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Continuous Prediction of Leg Kinematics During Ambulation using Peripheral Sensing of Muscle Activity and Morphology

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***Abstract*—The advancement of robotic lower-limb assistive devices has heightened the need for accurate and continuous sensing of user intent. Surface electromyography (EMG) has been extensively used to sense muscles, and estimate locomotion modes and limb motion. Recently, sonomyography has also been investigated as a novel sensing modality. However, the fusion of multiple sensing modalities has not been explored for the continuous prediction of multiple degrees-of-freedom of the lower limb, and during multiple ambulation tasks. In the present study, nine able-bodied subjects completed level, incline, decline, stair ascent, and stair descent tasks. Motion capture data was collected during each task, as well as data from a portable ultrasound transducer (aligned in a transverse orientation) on the anterior thigh and surface EMG sensors on eight lower-limb muscles. Subject-dependent, task-independent Gaussian process regression models were implemented for continuous prediction of knee and ankle angle and angular velocity during these ambulation tasks using three feature sets: (1) surface EMG, (2) sonomyography, and (3) sensor fusion of EMG with sonomyography. Surprisingly, there were no significant differences between sonomyography and sensor fusion-based prediction of knee or ankle angle and angular velocity during all tasks. However, sonomyography and sensor fusion resulted in reduced root mean square error of knee angle prediction during all ambulation tasks and knee angular velocity prediction during most ambulation tasks compared to surface EMG. Sensor fusion improved ankle angle prediction for all walking tasks except stair ascent in comparison to surface EMG. Ankle angular velocity prediction resulted in the lowest performance, overall.**

***Clinical Relevance*—This work compares the combination of surface electromyography and sonomyography, and each modality in isolation, for the continuous prediction of kinematics of the knee and ankle during widely-varying ambulatory tasks.**

I. Introduction

Limb loss presents a growing clinical problem in the United States with more than 1.9 million people currently living with the loss of a limb and an estimated two-fold increase by 2050 [1]. Furthermore, greater than 30% of people who have suffered the loss of a limb are unable to live independently and lower-limb loss is consistently associated with lower quality of life [2]. Assistive devices aiming to restore natural locomotor ability to individuals with lower-limb loss are crucial for improving the quality of life of these individuals. The introduction of assistive devices that contain robotic lower-limb joints have the ability to restore additional functionality to individuals with limb loss by increasing the amount of assistance provided to the user, and adapting to new environments. However, powered assistive devices rely on accurate sensing to enable robust control schemes for safe integration into the daily lives of users [3]. Ideally, accurate sensing over multiple degrees-of-freedom, such as the knee and ankle of a powered transfemoral prostheses.

Multiple wearable sensing technologies have been explored for the detection of user intent, including mechanical sensors, neural sensors, and, most recently, imaging sensors. Mechanical sensors (e.g., inertial measurement units, pressure insoles, and accelerometers) are used for detection of reaction forces and limb motion. In order to sense information that precedes limb motion, neural sensors (e.g. surface electromyography (EMG)) have been the primary peripheral sensing technology evaluated to date [4]–[6]. Surface EMG measures muscle activity of superficial muscles via electrodes placed over the skin, and therefore cannot access information from deep muscle tissue and is susceptible to muscle cross-talk, resulting in low signal resolution and susceptibility to signal noise [7]. To increase the resolution of surface EMG, high density surface EMG decomposition has been proposed for its ability to analyze individual motor unit discharge in multiple muscles simultaneously. However, similar to traditional surface EMG, this technology is limited to superficial muscles only, and can be more difficult to analyze neighboring muscles, as well as more computationally expensive [8]. Therefore, researchers have turned to new sensing modalities, such as dynamic real-time ultrasound imaging of skeletal muscle, or sonomyography, for detection of additional muscle features beyond muscle activity from both superficial and deep muscle tissue. Both brightness-modulated (B-mode) and amplitude (A-mode) ultrasound imaging features have been correlated with muscle force production, contraction, and resulting joint motion [9]–[13]. To further improve the individual drawbacks of each of these sensing technologies alone, scientists have explored the fusion of multiple sensing modalities, such as neuromechanical fusion (i.e. surface EMG with mechanical sensors) [14]–[16]. Due to the recent introduction of sonomyography for lower-limb device control applications, the fusion of surface EMG with sonomyography is less widely reported [17].

