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Mapping Thigh Motion to Knee Motion: Implications for Motion Planning of Active Prosthetic Knees

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Abstract— **One of the main challenges of the active assistive devices is how to estimate the motion of the missing/impaired limbs and joints in line with the remaining limbs. To do so, a motion planner is required. This study proposes a motion planner that can be used for active prosthetic/orthotic knees. The aim is to continuously estimate the knee joint positions based on the thigh motion, using as few inputs as possible. Data from thigh-mounted IMU (thigh acceleration and angle) are used as inputs to estimate knee joint positions as outputs. It is aimed to continuously estimate the outputs as opposed to the state-machine approaches which divide the gait cycles into different sections and require switching rules. The performance of the motion planner is investigated for five walking speeds (0.6, 0.9, 1.2, 1.4 and 1.6 m/s). The strengths and limitations of the motion planer are investigated at different scenarios.**

I. Introduction

The inter-segmental cooperation - or the synergy - existing in the lower extremities is a key factor for achieving a stable and efficient locomotion [1]. This cooperation however can be impaired or lost due to problems like aging, stroke, amputation, etc. Passive (e.g., Mauch-Knee [2]), semi-active (e.g., Ottobock's C-leg [3], Ossur's Rheo-Knee [4]) or active prosthetic knees (e.g., Ossur's Power-Knee [5]) are designed to tackle such limitations for above-knee amputees. Active devices are more attractive since potentially they can inject positive power for activities like ascending the stairs or standing up from a chair.

One of the main challenges of the active prosthetic knees is how to estimate the required motion of the missing joint in line with the remaining limbs and joints. To comply with the intention of the user, a motion planner is therefore required. A number of methods have been suggested for this purpose to estimate the joints' motions for such devices.

In echo control [6], the trajectories of the intact limb were replayed on the amputated side. This was achieved through considering the required time delay between the motions of the two sides. This method had intrinsic limitations like delay and the necessity to instrument the intact healthy side.

Finite-state machine was used in [7] to control a knee-ankle prosthesis during walking. In this approach, a single stride was divided into four distinct finite states (modes) and the actuator operation was adjusted based on switching rules. The rules were defined based on the ankle angle and torques, knee joint parameters and a load cell placed between the user and the prosthesis. The actuator performance was determined based on the impedance gains that were experimentally determined for each state. In [8], finite-state approach was used to divide the gait cycle (during walking) into five states. The transition criteria were defined based on the knee angle and angular velocity and a load sensor to measure the contact forces.

As opposed to the above-mentioned discrete algorithms, a continuous mortion planner was proposed in [9] to adjust actuator motions of an active knee-ankle prosthesis during walking on level ground and slopes. Semicircular curves were plotted using thigh angle and its integral. Next, a set of intermediate parameters was defined to compute phase angles and then based on the virtual kinematic constraints and discrete Fourier transform, desired joint trajectories were calculated. The results showed that the amputees had control over the timing of the prosthetic joints' motions which were based on the motion of the residual thigh.

The concept of the principal component analysis (PCA) was used in [10] to determine the most important input parameters for an active prosthetic knee. The gait modes (standing and walking at 0.61, 0.78 and 0.94 m/s) were then recognized using Gaussian mixture model (GMM). The input signals (into the motion planner) were composed of knee and ankle positions and velocities, socket sagittal plane moment and heel and ball of foot forces [10]. Such an algorithm was also used in [11] for designing a motion planner. GMM was also used in [12] to regulate the motion of a lower body exoskeleton using electroencephalography (EEG) signals. PCA was also used with complementary limb motion estimation (CLME) in [13] to identify possible couplings between limbs in healthy side. Then, it was used to estimate the corresponding motion of the patient's affected limbs. Different from echo-control [6], where the reference trajectory was a delayed replay of the sound leg's motion, in this approach, states were mapped instantaneously.

Ground reaction forces (GRF) together with electromyography (EMG) signals were used in [14] to classify the gait mode of trans-femoral amputees wearing passive prosthetics. Model predictive control was used in [15] to control the joint motions (knee and hip) of an exoskeleton. The controller needed gait characteristics such as walking speed, step length and swing duration to regulate the joint motions in swing phase. In addition to the above-mentioned algorithms, other methods were also used to process or classify the sensory inputs such as linear discriminant analysis (LDA) [16], [17], neural networks [16] or k-nearest neighbor (k-NN) [18].

