Application of Model Predictive Impedance Control (MPIC) in analysis of human walking on rough terrains

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Abstract. By using Model Predictive Impedance Control (MPIC), two essential questions about human walking control have been considered in this paper: Which parameters are controlled by the control system and what strategies are applied? As a general method, MPIC was proposed as a possible model for controlling human movements in the previous paper of one of the authors [1] and it was also applied to periodic movements such as walking [2]. According to the acceptable results of primary experiences, a more realistic walking model is presented in this paper to be controlled by MPIC strategy. A 3-dimensional 5-link simulated walking robot with 8 degrees of freedom in sagittal and lateral planes is employed to be analyzed while being controlled on an irregular condition, like ascending and descending stairs. The objective of the controller is to optimize the energy consumption, vertical orientation of the body, and forward speed of its center of mass. Visual feedback effect is applied when the robot targets specific footprints over the walking terrain. Each optimization sequence has been applied during the prediction horizon with one human step duration. The results have been animated for comparison with natural walking of a human in similar conditions.

Keywords: Model predictive impedance control, biped walking model, rough terrains

1. Introduction

Among the different kinds of human movements, bipedal walking has absorbed a great attention due to its different nature. More than 200 degrees of freedom, unstable nature, and periodicity are the main features of walking. Generally, keeping the balance for upward standing and walking control are two different aspects of human locomotion, which have to be considered in any control strategy which is proposed to model this control system. “Rhythmicity” makes locomotion appear to be a stereotyped action involving repetitions of the same movements. Indeed, as we will see, this repetitive quality allows locomotion to be controlled automatically at relatively low levels of the nervous system without intervention by higher centers. Nevertheless, locomotion usually takes place in unpredictable environments. Therefore, locomotor’s movements must be continually modified to adapt the new situation. In 1995 Smith, showed the role of cerebellum as a higher level, in adjusting walking control variables in different conditions [3]. In 1996 Drew and Jiang [4] studied the role of the motor cortex in visually triggered gait modifications, and recently, in [5], Mori proposed a conceptual scheme for
walking control and described the role of higher nervous system in anticipation, control of posture, and pattern generation, during bipedal walking.

Unlike the robotic systems that a task-oriented control strategy is applied to control the robot manipulator, in human motor control studies, it is more interesting to find a general model for different human motor control tasks. Based on Stark’s impedance model for musculoskeletal systems, and MPC control scheme, and according to the role of both higher level and local feedbacks, Model Predictive Impedance Control as a general method was developed by Towhidkhah et al. [1] to model the control system of human different movements. They showed the advantages of this method in modeling of different movements, including an elbow joint tracking of a periodic or a non-periodic trajectory and also a simple 2 DOF walking model in [2].

To make a more detailed study of the application of this method in human walking control, a 3 dimensional biped model with 8 degrees of freedom in sagittal, lateral and frontal planes is proposed to be controlled by the MPIC. Utilizing the reduced order dynamic equations to predict the limb angles and angular velocities of the bipedal model is described in Section 2. In Section 3, an appropriate performance index is proposed to be used in MPIC algorithm and in Section 4, two different optimization algorithms are developed to optimize the control variables over the pre-specified horizons. In Section 5, the results of simulation of this control system are depicted, and finally in Section 6, the previous sections are concluded.

2. Model predictive impedance control

MPIC control strategy as a model of human’s neural control system, is a result of using model predictive control method in impedance control strategy. As an earlier version of this strategy, tuning of joint stiffness was widely studied as to increase the resistance of the system against external disturbances in control of posture and movement. Due to the Feldman’s $\lambda$ model for joint movement, and Equilibrium Point Hypothesis (EPH), stiffness is defined as the torque which is needed to cause a unit of angle deviation to a joint from the slack angle (equilibrium point). In 1986, Hasan [6] suggested an optimal method for the regulation of stiffness in disturbed conditions. Although “Stiffness” was sufficient to analyze slow and quasi-static movements, to improve this method for fast movements, joint impedance was proposed by Hogan, Feldman and others by adding a dynamic term to stiffness concept, which is called joint viscosity. Viscosity is the torque which is needed to cause the unit deviation to the angular velocity of the joint from the slack velocity (second term of the equilibrium point, according to generalized EPH). By using impedance control theory, the role of the higher center in human movement control is modeled. Combining this to the earlier studies on the higher level control, such as internal models of the cerebellum, for relatively long-term predictions, results MPIC. In [1] Towhidkhah et al. utilized this scheme to model the role of the cerebellum in the control of an arm movement, they also suggested the same method for cyclic movements like bipedal walking. For this reason, a 2-DOF model was used to walk on a level terrain while disturbance exists. In this method, a linearized model was used to predict the states of the bipedal model. To perform a more detailed study some modifications has to be done on the previous model.

