Published in final edited form as:

Proc IEEE RAS EMBS Int Conf Biomed Robot Biomechatron. 2009 January 27; 2008: 66–72. doi: 10.1109/BIOROB.2008.4762860.

Real-time Gait Mode Intent Recognition of a Powered Knee and Ankle Prosthesis for Standing and Walking

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Abstract

This paper describes a real-time gait mode intent recognition approach for the supervisory control of a powered transfemoral prosthesis. The proposed approach infers user intent by recognizing patterns in the prosthesis sensor's signals in real-time, eliminating the need for sound-side instrumentation and allowing fast mode switching. Simple time based features extracted from frames of prosthesis signals are reduced to lower dimensions. Gaussian Mixture Models are trained using an experimental database for gait mode classification. A voting scheme is applied as a post-processing step to increase the robustness of decision making. The effectiveness of the proposed method is shown via gait experiments on a treadmill with a healthy subject using an able bodied adapter.

I. Introduction

The knee and ankle joints of healthy individuals generate significant net power over a gait cycle during many locomotive functions, including walking upstairs and up slopes, running, and jumping [1-8]. However, commercial transfemoral prosthesis can either store or dissipate energy, but no net power is generated over a gait cycle. In the absence of power, transfemoral amputees during level walking expend up to 60% more metabolic energy relative to healthy subjects [9] and exert as much as three times the affected-side hip power and torque [1].

Flowers and others developed a powered knee prosthesis which consisted of an electro-hydraulically actuated knee joint that utilized a tether to connect to a hydraulic power source, off-board electronics and computation [10-16]. In order to control this knee, Grimes et al. [13] developed a gait control scheme called “echo control,” in which a modified knee trajectory from the sound leg is played back on the contralateral (i.e., prosthetic) side. Popovic and Schwirtlich describe a knee joint, actuated by DC motors, that utilizes a finite state knee controller with robust position tracking control [17]. In [18], the design of an active ankle joint using McKibben pneumatic actuators is described. The feasibility of

electromyography based position control approach for transtibial prosthesis is assessed in [19]. Though no known scientific literature exists, Ossur, a major prosthetics company, has released a commercially available powered knee and a self-adjusting ankle. The “Power Knee” uses a control approach similar to echo control, which utilizes sensors on the sound leg. The ankle prosthesis, “Proprio Foot”, does not contribute net power to the gait cycle, but rather quasi-statically adjusts the angle of the ankle.

The authors recently reported on the development of a pneumatically powered knee and ankle prosthesis, in which they employ a finite-state based impedance control approach that utilizes sensors only on the prosthesis [20]. The recent advances in monopropellant based actuation [21-24] and the high energy densities it offers relative to batteries, led to the design of the pneumatic prototype. The authors believe that the monopropellant technology in its current state is not ready for near-term commercialization. Current lithium-polymer batteries have an energy density approaching 200 Wh/kg, which is projected to double in the next decade (driven primarily by the electric vehicle market) [25]. As such, the authors have developed an electrically powered transfemoral prosthesis prototype used as a testbed in this paper, which is shown in Fig.1.

II. Human-Machine Interface Approaches

Unlike existing passive prostheses (including microprocessor-controlled devices), the introduction of powered joints into a prosthesis enables it to act, rather than simply react. As such, a suitable controller for a powered prosthesis must provide for stable and reliable interaction between the user and prosthesis. The user interface and control issue can be addressed with widely varying approaches and degrees of invasiveness. The major categories of interface, in order of increasing invasiveness, are (1) mechanical sensory interface (MSI), (2) surface electromyography (EMG) interface, (3) implantable peripheral nervous systems (PNS) interface, and (4) implantable central nervous system (CNS) interface. MSI uses only non-physiological sensors, such as measurement of forces, torques, joint angles, and vertical orientation (i.e., inclination), all of which the user of the device has influence over. Surface EMG, which is the approach used by actively powered myoelectric upper extremity prostheses, incorporates surface electrodes (often in the prosthesis socket) to extract command signals from the muscles in the residual limb. Some researchers have investigated the use of surface EMG control approaches for knee control in lower limb prostheses [26-32]. In the case of an upper extremity above-elbow myoelectric prosthesis, the combination of the biceps and triceps EMG provides a single bipolar signal, which is switched between the control of the terminal device and control of the elbow (i.e., does not enable simultaneous control of both joints). This approach would not be appropriate for an active knee and ankle joint leg, however, since locomotion requires simultaneous control of the knee and ankle. As such, a direct EMG approach would presumably require at least two control channels (i.e., measurement from two sets of antagonist muscles). Implantable PNS approaches include the use of percutaneous electrodes implanted in the nerves, and/or the use of implantable capsules for extraction of the EMG signals, from which neural or EMG commands can be extracted. Finally, implantable CNS approaches utilize electrode arrays implanted in the cortex of the brain, from which motor commands can also be extracted. Presumably, the extent of control over the prosthesis would vary roughly inversely with the extent of invasiveness.

