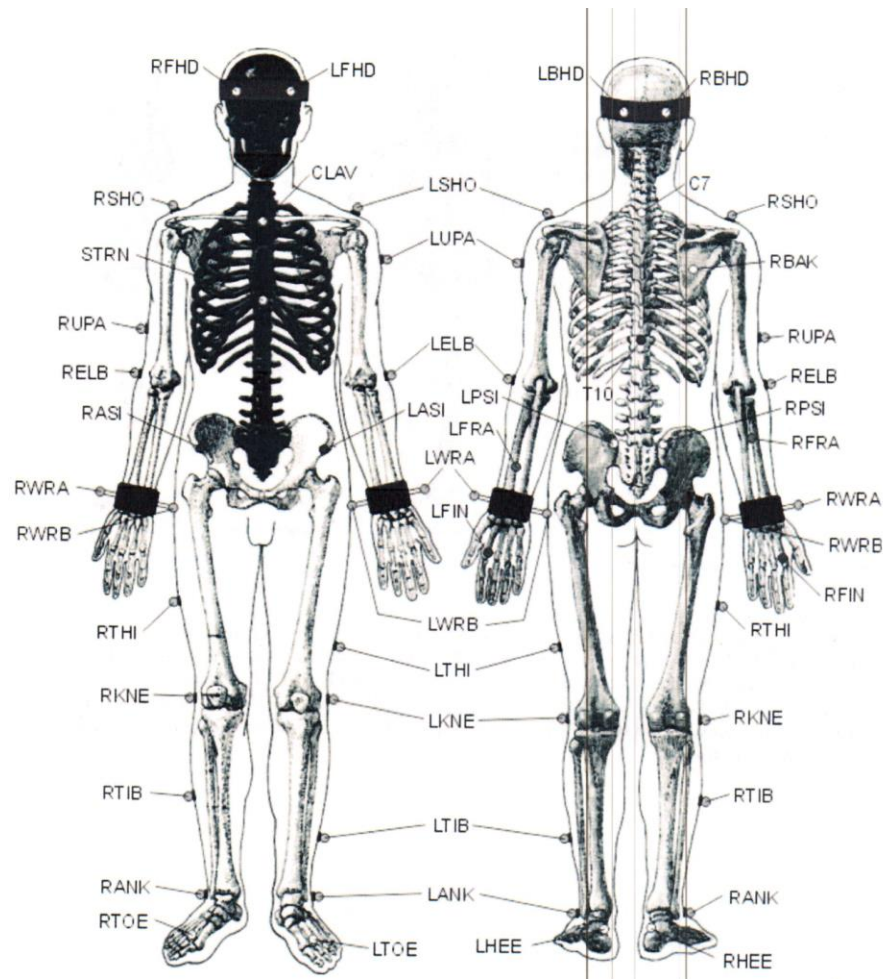


Figure 2-2. Marker locations for visualization of the human subject in Vicon

Markers at the epicondyle, tibial tuberosity, and the femoral head allowed for higher accuracy measurements of the frontal-plane KAM. The metatarsal and malleolus markers were included in accordance with the findings of Levinger *et al* which showed the importance of foot-ankle motion to knee OA gait analysis [17]. Markers were also added to the proximal and distal ends of the walking cane shaft (on both medial and lateral sides), as well as a single marker on the anterior curve of the cane's handle to observe the motion of the cane in Vicon during walking (Figure 2-2).

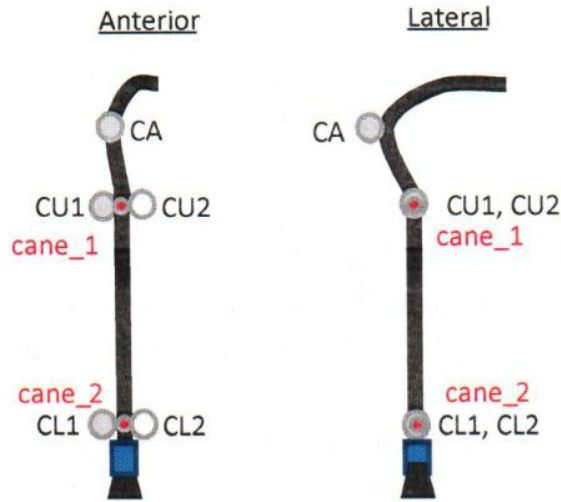


Figure 2-3. Marker locations for visualization of the walking cane in Vicon.

Adding MoCap markers to the cane also allowed for calculation of the times at which the cane made initial contact with the ground as well as when it left the ground.

The cane's feedback mechanism was tested before data collection and the microcontroller was updated with the participant's BW to set the threshold limit for delivery of the haptic feedback.

Participants were then instructed to walk at SSWS along an approximately 9-meter walkway containing five force-plates but remained unaware to the purpose of the plates throughout data collection, to avoid influencing gait. Walking trials were carried out under the following five conditions: 1) naïve, 2) scale training, 3) scale recall, 4) haptics training, and 5) haptics-only (Table 2-2). The order of the scale-based (C2A, C2B) and haptics-based conditions (C3A, C3B) was randomized at the beginning of data collection to avoid a learning bias.

Table 2-2. Descriptions of walking trial conditions

Condition	Description
C1: Naive	Conventional cane with no instruction
C2A: Scale Training	Conventional cane, scale training, and instruction on proper cane-use technique
Rest Period	5-minute break to test short-term instruction recall/adherence
C2B: Scale Recall	Conventional cane, recalling scale training with no further instruction/practice
C3A: Haptics Training	Haptic Biofeedback walking cane with an explanation of the feedback mechanism, including a practice session
Rest Period	5-minute break to test short-term instruction recall/adherence
C3B: Haptics-Only	Haptic Biofeedback cane with no further instruction/practice.

A script for the condition instructions can be found in Appendix A. The order of the scale-based (C2A, C2B) and haptics-based conditions (C3A, C3B) was randomized at the beginning of data collection to avoid a learning bias. During scale training participants practiced applying the suggested 20% BW to their canes using a beam scale that had been set to the correct weight, until they felt comfortable recreating the technique (usually less than five minutes). Before the ‘B’ conditions, a five-minute break was taken to test short-term instruction retention. For each condition, between 5 and 8 successful trials were collected. A trial was deemed successful when walking speed was kept within 10% of SSW to maintain gait characteristics and the foot of a participant’s arthritic leg landed entirely on a force-plate - referred to as a, ‘good-step.’ During data processing “successful” trials were excluded if there was excessive noise in the MoCap data, contact on the force-plate of interest from the cane or non-affected leg, or if a cane-strike did not occur during stance phase of the affected leg.

The modified cane’s embedded systems measured force data at 100 Hz for the duration of the walking trials. Data collection was initiated by a research team member who was stationed at the

computers running Vicon. The Arduino code on the cane's microcontroller (Appendix B) allowed for a signal to be sent from the Vicon computers to the cane through an auxiliary connection to initialize the cane's data collection and Vicon's data collection processes simultaneously. A team member would be holding the cane during at the start of each trial for this initialization, then the auxiliary cord would be unplugged, and the cane immediately handed to the subject to begin the walking trial. The participant was asked to turn off the cane (via simple button switch) at the end of the ~20m path. At the beginning of the next trial upon powering the cane a new data file would be created by the power-cycle.

2.4 MODEL CREATION

Marker labels were transferred from Vicon to C-Motion's Visual 3D software (V3D) where subject-specific models were created using MoCap and biometric data to calculate joint torques during walking (figure 2-3).

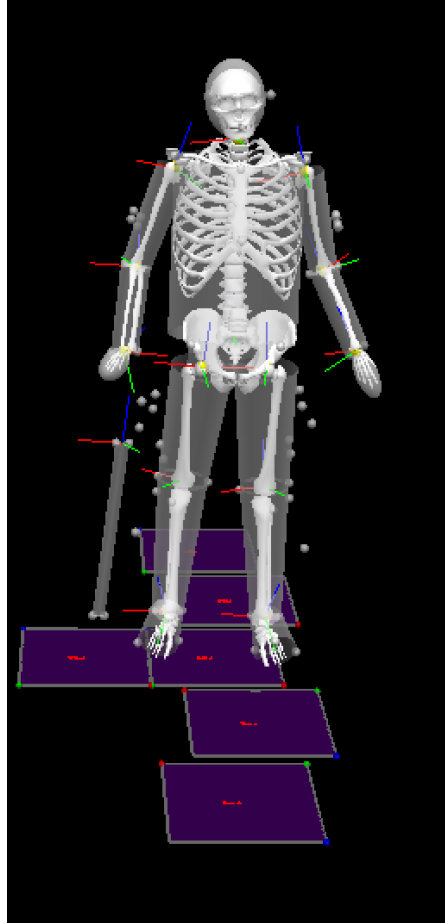


Figure 2-4. A subject-specific model created in Visual3D.

The generalized patient model has 13 joints; at the neck, right and left (R/L) hip, R/L knee, R/L shoulder, R/L elbow, R/L wrist, and R/L ankle. These joints connect the 15 body segments; the head, abdomen, pelvis, R/L upper arm, R/L forearm, R/L hand, R/L foot, R/L thigh, R/L shank, and a segment for the walking cane.

2.5 DATA PROCESSING

Markers in a static image of the participant, taken with the Vicon cameras, were labelled according to the marker convention described in Section 2.4. At first an auto-labeler in Vicon was used and checked for inconsistencies but eventually it became more time-effective to manually label the

static trial markers. The static model was then used as a template for auto-labelling of the markers in the dynamic trials. Small gaps in the MoCap marker trajectories during walking trials were filled using splines and the location of surrounding marker trajectories. It may be worth noting that there were far fewer gaps in dynamic trials that were associated with a manually labeled static trial, rather than an auto-labeled static model.

This data was then sent to Visual 3D for calculation of joint torques and gait events before being sent to MATLAB (Appendix C), along with the cane loading data, for further processing (Figure 2-4). This processing is described in greater detail in the following sections 2.6.1 & 2.6.2.

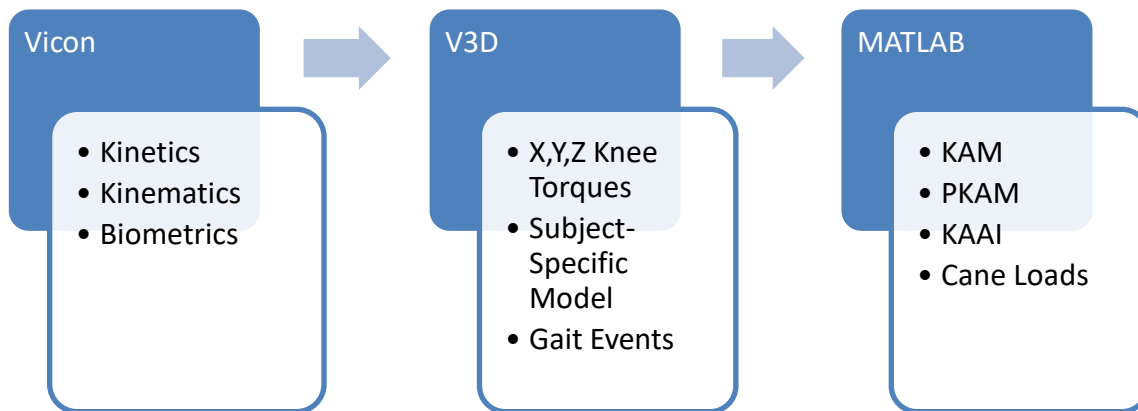


Figure 2-5. Flowchart depicting data processing pipeline.

2.5.1 *Knee Torque Calculation*

For each walking trial, gait events were created in V3D, using GRFs collected from the force plates, to establish heel-strike (HS) and toe-off (TO) times of the arthritic leg, as calculations were made between these events. All events not referencing a good-step were deleted. Up to three good-steps, per successful trial, were used for calculation of the KAM. Joint torques were calculated for the arthritic knee during stance phase of each good-step using the inverse kinematics packages in V3D. This tool uses a weighted least-squares fit at marker locations to position the model for each

frame, using the following equation [62]. Joint torques were then exported to MATLAB for further processing and initial analysis.

$$\sum_1^n k_n \left[\sum_i^m ((\bar{P}_i - T(q)A_i) - \bar{O}(q))^2 \right]$$

Where:

n , is the number of segments,

m , is the number of markers used to track that segment,

\bar{A}_i , is the location of the marker in the segment coordinate system (SCS),

\bar{P}_i , is the location of the marker in the laboratory coordinate system (LCS),

$T(q)$, is the rotation matrix from the SCS to LCS as a function of all the generalized coordinates,

And $O(q)$, is the translation between coordinate systems as a function of all the generalized coordinates.

MATLAB was used to isolate the frontal plane knee torque from the sagittal and transverse torques which were also included in the file from V3D and separate them into their respective conditions. A MATLAB “structure” was made for each study participant. Each structure had a non-identifying number, file-paths to the cane loading data, and associated KAM data, the number of good-steps used for analysis in each condition (for MATLAB indexing purposes), as well as the subject’s age, height, weight, WOMAC score. Within a given subject’s structure, five sub-structures were created for each condition type. Measures of PKAM and KAAI were allocated to their respective sub-structures. Additionally, using the HS and TO values from V3D, stance phase duration of each good-step was calculated. This was used to normalize the KAAI to the unique stance phase duration of each step and may be used for future analysis of other variables of interest, further

discussed in the Confounding Factors section of the Discussion Chapter (Section 4.3). Other normalizations such as for PKAM (using bodyweight and height) and cane load (using bodyweight) were also performed in MATLAB.

2.5.2 Cane Load Calculation

Cane files associated with walking trials in which a good-step was recorded were sent to MATLAB for further processing. In MATLAB, a peak-finding algorithm was used to locate peak cane forces. A minimum peak-width and the associated time-stamp in relation to the initialization of the trial's data collection. A minimum peak height, peak width, and frequency threshold was set to prevent noise from being interpreted as a cane peak (Figure 2-5).

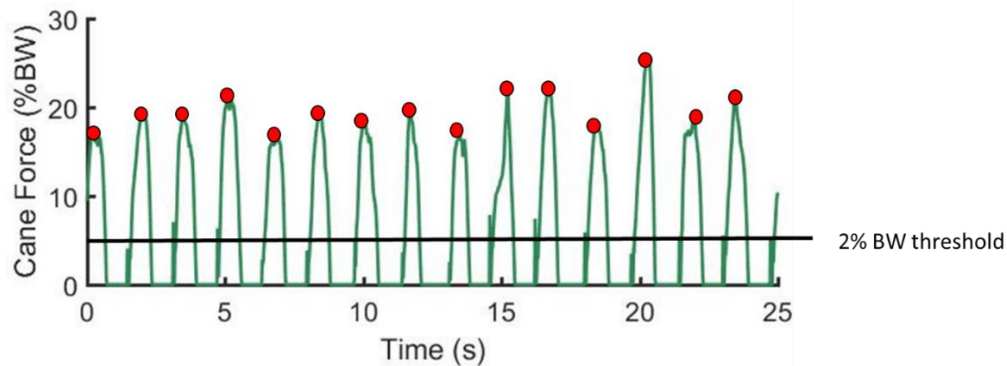


Figure 2-6. Hypothetical cane loading data from a walking trial, normalized to % BW with example 2% BW threshold. Valid peaks are signified by red dots.

To ensure that the cane loading occurred during the stance phase of the arthritic leg (Figure 2-7, reproduced from [63]), event markers were created for each instant that the cane made initial contact (cane-on) and final contact (cane-off) with the ground, during each cane loading epoch in a walking trial.

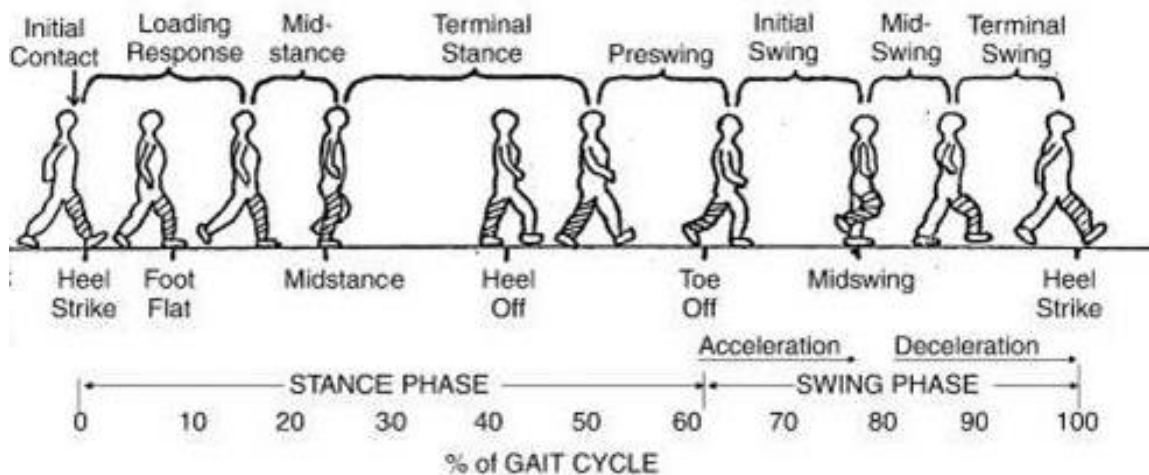


Figure 2-7. Phases of gait during walking. The phase of interest, stance phase, takes place from HS to TO [63].

In MATLAB, these event markers were compared to the heel-strike and toe-off event markers from the human subject V3D model. If cane-off occurred before HS or cane-on occurred after TO (i.e. the cane was not on the ground during stance phase of the arthritic leg) the KAM was removed from analysis as there was no cane-loading during stance to influence the KAM.

2.6 STATISTICAL METHODS

We employed linear mixed effects models with a random intercept for subject and a random slope for condition type to estimate and compare mean normalized PKAM and KAAI by condition type (fixed effect). Normalized PKAM and KAAI were modeled with the walking trial condition as the independent variable of interest. Linear mixed effects models were also used to determine the effect of each condition on normalized peak cane loading.

For both models, the naïve cane usage was used as the reference condition and contrasts were obtained for every condition type vs. the naïve condition as well as for the haptics-only vs. scale training recall.

Other independent variables of interest considered were: WOMAC score, weight, height, and age. If any of these additional characteristics were found to be associated with the outcome measure ($p < 0.05$), they would be considered for inclusion in a multivariable model.

