Haptic Gait Retraining for Knee Osteoarthritis Treatment

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ABSTRACT

In this paper we introduce haptic gait retraining as a new method for treating early stage medial compartment knee osteoarthritis and for reducing risk of the disease in individuals who may be susceptible. The hardware and software for implementation are presented including rotational skin stretch and vibration haptic devices used to inform subjects of alterations in gait movements. We also present a method based on real-time motion analysis for predicting new subject-specific gaits tailored to change knee joint loading. This approach uses correlation data between gait parameters and knee loading as well as a localized linearization technique to compute a final combined-parameter gait with minimum change from the subject's original, unaltered gait. Finally, we validate the haptic gait retraining system with a user experiment and show that, for the duration of the experiment, the user is able to positively change knee joint loading to approximately the same degree as HTO surgery.

Index Terms: H.1.2 [Models and Principles]: User/Machine Systems—Human information processing; H.5.2 [Information Interfaces and Presentation]: User Interfaces—Haptic I/O

1 INTRODUCTION

With the cost of health care rising and an aging baby boomer generation requiring increasing medical assistance, it is imperative that new technologies be developed and implemented to improve the quality of health care while simultaneously reducing costs. Arthritis is a major health concern that could benefit from such new technologies. The impact of preventing or more efficiently treating arthritis would be immense as seen in the following [8, 12]:

- Arthritis is the leading cause of disability among adults in the U.S.

- 46 million U.S. adults (20%) have doctor-diagnosed arthritis.

- $128 billion in total costs or 1.2% of the U.S. gross domestic product was spent on arthritis in 2003.

- Reducing the incidence of arthritis by even 1% would cut the total cost by $1.3 billion per year, a savings of more than $3.5 million per day

Knee osteoarthritis (OA) is the most prevalent form of arthritis afflicting 28% of U.S. adults over age 45 and 37% of U.S. adults over age 65 [12]. Knee OA causes pain leading to loss of mobility and often requires painful and expensive surgeries. OA affects the medial compartment (inside) of the knee approximately ten times more frequently than the lateral compartment (outside) [1], and the relative medial-to-lateral loading has been linked to the severity [20] and rate of progression [14] of knee OA. In light of this trend, current treatment methods often seek to shift mechanical loading from the diseased medial to the healthy lateral side of the

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knee in an effort to slow the progression of medial compartment knee OA.

One common method of treating knee OA is high tibial osteotomy (HTO) surgery. During this procedure, a triangular wedge of bone is either chiseled out of or added to the upper tibia. This physically changes the leg alignment to be more knock kneed as it shifts weight from the medial compartment to the lateral compartment, however the surgery is painful and expensive and requires a long recovery time. Nonsurgical solutions include wedged insoles [11], variable stiffness shoes [5] and valgus knee braces [18]. However, these methods only provide a modest amount of knee load transfer and are therefore limited in their effectiveness.

We present gait retraining with haptic feedback as a promising new alternative to treating knee osteoarthritis. This method utilizes *real-time motion analysis* to link gait parameters to knee joint loading and *real-time haptic feedback* from wearable vibration and skin stretch devices to train new gait patterns aimed at reducing knee loading. We choose haptic feedback for movement retraining because individual devices can be attached to the body and placed at or near each movement parameter to be altered, giving the user an intuitive sense of desired movement changes. In addition, the wearable devices can potentially be taken outside of the clinic or laboratory, for extended use if desired.

In the following sections we describe the haptic gait retraining system and test its effectiveness with a user study aimed at changing knee loading through gait alterations. We first define the knee adduction moment and discuss its relevance to knee osteoarthritis. We then describe the elements of the system, including the motion capture and haptic feedback devices and the computations used to correlate feedback with variations in gait parameters. We describe a user study conducted with ten subjects and present the results of gait retraining, followed by a discussion of the results and conclusions.

2 HAPTIC GAIT RETRAINING IN REAL-TIME

The purpose of haptic gait retraining is to change walking patterns to benefit the individual being tested. In this study, we focus on altering gait parameters associated with knee loading as a treatment method for osteoarthritis. In particular, we focus our gait modifications on changing the knee adduction moment, a measurement that has a well-documented correlation with knee osteoarthritis.

A system intended to produce gait retraining should contain the following main components: *sensing*, *computation* and *feedback*.

Table 1: Abbreviations

Osteoarthritis	OA
High tibial osteotomy	HTO
Knee adduction moment	KAM
Foot progression angle	FPA
Tibia angle	TA
Trunk sway angle	TSA
Stride length	SL

The presented system uses marker-based motion capture and tread-mill force plates for sensing. Feedback is achieved with portable haptic devices including a wearable skin stretch device and several vibration motors. A modeling method utilizing localized linearization is used as the intelligence connecting sensing to feedback.