This study proposes a motion planner that estimates knee joint positions based on the motion of the thigh. The method

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can be used to continuously estimate the knee joint positions in order to control active prosthetic knees. The interest is to use minimum input information and as opposed to the state-machine approaches, avoid using switching rules. To do this, thigh acceleration and thigh angle are used as inputs to the motion planner. Then, the corresponding knee joint positions are estimated as outputs. The procedure is explained in detail in the next section.

II. METHOD

In Fig. 1, an overall control structure for active prosthetic knees is shown. Part A is the motion planner which takes input data from thigh and estimates the corresponding knee joint positions. The motor controller (part B, e.g., a PD controller or impedance controller) then can create the error signal based on the estimated knee joint angle and the actual one obtained via other sensors to finally actuate the device. In this study, the concentration is on part A.

The inputs to the motion planner are the thigh acceleration A_{th} and the thigh angle θ_{th} (Fig. 1). The input data are obtained by an IMU (MTw Awinda IMUs, Xsens Technologies B.V., Enschede, Netherlands) attached to the thigh of a male subject measured in laboratory environment while walking on a treadmill (walking at 0.6, 0.9, 1.2, 1.4 and 1.6 m/s).

In human biomechanics, conventionally a gait cycle starts with the heel contact and ends with the next heel contact of the same foot. A gait cycle is divided into one hundred sections called gait percent [19]. For each speed and gait percent a corresponding thigh acceleration and angle and knee joint positions exists (see Fig. 3).

The proposed motion planner estimates knee joint positions (as outputs) according to each estimated speed and gait percent. The speed and gait percent are estimated based on the thigh acceleration and angle (inputs) as observed in Fig. 1.

To calculate the knee joint positions during the experiment, another IMU was attached to the shank of the subject to measure the shank angles θ_{sh}. This IMU is not required for the estimation task, but was required in order to obtain

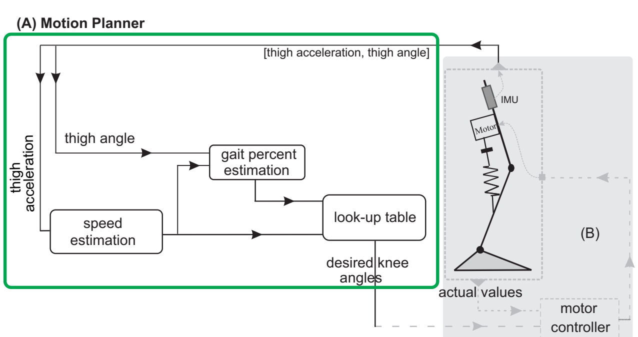

Fig. 1. A general overall control structure for an active prosthetic knee. The thigh accelerations and angles (inputs) are used by the motion planner (part A) to estimate the knee joint positions (outputs). Within the motor controller (part B), sensory data (e.g., motor position and/or velocity or actual knee angles) can be used to create the required command signal for the actuator (motor). This study concentrates on part A.

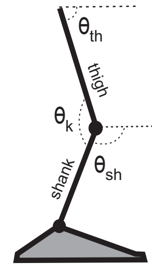

Fig. 2. Definitions of the angles.

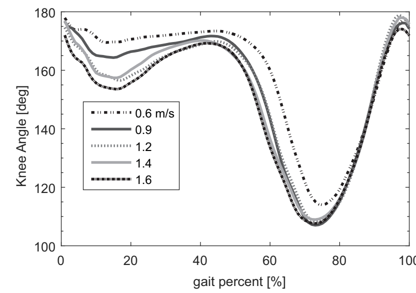

Fig. 3. Knee angles for 0.6, 0.9, 1.2, 1.4 and 1.6 m/s walking (each diagram is the mean of ten gait cycles).

the corresponding knee joint positions θ_k during walking experiments ($\theta_k = 180-(\theta_{sh}-\theta_{th})$, Fig. 2). These calculated knee joint positions, are then compared with the estimated knee joint angles (by the motion planner), to verify the estimation quality.

To estimate knee joint positions, the proposed motion planner estimates the speed and the gait percent (Fig. 1). These steps are explained in detail in the next subsections.