All analyses were performed in R version 3.3.2 [64] Linear mixed models were fit using the 'lme4' package with the restricted maximum likelihood approach. Alpha was set at 0.002 to account for 10 comparisons made within each a priori hypothesis.

All available cane loads from trials containing good-steps were evaluated by condition type to determine the effect of each condition type on cane loading. The naïve condition was used as the reference condition and contrasts were obtained for every condition type vs. the naïve condition as well as for the haptics-only vs. conventional recall. Cane load was normalized by height and weight. All cane loads, even those not associated with a step were included in this analysis as each cane loading epoch in a walking trial should be a valid measure. However, because event markers could only be created for good-steps – as there was no way to know the time of HS/TO if the relative part of the foot does not contact the plate – comparisons could not be made between the cane's event markers and not-good-steps. Our team decided this was acceptable as the analysis of the cane loading was separate from analysis of the KAM. KAM calculations only included measures associated with good-steps, as explained in the next section.

Chapter 3. RESULTS

3.1 COMPARISON OF CANE LOADING

Contrasts were obtained for every condition type vs. the naïve condition (used as reference) as well as for the haptics-only vs. scale training recall (Section 2.6.2). Compared to naïve cane loading, both scale training and the haptic biofeedback cane resulted in a statistically significant increase in cane loading ($p < 0.0001$). The model-adjusted mean cane load for the naïve condition was 6.91 ± 1.34 %BW which increased to 18.2 ± 2.11 %BW and 21.8 ± 1.37 %BW with scale training and training with the haptic cane, respectively. The scale training recall and haptics-only trials produced similar loading values of 17.3 ± 1.97 %BW and 22.8 ± 1.18 %BW, respectively. The model-adjusted mean cane loading in these recall trials was statistically significantly higher than the naïve trials ($p = 1e-6$). Comparison of mean cane loading between scale training recall and haptics-only trials showed a statistically significant increase in cane loading in the haptics-only condition ($p = 0.019$). Scale training and haptics-only cane loading were not statistically significantly different ($p = 0.0515$, $p = 0.064$). The 95% CI range for the haptics cane was found to be noticeably smaller than scale training and recall of the scale training, with a range similar to that of the naïve use condition's 95% CIs (Figure 3-1). Table 3-1 shows the full statistical outcomes related to cane loading analysis. Condition contrast results from the mixed-model and cane loadings can be found in Table 3-2 with their respective p-values. The effect estimate in the contrast table can be interpreted as the mean difference between the two conditions. For example, in the first row of Table 3-2, C2 vs C1 shows that naïve use of a conventional walking cane resulted in an average of 11.3 %BW applied to the cane compared to conventional cane use after scale training. Initial use of the haptic biofeedback cane caused the cane to be loaded an average of 14.9 %BW more than the naïve condition.

Table 3-1. Mean normalized Cane Loading for each cane condition

	Unadjusted Mean	SD	Model- Adjusted Mean	S.e of mean	Lower- bound CI	Upper- bound CI
Naïve	9.589	6.656	6.907	1.338	4.100	9.713
Scale Training	19.26	9.428	18.20	2.106	13.79	22.60
Scale Recall	19.34	7.900	17.29	1.972	13.16	21.42
Haptic Training	23.09	5.944	21.78	1.375	18.98	24.66
Haptics- Only	23.35	6.861	22.84	1.185	20.33	25.36

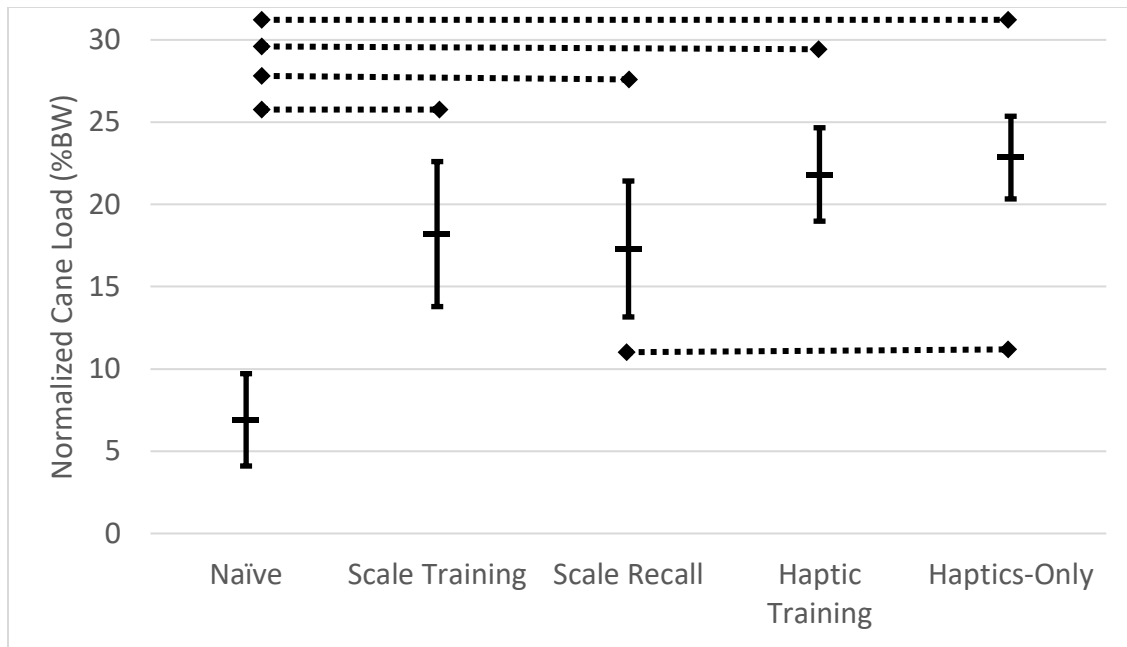


Figure 3-1. Model-adjusted mean cane loading by condition, as a percentage of bodyweight. Error-bars represent the 95% CIs. Dotted lines with square ends show pairwise comparisons with statistically significant differences in means ($p < 0.002$).

Table 3-2. Contrasts of conditions from mixed model for cane loading (significant comparisons in bold).

	Effect Est	S.E of Est	Lower-bound CI	Upper-bound CI	p-value
C2 vs C1	-11.2885	2.2606	-16.0205	-6.5565	1.00E-04
C3 vs C1	-10.3832	2.4995	-15.6263	-5.14	6.00E-04
C4 vs C1	-14.8767	1.9184	-18.888	-10.8653	0
C5 vs C1	-15.9379	1.6088	-19.3225	-12.5533	0
C3 vs C2	0.9053	2.3595	-4.0323	5.843	0.7055
C4 vs C2	-3.5882	2.382	-8.5697	1.3934	0.1482
C5 vs C2	-4.6494	2.2351	-9.3322	0.0334	0.0515
C4 vs C3	-4.4935	2.2836	-9.2764	0.2895	0.064
C5 vs C3	-5.5547	2.1675	-10.0967	-1.0127	0.0192
C5 vs C4	-1.0612	1.1928	-3.629	1.5066	0.3892

3.2 COMPARISONS OF KAM CHARACTERISTICS

Contrasts were obtained for every condition type vs. the naïve condition (used as reference) as well as for the haptics-only vs. scale training recall (Section 2.6.1). Scale training and use of the haptic biofeedback cane reduced KAM across stance phase with the primary reductions occurring in late-stance (Figure 3-2). The average was determined by averaging across trials within each subject and condition, and then averaging across all subjects within condition.

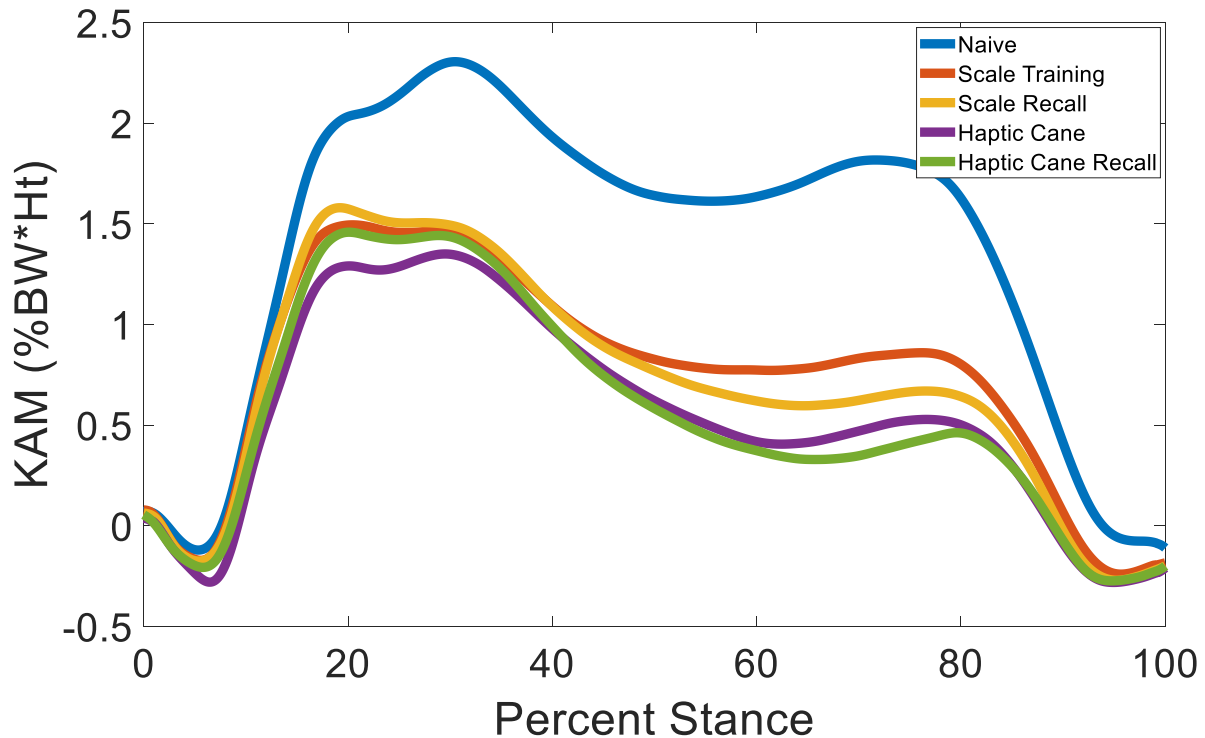


Figure 3-2. Average knee adduction moment for the naïve (blue), scale training (red), scale recall (yellow), haptic cane (purple), and haptic cane recall (green) conditions.

3.2.1 Comparison of PKAM

Both scale training and the haptic biofeedback cane significantly reduced PKAM. The model-adjusted mean PKAM was 2.58 ± 0.198 % BW*Ht in the naïve condition. Scale training resulted in a statistically significant reduction in PKAM to 1.83 ± 0.189 % BW*Ht ($p = 1e-4$). Haptic training also resulted in a statistically significant reduction in PKAM from the naïve condition to 1.79 ± 0.177 % BW*Ht. There was no statistically significant difference in mean PKAM when comparing scale training (1.83 ± 0.189 % BW*Ht) to haptics training (1.79 ± 0.177 % BW*Ht) ($p=0.710$) (Figure 3-3).

Mean PKAM did not show a statistically significant change between the scale training and haptic biofeedback conditions ($p=0.709$). There was also no statistically significant change in PKAM

between scale training ($1.83 \pm 0.189\% \text{BW} \cdot \text{Ht}$) and scale training recall ($1.87 \pm 0.206\% \text{BW} \cdot \text{Ht}$) ($p=0.564$) or between haptic training ($1.79 \pm 0.177\% \text{BW} \cdot \text{Ht}$) and haptics-only trials ($1.82 \pm 0.145\% \text{BW} \cdot \text{Ht}$) ($p=0.733$) (Figure 3-3).

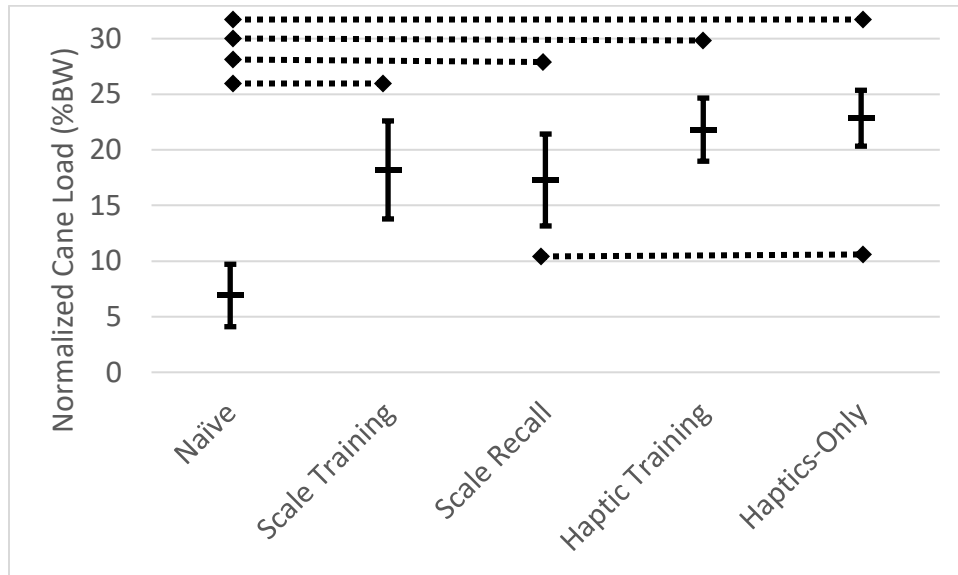


Figure 3-3. Model-adjusted mean PKAM by condition, as a percentage of bodyweight and height. Error-bars represent the 95% CIs. Dotted lines with square ends show pairwise comparisons with statistically significant differences in means ($p < 0.002$).

Table 3-3 shows the full statistical outcomes related to PKAM analysis. Condition contrast results from the mixed-model and PKAM can be found in table 3-4 with their respective p-values.

Table 3-3. Mean normalized PKAM for each cane condition

	Unadjusted Mean	Model-Adjusted Mean	S.e of mean	Lower-bound CI	Upper-bound CI
Naïve	2.56	2.5842	0.1978	2.1687	2.9997
Scale Training	1.863	1.8253	0.1892	1.4277	2.2228
Scale Recall	1.873	1.8713	0.2055	1.4397	2.3029
Haptic Training	1.749	1.7906	0.1774	1.4179	2.1633
Haptics-Only	1.809	1.8234	0.1786	1.4478	2.1989

The effect estimate in the contrast table can be interpreted as the mean difference between the two conditions. For example, in the first row of Table 3-4, C2 vs C1 shows that naïve use of a conventional walking cane resulted in a higher PKAM by 0.759 %BW*Ht, on average, compared to conventional cane use after scale training. Initial use of the haptic biofeedback cane resulted in the PKAM being lowered by an average of 0.794 %BW*Ht, compared to the naïve condition.

Table 3-4. Contrasts of conditions from mixed model for PKAM (significant comparisons in bold).

	Effect est	S.e of est	Lower-bound CI	Upper-bound CI	p-value
C2 vs C1	0.7589	0.1522	0.4394	1.0785	1.00E-04
C3 vs C1	0.7129	0.1445	0.409	1.0167	1.00E-04
C4 vs C1	0.7936	0.1371	0.505	1.0821	0
C5 vs C1	0.7608	0.1348	0.4766	1.045	0
C3 vs C2	-0.0461	0.0784	-0.2106	0.1185	0.564
C4 vs C2	0.0347	0.0916	-0.1585	0.2279	0.7098
C5 vs C2	0.0019	0.1101	-0.2314	0.2352	0.9866
C4 vs C3	0.0807	0.09	-0.1802	0.2696	0.3813
C5 vs C3	0.0479	0.0994	-0.1629	0.2588	0.6363
C5 vs C4	-0.0328	0.0937	-0.2404	0.1748	0.7334

Univariate comparisons used to determine the influence of the WOMAC score, weight, height, and age (Table 3-5) found *no significance* impact from these variables on PKAM, given by the p-values ($p < 0.05$). The effect estimate gives the unit change compared to the naïve condition. For example, for every point increase in WOMAC score, PKAM was reduced by 0.011 %BW*Ht. This was found to be insignificant, given the p-value ($p = 0.218$).

Table 3-5. Univariate results from mixed model for PKAM.

	Effect est.	S.e of est	p-value
WOMAC	-0.011	0.008	0.218
Weight	-0.01	0.008	0.195
Height	-2.549	1.882	0.194
Age	0.011	0.014	0.44

3.2.2 Comparison of KAAI

Both scale training and the haptic biofeedback cane significantly reduced KAAI. The model-adjusted mean KAAI was $1.39 \pm 0.158\%BW*Ht*s$ in the naïve condition. Scale training resulted in a statistically significant reduction in KAAI to $0.710 \pm 0.143\%BW*Ht*s$, while the haptics training KAAI of $0.569 \pm 0.111\%BW*Ht*s$ was also statistically significantly less than the naïve condition ($p < 1e-6$) (Figure 3-4).

Mean KAAI did not show a statistically significant change between the scale training and haptic biofeedback conditions. There was no statistically significant change in KAAI between scale training (to $0.710 \pm 0.143\%BW*Ht*s$) and scale training recall ($0.692 \pm 0.138\%BW*Ht*s$) ($p=0.742$) or between haptic training ($0.569 \pm 0.111\%BW*Ht*s$) and haptics-only ($0.581 \pm 0.121\%BW*Ht*s$) ($p=0.835$) (Figure 3-4).

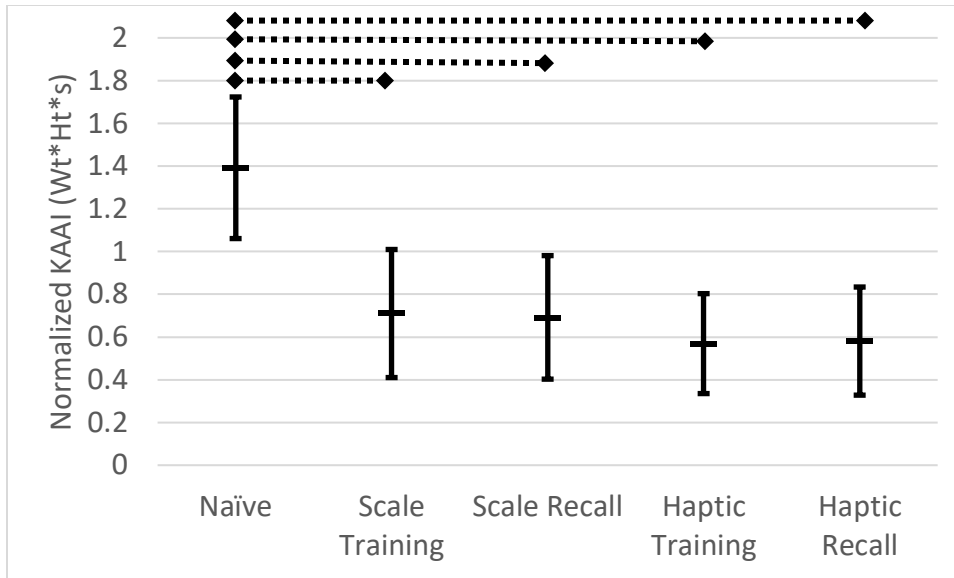


Figure 3-4. Model-adjusted mean KAAI by condition, as a percentage of bodyweight, height, and step-duration (in seconds). Error-bars represent the 95% CIs. Dotted lines with square ends show pairwise comparisons with statistically significant differences in means ($p < 0.002$).