Features of these sensing technologies can be used as an input for either model-based control approaches or model-free (e.g. machine learning or artificial intelligence) control

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approaches. While model-based approaches are beneficial for explicitly characterizing the transformation between input features to the desired output, these approaches can suffer from high computational cost that precludes real-time implementation [18]. Therefore, machine learning approaches, such as nonlinear regression, Gaussian regression models, neural networks, among others, have been proposed for mapping the features from surface EMG and sonomyography to device outputs, such as limb kinematics and kinetics [17], [19], [20]. Additionally, Gaussian process regression models have been proposed as alternatives to model-based solutions for inverse dynamics estimates of joint torque [21], [22]. Previous research demonstrated success in using these Gaussian models for continuous estimation of hip, knee and ankle moment, as well as knee angular velocity from sonomyography alone [23], [24]. However, the ability of these models to continuously predict knee and ankle angle and angular velocity from features of sonomyography alone, surface EMG alone, and the fusion of these two feature sets, has not been explored. Understanding these relationships can help to inform future integration of wearable sensing into powered assistive devices and their control systems.

The purpose of this study was to use sonomyography of the anterior thigh and electromyography sensors placed on various muscles of the same limb to continuously predict knee and ankle kinematics of able-bodied subjects during five ambulatory tasks. Features from both surface EMG and sonomyography were extracted individually. Then, the features of these two sensing modalities were combined to evaluate the prediction performance of sonomyography and electromyography, as well as a fused feature set. Because ultrasound imaging provides more information (i.e., muscle deformation of superficial and deep muscles) about muscle contraction in comparison to surface EMG (i.e., activity of superficial muscles only), we hypothesized that sonomyography features will result in improved regression performance for predicting knee and ankle angle and angular velocity when compared to surface EMG. However, we hypothesized that it would be more difficult to predict ankle angle and angular velocity from sonomyography features due to imaging muscles that do not span from the ankle joint. Furthermore, we hypothesized that the fusion of sonomyography with surface EMG would improve the regression performance for predicting ankle angle and angular velocity due to the unique contribution muscle activity information from muscles spanning the ankle.

II. Methods

A. Subjects and Data Collection

Nine able-bodied subjects, five male and four female, completed five ambulation tasks: level walk, 10° incline walk, 10° decline walk, stair ascent and stair descent. All walking trials were completed for one minute at a self-selected pace on a split-belt treadmill. Stair trials were completed on a four-step stair case, beginning with stair ascent followed by stair descent with subjects walking in a reciprocal gait pattern at a self-selected pace. Stair trials were repeated five times and walk-to-stair and stair-to-walk transition strides were included in the respective stair analyses. All subjects completed an institutional review board approved consent process prior to participation.

All subjects were equipped with ultrasound and surface EMG sensors on their left limb. A 128-element linear array transducer of a portable, handheld ultrasound scanner (mSonics, Lonshine Technologies, Inc) was affixed to the anterior thigh of each subject via a custom-designed probe holder. The transducer was placed transversely on the thigh at approximately half the distance between the anterior superior iliac spine and proximal base of the patella to collect grayscale images of the rectus femoris, vastus medialis (VM) and vastus