2.1 Reducing the knee adduction moment

The knee adduction moment (KAM) is an established surrogate measure of medial compartment knee OA [19] and provides an estimate of the relative loading between the medial and lateral compartments of the knee joint. Reducing the KAM shifts loads from the diseased medial compartment to the healthy lateral compartment of the knee and is seen as a treatment method for patients with early stage medial compartment knee OA [6]. The KAM occurs during the stance phase of gait while the foot is in contact with the ground, and it characteristically displays two peaks. The first peak specifically influences knee OA progression [9, 16, 22], and for this reason we focus our gait retraining on reducing the first peak of the KAM.

The KAM is calculated as the cross product between the moment arm and the ground reaction force (GRF):

$$KAM = r \times GRF \qquad (1)$$

where r is the position vector from the knee joint center to the center of pressure and GRF is the ground reaction force. As seen in Figure 1, the position vector is the vector from the knee joint center to the center of pressure at the contact point between the foot and the ground. The ground reaction force vector starts from the center of pressure and moves towards the center of mass.
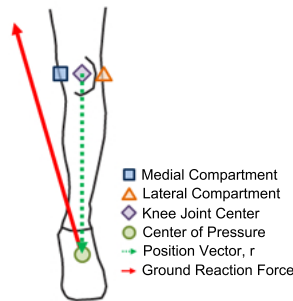

Figure 1: The knee adduction moment is calculated by taking the cross-product of the position vector r and the ground reaction force GRF.

2.2 Sensing and Feedback: System Setup

Since haptic gait retraining involves teaching subjects to change movements that are inherently dynamic (i.e., gait parameters), the philosophy behind using haptic feedback is to alter the subject's feedforward model of gait. This is different from many applications of wearable vibrotactile arrays that use haptic feedback as a means of closed-loop control of human movement [4, 10, 13]. In these types of studies, trained movements are significantly slower than movements required during gait. The delay in the human afferent-efferent loop causes closed loop movement control to become increasingly difficult for faster dynamic tasks such as gait alteration. Thus haptic feedback is used in gait retraining as an indicator during one step to update the feedforward model for the subsequent step or steps.

In the current study, feedback is administered through a combination of wearable vibration and skin stretch devices. The skin stretch device (Figure 2) provides feedback via two contact pads attached to the skin, which give localized rotational displacements,
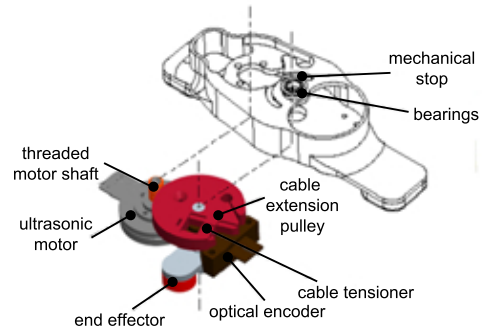

Figure 2: Skin Stretch Device

deforming the skin primarily in shear, tangential to the skin surface. This type of feedback can be useful for conveying position, velocity and direction information to the user [2, 3]. The device is powered by an ultrasonic motor for low weight, high torque and no perceptible vibrations.

For vibration feedback we use C2 Tactor motors by EAI due to their ability to control amplitude and vibration independently (unlike most pager motors). We vibrate the motors at 250 Hz to activate fast-acting mechanoreceptors near their peak of sensitivity [21]. The controller for the motors was implemented using the Matlab xPC real-time operating system running at 1 kHz and obtains information from the Vicon tracking system via a DLL file.
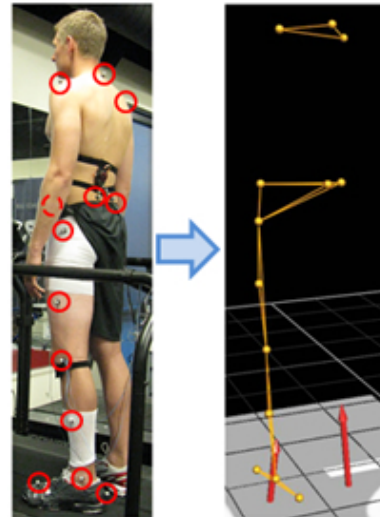

Figure 3: Reflective markers attached to the body are used to produce a real-time biomechanical model.