Table 3-6 shows the full statistical outcomes related to KAAI analysis. Condition contrast results from the mixed-model and KAAI can be found in Table 3-7 with their respective p-values. The effect estimate in the contrast table can be interpreted as the mean difference between the two conditions. For example, in the first row of Table 3-7, C2 vs C1 shows that naïve use of a conventional walking cane resulted in a higher KAAI by 0.682 %BW*Ht*s, on average, compared to conventional cane use after scale training. Initial use of the haptic biofeedback cane resulted in the KAAI being lowered by an average of 0.823 %BW*Ht*s, compared to the naïve condition.

Table 3-6. Mean normalized PKAM for each cane condition.

	Unadjusted Mean	Model-Adjusted Mean	S.e of mean	Lower-bound CI	Upper-bound CI
Naïve	1.377	1.392	0.1578	1.0607	1.7234
Scale Training	0.757	0.71	0.1427	0.4102	1.0097
Scale Recall	0.7	0.6919	0.1376	0.4028	0.981
Haptic Training	0.552	0.5691	0.1114	0.3353	0.803
Haptic Recall	0.557	0.5809	0.1205	0.3279	0.8339

Table 3-7. Contrasts of cane conditions from mixed model for KAAI (significant comparisons in bold)

	Effect est	S.e of est	Lower-bound CI	Upper-bound CI	p-value
C2 vs C1	0.6821	0.1164	0.4377	0.9264	0
C3 vs C1	0.7001	0.1084	0.4725	0.9277	0
C4 vs C1	0.8229	0.1071	0.5974	1.0484	0
C5 vs C1	0.8112	0.1004	0.6008	1.0215	0
C3 vs C2	0.0181	0.0541	-0.0948	0.1309	0.7423
C4 vs C2	0.1408	0.1043	-0.0787	0.3604	0.1941
C5 vs C2	0.1291	0.1081	-0.0978	0.356	0.2477
C4 vs C3	0.1228	0.078	-0.0406	0.2862	0.1321
C5 vs C3	0.111	0.0895	-0.0766	0.2987	0.2302
C5 vs C4	-0.0117	0.055	-0.1318	0.1083	0.8346

Univariate comparisons used to determine the influence of the WOMAC score, weight, height, and age (Table 3-8) found *no significance* impact from these variables on PKAM, given by the p-values ($p < 0.05$). The effect estimate gives the unit change compared to the naïve condition. For example, for every point increase in WOMAC score, PKAM was reduced by 0.009 %BW*Ht. This was found to be insignificant, given the p-value ($p = 0.106$).

Table 3-8. Univariate results from mixed model for KAAI.

	Effect Est.	S.e of est	p-value
WOMAC	-0.009	0.005	0.106
Weight	0.000	0.005	0.931
Height	-1.562	1.252	0.229
Age	0.008	0.009	0.390

Chapter 4. DISCUSSION

The aim of this study was to evaluate a novel cane with haptic biofeedback, in its ability to increase the amount of bodyweight applied to the cane (to a subject-specific percentage) and in-turn, lower measures of the frontal plane knee moment regularly associated with degeneration of the joint and progression of knee OA. We compared the haptic biofeedback cane to naïve traditional cane use and verbal instruction with scale training. To evaluate short term retention and learning we also measured cane and knee loading after a 5-minute break with no further instruction given (e.g. the recall and haptics-only conditions). The strengths and limitations of this study can be found in Section 4.4. Ongoing commercialization efforts and plans for the continuation of device development, including further clinical research with the device, are detailed in Sections 4.5 and 4.6, respectively.

4.1 CANE LOADING

Significant differences were found for all comparisons of scale training and haptic cane conditions to the naïve condition (Table 3-2). This supports our hypothesis (H1) that use of a cane modified with haptic biofeedback will increase the mean peak cane load compared to the use of a conventional cane with no training. The haptic biofeedback cane also brought the mean cane load closer to the target load of 20% BW, which the scale training conditions were consistently below. Additionally, the haptics-only condition (C3b) had significantly higher loading than the scale training recall condition (C2b) and the haptics training cane loads (C3a) were trending toward a significant increase from the scale training trials (C2a). From this, we inferred that the haptic cane's constant corrective feedback does a better job of reinforcing proper partial-weight bearing techniques than a single session of scale training.

4.2 PKAM AND KAAI

Significant differences were found for all comparisons of scale training and haptic cane conditions to the naïve condition (Table 3-4). This supports our hypotheses (H2.1 & H2.2) that use of a cane modified with haptic biofeedback will decrease the mean peak knee adduction moment and mean knee adduction angular impulse, compared to the use of a conventional cane with no training. This may indicate that the haptic biofeedback cane is better for knee OA patients than a conventional cane. PKAM and KAAI were reduced from 2.58 %BW*Ht and 1.39 %BW*Ht*s in the naïve condition to, 1.82 %BW*Ht and 0.58 %BW*Ht*s in the haptics-only condition. These are similar to results seen by Simic and Levinger, though our findings are somewhat lower than Simic's and we saw a greater decrease in PKAM with a similar increase in cane loading [16], [17].

Univariate results from the mixed model found that WOMAC score, age, weight, and height had no significant impact on PKAM (Table 3-5) or KAAI (Table 3-8). This is not terribly surprising as age, height, and weight do not determine severity of knee osteoarthritis and although WOMAC is used as a measure of how impactful knee OA is on daily life, there is a tremendous discordance between symptomatic pain (which would heavily influence scores) and actual joint degeneration (which would influence gait mechanics) [1], [7], [40], [42].

While some studies have brought into question the level to which decreasing the knee adduction moment reduces medial contact forces [10], [27], a majority of research in the field of knee osteoarthritis uses PKAM, KAAI, or some combination of the two as the best estimate for medial loading. Furthermore, this study did not use KAM as a quantitative measure of the degradation occurring in the knee but rather as a qualitative measure, to compare the effectiveness of the various walking cane conditions.

4.3 CONFOUNDING FACTORS

The outcome variables in this report were cane load, PKAM, and KAAI with the WOMAC score, age, height, weight, and condition type as potential predictor variables. Statistical analysis found that only condition type was statistically significant as a predictor of the PKAM and KAAI. However, there are other variables which could contribute to altered KAM during stance such as cane load impulse, timing characteristics of cane load, range of cane angle during loading, cane placement relative to foot, cane load relative to KAM, and stance phase duration, among others. A number of these – such as cane load impulse and cane placement - have been investigated by previously mentioned, related studies, such as those by Simic, Levinger, and Chan [16], [17], [28]. We chose only to focus on our particular set of predictor variables as our intention was for our device to be as intuitive as possible and we felt additional facets included in the feedback signal

could complicate interpretation. In any case, we do currently have the data for cane load impulse, timing characteristics of cane load, cane placement relative to foot, cane load relative to KAM, and stance phase duration and future studies may investigate these and other variables in order to further develop our modified haptic biofeedback device.

4.4 COMPARISON TO SIMILAR STUDIES

Current walking cane designs have failed to keep up with advances made in the field of movement science related to mobility and impairment. As a result, canes often do little to improve an individual's condition, as they are unable to provide symptomatic relief when used incorrectly [14], [29]. Prior studies have attempted to improve cane-use techniques through increased instruction as well as visual and auditory feedback systems [18], [53], [55], [56]. Unfortunately, these methods were only useful in a laboratory setting and were not conducive to everyday use. To the best of our knowledge, this study represents the first attempt to develop a modified cane with a purely mechanical (unpowered) haptic feedback system which deliver constant corrective feedback to improve cane use techniques.

4.5 STRENGTHS AND LIMITATIONS

This study introduces a novel walking cane which has the potential to improve the partial weight-bearing techniques used by injured and disabled individuals far beyond the osteoarthritic community. The technology implemented in our cane can also be applied to other weight-bearing mobility devices as well. However, the device is still under development. Certain design considerations yet to be finalized could substantially change the device - such as modifying or replacing the feedback mechanism, adjusting weight distribution, etc. – but the general functionality will remain the same. While our cane was able to successfully increase the amount

of bodyweight applied to the cane, there is an upper-limit to this increase weight application, as other studies have pointed out, too much weight applied to the walking cane can result in undue stress to the upper-body [61]. We have not yet implemented a feature to alert the cane user when they have applied too much weight to the cane, but this could be done through a feedback-band which would have an allowable range of bodyweight in which feedback would be delivered. If the applied load was too low or too high, the feedback would not be felt, letting the operator know the device was not being utilized properly. The feedback could also change the tactile sensation delivered for “under-loading” and “over-loading.”

Our study focused on subjects who had reported diagnoses of knee osteoarthritis. This was sufficient for our study as we were primarily interested in how cane use affected knee loading and OA patients have repeatable, measurable signs of problematic knee loading (e.g. KAM) and experience using walking canes. We did not set-out to determine the direct effect of improved cane usage on OA or how OA impacted cane use. In order to determine whether OA severity impacted cane usage or vice-versa, we would require more thorough reports and details of the individuals’ conditions, such as medical reports, doctor notes, or imaging of the joint.

Our study used a five-minute rest period to test short-term retention of partial weight-bearing instruction. Our results showed that haptics both increased loading in the haptics-only condition, compared to the scale training recall, and reduced the range of the confidence interval. However, for a better evaluation of short-term retention due to training methodology, a longer rest-period would be beneficial. We had originally planned to bring participants back to the lab after a week for a session of uninstructed walking trials with the haptic biofeedback cane and a conventional cane to further test instruction retention, but this was dropped due to participant unavailability.

4.6 COMMERCIALIZATION EFFORTS

Due to the relative simplicity of the device and its obvious and immediate utility for the disabled, injured, and aging populations, efforts have been made to commercialize the novel haptic biofeedback cane, to bring the benefits of the feedback to those who need it. In order to protect the intellectual property (IP) surrounding this device a patent was filed for the “systems, methods, and devices for sensing and providing biofeedback at target axial load.”

Market research revealed that a small number of companies have the majority of the walking cane market share. Because of this, penetration into the assistive walking device market could be difficult and licensing the IP to dominant companies may be a more effective way to get our device into the hands of people who need it.

4.7 FUTURE WORK

This study work presented in this manuscript was started as a continuation to the preliminary work conducted by the Puget Sound VA Medical Center’s CLIMB lab, which showed that haptic biofeedback reliably increased the amount of bodyweight applied to cane. The intention of this study was to determine if the increased cane load, driven by the haptic biofeedback, translated to reduced KAM in the arthritic leg. While the results in this study were promising, showing a reduction in both the PKAM and KAAI during use of the haptic biofeedback cane, more research needs to be conducted to determine the long-term effects of use of the modified cane on disease progression and symptomatic relief.

The current embodiment of the haptic biofeedback cane uses a purely mechanical interface to deliver the feedback (via the snapdome mechanism) and a modular electronics component comprised of the ProMicro, OpenLog, RTC, ADXL, two logic converters, and a voltage regulator.

Wiring schematics have been documented and under short, controlled walking trials the device works as intended. However, packaging the electrical components in the smallest possible housing has proven somewhat difficult to complete by hand and it has been decided to out-source the manufacturing of a custom printed circuit board to ensure satisfactory connections and robustness. Furthermore, there have been some issues with saving long files to the OpenLog, but this should be a simple matter of modifying the code on the ProMicro (easily done via included USB connection).

Once a robust and reliable version of the new haptic biofeedback cane model has been finalized, a longitudinal study can be conducted with this device to evaluate the impact of a cane with haptic biofeedback on the rate of disease progression and the quality of life of sufferers of OA.

Chapter 5. DEVICE DEVELOPMENT

5.1 DATA COLLECTION CANES

Our first haptic biofeedback cane embodiment was developed in 2015 for a preliminary study to investigate whether haptic feedback relative to a given load threshold would reliably encourage higher cane loading in subjects who had experience using canes [19]. A concern was that old habits would complicate the feedback training. However, the preliminary study showed that the haptic alerts effectively encouraged higher loading even in subjects who had experience using a walking cane. This prompted further work to determine if the higher cane loading was sufficient to reduce the KAM metrics commonly associated with knee joint degeneration – the focus of this report. The cane used in the preliminary study contained a force sensor to measure the load applied at the foot of the cane, a microcontroller, real-time clock (RTC), and data-logger. These components were used to initiate, time-stamp, and record data measured by the sensor, as well as activate the

haptic alerts, which were delivered by an off-weighted motor in the cane's handle. All of the electronics were stored in a PVC housing located below the curve of the handle, away from the user's hand and wrist during walking.

The preliminary proof-of-concept cane was improved for this study in both aesthetics and usability by moving the electronics inside the cane body. This shifted the weight of the instrumentation coaxially inside of the cane, normalizing its moment of inertia to that of a slightly heavier-than-average cane. While this was a vast improvement upon the initial cane design efforts to simplify cane data collection in conjunction with motion capture data collection introduced new components which made the cane less intuitive, and more cumbersome than a conventional cane – though these were mitigated to our best efforts. Exposed wires, necessary for syncing the cane data to the Vicon motion capture data, were taped to the side of the cane body to minimize protrusion. Six motion capture markers were attached to the cane for tracking with the Vicon cameras in locations intended to avoid contact with the subject's body during walking (though this proved unavoidable with some subjects and often resulted in a detached marker and subsequent recalibration of Vicon). A comparison of these two canes can be seen in Figure 5-1.

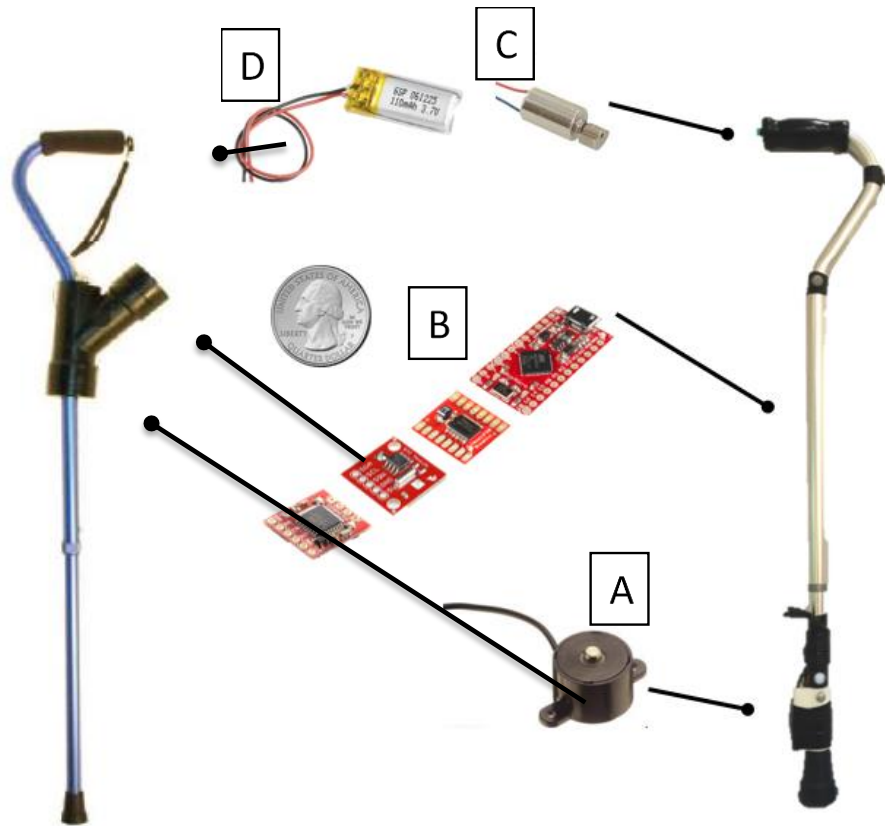


Figure 5-1. Comparison of component placement and design of the preliminary haptic biofeedback cane and the cane used for data collection in this study

After data collection sessions, conversations with participants allowed us to obtain their first impressions and general feedback about the device to inform future designs. It became apparent that while almost all our participants were excited about a device to subtly improve cane techniques, few seemed interested in a cane that was powered; with concerns of prohibitive cost, unnecessary/unwanted features (such as fitness tracking), charging requirements, and increased undue attention. This motivated us to move forward with the design of a purely mechanical version of the device that would deliver a functionally similar haptic alert but require no power source, thus simpler and more intuitive to use.

5.2 THE HEROCANE

Continued efforts towards commercialization resulted in the naming of the device for marketing purposes. The haptic-biofeedback cane was now dubbed the Haptics-Encouraged Response for Osteoarthritic Care and Ambulatory Needs Education, or HEROCANE. This work was presented at the 2017 and 2018 Northwest Biomechanics Symposia and for the UW Foundation Board at the 3-Minute Thesis Competition, the latter of which the work was awarded the Grand Prize.

The first step towards a purely mechanical haptic feedback providing cane was development of the new feedback mechanism. In the initial stages of development, ideation was rapid, with the main goal being to produce as many designs as possible (Figure 5-2). A large idea pool could then be selected from and chosen designs refined further. Initial inspiration was drawn from, center-punches, hand-buzzer prank toys, snap-bracelets, pop-top toys, and other simple tactile devices.