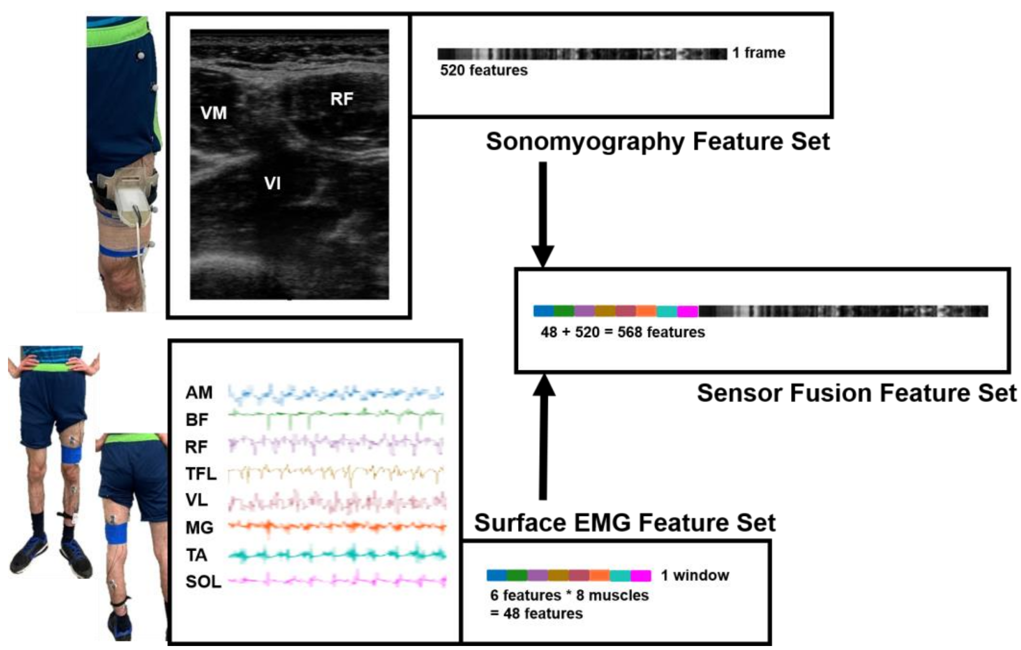

Figure 1. Sonomyography and Surface Electromyography (EMG) placement on a subject (left). Representative raw and 1-dimensional signals from each sensing modality (middle). Representation of sensor fusion feature set (right).

intermedius (VI) muscles (Fig. 1, left). Ultrasound images were collected with a transmit frequency of 7.5 MHz and a dynamic range of 50 dB and were streamed in real-time to the lab computer for synchronization with surface EMG and kinematic data.

Eight surface EMG sensors (Shimmer3 EMG Unit, Shimmer, Inc.) were placed over eight muscles on the same limb as ultrasound. Pre-gelled, self-adhesive electrodes (H124SG Covidien, Medtronic Inc.) were placed over the belly of the adductor magnus (AM), biceps femoris (BF), rectus femoris (RF), vastus lateralis (VL), tensor fascia latae (TFL), medial gastrocnemius (MG), tibialis anterior (TA) and soleus (SOL) muscles with an inter-electrode distance of 2 cm (Fig. 1, left). Surface EMG signals were collected at a frequency of 1200 Hz and streamed in real-time to the same lab computer as ultrasound.

Subjects' kinematic data were collected during all ambulation trials in a motion capture laboratory equipped with a ten-camera Vicon system (Vicon Motion Systems, Inc.) and recorded to the same computer as ultrasound and surface EMG at a sampling rate of 100 Hz (C-Motion, Inc.). Forty-two reflective markers were placed over anatomical landmarks on the bilateral feet, shanks, and thighs, as well as trunk and pelvis. Knee and ankle kinematic data were calculated in Visual 3D via inverse kinematics, and a custom MATLAB program was created to enable real-time recording and time stamping of data for synchronization.