To measure human movements, we used a Vicon 3D motion capture system. Reflective markers were attached to the subject and their positions were located in space via infrared cameras. Vicon's software was used to convert marker positions into a segmented biomechanical model which provides segment and joint positions and rotations (Figure 3). We used Vicon's real-time software, Nexus, to read in marker and segment values in real-time. Marker data were collected at 60 Hz. Ground reaction forces and center of pressure measurements were obtained through an instrumented Bertec treadmill at a rate of 1200 Hz. The treadmill also interfaced with the Nexus software to provide these measurements in real-time.

2.3 Computation: Localized Linearization Modeling to Predict New Gaits

The relationship between gait parameters and the KAM is complex due to the kinematics and dynamics of the human body, and is likely to be highly nonlinear and subject specific. As it would be impractical to collect data over the entire search space to create an accurate system model, we present an approach for reducing the KAM, which uses a limited amount of data in n-dimensional space of the chosen gait parameters. This approach utilizes localized linear models recomputed over successive iterations similar to Newton's method. We estimate the desired gait using a heuristic approach then iterate by modeling the system about a point and predicting subsequent gaits in an attempt to achieve a particular KAM reduction. With adequate initialization and reasonable iteration step sizes, this approach should converge on a specific gait pattern to achieve the desired KAM reduction.

2.3.1 Initialization Step

To initialize the localized linear method, we calculate a value for each gait parameter; we define this sequence of gait parameters as a *gait*. For the initialization, the value of each parameter is proportional to its correlation with the KAM and is only a small change from the subject's baseline gait. This approach provides an adequate initialization for the iterative algorithm using limited data, because with a high degree of confidence, each gait parameter moves in the direction that will reduce KAM, as predicted by the correlation metric. While this approach does not minimize the total changes from the unaltered gait, the initialization gait is a small but sufficient change from the baseline in the correct general direction. With this acceptable initialization, the gait converges in iterative steps.

Using data from the single parameter trials (see Section 3), we calculate the correlation coefficients between the KAM and each gait parameter, represented by c and define the initial gait as

$$gait_0^{des} = \frac{1}{4||c||_\infty} \begin{bmatrix} c^{(1)} p_{max}^{(1)} & c^{(2)} p_{max}^{(2)} & \dots & c^{(n)} p_{max}^{(n)} \end{bmatrix} \quad (2)$$

where p_{max} is the maximum value of each gait parameter. Thus, the value of each gait parameter is proportional to its correlation with KAM.

2.3.2 Iteration Step

Walking trial n of the method proceeds as follows: The subject is trained to walk with a specific combination of desired gait parameters $gait_{n-1}^{des}$, or the desired gait, predicted from the previous walking trial. Once the subject achieves this gait and the walking trial ends, the last ten steps are averaged to determine the final actual gait, $gait_{n-1}^{act}$, which will be slightly different from the desired gait. To predict the next desired gait, we create a localized linear model about the final actual gait, represented as

$$Ax = b \quad (3)$$

The equation for matrix A is

$$A = \begin{bmatrix} step_1 \\ step_2 \\ \vdots \\ step_m \end{bmatrix} - \mathbf{1} \otimes gait_{n-1}^{act} \quad (4)$$

where the $step_k$ and $gait_{n-1}^{act}$ vectors contain the measured gait parameters for step k and the final actual gait, respectively. Vector b contains the measured KAM on each individual step and is repre-
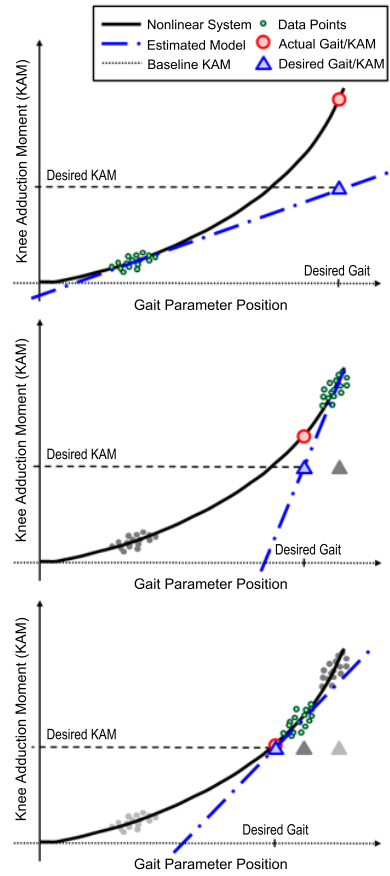

Figure 4: A simplified representation (using only a single gait parameter) of localized linear modeling to predict new gaits with a nonlinear system. The plots show successive iterations illustrating convergence to the gait parameter value which reduces the KAM moment by the desired amount.

sented as

$$b = \begin{bmatrix} KAM_1^{step} \\ KAM_2^{step} \\ \vdots \\ KAM_m^{step} \end{bmatrix} - \mathbf{1} \otimes KAM_{n-1}^{gait^{act}} \quad (5)$$

The final combination of gait parameters $gait_{n-1}^{act}$ and the final knee adduction moment $KAM_{n-1}^{gait^{act}}$ is subtracted from each step vector $step_k$ and step knee adduction moment KAM_k^{step}, respectively, to form the localized linear model about this point.