As with any medical device or procedure, one would optimally wish to incorporate the least invasive approach that achieves the desired specific aims, and as such, the proposed controller utilizes the non-invasive mechanical sensory interface approach. The lower limb, in particular, lends itself much more readily to non-invasive interface approaches than does

the upper limb, since (1) the lower limb fundamentally interacts mechanically with the environment (i.e., the ground and the user) and (2) the tasks in which the lower limb engages are typically periodic in nature. Both of these qualities are leveraged in the proposed interface design.

Although the commercially available passive computer controlled knee systems (e.g., C-leg, Rheo knee) make use of signals only taken from the instrumented prosthesis for real-time mode detection and subsequent knee control, the previously cited works on powered knees all incorporate a variation of echo control, in which the sound-side (i.e., unaffected) leg is instrumented to provide input commands for the powered prosthesis. The obvious drawback to such an approach is that the sound-side (or unaffected) leg must be instrumented, which requires the user to don and doff additional equipment and associated wiring. The echo control approach also restricts the use of the prosthesis to unilateral amputees and also presents a problem for “odd” numbers of steps, in which an echoed step is undesirable. A more subtle, although perhaps more significant shortcoming of the echo-type approach is that suitable motion tracking requires a high output impedance of the prosthesis, which forces the amputee to react to the limb rather than interact with it. Specifically, in order for the prosthesis to dictate the joint trajectory, it must assume a high output impedance (i.e., must be stiff), thus precluding any dynamic interaction with the user and the environment, which is in turn contrary to the way in which humans interact with their native limbs.

This work offers an alternative approach to address the interface between the user and the prosthesis that is both non-invasive and obviates the need for sound-side instrumentation. Rather than garnering the user's intent from an instrumented contralateral leg, the new approach infers user commands by recognizing patterns in the prosthesis sensor's signals in real-time. The proposed method has several inherent advantages. First, no additional instrumentation or wiring apart from the prosthesis need be worn by the user. Second, the information flow is much less delayed as compared to the half cycle in the echo control approach. Third, the prosthesis is decoupled from the unaffected side, and thus the user is not constrained to “even” patterns of gait. Lastly, the proposed approach can be utilized on bilateral amputees as well.

The proposed control architecture for the powered prosthesis consists of a supervisory intent recognizer and an underlying “intra-modal” gait controller (See Fig. 2.). The underlying intramodal controller leverages a finite-state based impedance approach developed by the authors, as described in [20], to generate joint torques rather than positions leveraging the natural dynamics of the prosthesis similar to normal gait. The supervisory intent recognizer switches between intramodal gait controllers to accommodate different gait modes such as standing, walking with different speeds and slopes, sitting, and stair ascent and descent. The supervisory intent recognizer consists of three parts: gait mode intent recognizer, cadence estimator and slope estimator. The latter two estimate the slope and cadence during walking to adjust the parameters of the walking mode controller. The gait mode intent recognizer distinguishes between different gait modes such as standing, sitting, stair climbing and walking. In this work, a gait mode intent recognition framework using Gaussian Mixture Models for the supervisory control of the prosthesis between standing and walking modes is presented. Experimental results are presented that validate the proposed real-time intent recognition approach.

III. Methodology

A. Database Generation

The main components of the experimental setup consist of a tethered powered prosthesis and a treadmill. The powered prosthesis is tethered to two Kepco BOP 36-12D servo-amplifiers, and a laptop computer running MATLAB Real Time Workshop for controller implementation. The prosthesis is tested using an able bodied adapter on a healthy male subject, shown in Fig. 3, who is 1.93 m tall and weighs 86 kg.

The prosthesis is tuned for the subject using the finite-state impedance approach [20] for three different walking speeds slow, normal and fast (2.2, 2.8 and 3.4 km/h) and standing. During the standing mode the test subject randomly shifts the body weight between limbs, turns in place, and stands still.