A. Speed Estimation

To estimate the walking speed, the concept of support vector machine (SVM) [20] has been used. SVM is a supervised machine learning approach which uses a set of training inputs for the learning process. The performance of the SVM is then tested by unseen test inputs. The fundamental of SVM is explained briefly here for a binary classification problem in the following paragraphs. The procedure can be generalized for multi-class classification or regression applications [20], [21]. The thigh accelerations are used for speed estimation (Fig. 1). For each speed, the inputs (i.e., thigh accelerations) of two gait cycles were used for the training process. Next, for testing procedure, the data of another ten gait cycles were used. The intra-subject testing was used in different studies, e.g., [22]. The outputs of the SV machine are those five walking speeds. The concept of SVM can be used both for discrete classification or continuous regression [21].

B. Gait Percent Identification

To obtain the gait percent, thigh angle is integrated. In Fig. 4, the integral of the thigh angle is shown with respect to gait percent. As observed, the relationship between the integral of the thigh angle and the gait percent is quasi-linear. Such a relationship was observed for different speeds.

Therefore, as an approximation, the integral value at each time can be used for the estimation of the gait percent. Next, the graphs were fit linearly to the identity function to obtain the fitting coefficients for each speed. For gait percent estimation, the curve of the mean thigh angle (of two gait cycles) was used for each speed. It should be noted that at this stage, no training is involved. Training is done for speed estimation (subsection II-A). Therefore, one can obtain the fitting coefficients regardless of the speed estimation subsection.

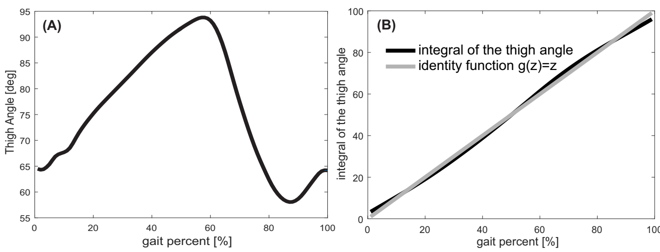

Fig. 4. The thigh angle (A) and its integral (B, using fitting coefficients) with respect to the gait cycle. The relationship between the thigh integral and the gait percent (B) is approx. quasi-linear and resembles the identity function ($g(z) = z$).

C. Estimation of the Corresponding Knee Joint Positions

Having estimated the speed and gait percent, the expected desired knee angles can be obtained using a look-up table (see Fig. 1 and Fig. 3). For real world applications, the look-up table can be saved offline and used in online applications (similar to study conducted in [23]). Furthermore, the knee angles can also be converted to motor (actuator) positions based on the geometry and type of the actuator of a prosthetic knee. See [24]–[28] for fully detailed discussions on how to calculate the expected desired motor positions offline based on the above-mentioned parameters.

To evaluate the estimation quality of the motion planner, the estimated knee angles are compared with the previously measured (calculated) knee angles. To do so, different scenarios are planned which will be explained later. To evaluate the estimation quality, the root mean square (RMS) errors, maximum (absolute) errors, mean absolute deviations (MAD) and the R^2 values are compared between those scenarios. These criteria were also employed in different studies, e.g., [22], [29].

Due to highly dynamic behavior of human locomotion, it is challenging to define which estimation quality should be deemed acceptable and which one as not acceptable. However, to be able to evaluate the performance of the motion planner, the criterion that was used in [29] to determine estimation acceptance, is also used in this study. In that study, R^2 values higher than 0.8 were a sign of acceptable estimations (ideal is 1). That criterion will also be used in this study in the following scenarios.

All-speeds-training: the motion planner was trained with thigh acceleration from two gait cycles from all of those speeds. Next, its estimation performance was tested by the input data from another ten gait cycles from those five speeds.

Leave-one-out: the leave-one-out cross validation [14], [16], [30], [31] was implemented. The motion planner was trained with the inputs of two gait cycles from four speeds. Then, it was tested to estimate the knee joint positions of ten gait cycles of the fifth speed. This was done for each of the speeds under investigation.

Interpolation: the motion planner was trained with the inputs of two gait cycles from 0.6 and 1.6 m/s. The goal was to evaluate the estimation performance of the motion planner in case of interpolation. Therefore, next, motion planner was tested to estimate the knee joint positions for ten gait cycles of 0.9, 1.2 and 1.4 m/s.