2.1. Generalizing the model for better imitation of human walking cinematic

Perry [7] has demonstrated in his book, Gait Analysis, different records of human walking kinematic; the aim of using a more complex biped model in this paper is to imitate these different movements, acted
by body limbs during walking. Different phases of a normal walking and the body’s movement in all 3 dimensions are qualitatively described by Perry. Because of the dynamic complexity of human walking, performing some simplifications on the model is inevitable. According to minimal compromising between the model and the human movements, these simplifications could be as follows:

1. The number of degrees of freedom is reduced in the model, compared to the human body, this model is supposed to have 8 degrees of freedom in 3 dimensions.
2. Masses are supposed to be lumped in the centers of mass for each modeled limb, and the whole trunk is modeled as one limb with the same mass.
3. The locomotion is modeled only in single support phase and to model the impact effect in leg switching, the swinging and stance leg states\(^1\) are substituted when they are changed. Such an impact model is used by Rostami in [8].

This model is depicted in Fig. 1, shank and thigh are jointed by a revolute joint and to model the hip joint, a 2 DOF universal joint is used. Another universal joint is used to model the ground contact of the standing foot.

2.2. Prediction model

In 2000, Jaffari et al. [9] used DMC\(^2\) algorithm to control a simple 2 DOF bipedal model. In this method a time series of the plant output to a unit step input is used to predict its output to different inputs. According to this method unit step response coefficients are implicitly implemented as a linearized model. However, a linearization to an 8 degree of freedom model, around its unstable equilibrium point, causes a large error between the predicted and the actual output of the plant. Therefore a nonlinear dynamic model is utilized in this paper to avoid the discussed error. This model is a reduced order dynamic model according to the model which has been proposed by Hemami [10] in 1976 (see Fig. 2). The aims of this order reduction are:

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1. Angular velocities.
2. Dynamic Matrix Control.
1. The fact that the main focus of higher level controller is forward movement and lateral movements of the body is only limited in amplitude for prevention of falling from sides. This movement is mainly non-controlled and naturally converges to a stable limit cycle in human walking.

2. This essential error between the plant and the predictive model proves the robustness of the controller when the model and therefore the predictions are inaccurate.

In Hemami’s 5-link 2-dimensional model, called BLR-G1 machine, all 5 links were modeled as rigid links, with lumped masses located in their relevant centers of mass. The dynamic equations of this model were derived by using Lagrange’s equation of motion.

The dynamic equations of motion for this model are given in Eq. (1):

\[ A(\theta)\ddot{\theta} + B(\theta)h(\dot{\theta}) + Cg(\theta) = DT \] (1)

Where:

\[ \theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5]^T \]
\[ h(\dot{\theta}) = [\dot{\theta}_1^2, \dot{\theta}_2^2, \dot{\theta}_3^2, \dot{\theta}_4^2, \dot{\theta}_5^2]^T \]
\[ g(\theta) = [\sin \theta_1 \sin \theta_2 \sin \theta_3 \sin \theta_4 \sin \theta_5]^T \]
\[ T = [T_1, T_2, T_3, T_4, T_5]^T \]

\( T_i \) is the torque at the \( i \)-th joint, and \( \theta_i, \dot{\theta}_i \) and \( \ddot{\theta}_i \) are the position, velocity and acceleration of link \( i \). And the coefficient matrices are:

\[ A(\theta) = \{q_{ij} \cos(\theta_i - \theta_j)\} \]
\[ B(\theta) = \{q_{ij} \sin(\theta_i - \theta_j)\} \]
\[ C = \text{diag}(-c_i) \]
The parameters, $q_{ij}$ and $c_i$ are constants derived by using Lagrange’s equation of motion.