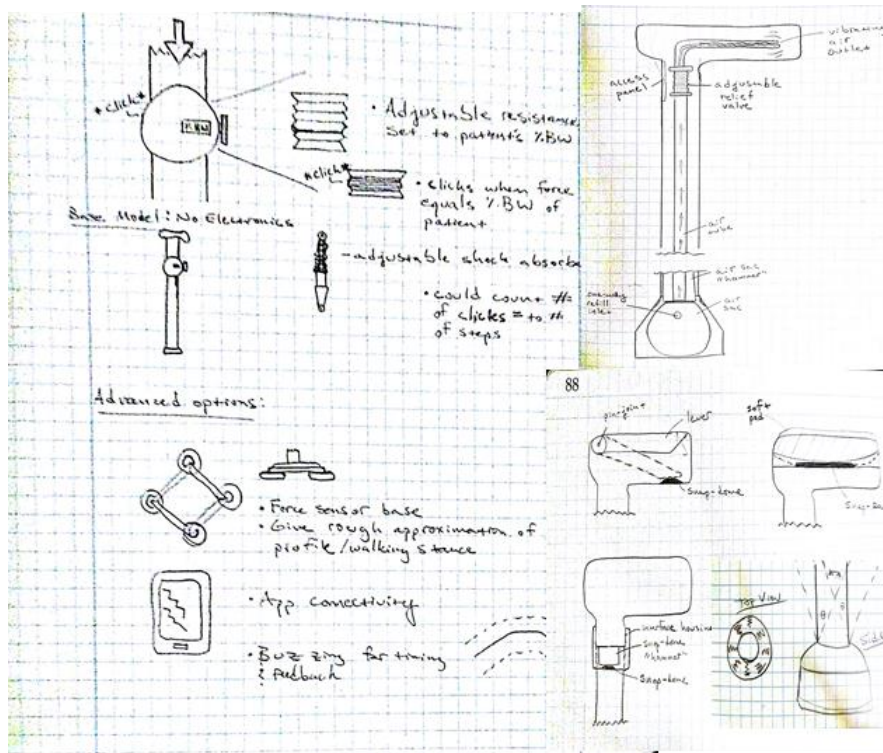


Figure 5-2. Some of the ideation to develop a mechanical interface for the haptic biofeedback mechanism.

During this time data collection sessions were being held regularly and we could present early prototypes to interested participants who gave us invaluable feedback. From this feedback it became clear that whatever feedback mechanism used, it was imperative that it did not draw additional undue attention to the cane owner. Because of this we focused our efforts on designing a mechanism that produced an unmistakable tactile feeling while minimizing any audible effects of the mechanism. We also realized that the more similar our cane was to a conventional cane, particularly in appearance and weighting, the more likely and quickly the modified cane would be adopted by the OA community. This prompted us to constrain designs for the mechanism to inside a conventional cane's existing tubing.

A design was settled-on that used a piston style mechanism, with the bottom of the cane's tube closed off and used to apply a distributed force to an adjustable number of metal "snap-domes" made by Snaptron®. These snap-domes create a single, subtle, rapid tactile sensation when a preset force is applied to the dome. By stacking the domes in series, the amount of force before the "snap" is delivered can be increased, thereby increasing the feedback threshold. This design was chosen for its simplicity and reliability. This design was also very conducive to using the same force sensor, and other data-logging components from the embodiment used for data collection.

The decision was made to make the new cane modular. A modular design would allow us to compartmentalize the mechanical feedback from electronic data logging. Haptic feedback was set and delivered by the aforementioned snap-dome mechanism - colloquially deemed the snap-cane (Figure 5-3).

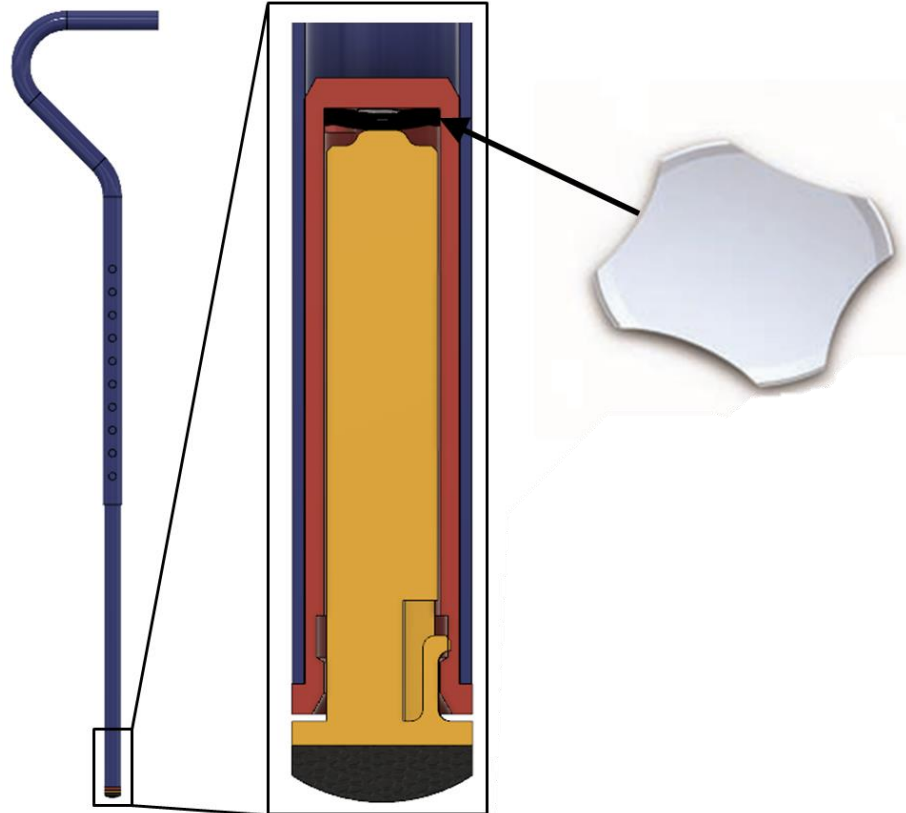


Figure 5-3. Illustration of snap-dome feedback mechanism placed in bottom of cane tube.

Applied cane force and time of usage was recorded to a micro-SD card by the same series of microcontroller components used in the data collection cane embodiment, which were mounted to the outside of the cane tube, just above the foot, hidden in a detachable housing (Figure 5-4).

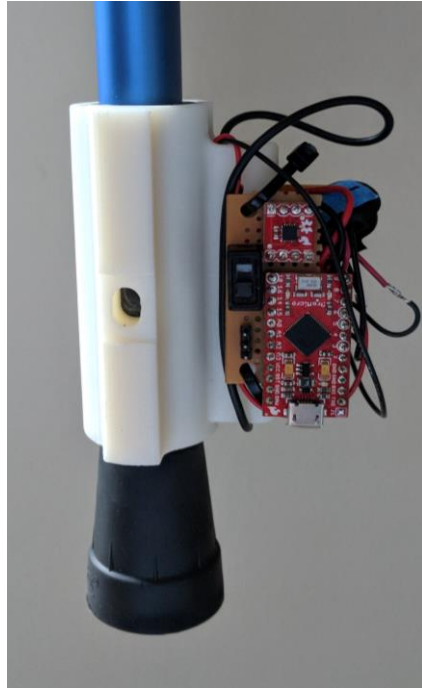


Figure 5-4. Data collection components mounted to cane foot attachment containing the feedback mechanism (electronics housing not pictured).

Additionally, an ADXL362 accelerometer was included in the design to implement a wake-on-shake functionality which would keep the cane in a low-power state when not being used. When the ADXL362 registered an acceleration, which we could adjust, the rest of the components would power-on and data would begin being collected. The ADXL introduced an issue with voltage inconsistency among the components as the ADXL operated at 3.3V while the other components operated at 5V. A make-shift voltage divider was used to drop the voltage delivered to the ADXL but was swapped for bi-directional logic converters once it became apparent communication channels between the ADXL and ProMicro all needed to be maintained at 3.3V (both receiving and sending data). The inclusion of these logic converters and a voltage regulator to supply the voltage drop to 5V to 3.3V significantly increased the number of connections required, making hand soldering difficult. After multiple failed attempts, an off-board electronics system was attached to the cane via a custom 3D printed mount for preliminary data collection with the new

haptic cane (Figure 5-4). Development of a more aesthetic and robust prototype are currently ongoing. Details on the upcoming device development and its intended use are further discussed in the Future Work section of the previous chapter. (Section 4.5)

Chapter 6. CONCLUSION

This manuscript summarizes an effort to implement haptic biofeedback into a walking cane to improve the partial-weight bearing techniques necessary for proper use of assistive walking devices. The haptic mechanism used for clinical data collection consisted of a microprocessor-based controller, force sensor, and off-weighted motor which were implemented into a conventional walking cane. These components measured the axial force applied to a walking cane and delivered a subtle vibration through the cane's handle, once a subject-specific threshold was reached. Over twenty local veterans and community members who had been diagnosed with knee OA and had experience using a walking cane volunteered for our study. Participants walked with a conventional cane and no instruction, a conventional cane with scale training, and our novel cane modified with haptic biofeedback. Trials were conducted along a path containing five force plates and subjects were recorded by a twelve-camera motion capture system for collection of kinetic and kinematic data during walking.

Use of the haptic biofeedback cane and scale training both significantly increased the average amount of bodyweight applied to the walking cane, as well as reduced the average knee adduction moment across stance phase, the peak knee adduction moment, and the knee adduction angular impulse. Additionally, haptics outperformed scale training in recall trials, when participants were asked to recall their scale training and use the haptic cane without further practice or instruction. In these trials cane loading was significantly higher with haptic biofeedback than when recalling

scale training. These results indicate that the constant corrective-feedback supplied by our modified walking cane does a better job at reinforcing proper weight-bearing techniques than attempting to recall a training session. Our results also show that use of the haptic biofeedback cane (with minimal verbal explanation of the mechanism) is at least as effective at teaching an individual proper partial weight-bearing technique as an instructional training session with explicit directions and practice using a scale. The decrease in knee adduction from scale training trials to haptic biofeedback trials may not have been statistically significant but the increase in cane loading in the haptic biofeedback trials in conjunction with the substantially smaller CIs indicate a trend which we believe would reveal statistical significance with a larger number of participants. This dose-response relationship between cane loading and the knee adduction moment is supported by numerous independent, related studies.

While these results represent a promising option for improving usage of mobility devices, questions remain regarding the primary factors leading to the progression of knee osteoarthritis, which this report did not set out to answer. Further investigation into the factors of knee degeneration could better inform the design of future mobility aids.

In conclusion, a cane with haptic biofeedback was shown to substantially reduce knee loading by encouraging proper cane loading. After brief instructions and practice, participants with knee OA were successful in using the haptic biofeedback cane and benefitted from a significant reduction in their frontal plane knee moment. Further investigation into the factors of knee joint degeneration and the progression of OA could reveal factors to mitigate more important than the knee adduction moment, but our device represents an effort to improve upon the conventional walking cane in a way that is conducive to use outside of a controlled lab environment. Improving the efficacy of

common walking aids may reduce pain, slow OA disease progression, delay the need for surgical intervention, and overall improve the quality of life for those with knee OA.

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APPENDIX A: A SCRIPT FOR CANE USE INSTRUCTIONS

Condition Instructions

1. Walk as you normally would when not using your cane.
2. Please use your cane as you normally would to offload your most symptomatic knee.
3. Cane Use: To properly use your cane hold the cane in the hand opposite to your most symptomatic knee. Advance the affected leg and cane simultaneously so that your heel and the bottom of the cane contact the ground at the same time. This will form a triangle.
Scale Training: The scale has been set to 20% of your measured body weight. This training is meant to provide a representation of how much effort is required to load 20% of your body weight on your cane. With the cane in the correct hand, stand next to the scale and push down until the lever raises.
4. Cane Use: To properly use your cane hold the cane in the hand opposite to your most symptomatic knee. Advance the affected leg and cane simultaneously so that your heel and the bottom of the cane contact the ground at the same time. This will form a triangle.
Smart cane: The smart cane has been programmed to your body weight. When you place at least 20% of your body weight on the cane you will feel a vibration in the handle. Please load the cane until you feel the vibration with each step.

APPENDIX B: CANE ARDUINO CODE FOR DATA COLLECTION

```
// Smart Cane Control Program.
```

```
//List of Revisions:
```

```
//6/18/2015: PMA - Added motor enable, and trigger start. Changed all forces to Newtons.
```

```
// 5/15/2015: Modified by Patrick Aubin for MS RTP 2015 study. Simplified code and increased loop rate to 100 hz.
```

```
// 5/19/2014: Modified for MS RTP 2014 data collection by Isabelle Pumford.
```

```
// 5/1/2014: First version created by Michelle Roland
```

```
//Description: This code reads in a load cell voltage and turns on a vibrational motor if the load
```

```
// reaches a certain threshold. Threshold is calculated based on 15.0% of subject body weight.
```

```
// Each subjects bodyweight must be entered into the first line of code at beginning of test.
```

```
// A 5 volt tigger (e.g. from Vicon) going from 5 volts to 0 volts starts the data collection.
```

```
// Once the cane is turned on the system is armed. Once the tigger voltage goes to 0 v data collection begins.
```

```
// A switch connected between the Enable_Motor_Pin and grnd enables or disables the vibor-motor.
```

```
#include "Wire.h"
```

```
#define DS1307_ADDRESS 0x68
```

```
//Variables that might need editing.
```

```
float BW = 240.4;//enter subject BW in lbs
```

```
float PercentBW = 20.00;//desired percent BW
```

```
//float Volts_to_LBS_Scale = 25; //Load cell amplifier scale ie: 25 lbf/volt NOTE: This needs to be updated based on exact load cell calibration and testing.
```

```

float Volts_to_N_Scale = 112.14; //Load cell amplifier scale ie: 112 Newtons/volt: Newtons = volts*Volts_to_N_Scale +
Volts_to_N_Intercept
float Volts_to_N_Intercept = -62.345; //Load cell amplifier y-axis intercept: Newtons = volts*Volts_to_N_Scale +
Volts_to_N_Intercept

//Initialize variables.
float minPercentBW = 5.00; //miniumum threshold to count as a "step"
//float Cane_Force_Volts=0; //Cane force (load cell output) in volts.
float Cane_Force_N = 0; //Cane force (load cell output) in Newtons.
float localMax = 0; //used later for finding the local maxiumums
long peakTime = 0;
long PpeakTime = 0;

float Load = 0;
//float threshold_V = (BW * PercentBW)/(Volts_to_LBS_Scale * 100); //Force in lbs above this will turn on vibration. //
calculate threshold based on body weight and load cell sensitivity(scale);
float threshold_N = 4.44*(BW * PercentBW)/100; //Force in newtons above this will turn on vibration. // calculate threshold
based on body weight and target percent BW load.
//float minthreshold = (BW * minPercentBW)/(Volts_to_LBS_Scale * 100); //Force must go above this to count as step.
//calculate minthreshold
boolean Motor_Enabled = true; //boolean to specify enabled/disabled state of vibro-motor.
boolean armed = true; //boolean to indicate if the cane is armed to begin data collection when trigger goes from 5 v to 0 volts
boolean LED2_state = LOW;
int i = 0; //count for for loop.
unsigned long ITime = millis();
unsigned long StartTime = 0;

//Pin Assignments
//motor A connected between A01 and A02
const int STBY = 10; //standby to pin 8 (A8)
const int PWMA = 9; //Speed control
const int AIN1 = 8; //Direction
const int AIN2 = 7; //Direction
const int Enable_Motor_Pin = 16; //Digital input pin to enable/disable vibro-motor. high=enable, low=disable.
const int Load_Cell_Pin = A0; //pin 18 (A0) load cell input voltage
const int DigitalTriggerPin = 14; //Use digital input pin 2 as digital trigger start pin.
const int LED_1_Pin = 4; //Pin attached to LED indicator #1.
const int LED_2_Pin = 5; //Pin attached to LED indicator #2.
const int LED_3_Pin = 6; //Pin attached to LED indicator #3.
// End Pin Assignments

void setup(){
  Serial1.begin(9600);
  pinMode(Load_Cell_Pin, INPUT); //Declare motor control pins as output
  //pinMode(Reset, OUTPUT); //No longer using the charge amp so remove the reset.
  pinMode(STBY, OUTPUT);
  pinMode(PWMA, OUTPUT);
  pinMode(AIN1, OUTPUT);
  pinMode(AIN2, OUTPUT);
  pinMode(LED_1_Pin, OUTPUT);
  pinMode(LED_2_Pin, OUTPUT);
  pinMode(LED_3_Pin, OUTPUT);
  pinMode(Enable_Motor_Pin, INPUT_PULLUP); //Make Enable_Motor digital pin an input. pin floating (switch open) = high =
enable, switch closed to GND = low = disable.
  pinMode(DigitalTriggerPin, INPUT_PULLUP);
  digitalWrite(LED_1_Pin, HIGH); //Turn on switch indicator LED

  Wire.begin();
  printDate(); //prints date/time given by RTC
  Serial1.print("Smart Cane MSRTP 2015"); //Feel free to change now that you're a new person
  Serial1.println();

```

```

Serial1.print("Software version: Smartcane_v4_MS RTP_2015");//Feel free to change now that you're a new person
Serial1.println();
Serial1.print("Cane force in newtons sampled at 100 Hz");//Scale factor of volts to pounds is 25.0
Serial1.println();
//Serial.println("Program start");//Use this line and serial monitor to debug the program.
//unsigned long ITime = millis();
Motor_Enabled = digitalRead(Enable_Motor_Pin); //Check to see if vibro-motor is enabled. If not enabled it will never be
turned on.
ITime = millis();
StartTime = millis();

}

void loop(){
  StartTime = millis();
  if(armed){
    //PMA: Wait in while loop until 5 v trigger goes low (0 volts).
    while(digitalRead(DigitalTriggerPin)==HIGH){
      //Serial.println("waiting for trigger");//Use this line and serial monitor to debug the program.
      //wait for digital trigger (e.g. vicon) to go low ( 0 volts).
      if(i>20000){
        i=0;//reset count
        LED2_state = !LED2_state;
        digitalWrite(LED_2_Pin, LED2_state);//toggle LED on/off every 1000 loops (~0.5 sec).
      }
      i++;
      //move(1, 100, 1);//PMA for debug purpose only. Turn on motor while waiting for trigger.
    }
    armed = false; //moved past while loop, so trigger went low, so unarm so that the next time through the loop the program will
skip IF block above.
    digitalWrite(LED_2_Pin, LOW);
    digitalWrite(LED_3_Pin, HIGH);
    //Serial.println("collecting data");
  }

  //for (i = 1; i <500 ; i++) { // Do a loop of 1000 and see how long it takes. //For debug purpose only. removed.
  //unsigned long ITime = millis();
  ITime = millis();
  //READ CANE FORCE
  //Cane_Force_Volts = analogRead(Load_Cell_Pin) * (5.0 / 1023.0); //Read in voltage on load cell, convert to volts (0-
5)//Removed. Now all forces are in newtons.
  Cane_Force_N = Volts_to_Newtons(analogRead(Load_Cell_Pin) * (5.0 / 1023.0)); //Read in voltage on load cell, convert to
volts then to Newtons.
  Serial1.print(Cane_Force_N);
  Serial1.println();//Prints new line so column is formed instead of row

  //TURN MOTOR ON or OFF
  if (Cane_Force_N >= threshold_N && Motor_Enabled) { //If the load is greater than Percent BW and the motor is enabled turn
the vibro-motor on
    move(1, 85, 1); //motor 1, left;
  }
  else {
    stop();
  }
  //WAIT, then repeat loop at 100 Hz.
  while ((millis() - ITime) < 10){ //Stay in while loop until 10 milliseconds are done. 10 ms per loop is 100 Hertz.
  ;
  }
  //}
  //Serial.println(millis()-StartTime);//Print how long it takes to do 500 samples //For debug purpose only. removed.

} //End of main program loop, repeat loop.