We then select thirty percent of all rows of A that lie closest to the final actual gait in the search space so that the linear model is localized. *Closeness* is defined as the magnitude of a row of A after normalization by the maximum value of each gait parameter. With the truncated A and b, we solve for x using Equation (3). To achieve the desired KAM reduction with minimum change in parameters from the subject's final gait, the new gait emanates in the x-direction from the final actual gait. We represent the new gait in context of the localized linear model as

$$(gait_n^{des} - gait_{n-1}^{act})x = KAM_n^{gait^{des}} - KAM_n^{gait^{act}} \quad (6)$$

$$wx^T x = KAM_n^{gait^{des}} - KAM_n^{gait^{act}} \quad (7)$$

Thus, the predicted gait on iteration n is

$$gait_n^{des} = wx + gait_{n-1}^{act} \qquad (8)$$

where

$$w = \frac{KAM_n^{gait^{des}} - KAM_n^{gait^{act}}}{||x||} \qquad (9)$$

A simplified representation of this process with only one gait parameter is shown in Figure 4.

3 GAIT TRAINING EXPERIMENT

A user study was performed to evaluate the haptic gait retraining system. Ten healthy subjects ages 23-37 participated in this study, which was approved by Stanford University's Institutional Review Board. Individualized gait patterns were identified through localized linear modeling aimed at significantly reducing the KAM with minimal change from normal walking movements. Subjects were trained to adopt these new gait patterns with feedback through the haptic gait retraining system.

We targeted four gait parameters for training and control, which previous studies had identified as having an influence on the KAM: trunk sway angle (TSA), tibia angle (TA), foot progression angle (FPA) and stride length (SA) [15, 6, 7, 17]. Trunk sway angle was defined as the maximum angle that a vector from the lower back to the upper back deviated from vertical in the frontal plane during a complete gait cycle. Tibia angle was the maximum angle that a vector from the outside of the ankle to the outside of the knee deviated from vertical in the frontal plane during the stance phase of each gait cycle. Positive tibia angle was toward the body. Foot progression angle was defined as the maximum angle that a vector from the heel to the toe deviated from a line pointing directly away from the front of the subject in the horizontal plane during the stance phase. Positive foot progression angle occurred when the toe pointed in toward the subject. Stride length was the length of each step normalized by the subject's height. Haptic feedback devices were placed at or near the associated gait parameters (Figure 5), and a metronome was used as an audio indicator to train subjects on stride length.

There are many possible ways to apply haptic feedback to indicate desired changes in up to four gait parameters for reducing the KAM. Based on the results of pilot tests, a combination of two vibration devices, one skin stretch device, and the audio metronome for stride length, was found to be relatively easy for subjects to use.

Rotational skin stretch was used to indicate the necessity to sway the upper torso by a certain amplitude to change the trunk sway angle. Skin stretch was applied continuously as a sinusoid, chosen for its similarity to the movement pattern of the torso during ambulation. The frequency of the sine wave was set to match the subject's gait frequency. Two amplitudes of sine waves were used for feedback. The larger amplitude was used when a large increase in trunk sway angle was desired and the small amplitude was used to indicate a small desired increase. If the subject walked with too much trunk sway, the skin stretch device rotated quickly three times at 5Hz. If the user's trunk sway was in an acceptable range, the skin stretch device did not rotate but remained in the neutral position. We used discrete sine wave amplitudes instead of continuously varying amplitudes to give users a clear indication of improving or declining performance.