2.3. MPIC algorithm for bipedal walking model

According to Feldman’s EPH and Winters’ impedance model of the joints, the neural control system, controls 4 variables for each joint, containing slack angle and slack velocity which are the states of the joints in the equilibrium point, and 2 coefficient variables, joint stiffness, and joint viscosity. In Fig. 3 the impedance model of the joint has been shown.

In the impedance model scheme, $\beta$ and $\dot{\beta}$ are slack angle and slack velocity, relatively, and $\sigma$ and $b$ are joint stiffness and viscosity. Due to MPIC scheme, shown in Fig. 4, these 4 parameters are adjusted by the MPC as the CNS model. Through this technique, an appropriate optimization method is utilized to find the optimal value of each variable, over the limited prediction horizon. Finding an appropriate and meaningful criterion function for optimization and also suitable values for prediction and control horizons is one other important issue in controller design.

In spite of great improvement in prediction of plant output by using an appropriate nonlinear model, it is engaged by time consuming recursive optimization methods. Towhidkhah et al. [1] described the fact that more nonlinearity of a prediction model causes more time consuming optimization process. It has been shown that when a function to be optimized is highly nonlinear, random search methods are utilized, where mild nonlinearity or in the other word, less variance makes the gradient based methods more suitable. Both two methods are prescribed in this paper to optimize the variables.

3. Walking criterions

In 1991 Kajata and Tani [5] defined some constraints and performance criterions to optimize the walking pattern of a biped robot on rugged terrains. Therefore a cumulative performance index was used to perform the optimization process for the best walking kinematic on an uneven plane. In 2001,

According to the optimization based nature of the MPC method, an appropriate criterion function can be used to find the optimal control variables for an optimal walking, when the exact cinematic of the walking is not specified. Therefore a well defined criterion function, which can express the quality of walking in different conditions is goal directed. The most important quality factors of walking are expressed by a positive definite function, which has to be minimized. These quality factors are reviewed below:

3.1. Walking speed

Walking forward speed is a constant value, tuned by the higher level of brain. To maintain this constancy, the term W.S. of the performance index is defined as the squared error between the forward speed of the body’s center of mass, and the desired speed.

\[
W.S = \Delta v \cdot Q \cdot \Delta v^T
\]  

While:

\[
\Delta v = \begin{bmatrix} v(t+1) - v_d & v(t+2) - v_d & \cdots & v(t+P) - v_d \end{bmatrix}
\]

\(Q\) is the weighting coefficient matrix and \(P\) is the prediction horizon.
3.2. Body orientation

Vertical orientation of the trunk is one other quality factor of a normal walking. Therefore the deviation between the trunk and vertical axis could be used as the other term of the criterion function. According to Fig. 2, B.O. is defined as:

\[ \text{B.O} = \theta_3 Q \dot{\theta}_3^T \]

While:

\[ \theta_3 = [\theta_3(t+1) \cdots \theta_3(t+P)] \]

3.3. Obtaining an essential step height

One of the walking characteristics is the height of the foot, in the peak of the swinging phase, which varies from one to one and also depends to the terrain conditions. According to some studies on human walking, the swinging foot traces a vertical parabola that passes initial and terminal points and tangents the horizontal plain at the peak. Supposing the prediction horizon, equal to one step, the term that expresses the error between maximum foot height and the prescribed desired height is shown as follows:

\[ \text{M.H} = \min \{ \| x_k - x_h \|, k = 1, \ldots, P \} \]

That is the minimum distance between the foot pattern and pre-specified peak point over the predicted step. In ideal conditions this value becomes zero and the foot reaches the exact height at the peak point. This fact has been shown in Fig. 5. The sampled trajectory of the end point of the swinging leg will be optimized where it hits \( x_h \) in any \( x_k \).