B. Sonomyography and Surface EMG Feature Generation

Ultrasound imaging can be used to visualize muscle motion by the rapidly changing image intensity of muscle tissue. Previous research demonstrated mean image intensity features and temporal intensity features are useful for estimation of knee kinematics from sonomyography [23]–[26]. Therefore, both mean intensity and temporal intensity features were included in feature arrays from ultrasound images of the anterior thigh muscles during all ambulation tasks. The image sequence from each trial was split by heel strikes to create an ultrasound image sequence for each stride. A spatial filter with a block size of 3x3 mm was used to extract mean intensity of each 3x3 mm block. Then, this 2-dimension array of 260 mean image intensity features was rearranged into 1-dimension by horizontal concatenating rows of features ranging from superficial to deep image features. The temporal features were created by taking the time derivative of each feature set between consecutive frames. Finally, the mean intensity and temporal intensity features were combined to create a single sonomyography feature set consisting of 520 features per frame (260 mean intensity + 260 temporal intensity) (Fig. 1, middle).

Six time-domain features were extracted from sliding windows of each of the eight signals of surface EMG [25], [27]. The sliding windows consisted of 200 ms windows with a 50 ms overlap, such that features were continuously extracted from EMG signals at a rate of 20 Hz. The six features included: mean absolute value, number of slope sign changes, number of zero crossings, waveform length, and the first two coefficients of a fourth-order autoregressive model. Features from all eight muscles were combined to create a single EMG-based feature set consisting of 48 features per window (Figure 1, middle).

TABLE I. MEAN AND STANDARD DEVIATION (SD) PARTICIPANT CHARACTERISTICS ($N = 9$).

Subject Characteristic	Mean (SD)
Age (years)	29.9 (11.2)
Height (m)	1.72 (0.11)
Weight (kg)	65.8 (10.4)
Ultrasound Penetration Depth (cm)	6.0 (0.6)
Level Walk Speed (m/s)	0.79 (0.15)
Incline Walk Speed (m/s)	0.64 (0.11)
Decline Walk Speed (m/s)	0.62 (0.11)
# of Stair Ascent Strides	7.8 (2.4)
# of Stair Descent Strides	9.6 (3.4)

A third feature set was created to evaluate the combination of sonomyography with surface EMG features for the continuous prediction of knee and ankle kinematics. All sonomyography features were resampled to match the 20 Hz sampling rate of the sliding windows of EMG features prior to combining the two feature sets. This third feature set consists of the 48 EMG features followed by the 520 sonomyography features and will be referred to as the "fusion set" (Fig. 1, right).

C. Estimation of Joint Kinematics and Model Evaluation

Each of the three feature sets were used to train and test a subject-dependent Gaussian process regression (GPR) model with a quadratic kernel for continuous prediction of knee and ankle angle and angular velocity. The GPR model is a nonparametric, Bayesian approach for solving nonlinear regression [21]. An instance of a single response variable y_i, given an input and latent variable $f(x_i)$ for each observation x_i, can be modeled by the following probabilistic equation:

$$P(y_i|f(x_i), x_i) \sim N(y_i|h(x_i)^T\beta + f(x_i), \sigma^2), \qquad (1)$$

Where $h(x_i)$ is a basis function that transforms the original feature vector in R^D into a set of new feature vector in R^P, β is a p-by-1 vector of basis function coefficients and σ^2 is the error variance [21].

We chose this model based off of previous work demonstrating success for prediction of knee kinematics during level, incline and decline walking [24], [28]. All subject-dependent GPR models were trained on a combined dataset containing strides from all five ambulation tasks. Leave-one-stride-out cross-validation was utilized and looped through all strides, such that each stride was the test stride once.

Average root mean square error (RMSE) of the GPR prediction of knee and ankle angle and angular velocity compared to the measured knee and ankle angle and angular velocity from inverse kinematics was calculated for each of the three feature sets (sonomyography, surface EMG, and fusion). A one-way analysis of variance (ANOVA) (α=0.05) was used to establish a significant difference between the RMSE from each of the three feature sets for each walking task. Subsequent multiple comparisons t-test were performed with Tukey-

Kramer corrections to assess statistical significance of each group. In addition to the RMSE, the coefficient of determination (R^2) was calculated as a "goodness of fit" metric between each of the sensing modalities prediction of knee and ankle kinematics with the measured kinematics.