In order to recognize standing and walking modes, a database is generated that contains the possible matched and unmatched prosthesis modes. Specifically, a matched prosthesis mode is when the activity corresponds to the current control mode (e.g., standing while the prosthesis is in standing mode), while an unmatched mode is when the activity corresponds to a different control mode (e.g., walking while the prosthesis is in standing mode). These datasets are listed in Table I. The database contains matched modes such as standing while in the standing mode controller and similarly for walking at each speed in the correct walking controller, and also cases for unmatched sets of the real and controller modes. Figure 4 illustrates the timing of mode transitions and makes clear why such unmatched datasets are required for proper intent recognition.

Using the scenarios outlined in Table I, a database was generated for the test subject with the tuned prosthesis to obtain four 50-second trials of which the middle 30 seconds were used for the database. The prosthesis sensor data was sampled at 1000 Hz consisted of seven signals: joint positions and velocities for the knee and ankle, respectively, and socket sagittal plane moment and heel and ball of foot forces. The first two trials of each scenario were used to generate the features for the design of the GMM classifier, while the other two trials were used to find the optimal voting scheme for real-time controller switching. From the first two trials of each scenario, 200 frames with random initial points for four different frame lengths, f of 50, 100, 200 and 400 samples are extracted. For each frame length, the final database included 3600 frames of walking data and 1600 frames of standing data.

B. Feature Extraction

The real-time nature of the problem requires that the features extracted from the seven prosthesis signals be computationally inexpensive, and as such, the mean and standard deviation were selected as features to extract from each frame, resulting in 14 fundamental simple time domain features. After the features are extracted, they are normalized into the range of $[-1, 1]$ to eliminate the scaling effects between different features. Balancing the information content of a frame against frame length is important since additional delay for intent recognition is introduced as the frame size grows. In order to find the optimal frame length, different frame sizes (50, 100, 200 and 400 samples) were considered.

C. Dimension Reduction

In order to decrease the time required for real-time intent recognition and training, the feature space was reduced (at the cost of information content) using Principal Component Analysis (PCA) [33] and Linear Discriminant Analysis (LDA) [34], from 14 dimensions to a feature space of 1, 2 and 3 dimensions. Both approaches employ linear transformations,

which only necessitate a matrix multiplication operation. Since orthonormal transformations tend to decrease the magnitude of the elements in the transformed matrix as compared to the initial matrix, the reduced features are normalized into the range of [-1, 1] to avoid any possible numerical instability in the GMM classification phase.

D. Gaussian Mixture Model Gait Mode Classification

The reduced dataset $X_i = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_j, \dots, \vec{x}_N\}$ with samples $x_j \in \mathbb{R}^D$ consisting of D dimensions and N_i samples for a gait mode, w_i can be represented using a multivariate Gaussian mixture with K components as

$$p(\vec{x}|w_i) = \sum_{k=1}^K \lambda_k^i p_k^i(\vec{x}) \quad (1)$$

$$p_k^i(\vec{x}) = \frac{1}{\sqrt{(2\pi)^D |\sum_k^i|}} \exp \left\{ -\frac{1}{2} (\vec{x} - \vec{\mu}_k^i)' (\sum_k^i)^{-1} (\vec{x} - \vec{\mu}_k^i) \right\} \quad (2)$$

where λ_k^i is the mixture parameter, of the i^{th} GMM for the k^{th} component satisfying the constraints $\sum_{k=1}^K \lambda_k^i = 1$ and $\lambda_k^i \geq 0$. The mixture component, $p_k^i(\vec{x})$, is a multivariate Gaussian probability density function with a $D \times 1$ mean vector, $\vec{\mu}_k^i$, and $D \times D$ full covariance matrix, $\sum_k^i$, with $D(D+1)/2$ free parameters. Each GMM can be parameterized by $K(1 + D + D(D+1)/2) - 1$ parameters, which are the mixture parameters, mean vectors and covariance matrices, notated as $w_i = \{\lambda_k^i, \vec{\mu}_k^i, \sum_k^i\}$.

The parameters of the GMM for a gait mode can be estimated in an iterative fashion using training data for a given number of mixture components, K , with the Expectation Maximization (EM) algorithm [35]. EM usually converges to local optima and its performance is affected by the initialization of the parameters. Several initialization schemes for EM are suggested in [36]. In this work, the reduced dataset for a gait mode, w_i , is roughly clustered using the k-means algorithm [37]. These clusters are used to initialize the EM algorithm for finding the mixtures. A key factor affecting the classification performance of GMM's is the number of mixture components, K . In this work, the reduced data for the standing and walking modes is modeled GMM's with K ranging from 2 to 8. Once the GMM's are created, the classification of a sample feature vector, $\vec{x}_s$, to a gait mode, w_m , is done according to the simple rule