```

```

byte bcdToDec(byte val) {
// Convert binary coded decimal to normal decimal numbers
return ( (val/16*10) + (val%16) );
}

float Volts_to_Newtons(float volts){
return ((volts*Volts_to_N_Scale) + Volts_to_N_Intercept);//Load cell amplifier scale ie: 112 Newtons/volt: Newtons =
volts*Volts_to_N_Scale + Volts_to_N_Intercept
}

void printDate(){

// Reset the register pointer
Wire.beginTransmission(DS1307_ADDRESS);

byte zero = 0x00;
Wire.write(zero);
Wire.endTransmission();

Wire.requestFrom(DS1307_ADDRESS, 7);

int second = bcdToDec(Wire.read());
int minute = bcdToDec(Wire.read());
int hour = bcdToDec(Wire.read() & 0b111111); //24 hour time
int weekDay = bcdToDec(Wire.read()); //0-6 -> sunday - Saturday
int monthDay = bcdToDec(Wire.read());
int month = bcdToDec(Wire.read());
int year = bcdToDec(Wire.read());

//print the date EG 3/1/11 23:59:59
Serial1.print(month);
Serial1.print("/");
Serial1.print(monthDay);
Serial1.print("/");
Serial1.print(year);
Serial1.print(" ");
Serial1.print(hour);
Serial1.print(":");
Serial1.print(minute);
Serial1.print(":");
Serial1.println(second);

}

void move(int motor, int speed, int direction){
//Move specific motor at speed and direction
//motor: 0 for B 1 for A
//speed: 0 is off, and 255 is full speed
//direction: 0 clockwise, 1 counter-clockwise

digitalWrite(STBY, HIGH); //disable standby

boolean inPin1 = LOW;
boolean inPin2 = HIGH;

if(direction == 1){
inPin1 = !inPin1;
inPin2 = !inPin2;
}
}

```

```

if(motor == 1){
    digitalWrite(AIN1, inPin1);
    digitalWrite(AIN2, inPin2);
    analogWrite(PWMA, speed);
}
}
void stop(){
//enable standby
    digitalWrite(STBY, LOW);
}

```

APPENDIX C: MATLAB CODE FOR DATA ORGANIZATION AND PROCESSING

```

clc, clear all, close all
%% SETTING UP SUBJECT DATA AND FILEPATH STRUCTURES
ind = 1; %initialize data_set index

data = struct('raw', [], 'mean', [], 'sd', []);
metrics = struct('steps', [], 'KAM', data, 'PKAM', data, 'KAAT', data, 'Cane_Load', data, 'canefiles', []);
subject(1:25) = struct('name', [], 'load', [], 'file', [], 'weight', [], 'height', [], 'condition', metrics, 'canepath', [], 'HS_file', [], 'TO_file',
[], 'gender', [], 'age', [], 'womac', []);

%subject 2
ind = ind+1; [subject(ind)] = SC2_define(subject(ind), 'SC2 OA 2', true, ...
    only_import_KAM('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
02\Results2\LKnee_Mom.txt', 6, 1006), ...
    117.0, 1.778, 3.5, 5.5, 4, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
02\Cane Data', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 02\Results2\LON.txt', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
02\Results2\LOFF.txt', 'M', 54, []);

%subject 3
ind = ind+1; [subject(ind)] = SC2_define(subject(ind), 'SC2 OA 3', true, ...
    only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
03\Results2\LKnee_Mom.txt', 6, 1006), ...
    128.6, 1.80, 6.6, 6.6, 6.6, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
03\Cane Data', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 03\Results2\LON.txt', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
03\Results2\LOFF.txt', 'M', 61, 57.3);

%subject 4
ind = ind+1; [subject(ind)] = SC2_define(subject(ind), 'SC2 OA 4', true, ...
    only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
04\Results2\LKnee_Mom.txt', 6, 1006), ...
    95.9, 1.61, 6.6, 6.6, 6.6, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
04\Cane Data', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 04\Results2\LON.txt', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
04\Results2\LOFF.txt', 'F', 56, 26.0);

%Subject 5
ind = ind+1; [subject(ind)] = SC2_define(subject(ind), 'SC2 OA 5', true, ...
    only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
05\Results2\LKnee_Mom.txt', 6, 1006), ...
    113.9, 1.94, 5.5, 5.5, 5.5, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA
05\Cane Data', ...
    'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 05\Results2\LON.txt', ...

```

```
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 05\Results2\LOFF.txt','M',56,[]);
```

%Subject 6

```
ind = ind+1:[subject(ind)] = SC2_define(subject(ind),'SC2 OA 6', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 06\Results2\LKnee_Mom.txt',6,1006),...  
112.5, 1.85,5,5,5,5,5, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 06\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 06\Results2\LON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 06\Results2\LOFF.txt','M',65,41.7);
```

%Subject 7

```
ind = ind+1:[subject(ind)] = SC2_define(subject(ind),'SC2 OA 7', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 07\Results2\RKnee_Mom.txt',6,1006),...  
129.7, 1.73,6,6,6,6,6, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 07\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 07\Results2\RON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 07\Results2\ROFF.txt','M',52,53.1);
```

%Subject 8

```
ind = ind+1:[subject(ind)] = SC2_define(subject(ind),'SC2 OA 8', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 08\Results2\LKnee_Mom.txt',6,1006),...  
82.55, 1.803,5,5,4,5,6, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 08\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 08\Results2\LON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 08\Results2\LOFF.txt','M',69,14.6);
```

%Subject 9

```
ind = ind+1:[subject(ind)] = SC2_define(subject(ind),'SC2 OA 9', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 09\Results3\RKnee_Mom.txt',6,1006),...  
101.6, 1.702,6,7,5,5,7, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 09\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 09\Results3\RON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC OA 09\Results3\ROFF.txt','M',61,47.9);
```

%Subject 10

```
ind = ind+1:[subject(ind)] = SC2_define(subject(ind),'SC2 OA 10', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 10\Results2\RKnee_Mom.txt',6,1006),...  
64.41, 1.791,5,6,5,5,5, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 10\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 10\Results2\RON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 10\Results2\ROFF.txt','M',62,55.2);
```

%Subject 11

```
ind = ind+1:[subject(ind)] = SC2_define(subject(ind),'SC2 OA 11', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 11\Results2\RKnee_Mom_reordered.txt',6,1006),...  
73.93, 1.8, 4, 4, 5, 6, 6, 'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 11\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 11\Results2\RON_reordered.txt',...
```

```
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 11\Results2\ROFF_reordered.txt','M',53,36.5);
```

%Subject 12

```
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 12', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 12\Results2\LKnee_Mom.txt',6,1006),...  
88.00, 1.778, 8, 6, 5, 5, 5,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 12\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 12\Results2\LON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 12\Results2\LOFF.txt','M',55,66.6);
```

%Subject 13

```
% - no camera data :(  
ind = ind+1; [subject(ind)] = SC2_define(subject(ind),'SC2 OA 13',false,...  
110.1,1.7,[],0,0,0,0,0,[],[],[],'M',45,57.3);
```

%Subject 14 - no good C4 steps

```
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 14', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 14\Results2\LKnee_Mom.txt',6,1006),...  
94.5, 1.872, 6, 7, 5, 2, 2,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 14\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 14\Results2\LON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 14\Results2\LOFF.txt','M',57,59.4);
```

%Subject 15

```
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 15', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 15\Results2\RKnee_Mom.txt',6,1006),...  
116.6, 1.829, 6, 5, 6, 6, 7,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 15\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 15\Results2\RON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 15\Results2\ROFF.txt','M',41,72.9);
```

%Subject 16

```
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 16', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 16\Results2\LKnee_Mom.txt',6,1006),...  
113.5, 1.753, 5, 6, 7, 6, 6,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 16\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 16\Results2\LON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 16\Results2\LOFF.txt','M',60,15.6);
```

%Subject 17

```
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 17', true,...  
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 17\Results2\LKnee_Mom.txt',6,1006),...  
125.2, 1.876, 7, 5, 6, 6, 6,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 17\Cane Data',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 17\Results2\LON.txt',...  
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA 17\Results2\LOFF.txt','M',33,55.2);
```

%Subject 18

```
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 18', true,...
```

```

only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
18\Results2\RKnee_Mom.txt',6,1006),...
77.56, 1.675, 4, 6, 3, 5, 6,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2
OA 18\Cane Data',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
18\Results2\RON.txt',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
18\Results2\ROFF.txt','M',87,22.9);

%Subject 19
% - took "good" steps for wrong leg
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 19', true,...
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
19\Results\RKnee_Mom2.txt',6,1006),...
93.9, 1.816, 1, 3, 4, 5, 1,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2
OA 19\Cane Data',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
19\Results\RON.txt',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
19\Results\ROFF.txt','M',78,50);

%Subject 20
% - no camera data :(
ind = ind+1; [subject(ind)] = SC2_define(subject(ind),'SC2 OA 20',false,...
110.1,1.622,[],0,0,0,0,[],[],[],'M',61,57.3);

%Subject 21
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 21', true,...
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
21\Results2\RKnee_Mom.txt',6,1006),...
59.6, 1.675, 7, 6, 5, 5, 6,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2
OA 21\Cane Data',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
21\Results2\RON.txt',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
21\Results2\ROFF.txt','M',69,64.6);

%Subject 22
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'SC2 OA 22', true,...
only_import_KAM2('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
22\Results2\RKnee_Mom.txt',6,1006),...
109.27, 1.943, 5, 4, 4, 6, 4,'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2
OA 22\Cane Data',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
22\Results2\RON.txt',...
'C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017\SC2 OA
22\Results2\ROFF.txt','M',68,82.3);

%GrandMean - subject, name, load, file,weight,height,steps1,steps2,steps3,steps4,steps5,canepath,HS_file,TO_file,gender,age
ind = ind+1;[subject(ind)] = SC2_define(subject(ind),'grand', true,[],[],[],[],[],[],[],[],[],[],[],[],[],[]);

%% ORGANIZING KAM DATA IN THE STRUCTURE
num_subs = 0;
for i = 2:(ind-1) % there is no subject #1
    if subject(i).load == false %don't load if set to "false"
        continue
    end

    num_subs = num_subs + 1; %the subject number that is being currently processed
    canepath = subject(i).canepath;

    subject(i).HS_time = Steptime_import(subject(i).HS_file);
    subject(i).HS_time = reshape(subject(i).HS_time,[1,numel(subject(i).HS_time)]); %turns HS times into single sequential row

% removes zeros and NaNs from HS times
nanCols = any(isnan(subject(i).HS_time), 1);

```

```

zeroCols = any(subject(i).HS_time==0, 1);
badCols = nanCols | zeroCols;
subject(i).HS_time(:,badCols) = [];

subject(i).TO_time = Steptime_import(subject(i).TO_file);
subject(i).TO_time = reshape(subject(i).TO_time,[1,numel(subject(i).TO_time)]); %turns TO times into single sequential row

%removes zeros and NaNs from TO times
nanCols = any(isnan(subject(i).TO_time), 1);
zeroCols = any(subject(i).TO_time==0, 1);
badCols = nanCols | zeroCols;
subject(i).TO_time(:,badCols) = [];

[rows,cols] = size(subject(i).file);

%ORGANIZING CONDITION 1 (NAIVE) DATA - determines number of KAM data columns to
%put in each condition

trial = 1:1:subject(i).condition(1).steps;

subject(i).condition(1).KAM.raw = subject(i).file(:,trial);
subject(i).condition(1).HS_time = subject(i).HS_time(:,trial);
subject(i).condition(1).TO_time = subject(i).TO_time(:,trial);

%ORGANIZING CONDITION 2 (SCALE TRAINING) DATA
trial = subject(i).condition(1).steps+1:1:subject(i).condition(1).steps+subject(i).condition(2).steps;

subject(i).condition(2).KAM.raw = subject(i).file(:,trial);
subject(i).condition(2).HS_time = subject(i).HS_time(:,trial);
subject(i).condition(2).TO_time = subject(i).TO_time(:,trial);

%ORGANIZING CONDITION 3 (SCALE TRAINING AFTER 5 MIN BREAK) DATA
trial =
subject(i).condition(1).steps+subject(i).condition(2).steps+1:1:subject(i).condition(1).steps+subject(i).condition(2).steps+subject(
i).condition(3).steps;

subject(i).condition(3).KAM.raw = subject(i).file(:,trial);
subject(i).condition(3).HS_time = subject(i).HS_time(:,trial);
subject(i).condition(3).TO_time = subject(i).TO_time(:,trial);

%ORGANIZING CONDITION 4 (SMART CANE) DATA
trial =
subject(i).condition(1).steps+subject(i).condition(2).steps+subject(i).condition(3).steps+1:1:subject(i).condition(1).steps+subject(
i).condition(2).steps+subject(i).condition(3).steps+...
subject(i).condition(4).steps;

subject(i).condition(4).KAM.raw = subject(i).file(:,trial);
subject(i).condition(4).HS_time = subject(i).HS_time(:,trial);
subject(i).condition(4).TO_time = subject(i).TO_time(:,trial);

%ORGANIZING CONDITION 5 (SMART CANE AFTER 5 MIN BREAK) DATA
trial = subject(i).condition(1).steps+subject(i).condition(2).steps+subject(i).condition(3).steps+...
subject(i).condition(4).steps+1:1:subject(i).condition(1).steps+subject(i).condition(2).steps+subject(i).condition(3).steps+...
+subject(i).condition(4).steps+subject(i).condition(5).steps;

try
subject(i).condition(5).KAM.raw = subject(i).file(:,trial);
subject(i).condition(5).HS_time = subject(i).HS_time(:,trial);
subject(i).condition(5).TO_time = subject(i).TO_time(:,trial);
catch
subject(i).condition(5).KAM.raw = NaN(length(subject(i).condition(4).KAM.raw),1);
subject(i).condition(5).HS_time = NaN(1,length(subject(i).condition(4).HS_time));
subject(i).condition(5).TO_time = NaN(1,length(subject(i).condition(4).TO_time));
end

%% Load Cane Data

%changes directory to subject's "Cane Data" folder - the cane plot

```

```

%function then goes into the "GoodTrials" folder
cd(subject(i).canepath)

[subject(i).condition(1).Cane_Load.raw, subject(i).condition(2).Cane_Load.raw, subject(i).condition(3).Cane_Load.raw,...
 subject(i).condition(4).Cane_Load.raw, subject(i).condition(5).Cane_Load.raw] = Plot_Cane_Data_SC2_v7(canepath);

for c = 1:5
    subject(i).condition(c).canefiles = length(subject(i).condition(c).Cane_Load.raw);

    for n = 1:subject(i).condition(c).canefiles
        %identify outliers in cane load peaks
        outpeaks = isoutlier(subject(i).condition(c).Cane_Load.raw(n).peaks);
        %remove outlier peaks
        subject(i).condition(c).Cane_Load.raw(n).peaks(outpeaks, :) = [];
        %make matrix of mean cane load values
        subject(i).condition(c).Cane_Load.mean_matrix(:,n) = subject(i).condition(c).Cane_Load.raw(n).peaks_avg;
    end
    subject(i).condition(c).Cane_Load.mean = nanmean(subject(i).condition(c).Cane_Load.mean_matrix);
    subject(i).condition(c).Cane_Load.mean = 100*subject(i).condition(c).Cane_Load.mean/9.81/subject(i).weight; %normalize
to %BW
    subject(i).condition(c).Cane_Load.sd = std(subject(i).condition(c).Cane_Load.mean_matrix);
    if subject(i).condition(c).Cane_Load.sd < .000001
        subject(i).condition(c).Cane_Load.sd = NaN;
    end
end

cd('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MS RTP 2017');
end

% REVERSE KAM SIGN FOR RIGHT-LEGGED-OA SUBJECTS
for i = 1:5
    subject(7).condition(i).KAM.raw = -subject(7).condition(i).KAM.raw;
    subject(9).condition(i).KAM.raw = -subject(9).condition(i).KAM.raw;
    subject(10).condition(i).KAM.raw = -subject(10).condition(i).KAM.raw;
    subject(11).condition(i).KAM.raw = -subject(11).condition(i).KAM.raw;
    subject(15).condition(i).KAM.raw = -subject(15).condition(i).KAM.raw;
    subject(18).condition(i).KAM.raw = -subject(18).condition(i).KAM.raw;
    subject(19).condition(i).KAM.raw = -subject(19).condition(i).KAM.raw;
    subject(21).condition(i).KAM.raw = -subject(21).condition(i).KAM.raw;
    subject(22).condition(i).KAM.raw = -subject(22).condition(i).KAM.raw;
end

\ %% import subject data with SC2_master.m
clc, close all
% error_reminder = 'step duration is not working, look at subject(7) step_dur and cane2perstance as evidence'

%% find PKAM and KAAI