III. RESULTS

Fifteen level, incline and decline strides, as well as the maximum available strides for stair ascent and stair descent were included in the training and testing datasets for each GPR model (additional subject characteristics given in Table I). Some stair strides were removed from the dataset due to kinematic marker error. Features from sonomyography as well as sensor fusion features significantly reduced the overall average RMSE of knee and ankle angular velocity and angle prediction in comparison to features from surface EMG only (Table II). However, there was no significant difference of RMSE between features from sensor fusion and sonomyography only for knee and ankle angle and angular velocity.

A. Continuous Prediction of Knee Kinematics

In general, for all sensing modalities during all ambulation tasks, the GPR model more accurately predicted knee angle in comparison to knee angular velocity (R^2 values, Fig. 2A). Sensor fusion features as well as sonomyography features alone significantly reduced RMSE of knee angle prediction in comparison to surface EMG features during all ambulation tasks, however there were no significant differences between sensor fusion and sonomyography-based predictions of knee angle (Table II, top section). The tasks with the lowest RMSE for knee angle prediction within each sensing modality (and greatest R^2 values) were incline and decline walk, while the tasks with the greatest RMSE for knee angle prediction (and lowest R^2 values) within each sensing modality were the stair ascent and descent tasks.

Conversely, sensor fusion significantly reduced RMSE of knee angular velocity prediction in comparison to surface EMG-based prediction during all ambulation tasks, while sonomyography only reduced RMSE of incline walk, stair ascent and stair descent. Within each sensing modality, the task with the lowest RMSE (and greatest R^2 values) for knee angular velocity prediction was incline walk, while the task with the greatest RMSE (and lowest R^2 values) for knee angular velocity prediction was stair descent.

B. Continuous Prediction of Ankle Kinematics

Similar to GPR prediction of knee kinematics, for all sensing modalities during all ambulation tasks, the GPR model more accurately predicted ankle angle in comparison to ankle angular velocity (R^2 values, Fig. 2B). Sensor fusion significantly reduced RMSE of ankle angle prediction of level walk, incline walk, decline walk and stair descent compared to surface-EMG based prediction of ankle angle. Additionally, sonomyography sensing alone significantly reduced RMSE of ankle angle prediction incline walk, decline walk and stair descent tasks in comparison to surface-EMG. There were no significant differences between sonomyography alone and sensor fusion for prediction of ankle angle during any ambulation task. Within each sensing modality, the task with the lowest RMSE (and greatest R^2 values) for ankle angle prediction was level walk, while the task with the greatest RMSE for ankle angle prediction was stair descent. However, the task with the lowest R^2 values for ankle angle prediction was stair ascent.

Sensor fusion significantly reduced the RMSE of ankle angular velocity prediction during stair descent only in comparison to surface EMG-based prediction of ankle angular velocity. There were no significant differences between sonomyography and surface EMG-based prediction of ankle angular velocity. Within sensing modalities, the task

TABLE II. MEAN AND STANDARD DEVIATION (SD) ROOT MEAN SQUARE ERROR (RMSE) OF SURFACE ELECTROMYOGRAPHY (EMG) SONOMYOGRAPHY, AND SENSOR FUSION INFORMED GAUSSIAN PROCESS REGRESSION MODEL PREDICTION OF KNEE KINEMATICS.