$$w_m = \arg \max_{w_i} (p(\vec{x}_s | w_i)). \quad (3)$$

E. Model Selection

The model search space consists of 42 models, which in turn consist of 6 dimension methods (i.e., PCA 1-3 and LDA 1-3) applied to 7 GMM models ranging from order 2 to 8,

for each frame length. In order to find the best classifier for each frame length, the Area under the Receiver Operator Characteristics curve (AUC) [38] is used as the performance metric. The reason for choosing AUC is twofold. Firstly, it provides a comprehensive metric that computes true and false positives for all possible classification thresholds observed in the data. Secondly, the AUC metric is insensitive to class distribution. K-fold cross-validation (CV) [39] is employed to avoid overfitting. In K-fold CV, the data is split into 10 sets of size $N/10$. For purposes of model selection, the classifier is trained on 9 datasets and tested for the AUC on the remaining one. This is repeated ten times until all the data splits are tested and the mean AUC score is recorded as the performance metric of a specific classifier.

F. Voting Scheme for Controller Mode Switching

The gait mode intent recognizer is a component of the supervisory controller for the powered prosthesis and has two performance objectives. The first objective is to switch to another mode in the shortest time possible when a mode transition occurs, and the second objective is to avoid switching to another mode when there is no real transition. With respect to the first objective, a longer switching time will decrease the quality of gait since the user will be walking in a mismatched controller-gait mode. However, failure to meet the second objective could have more severe consequences (i.e. causing the user to stumble or fall). Therefore, to increase assurance of correct mode switching, a voting scheme is used.

In the real-time implementation, overlapping frames are classified at each 10 ms interval (Δt). In the voting scheme, the last l classifier decisions are stored in a voting vector and mode switching occurs if more than 90 percent of the classification results are in agreement. The gait mode switching logic based on the voting scheme for the standing and walking modes is demonstrated in Fig. 5. To avoid chattering during transition and increase the robustness of the powered prosthesis control, a rule was introduced to not allow the controller mode to switch for 500 ms after a mode switching occurs.

The combination of the voting length, l , and the frame length, f , determines the delay of gait mode intent recognition. To optimize the voting vector length, l , the last two trials for each scenario in the experimental database are used. In this process, the real-time gait intent recognizer is implemented offline with possible voting vector length from 2 to 100 in increments of 2. For a specific frame length, f , the smallest voting length, l_s , which does not switch to standing for the walking trials and to walking for standing trials, is selected as the optimal voting vector length.

Once the optimal voting length for each frame is found, the best frame length for the real-time gait intent mode recognition needs to be determined. It is assumed that the two trials for each scenario encompass all the possible cases and the best models for each frame length are reliable, meaning they do not result in wrong controller switching. Hence, the problem becomes to select the frame length, which yields the least amount of delay, d , in the intent recognition. This is accomplished by computing an approximate delay score, $d = f / (2 + 10l)$, for each frame length.

IV. Results and Discussions

A. PCA vs. LDA for Dimension Reduction

PCA and LDA reduced datasets for the frame length 100 are shown in Figs. 6 and 7. One might think that LDA dimension reduction will result in better classification results compared to PCA since LDA takes into account the labels of the classes. For reduction from 14 dimensions to one and two dimensions, the mean AUC scores for the GMM standing and

walking mode classification for each frame length support this assumption. Interestingly, for reduction of the dataset to three dimensions the PCA reduced GMM classification outperforms the LDA version for all the model orders. As an example, Fig. 8 shows the mean AUC scores for both PCA and LDA reduced GMM classification for the frame length 50. As stated by [40] for the case of face recognition, PCA might outperform LDA when the inherent distribution of the data is non-normal. Such is also the case for the gait mode intent recognition (with the current feature set) for the powered prosthesis for 3 dimensional dimension reduction.

B. Gaussian Mixture Model Selection

The best AUC scores are obtained from the PCA dimension reduced 3 dimensional GMM's with 6, 7, 6, 5 mixtures for the frame lengths 50, 100, 200 and 400 respectively. It is observed that the best AUC score increases with the increasing frame length. The standing and walking mixture models with the best parameter sets for each frame length are generated using the whole dataset. These datasets are used in the voting vector length selection. Surface plots of the standing and walking mixture models for frame length 100, showing the portions of the feature space with greater than 0.05 probability densities are presented in Fig. 9. As can be seen from the figure, the dynamic nature of walking can be seen in the walking mixture model which creates a three dimensional loop consisting of several ellipsoids of areas with high probability density. On the other hand, the standing mixture model resides in a smaller area of the reduced feature space.