Extrapolation: the motion planner was trained with the inputs of two gait cycles from 0.6 and 0.9 m/s. The goal was to evaluate the estimation performance of the motion planner in case of extrapolation. Next, the motion planner was tested to estimate the knee joint positions for ten gait cycles from 1.2, 1.4 and 1.6 m/s. The results are explained in the next section.

III. Results

The performance of the motion planner under the respective testing scenarios is shown in Fig. 5, in which, the results for root mean square (RMS) errors, mean absolute deviations (MADs), maximum absolute errors and R^2 values are compared.

The estimation quality is quite similar between All-speeds-training and Leave-one-out scenarios. The only difference is related to 0.6 m/s. Furthermore, the Interpolation scenario (training with 0.6 and 1.6 m/s and testing with 0.9, 1.2, 1.4 m/s), have similar results in comparison to All-speeds-training and Leave-one-out scenarios. The R^2 values related to these scenarios are above the 0.8 threshold.

The worst results are related to Extrapolation scenario, in which, the root mean square errors, mean absolute deviations, maximum absolute errors and R^2 values have the lowest quality. Furthermore, at 1.4 m/s the R^2 value is below the 0.8 threshold.

In general, the results of MADs are comparable to the results reported in [32], and the RMS errors are similar to the outcomes seen in [33], while less input information was used in this study.

IV. Discussions, Conclusions & Suggestions

In this work, a motion planner was proposed which estimated the knee joint positions based on the thigh acceleration and thigh angles. It was not required to divide the gait cycle into four or five sections and define switching rules to transit between the states (which is done in state-machine approaches). On the contrary, the estimation of the knee joint positions was done continuously. Thigh acceleration was used to estimate walking speeds (0.6 - 1.6 m/s) and the integration of the thigh angle was used for approximation of the gait percent. The proposed method can potentially be used to design high-level controllers for active prosthetic