Mean (SD) Root Mean Square Error								
	Angle (deg)				Angular Velocity (deg/s)			
	Ambulation Task	Sensing Modality			Ambulation Task	Sensing Modality		
		Surface EMG	*Sonomyography*	*Sensor Fusion*		*Surface EMG*	*Sonomyography*	*Sensor Fusion*
Knee	***Level Walk***	7.24 (1.80) [a,b]	4.73 (1.25)	3.77 (0.81)	***Level Walk***	89.81 (22.36) [b]	67.33 (22.56)	64.57 (19.03)
	Incline Walk	6.60 (1.11) [a,b]	4.03 (1.39)	3.22 (0.91)	***Incline Walk***	48.84 (7.54) [a,b]	35.93 (14.58)	27.61 (9.13)
	Decline Walk	6.88 (1.71) [a,b]	4.97 (1.10)	3.94 (1.03)	***Decline Walk***	61.56 (9.71) [b]	53.12 (14.00)	45.37 (11.22)
	Stair Ascent	11.87 (1.61) [a,b]	8.56 (1.56)	7.63 (1.56)	***Stair Ascent***	90.21 (29.35) [a,b]	62.77 (10.78)	55.20 (13.59)
	Stair Descent	14.49 (3.27) [a,b]	8.25 (2.95)	7.67 (2.57)	***Stair Descent***	109.12 (23.87) [a,b]	72.41 (21.90)	67.12 (16.00)
	Overall Average	10.49 (2.15) [a,b]	6.11 (1.65)	5.25 (1.38)	***Overall Average***	79.91 (18.57) [a,b]	58.31 (16.76)	51.97 (13.79)
Ankle	***Level Walk***	3.01 (0.87) [b]	2.55 (0.57)	2.21 (0.47)	***Level Walk***	46.51 (12.84)	45.90 (10.30)	41.36 (8.11)
	Incline Walk	4.50 (1.07) [a,b]	2.66 (0.91)	2.29 (0.70)	***Incline Walk***	41.99 (10.31)	36.64 (10.11)	33.32 (8.07)
	Decline Walk	3.68 (1.23) [a,b]	2.34 (0.68)	2.17 (0.55)	***Decline Walk***	42.31 (8.20)	42.52 (7.91)	40.14 (7.59)
	Stair Ascent	5.97 (2.31)	4.36 (1.27)	3.95 (1.54)	***Stair Ascent***	57.89 (16.02)	50.19 (10.78)	46.83 (9.93)
	Stair Descent	7.68 (2.40) [a,b]	4.83 (1.75)	4.36 (1.54)	***Stair Descent***	82.13 (14.41) [b]	67.31 (14.37)	65.25 (10.65)
	Overall Average	4.97 (1.58) [a,b]	3.35 (1.04)	3.00 (0.96)	***Overall Average***	54.16 (12.36) [b]	48.51 (10.70)	45.38 (8.87)

a. Significant difference (p<0.05) between RMSE of surface EMG and sonomyography sensing.

b. Significant difference (p<0.05) between RMSE of surface EMG and sensor fusion.