Vibration motors were used as feedback indicators for tibia angle and foot progression angle. Unlike trunk sway, which was perpetually changing, these gait parameters are nearly constant during the stance phase of gait. Thus, vibration was used as an indicator to simulate a type of restoring force to move the gait parameter back to a specific static location during stance. One vibration motor was
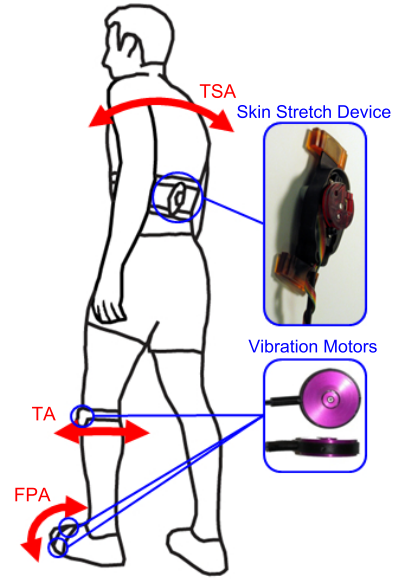

Figure 5: Haptic feedback device locations and associated gait parameters

placed on the lateral side of the knee to indicate desired mediolateral knee position and the associated tibia angle. During each step a 500 ms pulse vibrated to alert the user that the knee position should be more medial. A large amplitude pulse indicated a large change and a small amplitude pulse indicated a small change. If the knee position was too medial, the motor gave three short 100 ms pulses, and if the knee position was in an acceptable range the motor did not vibrate. Two vibration motors were attached to the foot and worked in a similar manner to control the foot progression angle. Lateral motor vibrations indicated a need to point the toe more inward during static stance alignment and medial motor vibrations to point the toe more outward.

The haptic feedback devices were attached to each subject via Velcro straps. Hypoallergenic, double-sided tape adhered the skin stretch device to two contact areas on the skin of the lower back. Each feedback device was calibrated to the subject before testing so that the subject could clearly sense a difference between each level of feedback for each feedback device.

Thirteen reflective markers were placed on each subject to track motions (Figure 3). Markers were placed at the following places: calcaneous (heel), second metatarsal (front of foot), lateral malleolus (outside ankle), outside of the knee, middle of the shank, greater trochanter (hip), middle of the thigh, left anterior superior iliac spine (front pelvis), left posterior superior iliac spine (back pelvis), right posterior superior iliac spine (back pelvis), left shoulder, right shoulder, and the seventh cervical vertebrae (upper spine). In addition to these, markers were added to the medial malleolus and inner knee for static trials to obtain the knee offset and create musculoskeletal models for post-processing.

After all of the markers and feedback devices were attached, each subject initially walked normally for two to five minutes to get used to using to the treadmill. During this time all of the baseline parameters were recorded and stored, including the knee adduction moment, trunk sway angle, tibia angle, foot progression angle and stride length.

After collecting baseline data, the subject was trained to walk with several new gait patterns, each with a change to a single gait parameter. These single parameter gait trials lasted one to five minutes depending on how long it took to learn the new gait. During
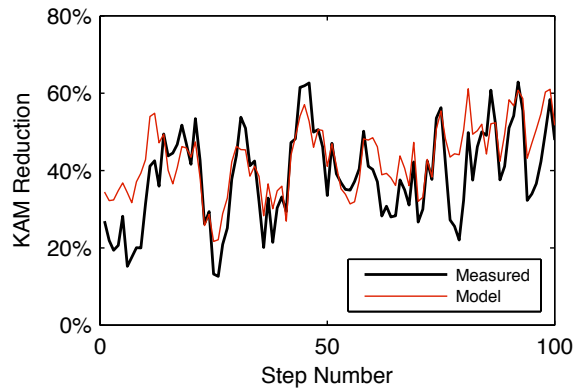
Figure 6: Example data shows comparison of measured KAM reduction and predicted KAM reduction for a multi-parameter gait. The data shown is after a four-sample moving average.

the trunk sway angle, tibia angle and foot progression angle gaits, subjects were either given haptic feedback as described above or a visual display with arrows indicating required changes. Stride length feedback was auditory through a metronome. The purpose of the single gait parameter tests was to give each subject a feeling for using changing individual gait parameters with feedback while walking. Additionally, the data recorded during this session was used to correlate gait parameters with the KAM to initialize the localized linear modeling process.

Once the single parameter gait trials were complete, the subject was trained to walk with three new gaits involving multiple parameter changes: *Initialization Gait*, *Gait 1* and *Gait 2*. The parameter values for the Initialization Gait were determined using the correlation model detailed in Section 2.3.1. Gait 1 parameters were computed based on the first iteration of the localized linear modeling method shown in Section 2.3.2 and Gait 2 was based on a second iteration using the same algorithm.