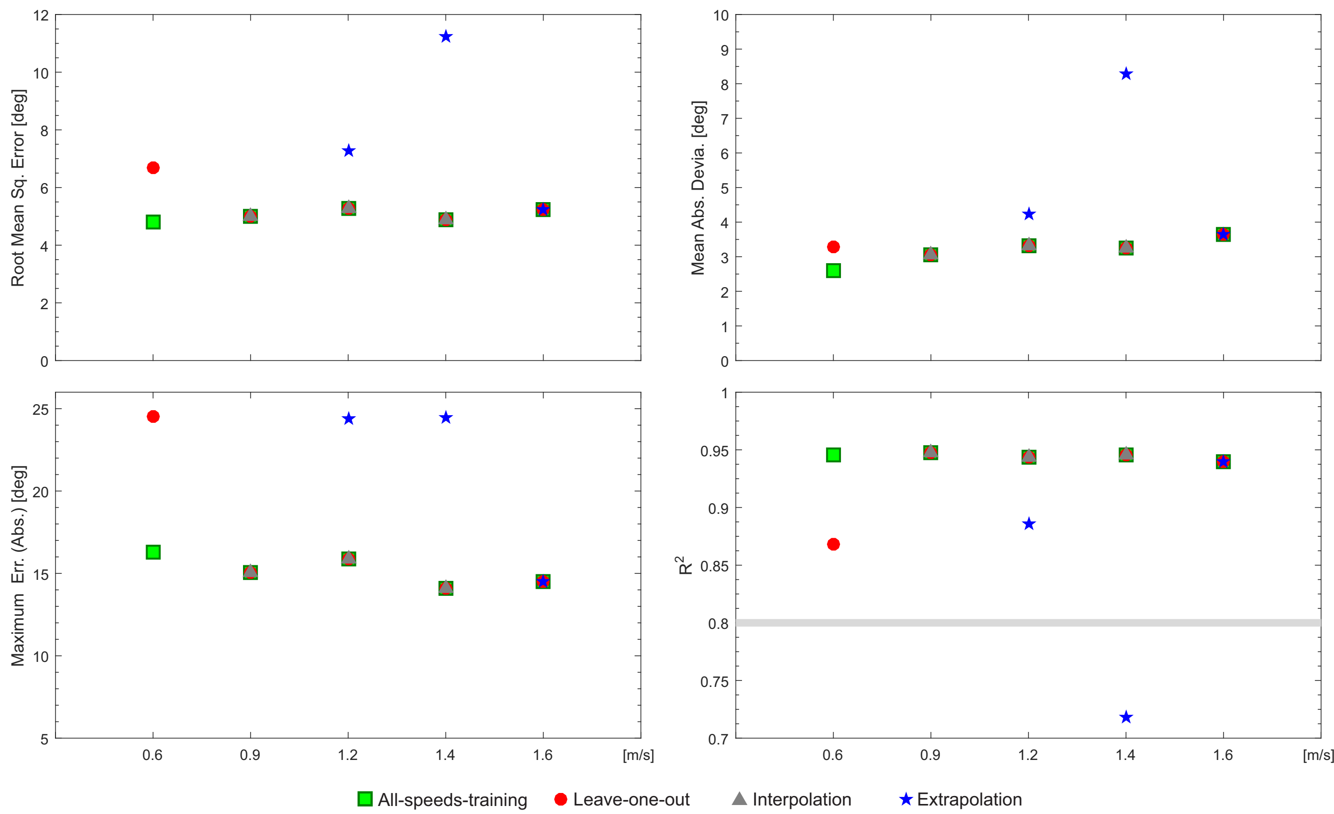

Fig. 5. The comparison of the results for root mean square errors, mean absolute deviations, maximum absolute errors and R^2 values for the scenarios explained in Method section. The results are related to the mean of ten gait cycles.

knees whose actuation mechanisms use a stiff spring [34] or no spring [35]. In these cases, the trajectories of motor positions would be similar to the knee joint positions.

The best performance was seen at All-speeds-training, Leave-one-out and Interpolation scenarios. However, the results observed in Interpolation scenario were more interesting, since it received less training. As observed in Fig. 5, the performance of Interpolation scenario was very slightly lower than All-speeds-training scenario. This showed that the motion planner was robust enough to meaningfully estimate the knee position, although with less training. This can lead to less efforts in training procedure.

At the same time, looking at results for Extrapolation scenario, it is understood that the method of training can play a key role in the success of the motion planner. In both Interpolation and Extrapolation scenarios, two speeds were used for training, but as observed it makes a key difference which speeds are selected in this regard. The results suggest that an efficient strategy maybe to first train the motion planner with boundary conditions, and then test it with within-limits data to evaluate its performance. This can be valuable in case a huge amount of data is available for training.

The performance of the motion planner was dependent on the identification of the speed and gait percent simultaneously. The thigh angle was used to estimate the gait percent. Although integration of the thigh angle might have no physical meaning, it was shown that it could be used as a gait percent estimator. According to Fig. 4B, even if the speed estimations were perfect, due to gait percent approximations, some knee position errors will occur.

The proposed motion planner was tested for walking gait. Since human beings walk through different terrains, next steps in future works will be to evaluate the performance of the planner for ascending/descending the stairs and slopes. In addition, since the integration of the thigh angles accumulates through the time, in real world application it needs to be reset at the beginning of the gait cycles. To do so, a heel-strike sensor might do the work.

In this study a look-up table was used for estimation. In

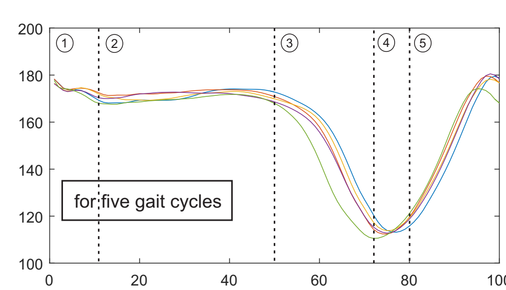

Fig. 6. Comparison of the measured knee joint positions between five gait cycles, curves for 0.6 m/s. For dashed lines, see discussions related to Figs. 7 and 8.