```

```

cd('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Evan Smart Cane MSRTP 2017')
t = 0:.01:10;
g = 9.81;
normalize = 1;
pos_offset = 1;

%randomizing colors for subjects
for n = 2:(ind-1)

    if subject(n).load == false %don't load if set to "false"
        continue
    end
    colors = rand(1,3);
end

% [[1 0 0];[1 165/255 0];[1 1 0];[0 1 0];[0 0 1];[0 1 1];[1 0 1];[.5 .5 .5]; [.75 .75 .75]; [.25 .25 .25]; [.33 .33 .33];...
%   [.66 .66 .66]; [0 0 .33]; [.33 0 0]; ];
condition_names = {'Naive'; 'Scale Training'; 'Scale Recall'; 'Haptic Cane'; 'Haptic Cane Recall'};

%selecting which subjects' data to structure
% n = 2;
for n = 2:(ind-1)
    if subject(n).load == false %don't load if set to "false"
        continue
    end
    for i = 1:5
        if normalize == 1 %if 1, normalizes the KAM data
            subject(n).condition(i).KAM.normal = 100*subject(n).condition(i).KAM.raw./(subject(n).height * g);
        else
            %resets normalized data to raw data
            subject(n).condition(i).KAM.normal = subject(n).condition(i).KAM.raw;
        end
    end

    %   nanRows = any(isnan(subject(n).condition(i).KAM.normal), 2);
    %   badRows = nanRows;
    %   subject(n).condition(i).steptime(badRows, :) = [];

    %CALCULATE SUBJECT KAM MEAN/SD
    if sum(nansum(isnan(subject(n).condition(i).KAM.normal))) < 1000

        subject(n).condition(i).KAM.mean = nanmean(subject(n).condition(i).KAM.normal,2);
        subject(n).condition(i).KAM.sd = nanstd(subject(n).condition(i).KAM.normal,0,2);

        %CALCULATE SUBJECT PKAM MEAN/SD
        [subject(n).condition(i).PKAM.raw,subject(n).condition(i).PKAM.time] = max(subject(n).condition(i).KAM.normal);
        subject(n).condition(i).PKAM.mean = nanmean(subject(n).condition(i).PKAM.raw,2);
        subject(n).condition(i).PKAM.sd = nanstd(subject(n).condition(i).PKAM.raw,0,2);

        %CALCULATE SUBJECT KAAI MEAN/SD

        subject(n).condition(i).KAAI.raw = nansum(subject(n).condition(i).KAM.normal)/1000;
        subject(n).condition(i).KAAI.mean = nanmean(subject(n).condition(i).KAAI.raw,2);
        subject(n).condition(i).KAAI.sd = nanstd(subject(n).condition(i).KAAI.raw,0,2);

        %CALCULATE SUBJECT STEP TIME
        subject(n).condition(i).steptime = [subject(n).condition(i).HS_time;subject(n).condition(i).TO_time];
    else
        subject(n).condition(i).PKAM.raw = NaN;
        subject(n).condition(i).KAM.mean = NaN;
        subject(n).condition(i).KAM.sd = NaN;

        %CALCULATE SUBJECT PKAM MEAN/SD

```

```

% [subject(n).condition(i).PKAM.raw,subject(n).condition(i).PKAM.time] =
[NaN(1,(subject(n).condition(i).steps)),NaN(1,(subject(n).condition(i).steps))];
subject(n).condition(i).PKAM.mean = NaN;
subject(n).condition(i).PKAM.sd = NaN;

%CALCULATE SUBJECT KAAI MEAN/SD

subject(n).condition(i).KAAI.raw = NaN;
subject(n).condition(i).KAAI.mean = NaN;
subject(n).condition(i).KAAI.sd = NaN;

%CALCULATE SUBJECT STEP TIME
subject(n).condition(i).steptime = [subject(n).condition(i).HS_time;subject(n).condition(i).TO_time];
end

nanRows = any(isnan(subject(n).condition(i).steptime), 2);
zeroRows = any(subject(n).condition(i).steptime==0, 2);
badRows = nanRows | zeroRows;
subject(n).condition(i).steptime(badRows, :) = [];

end
end

%% FIXES CROPPED VICON FILES BY ADDING OFFSET TO HS/TO TIMES

%import steps
%S1-S9
steps_per_trial1 = xlsread('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Visual 3D Notes - Only Good Steps',1,'E2:E159');
%S10-S22
steps_per_trial2 = xlsread('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Visual 3D Notes - Only Good Steps',2,'E2:E231');
% steps_per_trial = steps_per_trial2; % delete after troubleshooting
%combining offsets
steps_per_trial = [steps_per_trial1; steps_per_trial2];

%import offsets
%S1-S9
subject_offsets1 = xlsread('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Visual 3D Notes - Only Good Steps','S1-9','K2:K338');
%S10-S22
subject_offsets2 = xlsread('C:\Users\Evan Schuster\Documents\Masters Thesis\Visual3D\Visual 3D Notes - Only Good Steps','Subjects 10+','I2:I231');
% subject_offsets = subject_offsets2; % delete after troubleshooting
%combining offsets
subject_offsets = [subject_offsets1 ; subject_offsets2];

nanRows = any(isnan(steps_per_trial), 2); %finds rows with 'NaN'
badRows = nanRows;
steps_per_trial(badRows, :) = [];

nanRows = any(isnan(subject_offsets), 2); %finds rows with 'NaN'
badRows = nanRows;
subject_offsets(badRows, :) = [];

for n = 2:22 %subjects being processed

if subject(n).load == false %don't load if set to "false"
continue
end

```

```

subject(n).canefilecount = 0;

for i = 1:5 %conditions being processed
subject(n).condition(i).canefilecount = subject(n).canefilecount + subject(n).condition(i).canefiles;
end

i = 1:5;
subject(n).canefilecount = sum([subject(n).condition(i).canefilecount]);

if n~= 2
    %adding previous number of canefiles to current running total
    subject(n).canefilecount = subject(n-1).canefilecount+subject(n).canefilecount;
else
    subject(n).canefilecount = subject(n).canefilecount;
end

%skipping the zero canefile count of subjects w/o data
subject(13).canefilecount = subject(12).canefilecount;
subject(20).canefilecount = subject(19).canefilecount;

if n == 2 %first subject on excel sheets
%associate offsets with subject
subject(n).offsets = subject_offsets(1:(subject(n).canefilecount));
%associate stepcount with subject
subject(n).trialsteps = steps_per_trial(1:(subject(n).canefilecount));
else
%associate offsets with subject
subject(n).offsets = subject_offsets(subject(n-1).canefilecount+1:subject(n).canefilecount);
%associate stepcount with subject
subject(n).trialsteps = steps_per_trial(subject(n-1).canefilecount+1:subject(n).canefilecount);
end

%condition 1
trial = 1:1:subject(n).condition(1).canefiles;

subject(n).condition(1).offsets = subject(n).offsets(trial);
subject(n).condition(1).trialsteps = subject(n).trialsteps(trial);

%condition 2
trial = subject(n).condition(1).canefiles+1:1:subject(n).condition(1).canefiles+subject(n).condition(2).canefiles;

subject(n).condition(2).offsets = subject(n).offsets(trial);
subject(n).condition(2).trialsteps = subject(n).trialsteps(trial);

%condition 3
trial =
subject(n).condition(1).canefiles+subject(n).condition(2).canefiles+1:1:subject(n).condition(1).canefiles+subject(n).condition(2).
canefiles+subject(n).condition(3).canefiles;
    subject(n).condition(4).canefiles;

subject(n).condition(3).offsets = subject(n).offsets(trial);
subject(n).condition(3).trialsteps = subject(n).trialsteps(trial);

%condition 4
trial =
subject(n).condition(1).canefiles+subject(n).condition(2).canefiles+subject(n).condition(3).canefiles+1:1:subject(n).condition(1).
canefiles+subject(n).condition(2).canefiles+subject(n).condition(3).canefiles+...
    subject(n).condition(4).canefiles;

```

```

subject(n).condition(4).offsets = subject(n).offsets(trial);
subject(n).condition(4).trialsteps = subject(n).trialsteps(trial);

%condition 5
trial = subject(n).condition(1).canefiles+subject(n).condition(2).canefiles+subject(n).condition(3).canefiles+...

subject(n).condition(4).canefiles+1:1:subject(n).condition(1).canefiles+subject(n).condition(2).canefiles+subject(n).condition(3).
canefiles+...
    subject(n).condition(4).canefiles+subject(n).condition(5).canefiles;

subject(n).condition(5).offsets = subject(n).offsets(trial);
subject(n).condition(5).trialsteps = subject(n).trialsteps(trial);

% file = 1;
% error = 0;
for i = 1:5 %selecting which conditions to offset (should be all, 1-5, after initial testing)
    stepcount = 0;
    KAMcount = 0;

    for file = 1 : subject(n).condition(i).canefiles

        subject(n).condition(i).file(file).cane_on = [];
        subject(n).condition(i).file(file).cane_off = [];
%     current step being processed - useful for troubleshooting
        stepcount = stepcount + subject(n).condition(i).trialsteps(file);

%checking that there are steps in a trial
if subject(n).condition(i).trialsteps(file) > 0

    KAMcount = stepcount-(subject(n).condition(i).trialsteps(file)-1):stepcount;
    if pos_offset == 1
        %calculate steptime
        subject(n).condition(i).steptime(:,KAMcount) =
subject(n).condition(i).steptime(:,KAMcount)+subject(n).condition(i).offsets(file);
        %find canestrike that falls within stance phase of "good" step
        %(adjustthshold if canestrike not within stance phase)
        for KAMcount = KAMcount(1):KAMcount(end)
            strike_count = 0;

            %find where cane signal starts and stops
            strike_thresh = (subject(n).condition(i).Cane_Load.raw(file).data > 0);

            for x = 20:length(strike_thresh)
                if strike_thresh(x-18:x) == 1 & strike_thresh(x-19) == 0 %makes sure signal is on for 18 frames and 0 before that
                    strike_count = strike_count + 1;
                    subject(n).condition(i).file(file).cane_on(strike_count) = (x-18)/120;

                    %removing zeros from cane_on times (not sure why
                    %they're there)
                    zeroCols = any(subject(n).condition(i).file(file).cane_on==0, 1);
                    badCols = zeroCols;
                    subject(n).condition(i).file(file).cane_on(:,badCols) = [];

                elseif strike_thresh(x) == 0 & strike_thresh(x-19:x-1) == 1 & strike_count > 0 %makes sure the signal is at least 20
frames long
                    subject(n).condition(i).file(file).cane_off(strike_count) = (x-1)/120;
                    %removing zeros from cane_off times (not sure why
                    %they're there)
                    zeroCols = any(subject(n).condition(i).file(file).cane_off==0, 1);
                    badCols = zeroCols;
                    subject(n).condition(i).file(file).cane_off(:,badCols) = [];

```

```

        end
    end

    %find times where cane_off occurs
    strike_off_times =
subject(n).condition(i).file(file).cane_off(subject(n).condition(i).file(file).cane_off>(subject(n).condition(i).steptime(1,KAMcount)));
    [TO2off, off_idx] = min(abs(subject(n).condition(i).steptime(1,KAMcount)-strike_off_times));
    if sum(off_idx) > 0
        subject(n).condition(i).strike_off(KAMcount) = strike_off_times(off_idx);
    else
        subject(n).condition(i).strike_off(KAMcount) = NaN;
    end

    %find times where cane_on occurs
    strike_on_times =
subject(n).condition(i).file(file).cane_on(subject(n).condition(i).file(file).cane_on<(subject(n).condition(i).steptime(2,KAMcount)) &...
        subject(n).condition(i).file(file).cane_on < subject(n).condition(i).strike_off(KAMcount));
    [HS2on, on_idx] = min(abs(subject(n).condition(i).steptime(2,KAMcount)-strike_on_times));
    if sum(on_idx) > 0
        subject(n).condition(i).strike_on(KAMcount) = strike_on_times(on_idx);
    else
        subject(n).condition(i).strike_on(KAMcount) = NaN;
    end

%     if (strike_off-strike_on) > 1.5
%         strike_on = NaN;
%         strike_off = NaN;
%     end

% PLOT A SUBJECTS CANE LOAD AND THRESHOLD PLOTS
% figure()
% file_frames = length(subject(n).condition(i).Cane_Load.raw(file).data);
% file_time = file_frames/120;
% plot(subject(n).condition(i).Cane_Load.raw(file).data)
% hold on
% plot(strike_thresh*10)

    if sum(subject(n).condition(i).strike_on) > 0 && sum(subject(n).condition(i).strike_off) > 0 &&...
        (subject(n).condition(i).strike_off(KAMcount)-subject(n).condition(i).strike_on(KAMcount)) < 1.5

        subject(n).condition(i).Cane_Load.goodstrike.time(KAMcount) =
(subject(n).condition(i).Cane_Load.raw(file).peak_ts(subject(n).condition(i).Cane_Load.raw(file).peak_ts<(subject(n).condition(i)
).strike_off(KAMcount)) &...
        subject(n).condition(i).Cane_Load.raw(file).peak_ts>(subject(n).condition(i).strike_on(KAMcount)));
        strike_idx = round(subject(n).condition(i).Cane_Load.goodstrike.time(KAMcount)*120);
        goodstrike_val = (subject(n).condition(i).Cane_Load.raw(file).data(strike_idx));
        subject(n).condition(i).Cane_Load.goodstrike.raw(KAMcount) = goodstrike_val;
        goodstrike = mean(goodstrike_val);
%         subject(n).condition(i).goodstrike.time(KAMcount) = strike_on(strike
    else
        goodstrike = NaN;
        subject(n).condition(i).Cane_Load.goodstrike.time(KAMcount) = NaN;
        subject(n).condition(i).Cane_Load.goodstrike.raw(KAMcount) = NaN;
        goodstrike_val = NaN;
    end

%checking if there is a canestrike that falls within stance phase

```

```

    if goodstrike > 0
        %select the "good" canestrike
        subject(n).condition(i).canestrike(KAMcount) =
nanmean(subject(n).condition(i).Cane_Load.goodstrike.time(KAMcount));
        %calculate duration of step
        subject(n).condition(i).stepdur(KAMcount) = (subject(n).condition(i).steptime(2,KAMcount)-
subject(n).condition(i).steptime(1,KAMcount));
        %calculate PKAM time during trial
        subject(n).condition(i).PKAMtime(KAMcount) = subject(n).condition(i).steptime(1,KAMcount)+
subject(n).condition(i).stepdur(KAMcount).*(subject(n).condition(i).PKAM.time(KAMcount)./1000);
        %calculate time difference of cane load peak to PKAM in seconds
        subject(n).condition(i).p2p_timediff(KAMcount) = (subject(n).condition(i).canestrike(KAMcount) -
subject(n).condition(i).PKAMtime(KAMcount));
        %calculate time of canestrike in %stance
        subject(n).condition(i).cane2perstance(KAMcount) = (subject(n).condition(i).canestrike(KAMcount) -
subject(n).condition(i).steptime(1,KAMcount))./subject(n).condition(i).stepdur(KAMcount).*100;
        subject(n).condition(i).cane_on2perstance(KAMcount) = (subject(n).condition(i).strike_on(KAMcount) -
subject(n).condition(i).steptime(1,KAMcount))./subject(n).condition(i).stepdur(KAMcount).*100;
        subject(n).condition(i).cane_off2perstance(KAMcount) = (subject(n).condition(i).strike_off(KAMcount) -
subject(n).condition(i).steptime(1,KAMcount))./subject(n).condition(i).stepdur(KAMcount).*100;

        %if there aren't "good" canestrikes in a trial make everything NaN
    else
        subject(n).condition(i).canestrike(KAMcount) = NaN;
        subject(n).condition(i).cane2perstance(KAMcount) = NaN;
        subject(n).condition(i).stepdur(KAMcount) = NaN;
        subject(n).condition(i).cane_on2perstance(KAMcount) = NaN;
        subject(n).condition(i).cane_off2perstance(KAMcount) = NaN;

    end

end

end
end
hmm = stepcount - KAMcount;
end

end
end

%% Grand Means
% subject(19).condition(5).KAM.raw = NaN;
% subject(19).condition(5).KAAI.raw = NaN;
% subject(19).condition(5).PKAM.raw = NaN;
subject(19).condition(5).cane2perstance = NaN;
subject(19).condition(5).strike_on = NaN;
subject(19).condition(5).strike_off = NaN;
subject(19).condition(5).cane_on2perstance = NaN;
subject(19).condition(5).cane_off2perstance = NaN;
subject(19).condition(5).Cane_Load.goodstrike.raw = NaN;
for n = 2:(ind-1)

    if subject(n).load == false %don't load if set to "false"
        continue
    end
    for i = 1:5
        subject(n).condition(i).Cane_Load.goodstrike.mean = mean(subject(n).condition(i).Cane_Load.goodstrike.raw);
        subject(n).condition(i).Cane_Load.goodstrike.sd = std(subject(n).condition(i).Cane_Load.goodstrike.raw);
        subject(n).condition(i).Cane_Load.goodstrike.normal =
100*mean(subject(n).condition(i).Cane_Load.goodstrike.raw/g/subject(n).weight);