A. Voting Vector Length Selection

The voting vector lengths for frame lengths 50, 100, 200 and 400 are 58, 38, 48, and 36, respectively. The approximate intent recognition delay for each frame length is listed in Table II. As can be observed from the table, the shortest approximate delay for the intent recognition is obtained for the frame length 100 even though the shortest voting length is obtained for the 400 samples long case. The additional delay due to frame size is the reason for this. The results show that the intent recognition will switch to a new mode after approximately 0.4-0.5 seconds.

B. Real-time Supervisory Control

The best model (three dimensional PCA dimension reduction with GMM with 7 mixtures using 100 sample-long frames) is used for real-time gait mode intent recognition. Ten level-walking trials lasting 100 seconds on a treadmill were conducted to verify that the method works in a closed feedback loop as a supervisory controller. In each trial, the treadmill was randomly started and stopped several times requiring the test subject to switch between walking and standing. During the ten trials, no wrong mode switching is observed and in all the cases the switching to the correct controller mode occurred after gait mode transition. The gait mode and treadmill velocity for one of the trials is shown in Fig. 10.

Even though the method required intensive computation for training (generating GMM's for all the combinations, CV and frame length optimization) the real-time implementation does not require extensive computation. The whole powered prosthesis control system with the gait mode intent recognizer implemented in real-time using Matlab Real-Time Workshop uses around 10 percent of the processor utilization at a Pentium 4, 2 GHz desktop computer. It should be noted that real-time implementation the algorithm will scale linearly with the addition of other gait modes such as stair ascent/descent and sitting and will allow the real-time implementation on an embedded microcomputer for the powered prosthesis with on-board electronics.

V. Conclusion

The authors propose a gait mode intent recognition framework for a powered knee and ankle prosthesis which uses only signals from the prosthesis with a non-invasive approach. PCA dimension reduction with 100 sample-long frames yielded the best results for standing and walking mode recognition using GMM as a classifier. Experiments with a healthy subject using an able-bodied adapter showed that the gait mode intent recognition framework extracts the user intent in real-time and switches to the correct underlying gait controller.

Future work includes the testing of the proposed framework with amputee subjects and the addition of new modes such as sitting, stair ascent/descent and backward walking to the gait mode intent recognition framework. The potential of different pattern recognition methods such as artificial neural networks, support vector machines and decision trees for the problem should also be investigated.

Acknowledgments

This work was supported by the National Institutes of Health grant no. R01EB005684-01. The authors also gratefully acknowledge the support of Otto Bock Healthcare Products for donation of prosthetic components.

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Fig. 1.
The power tethered prototype.

Fig. 2.
Powered knee and ankle prosthesis control architecture.

Fig. 3.
Healthy subject with the able-bodied testing adapter on the treadmill.

Fig. 4.
Demonstration of the controller and real mode discrepancy during mode transitions.

Fig. 5.
Controller mode switching logic for gait mode intent recognition

Fig. 6.
PCA dimension reduced features extracted from 100 sample-long frames.

Fig. 7.
LDA dimension reduced features extracted from 100 sample-long frames.

Fig. 8. Classification performance of different model order GMM's with PCA and LDA dimension reduction to one (a), two (b) and three (c) dimensions for frame length 50.

Fig. 9. Gaussian Mixture Models surface plots of the standing (left) and walking mode (right) showing the portions of the feature space, where probability density function is greater than 0.05, for three dimensional PCA reduced data.

Fig. 10. Real-time controller mode switching (up) and treadmill velocity (bottom) for a 100 seconds long treadmill trial.

Table I
Different Walking Scenarios for Database Generation

Scenario	#. of trials	Prosthesis Mode	Activity
1	4	Walking Fast	Walking with 3.4 km/h
2	4	Walking Fast	Walking with 2.8 km/h
3	4	Walking Normal	Walking with 3.4 km/h
4	4	Walking Normal	Walking with 2.8 km/h
5	4	Walking Normal	Walking with 2.2 km/h
6	4	Walking Slow	Walking with 2.8 km/h
7	4	Walking Slow	Walking with 2.2 km/h
8	4	Standing	Walking with 2.2 km/h
9	4	Standing	Walking with 1.6 km/h
10	4	Standing	Standing
11	4	Walking Slow	Standing
12	4	Walking Normal	Standing
13	4	Walking Fast	Standing

Table II
Approximate Intent Recognition Delay for different frame lengths

Frame Length	Frame Delay (ms)	Voting Delay (ms)	Total delay (ms)
50	25	580	605
100	50	380	430
200	100	480	580
400	200	360	560