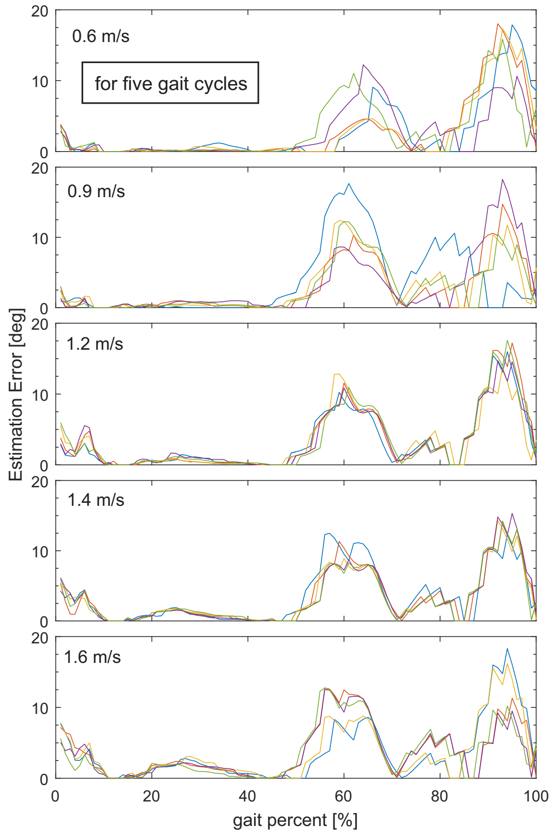

Fig. 7. Estimation errors for knee joint positions, related to All-speeds-training scenario (five gait cycles at 0.6, 0.9, 1.2, 1.4 and 1.6 m/s).

[23], a look-up table was used to control an active foot prosthesis. While for healthy able-bodied individuals this might be of little problem (since the data can be obtained through real world measurements), for amputees more considerations should be taken into account. In the latter, the desired values for knee joint positions are missing and no such data exist in the real world. In these cases, usually the look-up table will be based on the average data from healthy subjects. Next, the look-up values can be modified when necessary through multiple trial and error experiments to find out acceptable knee trajectories for a specific amputee. In this regard, the proposed algorithm in this study needs more investigations to reduce the time required for such a process.

Another limiting issue is the natural variations existing in human locomotion. The knee trajectories vary even at a specific speed and for a specific person. Fig. 6 illustrates the knee trajectories for five gait cycles of the subject walking at 0.6 m/s. This physiological variation makes it even more challenging for a motion planner to estimate the knee joint positions with a perfect precision.

To find out at which sections of the gait cycles, errors occurred more, the knee position estimation errors are shown in Fig. 7 (related to All-speeds-training scenario). As observed, nearly for all of the speeds, errors are visible at the beginning, then they decrease somewhere between 10-50%, and then they rise again from approximately 50%, with a

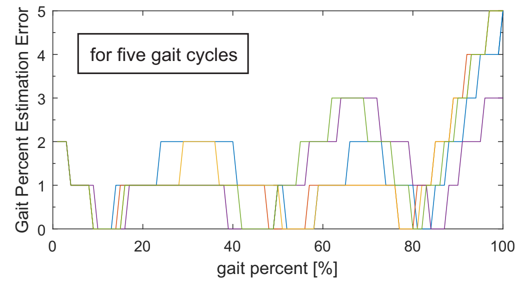

Fig. 8. Gait percent estimation errors (related to All-speeds-training scenario, five gait cycles at 0.6 m/s).

reduction somewhere between 70-85% and again an increase (the numbers are not exact due to the obvious variations). This trend is more or less similar between different speeds and gait cycles.

In order to investigate more, the gait percent estimation errors are also shown in Fig. 8 (All-speeds-training scenario, 0.6 m/s). As observed, the estimations errors are more or less seen throughout the gait cycles. But looking at Fig. 7, it is seen that at some sections of the gait cycles, the errors are higher.

One possible reason is that not only the gait percent estimation errors are important, but also, where they occur. In other words, although gait percent estimation errors are seen throughout the gait cycles (Fig. 8), according to Fig. 6, the slope of the knee trajectories influences the impact of the gait percent error.

Therefore, due to the slope of the knee trajectories, a gait percent estimation error which occurs, e.g., during 50-70% of the gait cycle (third section in Fig. 6), could result in higher knee position estimation errors (Fig. 7), in comparison to a similar gait percent error which occurs, e.g., during 10-50% of the gait cycle (second section in Fig. 6). That can be also one reason why at the beginning of the gait cycles (approx. 1-10%), the errors are higher than the 10-50% interval (check Fig. 7 and Fig. 6).

To evaluate the estimation quality, different measures were used as discussed and R^2 values higher than 0.8 were used to define the acceptance [29]. However, there are some studies with lower experimental R^2 values than the above-mentioned threshold, [36], but the experiments were apparently conducted with satisfactory user performance. Furthermore, looking at different studies, it is seen that variations between the planned trajectories and the obtained trajectories are visible e.g., [9], [37], but apparently the experiments were done with user satisfaction or at least no severe impact on the user was observed during those experiments. This matter makes it even more challenging to determine how exactly joint motions should be estimated. Therefore, a comprehensive criterion that can provide a better evaluation tool to evaluate the estimation quality seems to be required. This might necessitate taking different parameters into attention, for instance kinematics, kinetics and muscular activities (EMG signals). However, it may be challenging to develop a success criterion while taking into account those different variables.