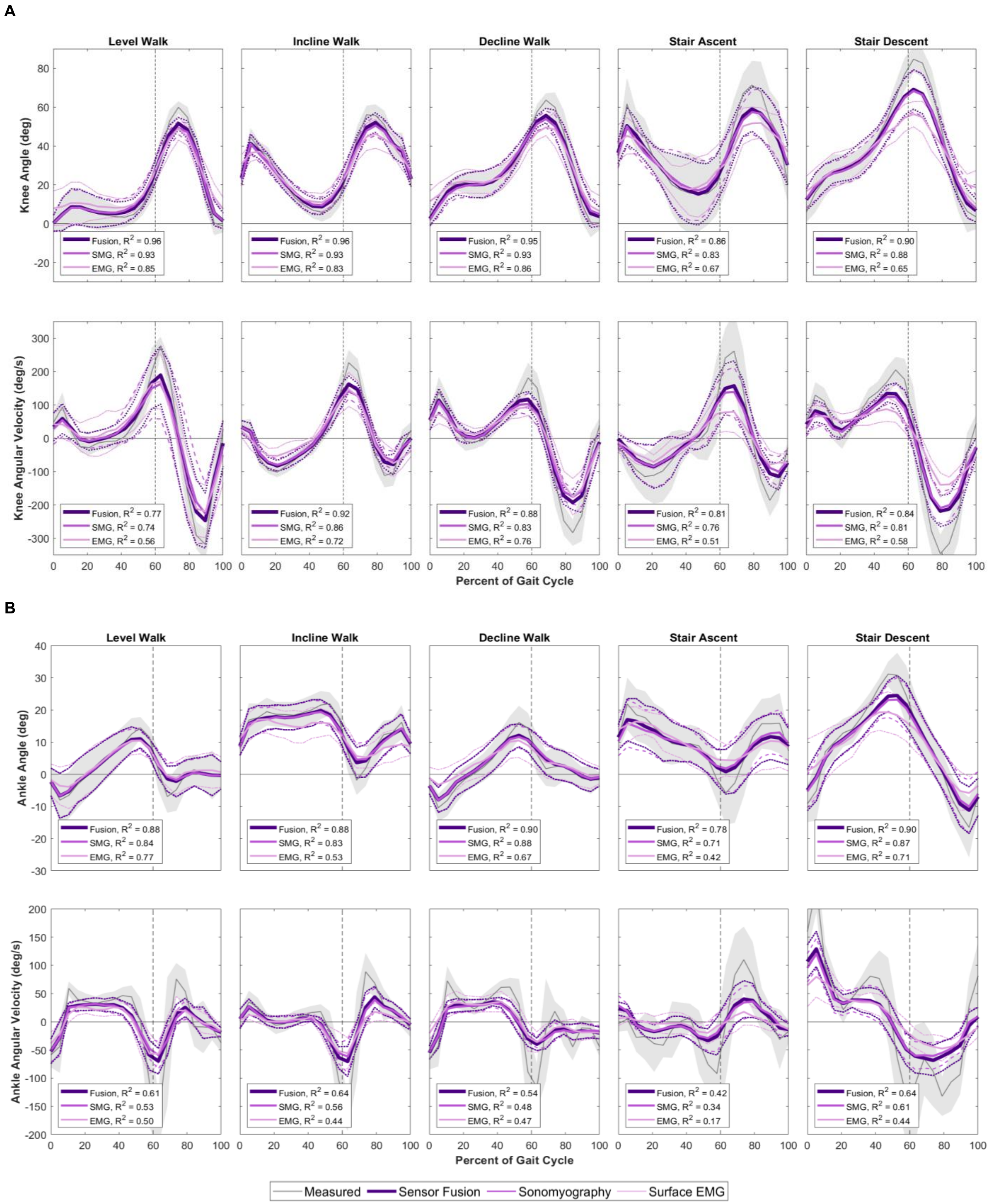

Figure 3. Measured vs. Predicted (A) Knee and (B) Ankle Kinematics During Level Walk, Incline Walk, Decline Walk, Stair Ascent and Stair Descent as a Function of the Gait Cycle. *Knee and ankle angle and angular velocity were measured using inverse kinematics; means are displayed in solid gray lines with standard deviations displayed in shaded regions. Predicted knee and ankle angle and angular velocity were estimated from Gaussian processes regression models trained with features from sonomyography, surface electromyography and sensor fusion. Coefficients of determination (R^2) are calculated between the predicted kinematics from the respective sensing modality and the measured values. Dashed vertical line signifies average transition from stance to swing phase of gait.*

with the lowest RMSE (and greatest R^2 values) of ankle angular velocity prediction was incline walk, while the task with the greatest RMSE (and lowest R^2 values) for ankle angular velocity prediction was stair descent.

C. Computational Cost

All signal processing, extraction of sensing features and implementation of the GPR model was completed on a single CPU (Intel(R) Core i7-7700 at 3.60 GHz). Average computational speed for training and testing the GPR model with each of the three feature sets are displayed in Table III.

TABLE III. AVERAGE COMPUTATIONAL TIME.