Our goal was to reduce the KAM by at least 30% on either or both of Gait 1 and Gait 2. The final desired KAM, step vector and the max gait parameter vectors were set as follows:

$$KAM_n^{gait^{des}} = 30\% \tag{10}$$

$$step_k = \begin{bmatrix} FPA_k & TA_k & TSA_k & SL_k \end{bmatrix} \tag{11}$$

$$p_{max} = \begin{bmatrix} 20° & 8° & 15° & 20\% \end{bmatrix} \tag{12}$$

where foot progression angle (FPA), tibia angle (TA), trunk sway angle (TSA) and stride length (SL) were the gait parameters the subjects were trained to alter. These gait parameters, $step_k$, and maximum gait values, p_{max}, were relative to the baseline values. The maximum values were determined based on preliminary testing. During testing for each of these new multiparameter gait trials, all feedback devices were used to train each of the four gait parameters.

Subjects were determined to have correctly adopted the new gait if they were able to move all of the gait parameters correctly on eight out of ten steps. Subjects were given two-hundred steps to accomplish this. Once the new multiparameter gait was successfully adopted or two-hundred steps were taken, the gait parameters and KAM were averaged over those final ten steps (or best ten steps in
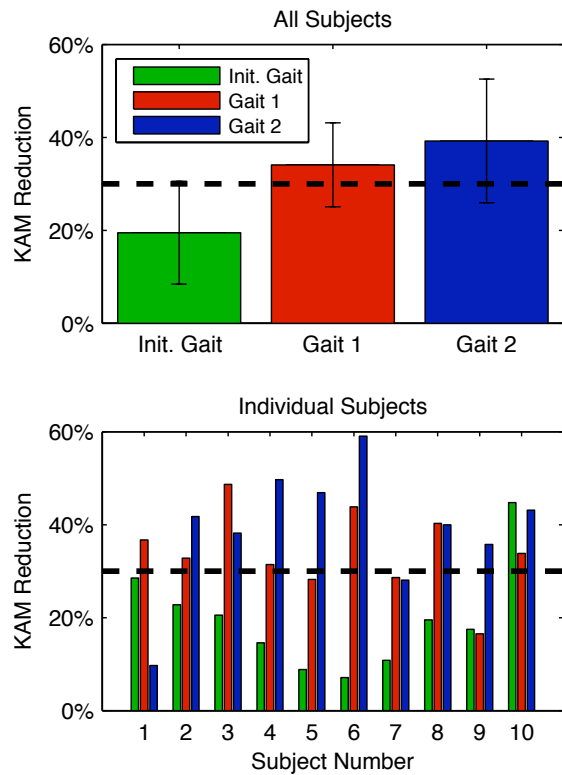

Figure 7: KAM reduction for multi-parameter gaits. The target was at least a 30% KAM reduction on either or both of Gait 1 and Gait 2. Initialization parameters were determined from correlation data (Section 2.3.1) and Gait 1 and Gait 2 were the first and second iterations from the localized linear model (Section 2.3.2).

the case where the gait was never correctly adopted for eight out of ten steps) and set as the final gait values. Final values were post-processed for analysis.

4 RESULTS AND DISCUSSION

Data from the experiments were analyzed to evaluate the haptic gait retraining system and motivate future work. The main results demonstrate that the localized linearization algorithm is adequate and allows subjects to reduce KAM by the desired amount. Additional results show the correlation between gait parameters and the KAM. Further, we observe that the baseline and desired gaits are both subject-specific and that a modest change to multiple parameters can effect a substantial change in the KAM.

4.1 Model Accuracy

The localized linear model predicts the KAM from the subject's measured gait parameters. For example, Figure 6 illustrates a comparison between the measured KAM and the localized linear model KAM prediction. The local linear model tracks the measured data and, after filtering the data with a four-sample moving average, the mean error is 6.8%. The ability to accurately predict KAM provides confidence in our multi-parameter gait predictions, since we use the localized linear modeling approach to predict a subject's ideal gait.

4.2 KAM Reduction with Haptic Gait Retraining

All ten subjects were able to reduce their KAM by at least 28% and nine of the ten subjects were able to reduce it by at least the target amount of 30% (Figure 7). Although the localized linear modeling algorithm computes a gait which will reduce the KAM
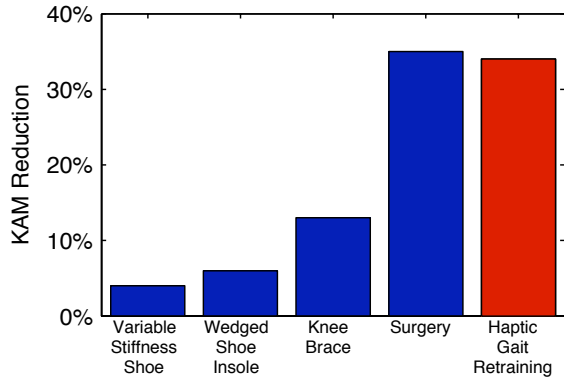
Figure 8: KAM reduction for current OA treatments compared to haptic gait retraining [5, 11, 18, 19].

by 30%, the haptic feedback was set up so as to encourage subjects to achieve a final gait with an effect equal to that of the predicted gait, or greater. Thus, we expect that some subjects would exceed the targeted reduction of 30%. Since the haptic gait retraining system allows the subject to walk with a gait that differs further than the predicted gait, with respect the to the baseline, there may be significant changes between iterations. This effect could lead to increasing KAM reductions with successive iterations.