```

```
end  
end
```

```
for i = 1:5
```

```
    %Grand-mean KAM matrix  
    subject(ind).condition(i).KAM.normal =  
[subject(2).condition(i).KAM.normal,subject(3).condition(i).KAM.normal,subject(4).condition(i).KAM.normal,subject(5).condition(i).KAM.normal,...
```

```
subject(6).condition(i).KAM.normal,subject(7).condition(i).KAM.normal,subject(8).condition(i).KAM.normal,subject(9).condition(i).KAM.normal,subject(10).condition(i).KAM.normal,...
```

```
subject(11).condition(i).KAM.normal,subject(12).condition(i).KAM.normal,subject(14).condition(i).KAM.normal,subject(15).condition(i).KAM.normal,...
```

```
subject(16).condition(i).KAM.normal,subject(17).condition(i).KAM.normal,subject(18).condition(i).KAM.normal,subject(19).condition(i).KAM.normal,...
```

```
    subject(21).condition(i).KAM.normal,subject(22).condition(i).KAM.normal];
```

```
    %CALCULATE GRAND MEAN KAM MEAN/SD
```

```
    subject(ind).condition(i).KAM.mean = nanmean(subject(ind).condition(i).KAM.normal,2);  
    subject(ind).condition(i).KAM.sd = nanstd(subject(ind).condition(i).KAM.normal,0,2);
```

```
    %Grand-mean PKAM matrix
```

```
    subject(ind).condition(i).PKAM.raw =  
[subject(2).condition(i).PKAM.raw,subject(3).condition(i).PKAM.raw,subject(4).condition(i).PKAM.raw,subject(5).condition(i).PKAM.raw,...
```

```
subject(6).condition(i).PKAM.raw,subject(7).condition(i).PKAM.raw,subject(8).condition(i).PKAM.raw,subject(9).condition(i).PKAM.raw,subject(10).condition(i).PKAM.raw,...
```

```
subject(11).condition(i).PKAM.raw,subject(12).condition(i).PKAM.raw,subject(14).condition(i).PKAM.raw,subject(15).condition(i).PKAM.raw...
```

```
subject(16).condition(i).PKAM.raw,subject(17).condition(i).PKAM.raw,subject(18).condition(i).PKAM.raw,subject(19).condition(i).PKAM.raw...
```

```
    subject(21).condition(i).PKAM.raw,subject(22).condition(i).PKAM.raw];
```

```
    %CALCULATE GRAND MEAN PKAM MEAN/SD
```

```
    subject(ind).condition(i).PKAM.mean = nanmean(subject(ind).condition(i).PKAM.raw);  
    subject(ind).condition(i).PKAM.sd = nanstd(subject(ind).condition(i).PKAM.raw);
```

```
% %Grand-mean Cane2Perstance matrix
```

```
    %all subject trials
```

```
    subject(ind).condition(i).cane2perstance.raw =  
[subject(2).condition(i).cane2perstance,subject(3).condition(i).cane2perstance,subject(4).condition(i).cane2perstance,subject(5).condition(i).cane2perstance,...
```

```
subject(6).condition(i).cane2perstance,subject(7).condition(i).cane2perstance,subject(8).condition(i).cane2perstance,subject(9).condition(i).cane2perstance,subject(10).condition(i).cane2perstance,...
```

```
subject(11).condition(i).cane2perstance,subject(12).condition(i).cane2perstance,subject(14).condition(i).cane2perstance,subject(15).condition(i).cane2perstance...
```

```
subject(16).condition(i).cane2perstance,subject(17).condition(i).cane2perstance,subject(18).condition(i).cane2perstance,subject(19).condition(i).cane2perstance...
```

```
    subject(21).condition(i).cane2perstance,subject(22).condition(i).cane2perstance];
```

```
    %Subject averages
```

```

% subject(ind).condition(i).cane2perstance.raw =
[nanmean(subject(2).condition(i).cane2perstance),nanmean(subject(3).condition(i).cane2perstance),nanmean(subject(4).conditio
n(i).cane2perstance),nanmean(subject(5).condition(i).cane2perstance),...
%
nanmean(subject(6).condition(i).cane2perstance),nanmean(subject(7).condition(i).cane2perstance),nanmean(subject(8).condition
(i).cane2perstance),nanmean(subject(9).condition(i).cane2perstance),nanmean(subject(10).condition(i).cane2perstance),...
%
nanmean(subject(11).condition(i).cane2perstance),nanmean(subject(12).condition(i).cane2perstance),nanmean(subject(14).condit
ion(i).cane2perstance),nanmean(subject(15).condition(i).cane2perstance),...
%
nanmean(subject(16).condition(i).cane2perstance),nanmean(subject(17).condition(i).cane2perstance),nanmean(subject(18).condit
ion(i).cane2perstance),nanmean(subject(19).condition(i).cane2perstance),...
% nanmean(subject(21).condition(i).cane2perstance),nanmean(subject(22).condition(i).cane2perstance)];

%CALCULATE GRAND MEAN cane2perstance MEAN/SD
subject(ind).condition(i).cane2perstance.mean = nanmean(subject(ind).condition(i).cane2perstance.raw);
subject(ind).condition(i).cane2perstance.sd = nanstd(subject(ind).condition(i).cane2perstance.raw);

%Grand-mean Cane_ON matrix
subject(ind).condition(i).cane_on2perstance.raw =
[subject(2).condition(i).cane_on2perstance,subject(3).condition(i).cane_on2perstance,subject(4).condition(i).cane_on2perstance,s
ubject(5).condition(i).cane_on2perstance,...

subject(6).condition(i).cane_on2perstance,subject(7).condition(i).cane_on2perstance,subject(8).condition(i).cane_on2perstance,s
ubject(9).condition(i).cane_on2perstance,subject(10).condition(i).cane_on2perstance,...

subject(11).condition(i).cane_on2perstance,subject(12).condition(i).cane_on2perstance,subject(14).condition(i).cane_on2perstan
ce,subject(15).condition(i).cane_on2perstance...

subject(16).condition(i).cane_on2perstance,subject(17).condition(i).cane_on2perstance,subject(18).condition(i).cane_on2perstan
ce,subject(19).condition(i).cane_on2perstance...
subject(21).condition(i).cane_on2perstance,subject(22).condition(i).cane_on2perstance];

%Grand-mean Cane_OFF matrix
subject(ind).condition(i).cane_off2perstance.raw =
[subject(2).condition(i).cane_off2perstance,subject(3).condition(i).cane_off2perstance,subject(4).condition(i).cane_off2perstance
,subject(5).condition(i).cane_off2perstance,...

subject(6).condition(i).cane_off2perstance,subject(7).condition(i).cane_off2perstance,subject(8).condition(i).cane_off2perstance,
subject(9).condition(i).cane_off2perstance,subject(10).condition(i).cane_off2perstance,...

subject(11).condition(i).cane_off2perstance,subject(12).condition(i).cane_off2perstance,subject(14).condition(i).cane_off2persta
nce,subject(15).condition(i).cane_off2perstance...

subject(16).condition(i).cane_off2perstance,subject(17).condition(i).cane_off2perstance,subject(18).condition(i).cane_off2persta
nce,subject(19).condition(i).cane_off2perstance...
subject(21).condition(i).cane_off2perstance,subject(22).condition(i).cane_off2perstance];

%Grand-mean KAAI matrix

%subject averages
% subject(ind).condition(i).KAAI.raw =
[subject(2).condition(i).KAAI.mean,subject(3).condition(i).KAAI.mean,subject(4).condition(i).KAAI.mean,subject(5).condition(
i).KAAI.mean,...
%
subject(6).condition(i).KAAI.mean,subject(7).condition(i).KAAI.mean,subject(8).condition(i).KAAI.mean,subject(9).condition(i
).KAAI.mean,subject(10).condition(i).KAAI.mean...
%
subject(11).condition(i).KAAI.mean,subject(12).condition(i).KAAI.mean,subject(14).condition(i).KAAI.mean,subject(15).condit
ion(i).KAAI.mean...

```

```

%
subject(16).condition(i).KAAI.mean,subject(17).condition(i).KAAI.mean,subject(18).condition(i).KAAI.mean,subject(19).condition(i).KAAI.mean...
% subject(21).condition(i).KAAI.mean,subject(22).condition(i).KAAI.mean];

%all subject trials
subject(ind).condition(i).KAAI.raw =
[subject(2).condition(i).KAAI.raw,subject(3).condition(i).KAAI.raw,subject(4).condition(i).KAAI.raw,subject(5).condition(i).KAAI.raw,...
subject(6).condition(i).KAAI.raw,subject(7).condition(i).KAAI.raw,subject(8).condition(i).KAAI.raw,subject(9).condition(i).KAAI.raw,subject(10).condition(i).KAAI.raw...
subject(11).condition(i).KAAI.raw,subject(12).condition(i).KAAI.raw,subject(14).condition(i).KAAI.raw,subject(15).condition(i).KAAI.raw...
subject(16).condition(i).KAAI.raw,subject(17).condition(i).KAAI.raw,subject(18).condition(i).KAAI.raw,subject(19).condition(i).KAAI.raw...
subject(21).condition(i).KAAI.raw,subject(22).condition(i).KAAI.raw];

subject(ind).condition(i).KAAI.sd_matrix =
[subject(2).condition(i).KAAI.sd,subject(3).condition(i).KAAI.sd,subject(4).condition(i).KAAI.sd,subject(5).condition(i).KAAI.sd,...
subject(6).condition(i).KAAI.sd,subject(7).condition(i).KAAI.sd,subject(8).condition(i).KAAI.sd,subject(9).condition(i).KAAI.sd,subject(10).condition(i).KAAI.sd...
subject(11).condition(i).KAAI.sd,subject(12).condition(i).KAAI.sd,subject(14).condition(i).KAAI.sd,subject(15).condition(i).KAAI.sd...
subject(16).condition(i).KAAI.sd,subject(17).condition(i).KAAI.sd,subject(18).condition(i).KAAI.sd,subject(19).condition(i).KAAI.sd...
subject(21).condition(i).KAAI.sd,subject(22).condition(i).KAAI.sd];

%KAAI - mean/SD
subject(ind).condition(i).KAAI.raw = subject(ind).condition(i).KAAI.raw;
subject(ind).condition(i).KAAI.mean = nanmean(subject(ind).condition(i).KAAI.raw,2);
subject(ind).condition(i).KAAI.sd = nanmean(subject(ind).condition(i).KAAI.sd_matrix,2);

%Grand-mean Cane Data matrix (NOT A TRUE GRAND-MEAN SINCE IT USES AVERAGES)
subject(ind).condition(i).Cane_Load.raw =
[subject(2).condition(i).Cane_Load.mean,subject(3).condition(i).Cane_Load.mean,subject(4).condition(i).Cane_Load.mean,subject(5).condition(i).Cane_Load.mean,...
subject(6).condition(i).Cane_Load.mean,subject(7).condition(i).Cane_Load.mean,subject(8).condition(i).Cane_Load.mean,subject(9).condition(i).Cane_Load.mean,subject(10).condition(i).Cane_Load.mean,...
subject(11).condition(i).Cane_Load.mean,subject(12).condition(i).Cane_Load.mean,subject(14).condition(i).Cane_Load.mean,subject(15).condition(i).Cane_Load.mean...
subject(16).condition(i).Cane_Load.mean,subject(17).condition(i).Cane_Load.mean,subject(18).condition(i).Cane_Load.mean,subject(19).condition(i).Cane_Load.mean...
subject(21).condition(i).Cane_Load.mean,subject(22).condition(i).Cane_Load.mean];

%Grand-mean Cane Load SD
subject(ind).condition(i).Cane_Load.sd_matrix =
[subject(2).condition(i).Cane_Load.sd,subject(3).condition(i).Cane_Load.sd,subject(4).condition(i).Cane_Load.sd,subject(5).condition(i).Cane_Load.sd,...
subject(6).condition(i).Cane_Load.sd,subject(7).condition(i).Cane_Load.sd,subject(8).condition(i).Cane_Load.sd,subject(9).condition(i).Cane_Load.sd,subject(10).condition(i).Cane_Load.sd,...

```

```
subject(11).condition(i).Cane_Load.sd,subject(12).condition(i).Cane_Load.sd,subject(14).condition(i).Cane_Load.sd,
subject(15).condition(i).Cane_Load.sd...
```

```
subject(16).condition(i).Cane_Load.sd,subject(17).condition(i).Cane_Load.sd,subject(18).condition(i).Cane_Load.sd,subject(19).
condition(i).Cane_Load.sd...
```

```
subject(21).condition(i).Cane_Load.sd,subject(22).condition(i).Cane_Load.sd];
```

% Cane Data - mean/SD

```
subject(ind).condition(i).Cane_Load.mean = nanmean(subject(ind).condition(i).Cane_Load.raw);
subject(ind).condition(i).Cane_Load.sd = nanmean(subject(ind).condition(i).Cane_Load.sd_matrix);
```

% Grand-mean Step-Specific Cane Load, Step-Specific

```
subject(ind).condition(i).Cane_Load.goodstrike.raw =
[subject(2).condition(i).Cane_Load.goodstrike.raw,subject(3).condition(i).Cane_Load.goodstrike.raw,subject(4).condition(i).Cane_
_Load.goodstrike.raw,subject(5).condition(i).Cane_Load.goodstrike.raw,...
```

```
subject(6).condition(i).Cane_Load.goodstrike.raw,subject(7).condition(i).Cane_Load.goodstrike.raw,subject(8).condition(i).Cane_
_Load.goodstrike.raw,subject(9).condition(i).Cane_Load.goodstrike.raw,subject(10).condition(i).Cane_Load.goodstrike.raw,...
```

```
subject(11).condition(i).Cane_Load.goodstrike.raw,subject(12).condition(i).Cane_Load.goodstrike.raw,subject(14).condition(i).Cane_
_Load.goodstrike.raw, subject(15).condition(i).Cane_Load.goodstrike.raw...
```

```
subject(16).condition(i).Cane_Load.goodstrike.raw,subject(17).condition(i).Cane_Load.goodstrike.raw,subject(18).condition(i).Cane_
_Load.goodstrike.raw,subject(19).condition(i).Cane_Load.goodstrike.raw...
```

```
subject(21).condition(i).Cane_Load.goodstrike.raw,subject(22).condition(i).Cane_Load.goodstrike.raw];
```

% Grand-mean Step-Specific Cane Load

```
subject(ind).condition(i).Cane_Load.goodstrike.mean_matrix =
[subject(2).condition(i).Cane_Load.goodstrike.mean,subject(3).condition(i).Cane_Load.goodstrike.mean,subject(4).condition(i).
Cane_Load.goodstrike.mean,subject(5).condition(i).Cane_Load.goodstrike.mean,...
```

```
subject(6).condition(i).Cane_Load.goodstrike.mean,subject(7).condition(i).Cane_Load.goodstrike.mean,subject(8).condition(i).Cane_
_Load.goodstrike.mean,subject(9).condition(i).Cane_Load.goodstrike.mean,subject(10).condition(i).Cane_Load.goodstrike.mean,...
```

```
subject(11).condition(i).Cane_Load.goodstrike.mean,subject(12).condition(i).Cane_Load.goodstrike.mean,subject(14).condition(
i).Cane_Load.goodstrike.mean, subject(15).condition(i).Cane_Load.goodstrike.mean...
```

```
subject(16).condition(i).Cane_Load.goodstrike.mean,subject(17).condition(i).Cane_Load.goodstrike.mean,subject(18).condition(
i).Cane_Load.goodstrike.mean,subject(19).condition(i).Cane_Load.goodstrike.mean...
```

```
subject(21).condition(i).Cane_Load.goodstrike.mean,subject(22).condition(i).Cane_Load.goodstrike.mean];
```

% Grand-mean Step-Specific Cane Load

```
subject(ind).condition(i).Cane_Load.goodstrike.normal_matrix =
[subject(2).condition(i).Cane_Load.goodstrike.normal,subject(3).condition(i).Cane_Load.goodstrike.normal,subject(4).condition(
i).Cane_Load.goodstrike.normal,subject(5).condition(i).Cane_Load.goodstrike.normal,...
```

```
subject(6).condition(i).Cane_Load.goodstrike.normal,subject(7).condition(i).Cane_Load.goodstrike.normal,subject(8).condition(i)
).Cane_Load.goodstrike.normal,subject(9).condition(i).Cane_Load.goodstrike.normal,subject(10).condition(i).Cane_Load.goodst
rike.normal,...
```

```
subject(11).condition(i).Cane_Load.goodstrike.normal,subject(12).condition(i).Cane_Load.goodstrike.normal,subject(14).conditi
on(i).Cane_Load.goodstrike.normal, subject(15).condition(i).Cane_Load.goodstrike.normal...
```

```
subject(16).condition(i).Cane_Load.goodstrike.normal,subject(17).condition(i).Cane_Load.goodstrike.normal,subject(18).conditi
on(i).Cane_Load.goodstrike.normal,subject(19).condition(i).Cane_Load.goodstrike.normal...
```

```
subject(21).condition(i).Cane_Load.goodstrike.normal,subject(22).condition(i).Cane_Load.goodstrike.normal];
```