As seen, designing a fully comprehensive motion planner that can be used for several situations, requires attention to multiple different issues. Moreover, to have more robust conclusions about the performance of the motion planner, it will be important to test the planner in clinical experiments for different subjects. This creates the path for the future works.

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REFERENCES

[1] N. A. Borghese, L. Bianchi, and F. Lacquaniti, "Kinematic determinants of human locomotion." *The Journal of physiology*, vol. 494, no. 3, pp. 863–879, 1996.

[2] [Online]. Available: https://www.ossur.com/prostheticsolutions/products/all-products/knees-and-legs/mauch-knee

[3] [Online]. Available: http://www.ottobockus.com/C-Leg.html

[4] [Online]. Available: https://www.ossur.com/prostheticsolutions/products /dynamic-solutions/rheo-knee-3

[5] [Online]. Available: https://www.ossur.com/prostheticsolutions/products /dynamic-solutions/power-knee

[6] D. L. Grimes, "An active multi-mode above knee prosthesis controller," Ph.D. dissertation, Massachusetts Institute of Technology, 1979.

[7] F. Sup, A. Bohara, and M. Goldfarb, "Design and control of a powered transfemoral prosthesis," *The International journal of robotics research*, vol. 27, no. 2, pp. 263–273, 2008.

[8] E. J. Rouse, L. M. Mooney, and H. M. Herr, "Clutchable series-elastic actuator: Implications for prosthetic knee design," *The International Journal of Robotics Research*, vol. 33, no. 13, pp. 1611–1625, 2014.

[9] D. Quintero, D. J. Villarreal, D. J. Lambert, S. Kapp, and R. D. Gregg, "Continuous-phase control of a powered knee–ankle prosthesis: Amputee experiments across speeds and inclines," *IEEE Transactions on Robotics*, 2018.

[10] H. Varol, F. Sup, and M. Goldfarb, "Real-time gait mode intent recognition of a powered knee and ankle prosthesis for standing and walking," in *IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics BioRob*. IEEE, 2009, pp. 66–72.

[11] H. Varol, F. Sup, and M. Goldfarb, "Multiclass real-time intent recognition of a powered lower limb prosthesis," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 3, pp. 542–551, 2010.

[12] A. Kilicarslan, S. Prasad, R. G. Grossman, and J. L. Contreras-Vidal, "High accuracy decoding of user intentions using eeg to control a lower-body exoskeleton," in *Engineering in medicine and biology society (EMBC), 2013 35th annual international conference of the IEEE*. IEEE, 2013, pp. 5606–5609.

[13] H. Vallery, E. H. Van Asseldonk, M. Buss, and H. Van Der Kooij, "Reference trajectory generation for rehabilitation robots: complementary limb motion estimation," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 17, no. 1, pp. 23–30, 2009.

[14] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, and K. B. Englehart, "Continuous locomotion-mode identification for prosthetic legs based on neuromuscular–mechanical fusion," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 10, pp. 286–2875, 2011.

[15] L. Wang, E. H. van Asseldonk, and H. van der Kooij, "Model predictive control-based gait pattern generation for wearable exoskeletons," in *IEEE International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2011, pp. 1–6.

[16] H. Huang, T. Kuiken, and R. Lipschutz, "A strategy for identifying locomotion modes using surface electromyography," *IEEE Transactions on Biomedical Engineering*, vol. 56, pp. 65–73, 2009.

[17] A. J. Young, A. M. Simon, N. P. Fey, and L. J. Hargrove, "Classifying the intent of novel users during human locomotion using powered lower limb prostheses," in *International IEEE EMBS conference on Neural engineering (NER)*. IEEE, 2013, pp. 311–314.

[18] H. Varol and M. Goldfarb, "Real-time intent recognition for a powered knee and ankle transfemoral prosthesis," in *International Conference on Rehabilitation Robotics ICORR*, 2007, pp. 16–23.

[19] M. W. Whittle, *Gait analysis: an introduction*. Butterworth-Heinemann, 2003, ISBN: 0-7506-5262-4.