Some subjects were unable to achieve the desired gait for eight out of ten consecutive steps over a two-hundred step trial. Subjects 7 and 10 never achieved Gait 1 and subjects 1, 9, and 10 never achieved Gait 2. This may explain why some subjects did not reduce KAM by at least 30% in the multi-parameter gait trials.

In agreement with our hypothesis, subjects were on average able to reduce KAM by 34% with Gait 1 and 39% with Gait 2 using haptic gait retraining. Remarkably, this reduction is comparable to the results of HTO surgery and more that doubles the reductions reported in tests of orthotics [5, 11, 18, 19] which is depicted in Figure 8. The HTO surgery results are for a large population sample while some of the nonsurgical results have relativity smaller sample sizes.

4.3 Subject Specificity in Gait Predictions

KAM reduction was also computed for each single parameter gait. Figure 9 illustrates that decreased foot progression angle and tibia angle decreased KAM, but increased trunk sway and stride length had different effects among subjects; that is, increasing trunk sway and stride length did not always reduce KAM.
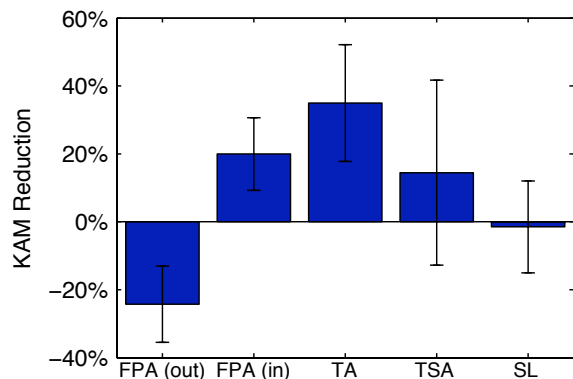

Figure 9: Average KAM reduction for single parameter gaits

Table 2: Comparison of gaits between two subjects illustrates how the local linear modeling algorithm predicts subject specific gaits

	Trunk Sway Angle Gait		Multi-parameter Gait 1	
Parameter	*Subject 2*	*Subject 10*	*Subject 2*	*Subject 10*
FPA	3.50°	-1.46°	-14.24°	-10.90°
TA	-1.29°	-3.35°	-5.31°	-6.42°
TSA	**7.88°**	**11.84°**	**-2.67°**	**5.18°**
SL	0.03	-0.01	-0.01	-0.05
KAM	**-6.95%**	**42.44%**	**33.73%**	**33.83%**

Since the effect of each parameter on KAM reduction varies amongst subjects, it is necessary for the desired gaits to be subject specific. This specificity is reflected in the multi-parameter gaits, which the localized linear algorithm predicts for each subject. For example, Table 2 illustrates that increasing trunk sway angle increases KAM for Subject 2, but decreases KAM for Subject 10, where all other parameters remain close to baseline. This variation in the effect of trunk sway angle is reflected in the predicted gait as Subject 2's trunk sway angle decreases and Subject 10's increases. Both subjects, however, achieve approximately the same KAM reduction with their multi-parameter Gait 1, despite significant differences in the final gait parameters.

4.4 Moderate Gaits Can Reduce KAM

In the single gait trials, subjects generally needed to change one parameter by a large amount. The ideal multimodal gait, in contrast, minimizes changes to any single parameter. As depicted in Table 3, in two single-parameter trials, the subject was able to change tibia and trunk sway angles by large amounts, reducing the KAM by about 40%; however, the subject was able to reduce the KAM by a similar amount in the multi-parameter gait with less pronounced tibia and trunk sway angles. Thus, it is possible for the KAM to be reduced significantly with a moderate gait. A moderate multi-parameter gait is likely to be more attractive for the subject to adopt as it requires fewer large modifications and from outside observation appears to more closely resemble normal gait than changing one parameter in a more extreme way.