% %Grand-mean Cane Load Step-spec SD

```
subject(ind).condition(i).Cane_Load.goodstrike.sd_matrix =
[subject(2).condition(i).Cane_Load.goodstrike.sd,subject(3).condition(i).Cane_Load.goodstrike.sd,subject(4).condition(i).Cane_
_Load.goodstrike.sd,subject(5).condition(i).Cane_Load.goodstrike.sd,...
```

```
subject(6).condition(i).Cane_Load.goodstrike.sd,subject(7).condition(i).Cane_Load.goodstrike.sd,subject(8).condition(i).Cane_Load.goodstrike.sd,subject(9).condition(i).Cane_Load.goodstrike.sd,subject(10).condition(i).Cane_Load.goodstrike.sd,...
```

```
subject(11).condition(i).Cane_Load.goodstrike.sd,subject(12).condition(i).Cane_Load.goodstrike.sd,subject(14).condition(i).Cane_Load.goodstrike.sd, subject(15).condition(i).Cane_Load.goodstrike.sd...
```

```
subject(16).condition(i).Cane_Load.goodstrike.sd,subject(17).condition(i).Cane_Load.goodstrike.sd,subject(18).condition(i).Cane_Load.goodstrike.sd,subject(19).condition(i).Cane_Load.goodstrike.sd...  
subject(21).condition(i).Cane_Load.goodstrike.sd,subject(22).condition(i).Cane_Load.goodstrike.sd];
```

```
%Step-Specific Cane Data - mean/SD
```

```
subject(ind).condition(i).Cane_Load.goodstrike.mean =  
nanmean(subject(ind).condition(i).Cane_Load.goodstrike.mean_matrix);  
subject(ind).condition(i).Cane_Load.goodstrike.normal =  
nanmean(subject(ind).condition(i).Cane_Load.goodstrike.normal_matrix);  
subject(ind).condition(i).Cane_Load.goodstrike.sd = nanmean(subject(ind).condition(i).Cane_Load.goodstrike.sd_matrix);
```

```
%
```

```
% ShadedErrorBar(10*t,subject(10).condition(i).KAM.mean,subject(10).condition(i).KAM.sd)
```

```
% hold on
```

```
plot(10*t,subject(ind).condition(i).KAM.mean,'LineWidth',8)
```

```
hold on
```

```
end
```

```
%Grand-mean weight matrix
```

```
subject(ind).weight = [subject(2).weight,subject(3).weight,subject(4).weight,subject(5).weight,...
```

```
subject(6).weight,subject(7).weight,subject(8).weight,subject(9).weight,subject(10).weight,subject(11).weight,subject(12).weight  
...  
subject(14).weight, subject(15).weight,  
subject(16).weight,subject(17).weight,subject(18).weight,subject(19).weight,subject(21).weight,...  
subject(22).weight];
```

```
% weight - mean/SD
```

```
weight_mean = nanmean(subject(ind).weight);
```

```
weight_sd = nanstd(subject(ind).weight);
```

```
%Grand-mean height matrix
```

```
subject(ind).height = [subject(2).height,subject(3).height,subject(4).height,subject(5).height,...
```

```
subject(6).height,subject(7).height,subject(8).height,subject(9).height,subject(10).height,subject(11).height,subject(12).height,...  
subject(14).height, subject(15).height,  
subject(16).height,subject(17).height,subject(18).height,subject(19).height,subject(21).height,...  
subject(22).height];
```

```
% height - mean/SD
```

```
height_mean = nanmean(subject(ind).height);
```

```
height_sd = nanstd(subject(ind).height);
```

```
%%Grand-mean age matrix
```

```
subject(ind).age = [subject(2).age,subject(3).age,subject(4).age,subject(5).age,...  
subject(6).age,subject(7).age,subject(8).age,subject(9).age,subject(10).age,subject(11).age,subject(12).age,...  
subject(14).age, subject(15).age,  
subject(16).age,subject(17).age,subject(18).age,subject(19).age,subject(21).age,subject(22).age];
```

```
% Age - mean/SD
```

```
age_mean = nanmean(subject(ind).age);
```

```
age_sd = nanstd(subject(ind).age);
```

```

%Grand-mean WOMAC matrix
subject(ind).womac = [subject(2).womac,subject(3).womac,subject(4).womac,subject(5).womac,...
subject(6).womac,subject(7).womac,subject(8).womac,subject(9).womac,subject(10).womac,subject(11).womac,subject(12).wo
mac,...
subject(14).womac, subject(15).womac, subject(16).womac,
subject(17).womac,subject(18).womac,subject(19).womac,subject(21).womac,subject(22).womac];

% WOMAC - mean/SD
womac_mean = nanmean(subject(ind).womac);
womac_sd = nanstd(subject(ind).womac);

%% PLOTS AND FIGURES

% KAM vs. %Stance
legend('Naive','Scale Training','Scale Recall','Haptic Cane','Haptic Cane Recall')
set(legend,'FontSize',40,'Location','Best')
set(gca,'FontSize',35)
% title('Knee Adduction Moment vs. Percent Stance','FontSize',42);
xlabel('Percent Stance','FontSize',40),ylabel('Adduction(%BW*Ht)','FontSize',40);

%Putting Mean/SD KAM per condition into matrix
KAM_avg_matrix = [subject(ind).condition(1).KAM.mean, subject(ind).condition(2).KAM.mean,
subject(ind).condition(3).KAM.mean,...
subject(ind).condition(4).KAM.mean, subject(ind).condition(5).KAM.mean];
KAM_avg = mean(KAM_avg_matrix,2);
KAM_sd = [subject(ind).condition(1).KAM.sd, subject(ind).condition(2).KAM.sd, subject(ind).condition(3).KAM.sd,...
subject(ind).condition(4).KAM.sd, subject(ind).condition(5).KAM.sd];

%Putting Mean/SD PKAM per condition into matrix
PKAM_avg = [subject(ind).condition(1).PKAM.mean, subject(ind).condition(2).PKAM.mean,
subject(ind).condition(3).PKAM.mean,...
subject(ind).condition(4).PKAM.mean, subject(ind).condition(5).PKAM.mean];
PKAM_sd = [subject(ind).condition(1).PKAM.sd, subject(ind).condition(2).PKAM.sd, subject(ind).condition(3).PKAM.sd,...
subject(ind).condition(4).PKAM.sd, subject(ind).condition(5).PKAM.sd];

figure()
subplot(1,2,1),bar(PKAM_avg)
hold on
errorbar(PKAM_avg, PKAM_sd, 'o', 'LineWidth', 3)
% title('Average PKAM vs Condition','FontSize',42)
title('(A)','FontSize',42)
set(legend,'FontSize',30)
set(gca,'FontSize',40)
% xlabel('Condition','FontSize',28)
ylabel('PKAM (%BW*Ht)','FontSize',40)
xticklabels(condition_names)
xtickangle(45)
hold on

for i = 2:ind-1
    if subject(i).load == false %don't load if set to "false"
        continue
    end
    PKAM_subavg = [subject(i).condition(1).PKAM.mean, subject(i).condition(2).PKAM.mean,
subject(i).condition(3).PKAM.mean,...
subject(i).condition(4).PKAM.mean, subject(i).condition(5).PKAM.mean];
% plot(PKAM_subavg,'o','MarkerSize',8,'LineWidth',3,'Color',rand(1,3))
hold on

```

```
end
```

```
%% Grand Mean KAAI
```

```
KAAI_avg = [subject(ind).condition(1).KAAI.mean, subject(ind).condition(2).KAAI.mean,  
subject(ind).condition(3).KAAI.mean,...  
subject(ind).condition(4).KAAI.mean, subject(ind).condition(5).KAAI.mean];  
KAAI_sd = [subject(ind).condition(1).KAAI.sd, subject(ind).condition(2).KAAI.sd, subject(ind).condition(3).KAAI.sd,...  
subject(ind).condition(4).KAAI.sd, subject(ind).condition(5).KAAI.sd];  
% figure()  
subplot(1,2,2),bar(KAAI_avg,'FaceColor','r')  
hold on  
errorbar(KAAI_avg, KAAI_sd,','LineWidth',3,'Color','k')  
% title('Average KAAI vs Condition','FontSize',42)  
title('(B)','FontSize',42)  
set(legend,'FontSize',30)  
set(gca,'FontSize',30)  
% xlabel('Condition','FontSize',28)  
xlabel('KAAI average (%BW*Ht*time)', 'FontSize',30)  
xticklabels(condition_names)  
xtickangle(45)
```

```
% KAAI graph
```

```
hold on  
for i = 2:ind-1  
if subject(i).load == false %don't load if set to "false"  
continue  
end  
KAAI_subavg = [subject(i).condition(1).KAAI.mean, subject(i).condition(2).KAAI.mean,  
subject(i).condition(3).KAAI.mean,...  
subject(i).condition(4).KAAI.mean, subject(i).condition(5).KAAI.mean];  
% plot(KAAI_subavg,'o','MarkerSize',8,'LineWidth',3,'Color',rand(1,3))  
hold on  
end
```

```
%% Grand Mean Cane Load Data
```

```
figure()  
CaneLoad_avg = [subject(ind).condition(1).Cane_Load.mean, subject(ind).condition(2).Cane_Load.mean,  
subject(ind).condition(3).Cane_Load.mean,...  
subject(ind).condition(4).Cane_Load.mean, subject(ind).condition(5).Cane_Load.mean];
```

```
CaneLoad_sd = [subject(ind).condition(1).Cane_Load.sd, subject(ind).condition(2).Cane_Load.sd,  
subject(ind).condition(3).Cane_Load.sd,...  
subject(ind).condition(4).Cane_Load.sd, subject(ind).condition(5).Cane_Load.sd];
```

```
Cane2Perstance_avg = [subject(ind).condition(1).cane2perstance.mean, subject(ind).condition(2).cane2perstance.mean,  
subject(ind).condition(3).cane2perstance.mean,...  
subject(ind).condition(4).cane2perstance.mean, subject(ind).condition(5).cane2perstance.mean];
```

```
Cane2Perstance_sd = [subject(ind).condition(1).cane2perstance.sd, subject(ind).condition(2).cane2perstance.sd,  
subject(ind).condition(3).cane2perstance.sd,...  
subject(ind).condition(4).cane2perstance.sd, subject(ind).condition(5).cane2perstance.sd];
```

```
bar(CaneLoad_avg)  
hold on  
errorbar(CaneLoad_avg,CaneLoad_sd,','LineWidth',3)  
hold on  
% title('Average Cane Load vs Condition','FontSize',42)  
set(legend,'FontSize',30)  
set(gca,'FontSize',40)
```

```

% xlabel('Condition',FontSize,28)
ylabel('Cane Load (%BW)',FontSize,28)
ref1 = [20 20 20 20 20 20 20];
ref2 = 20;
plot(0:6,ref1,'r--','LineWidth',2)
xticklabels(condition_names)
xtickangle(45)
hold on
for i = 2:ind-1
    if subject(i).load == false %don't load if set to "false"
        continue
    end
    CaneLoad_subavg = [subject(i).condition(1).Cane_Load.mean, subject(i).condition(2).Cane_Load.mean,
subject(i).condition(3).Cane_Load.mean,...
    subject(i).condition(4).Cane_Load.mean, subject(i).condition(5).Cane_Load.mean];
    % plot(CaneLoad_subavg,'o','MarkerSize',8,'LineWidth',3,'Color',rand(1,3))
    hold on
end

%Plot Naive KAM and 2 peaks
figure()
area(10*t,subject(ind).condition(1).KAM.mean,'LineWidth',2)
title('Knee Adduction Moment',FontSize,60)
xlabel('Percent Stance',FontSize,28),ylabel('Adduction(%BW*Ht)',FontSize,28)
set(gca,FontSize,40)
hold on
[KAMpeak,KAMpeak_t] = findpeaks(subject(ind).condition(1).KAM.mean,'MinPeakDistance',400);
plot(KAMpeak_t/10,KAMpeak,'ro','MarkerSize',36,'LineWidth',3)

figure()
%Plot Average KAM with canestrike locations and amplitudes/50
area(10*t,KAM_avg,'LineWidth',2)
title('Knee Adduction Moment',FontSize,60)
xlabel('Percent Stance',FontSize,28),ylabel('Adduction(%BW*Ht)',FontSize,28)
set(gca,FontSize,24)
hold on
strikecolors = ['b','r','y','m','g'];
conditionlabels = ['C1','C2','C3','C4','C5'];
for i = 1:5
    cane_timing_data(i,:) = [subject(23).condition(i).cane2perstance.mean,CaneLoad_avg(i)/10]; %[cane2perstance, average cane
load]
    hold on
    bar(cane_timing_data(i,1),cane_timing_data(i,2),'FaceColor',strikecolors(i))
    % legend(strcat('C',num2str(i)),strikecolors(i))
end
legend('KAM','C1','C2','C3','C4','C5')

%plot individual KAM plots w/ canestrike per condition
figure()
for i = 1:5
    hold on
    % subplot(2,3,i),title('Knee Adduction Moment',FontSize,60)
    subplot(2,3,i),area(10*t,KAM_avg_matrix(:,i),'LineWidth',2)
    xlabel('Percent Stance',FontSize,28),ylabel('Adduction(%BW*Ht)',FontSize,28)
    set(gca,FontSize,24)
    hold on
    conditionlabels = strcat('C',num2str(i));
    bar(cane_timing_data(i,1),cane_timing_data(i,2),'FaceColor',strikecolors(i))
    title(strcat('Condition ',num2str(i)),FontSize,16)
    hold on
end
suplabel('Canestrike in Relation to KAM','t');

```

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%% ORGANIZING SUBJECT DATA FOR EASY-TO-READ OUTPUT

% for i = 1:ind
%   for n = 1:5
%     subject_data(i) = [strcat('Condition',num2str(n));
%
%% plot KAAI vs. cane2perstance
figure()
for i = 1:5

subject(23).condition(i).strike2KAAI = [subject(23).condition(i).cane2perstance.raw',subject(23).condition(i).KAAI.raw'];

scatter(subject(23).condition(i).cane2perstance.raw,subject(23).condition(i).KAAI.raw,'FaceColor',strikecolors(i))
% Const = ones(size(subject(23).condition(i).cane2perstance.raw'));
% Coeffs = [subject(23).condition(i).cane2perstance.raw' Const]\subject(23).condition(i).KAAI.raw';
% [p,S] = polyfit(subject(23).condition(i).cane2perstance.raw,subject(23).condition(i).KAAI.raw,0)
% f = polyval(subject(23).condition(i).cane2perstance.raw,p)
hold on
% plot(subject(23).condition(i).cane2perstance.raw
end

strike2KAAI_1 = subject(23).condition(1).strike2KAAI;
strikes1 = subject(23).condition(1).strike2KAAI(:,1);
KAAIs1 = subject(23).condition(1).strike2KAAI(:,2);

strike2KAAI_2 = subject(23).condition(2).strike2KAAI;
strikes2 = subject(23).condition(2).strike2KAAI(:,1);
KAAIs2 = subject(23).condition(2).strike2KAAI(:,2);

strike2KAAI_3 = subject(23).condition(3).strike2KAAI;
strikes3 = subject(23).condition(3).strike2KAAI(:,1);
KAAIs3 = subject(23).condition(3).strike2KAAI(:,2);

strike2KAAI_4 = subject(23).condition(4).strike2KAAI;
strikes4 = subject(23).condition(4).strike2KAAI(:,1);
KAAIs4 = subject(23).condition(4).strike2KAAI(:,2);

strike2KAAI_5 = subject(23).condition(5).strike2KAAI;
strikes5 = subject(23).condition(5).strike2KAAI(:,1);
KAAIs5 = subject(23).condition(5).strike2KAAI(:,2);

xlabel('Peak Cane Load Time (%Stance)','FontSize',28),ylabel('KAAI(%BW*Ht)','FontSize',28)

%% plot PKAM vs. cane2perstance
figure()
for i = 1:5

subject(23).condition(i).strike2PKAM = [subject(23).condition(i).cane2perstance.raw',subject(23).condition(i).PKAM.raw'];

scatter(subject(23).condition(i).cane2perstance.raw,subject(23).condition(i).PKAM.raw,'FaceColor',strikecolors(i))
% Const = ones(size(subject(23).condition(i).cane2perstance.raw'));
% Coeffs = [subject(23).condition(i).cane2perstance.raw' Const]\subject(23).condition(i).KAAI.raw';
% [p,S] = polyfit(subject(23).condition(i).cane2perstance.raw,subject(23).condition(i).KAAI.raw,0)
% f = polyval(subject(23).condition(i).cane2perstance.raw,p)
hold on
% plot(subject(23).condition(i).cane2perstance.raw
end

```

```

xlabel('Peak Cane Load Time (%Stance)',FontSize,28),ylabel('PKAM(%BW*Ht)',FontSize,28)
legend('Naive','Scale Training','Scale Recall','Haptics','Haptic Recall')
%% plot Cane_ON vs. KAAI
figure()
for i = 1:5

subject(23).condition(i).cane_on2KAAI = [subject(23).condition(i).cane_on2perstance.raw',subject(23).condition(i).KAAI.raw'];

scatter(subject(23).condition(i).cane_on2perstance.raw,subject(23).condition(i).KAAI.raw,'FaceColor',strikecolors(i))

hold on
end

xlabel('Cane Strike (%stance)',FontSize,28),ylabel('KAAI(%BW*Ht)',FontSize,28)
legend('Naive','Scale Training','Scale Recall','Haptics','Haptic Recall')

figure()
for i = 1:5

subject(23).condition(i).cane_on2PKAM =
[subject(23).condition(i).cane_on2perstance.raw',subject(23).condition(i).PKAM.raw'];

scatter(subject(23).condition(i).cane_on2perstance.raw,subject(23).condition(i).PKAM.raw,'FaceColor',strikecolors(i))

hold on
end

xlabel('Cane Push-on (%stance)',FontSize,28),ylabel('PKAM(%BW*Ht)',FontSize,28)
legend('Naive','Scale Training','Scale Recall','Haptics','Haptic Recall')

%% plot Cane_OFF vs. KAAI and PKAM
figure()
for i = 1:5

subject(23).condition(i).cane_off2KAAI =
[subject(23).condition(i).cane_off2perstance.raw',subject(23).condition(i).KAAI.raw'];

scatter(subject(23).condition(i).cane_off2perstance.raw,subject(23).condition(i).KAAI.raw,'FaceColor',strikecolors(i))

hold on
end

xlabel('Cane Push-off (%stance)',FontSize,28),ylabel('KAAI(%BW*Ht)',FontSize,28)
legend('Naive','Scale Training','Scale Recall','Haptics','Haptic Recall')

figure()
for i = 1:5

subject(23).condition(i).cane_off2PKAM =
[subject(23).condition(i).cane_off2perstance.raw',subject(23).condition(i).PKAM.raw'];

scatter(subject(23).condition(i).cane_off2perstance.raw,subject(23).condition(i).PKAM.raw,'FaceColor',strikecolors(i))

hold on
end

xlabel('Cane Push-off (%stance)',FontSize,28),ylabel('PKAM(%BW*Ht)',FontSize,28)
legend('Naive','Scale Training','Scale Recall','Haptics','Haptic Recall')

%% plot individual subjects KAM
% clf
% for n = 1:5

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% plot(subject(n).condition(i).KAM.normal)
% hold on
% end

%% plot individual subject's cane data
% for c=1:5
% for s = 1:length(subject(14).condition(n).canefiles)
% hold on
% plot(subject(13).condition(n).Cane_Load.raw(s).data)
% end
% end

%% plot womac
%figure()
% subplot(1,2,1),bar(womac_avg)
% hold on
% errorbar(womac_avg, womac_sd,',' ,LineWidth',3)
% title('Average womac vs Condition','FontSize',42)
% set(legend,'FontSize',30)
% set(gca,'FontSize',24)
% % xlabel('Condition','FontSize',28)
% ylabel('(%BW*Ht)','FontSize',28)
% xticklabels(condition_names)
% xtickangle(45)
% hold on

% for i = 2:ind-1
%
%   womac_subavg = [subject(i).condition(1).womac.mean, subject(i).condition(2).womac.mean,
subject(i).condition(3).womac.mean,...
%   subject(i).condition(4).womac.mean, subject(i).condition(5).womac.mean];
%   plot(womac_subavg,'o','MarkerSize',8,'LineWidth',3,'Color',rand(1,3)(i-1,:))
%   hold on
%
% end
% %search for subject.name, rather than index (google matlab logical indexing) --> subject(subject.name == 'grand')

%% plot Cane Load step-specific
figure()
CaneLoadSS_avg = [subject(ind).condition(1).Cane_Load.goodstrike.normal,
subject(ind).condition(2).Cane_Load.goodstrike.normal, subject(ind).condition(3).Cane_Load.goodstrike.normal,...
subject(ind).condition(4).Cane_Load.goodstrike.normal, subject(ind).condition(5).Cane_Load.goodstrike.normal];

CaneLoadSS_sd = [subject(ind).condition(1).Cane_Load.sd, subject(ind).condition(2).Cane_Load.sd,
subject(ind).condition(3).Cane_Load.sd,...
subject(ind).condition(4).Cane_Load.sd, subject(ind).condition(5).Cane_Load.sd];

bar(CaneLoadSS_avg)
hold on
errorbar(CaneLoadSS_avg,CaneLoadSS_sd,',' ,LineWidth',3)
hold on
title('Average Cane Load vs Condition','FontSize',42)
set(legend,'FontSize',30)
set(gca,'FontSize',24)
% xlabel('Condition','FontSize',28)
ylabel('Cane Load (%BW)','FontSize',28)
ref1 = [20 20 20 20 20 20 20];
ref2 = 20;
plot(0:6,ref1,'r--','LineWidth',2)
xticklabels(condition_names)
xtickangle(45)

```