[20] C. Cortes and V. Vapnik, "Support-vector networks," in *Machine Learning*, 1995, pp. 273–297.

[21] C.-C. Chang and C.-J. Lin, "Libsvm: A library for support vector machines," *ACM transactions on intelligent systems and technology (TIST)*, vol. 2, no. 3, pp. 1–27, 2011.

[22] J. Goulermas, D. Howard, C. Nester, R. Jones, and L. Ren, "Regression techniques for the prediction of lower limb kinematics," *Journal of biomechanical engineering*, vol. 127, no. 6, pp. 1020–1024, 2005.

[23] M. Holgate, T. Sugar, and A. Bohler, "A novel control algorithm for wearable robotics using phase plane invariants," in *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2009, pp. 3845–3850.

[24] K. W. Hollander, R. Ilg, T. Sugar, and D. Herring, "An efficient robotic tendon for gait assistance," *ASME Jour. of. Biomech. Eng.*, vol. 128, pp. 788–791, 2006.

[25] M. Grimmer, M. Eslamy, S. Gliech, and A. Seyfarth, "A comparison of parallel- and series elastic elements in an actuator for mimicking human ankle joint in walking and running," in *IEEE Int'l Conf. Robo. Auto.*, 2012, pp. 2463–2470.

[26] M. Eslamy, M. Grimmer, and A. Seyfarth, "Effects of unidirectional parallel springs on required peak power and energy in powered prosthetic ankles: Comparison between different active actuation concepts," *IEEE Int'l Conf. on Robo. Biomim.*, pp. 2406–2412, 2012.

[27] M. Eslamy, M. Grimmer, S. Rinderknecht, and A. Seyfarth, "Does it pay to have a damper in a powered ankle prosthesis? a power-energy perspective," *IEEE Int'l Conf. on Rehab. Robo.*, pp. 1–8, 2013.

[28] P. Scholl, V. Grabosch, M. Eslamy, and A. Seyfarth, "Comparison of peak power and energy requirements in different actuation concepts for active knee prosthesis," in *IEEE International Conference on Mechatronics and Automation*. IEEE, 2015, pp. 1448–1453.

[29] R. A. Bogey and L. A. Barnes, "An emg-to-force processing approach for estimating in vivo hip muscle forces in normal human walking," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 8, pp. 1172–1179, 2017.

[30] A. J. Young, A. M. Simon, N. P. Fey, and L. J. Hargrove, "Intent recognition in a powered lower limb prosthesis using time history information," *Annals of biomedical engineering*, vol. 42, no. 3, pp. 631–641, 2014.

[31] A. J. Young, A. M. Simon, and L. J. Hargrove, "A training method for locomotion mode prediction using powered lower limb prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 3, pp. 671–677, 2013.

[32] A. Findlow, J. Goulermas, C. Nester, D. Howard, and L. Kenney, "Predicting lower limb joint kinematics using wearable motion sensors," *Gait & posture*, vol. 28, no. 1, pp. 120–126, 2008.

[33] R. Takeda, S. Tadano, A. Natorigawa, M. Todoh, and S. Yoshinari, "Gait posture estimation using wearable acceleration and gyro sensors," *Journal of biomechanics*, vol. 42, no. 15, pp. 2486–2494, 2009.

[34] M. Grimmer and A. Seyfarth, "Stiffness adjustment of a series elastic actuator in a knee prosthesis for walking and running: The trade-off between energy and peak power optimization," in *Intelligent Robots and Systems, 2011. IROS'11. IEEE International Conference on*, 2011.

[35] F. Sup, H. A. Varol, J. Mitchell, T. Withrow, and M. Goldfarb, "Design and control of an active electrical knee and ankle prosthesis," in *IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2008, pp. 523–528.

[36] N. Dhir, H. Dallali, E. M. Ficanha, G. A. Ribeiro, and M. Rastgaar, "Locomotion envelopes for adaptive control of powered ankle prostheses," in *IEEE International Conference on Robotics and Automation (ICRA)*, 2018, pp. 1488–1495.

[37] A. H. Shultz, J. E. Mitchell, D. Truex, B. E. Lawson, E. Ledoux, and M. Goldfarb, "A walking controller for a powered ankle prosthesis," in *IEEE Engineering in Medicine and Biology Society Conference*. IEEE, 2014, pp. 6203–6206.