Regression Model	Mean Time (s)	
	Train	***Test***
Surface Electromyography	6.45	0.001
Sonomyography	6.21	0.004
Sensor Fusion	24.16	0.005

IV. DISCUSSION

Fusion of sonomyography and electromyography improved the GPR model's accuracy of knee and ankle angle and angular velocity prediction in comparison to sonomyography and surface EMG alone. Surprisingly, there were no significant differences between sensor fusion and sonomyography sensing alone when comparing the GPR model's prediction of any of the knee or ankle kinematics. As hypothesized, both sensor fusion and sonomyography features alone resulted in significantly reduced RMSE of knee angle prediction from the GPR models for all ambulation tasks in comparison to surface EMG features. Additionally, sensor fusion resulted in significantly reduced RMSE of ankle angle prediction during all tasks, while sonomyography alone resulted in significantly improved RMSE of ankle angle prediction during most (incline walk, stair ascent, stair descent) tasks in comparison to surface EMG. In general, for all sensing modalities, stair ambulation resulted in the greatest RMSE and lowest R^2. This can likely be attributed to the reduced number of stair strides available for training the GPR models as well as increased variability of the stair kinematics due to inclusion of both the transition and steady state strides. For both joints, angular velocity proved more difficult for the GPR model to predict. Sensor fusion improved knee angular velocity prediction during all ambulation tasks, and sonomyography alone resulted in significantly reduced RMSE of knee angular velocity prediction during most ambulation tasks (incline walk, stair ascent, stair descent) in comparison to surface EMG features.

One explanation as to why angular velocity was more difficult to predict compared to the respective joint's angle during all walking tasks is due to the increase in input noise of the angular velocity signal. GPR models make two assumptions about noise in datasets: the input to the model is noise-free and the output of the model have constant-variance Gaussian noise [29]. Therefore, due to the potential for noise in both the input (sonomyography and surface EMG features), as well as the output (angular velocity) during these ambulation tasks, other non-linear regression models could potentially be more beneficial for predicting angular velocity of the knee and ankle.

The present results confirm previous findings that sonomyography can be used to accurately predict knee angular velocity during walking tasks [24], and extend these findings to knee angular velocity, as well as ankle angle and angular velocity. As expected, the performance of ankle kinematic prediction decreased in comparison to knee kinematic prediction. However, the addition of surface EMG sensing to sonomyography did not significantly improve the performance relative to sonomyography alone, indicating that sonomyography of the anterior thigh may be sufficient for estimating distal ankle angle. Although there was no significant improvement when comparing sonomyography alone to sensor fusion, there are potential benefits of including surface EMG that are unforeseen by this study design, such as generalizability to new tasks and ability for users to improve upon learned tasks. Given that surface EMG is a purely neural signal, with additional practice, it has been suggested that users may be able to "strengthen" the neural signal and learn to create and reproduce unique surface EMG contraction patterns that improve prediction [30].

There are limitations of the present study that justify future work. This study evaluates the three sensing modalities for three steady-state walking tasks as well as two stair tasks that include transition strides, however additional walking tasks at varying speeds and inclines, as well as non-cyclical movements could be evaluated. Additionally, these results should be extended to people with mobility limitations such as lower-limb loss. However, similar research in the upper-limb confirms sonomyography translates from able-bodied subjects to individuals with upper-limb loss, thus we expect a similar outcome in individuals with lower-limb loss.[10]. Finally, additional work is required to further minimize the size of ultrasound sensing technology and evaluate online performance of sonomyography for continuous prediction of joint kinematics.

V. CONCLUSION

This work evaluated three sensing modalities (surface EMG, sonomyography and sensor fusion) for the continuous prediction of knee and ankle angle and angular velocity. Sonomyography significantly improved the predictive performance of the GPR models for knee angle and angular velocity in comparison to surface EMG. However, there were no significant differences between sensing modalities for ankle angle and angular velocity during most ambulation tasks. The addition of surface EMG features to sonomyography did not significantly improve kinematic prediction results for either joint. These results support the translation of sonomyography and electromyography for continuous prediction of kinematics of multi- degrees-of-freedom assistive robotics.

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