Table 3: Example data for one subject shows moderate multiparameter gaits can achieve the same reduction as extreme single parameter gaits

	Tibia	Trunk Sway	Multi-Parameter
Parameter	**Angle Gait**	**Angle Gait**	**Init. Gait**
FPA	-4.11°	-1.46°	-5.79°
TA	**-7.64°**	-3.35°	**-4.17°**
TSA	-0.98°	**11.84°**	4.47°
SL	-0.07	0.01	-0.05
KAM	**37.09%**	**42.44%**	**42.45%**

4.5 Correlations between Gait Parameters

Table 4 illustrates the correlations between gait parameters measured using all of the data taken for each subject. There is negligible subject-to-subject variability in these correlations. Thus, for each subject, foot progression angle and tibia angle are correlated while the other gait parameters are not significantly correlated. The positive correlation between foot progression angle and tibia angle means that pointing the toe inward causes the knee position and the angle of the tibia to bend inward. Similarly, pointing the toe outward causes the knee position to move laterally. The same response

is true for the foot progression angle when knee movement is initiated. Individual feedback modalities for trunk sway angle, stride length, and either tibia angle or foot progression angle are justified as these parameters are uncorrelated. Further, although tibia angle and foot progression angle are correlated, the correlation coefficient is only 0.60, which suggests that the parameters are not completely dependent and motivates individual feedback modalities for these parameters.

Table 4: Correlation between gait parameters

	FPA	TA	TSA	SL
FPA	1.00	-	-	-
TA	**0.60 ± 0.09**	1.00	-	-
TSA	-0.02 ± 0.11	-0.06 ± 0.12	1.00	-
SL	0.03 ± 0.07	0.08 ± 0.07	0.05 ± 0.08	1.00

5 CONCLUSIONS AND FUTURE WORK

The reported results illustrate the promise of a haptic gait retraining system, based on initial experiments with healthy subjects. The results show reductions in the KAM comparable to those obtained from surgery, and larger than those typically obtained with orthotics. We plan to explore this type of haptic gait retraining in clinical applications by testing patients with early-stage medial compartment knee OA. Such patients might benefit greatly with gait retraining, since it has the potential to slow the progression of osteoarthritis preventing costly and painful knee surgeries.

However, additional studies are necessary to improve and justify the system as a viable knee OA treatment. Future work will seek to (1) improve the gait prediction algorithm, (2) investigate and improve the human-feedback interface, and (3) demonstrate that the system can reduce KAM with early-stage knee OA patients. In particular, the experiments reported here were performed on healthy subjects who may find it easier to modify their gaits than OA patients, who are often older and heavier. Also, it remains to be seen whether the improvements in gait will be retained outside of the laboratory. In this regard, part of the motivation for using wearable haptic feedback devices is that they can be worn outside of a laboratory or clinic setting, perhaps using a combination of force and inertial sensing to detect when a patient's gait is reverting to the previous baseline.

Future iterations of the localized linear modeling algorithm will improve predicted gait feasibility by accounting for correlations between, and subject-specific ranges of, gait parameters. Additionally, a future algorithm should be able to decrease divergence from the targeted KAM reduction. While the maximum value for each gait parameter was fixed in the gait prediction algorithm, the range was observed to be different for each subject. Adjusting the algorithm for subject-specific ranges will help predict gaits that are feasible for a particular subject. To set the maximum value for each parameter, subjects would be asked to modify a particular gait parameter as far as comfortable, with some minimum change required.

Further, to predict a gait, we assumed that individual gait parameters were independent. Measuring the correlation between these parameters revealed that while most are independent, tibia and foot progression angles are correlated. Thus in future versions of the modeling algorithm, feasible foot progression angle / tibia angle combinations will be predicted while also ensuring minimum gait changes from baseline.

The gait prediction algorithm assumes that we will converge to the desired gait; however, two main factors may lead to divergence, or to a gait that does not produce minimum changes: (1) subjects are allowed to walk at the predicted gait or at a more extreme gait and (2) large jumps from the initialization gait to the 30% mark can be made. For future iterations of the gait prediction algorithm, the sequential changes to gaits should be minimal to both reduce the possibility of divergence and the possibility of overshooting the 30% target, as this will cause the subject to adopt a gait with a larger than necessary deviation from his or her baseline.

The human-feedback interface allowed subjects to be trained to the multi-parameter gaits using only haptic and sound feedback. In future experiments, we plan to study how subjects respond to multimodal feedback when receiving the same information through vision, haptics, and a haptics-vision redundant combination. With several gait parameters that require attention it is unclear how a purely haptic system will compare to a system with vision feedback. This comparison is necessary as we hope this preliminary work can lead to a portable system for gait retraining outside of the laboratory.

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