3.4. Passing the terminal point in each step

According to some studies, on an even terrain, body limbs repeat a fixed periodic movement. Drew and Jiang [4] showed the effect of visual feedback in gait modification. In order to consider this effect as a term of the quantitative performance index, the footprints to be followed are predetermined. By supposing the prediction horizon, equal to one step duration, the term that expresses the distance between the terminal of the swinging foot and the predetermined foot target is derived as follows:

\[ \text{T.F} = \min \{ \| x_k - x_t \|, k = 1, \ldots, P \} \]

That is the minimum distance between the foot pattern and pre-specified footprint over the predicted step. In ideal conditions one of \( x_k \) values reaches the exact target and one complete stride terminates. This fact is shown in Fig. 5. The sampled trajectory of the end point of the swinging leg will be optimized where it hits the targeted point in any \( x_k \).

3.5. Minimum mechanical energy consumption

To restrict the limbs’ extra movement that consumes more mechanical energy in each step, the E.C. term is considered as the consumed energy per step. Therefore according to Eq. (1) this term can be defined as:

\[ \text{E.C} = \sum_{k=1}^{P} T^T (t + k) \dot{\theta} (t + k) \]
This term is an energy coefficient, by the same dimension.

Finally the cumulative criterion function is obtained when these terms are added together by appropriate weights:

\[ J = \eta_1 E.C + \eta_2 T.F + \eta_3 W.S + \eta_4 M.H + \eta_5 B.O \tag{7} \]

Where, \( \eta_1 \cdots \eta_5 \) are the weighting factors. By tuning these coefficients, different walking styles would be generated.

4. Optimization algorithm

Using the Eq. (7) as the performance index could yield the desired walking quality, by utilizing an appropriate optimization method.

In this paper, two different optimization methods are used to optimize slack angle and impedance parameters as the control variables. The other parameter, slack velocity, is calculated by taking numerical derivative of the optimal slack angle. In 2001, Kordari \[12\] used the gradient decent method to find the optimal values of the impedance parameters and the slack angle of a single joint, before that in 1999, Ebrahimzadeh \[13\] used the grid method to find the optimal values of the mean impedance for each movement sequence, in a sequenced movement of the similar joint.

4.1. Optimization of the slack angle

A recursive, gradient method is utilized for optimizing the slack angle, or in the other word, the control signal. For this reason, the previous method which was used by Kordari is generalized to be used for a MIMO case. After setting the starting point for the optimization, the following algorithm is applied recursively:

\[ B_{\text{new}} = B_{\text{old}} - \alpha \begin{bmatrix} \nabla_{\beta_1} J \\ \nabla_{\beta_2} J \\ \nabla_{\beta_3} J \\ \nabla_{\beta_4} J \\ \nabla_{\beta_5} J \end{bmatrix} \tag{8} \]

Where:

\[ 5 \times M B = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} = \begin{bmatrix} \beta_1(t) & \cdots & \beta_5(t) \\ \beta_1(t+1) & \cdots & \beta_5(t+1) \\ \vdots & \ddots & \vdots \\ \beta_1(t+M-1) & \cdots & \beta_5(t+M-1) \end{bmatrix}^T \]

And the generalized gradient is:

\[ \nabla_{\beta_i} J = \begin{bmatrix} \frac{\partial J}{\partial \beta_1(t)} & \frac{\partial J}{\partial \beta_1(t+1)} & \frac{\partial J}{\partial \beta_1(t+M-1)} \\ \frac{\partial J}{\partial \beta_2(t)} & \frac{\partial J}{\partial \beta_2(t+1)} & \frac{\partial J}{\partial \beta_2(t+M-1)} \\ \vdots & \ddots & \vdots \\ \frac{\partial J}{\partial \beta_5(t)} & \frac{\partial J}{\partial \beta_5(t+1)} & \frac{\partial J}{\partial \beta_5(t+M-1)} \end{bmatrix}^T \]
Fig. 6. The reduced order searching space of viscosity and stiffness normalized values. The specific value in each joint is calculated by multiplication of this value and mean torque of the relevant joint.

M is the control horizon, and $\alpha$ is the optimization index.

As it’s been shown, the slack angle is optimized for all links over the whole control horizon, at any sampling time.

4.2. Optimization of the impedance parameters

To find the optimal stiffness and viscosity of a joint, Ebrahimzadeh utilized the sequencing method to find the best mean impedance for every sequence. According to the sequential nature of walking, a similar method has been utilized. Therefore in every step, the best stiffness and viscosity of every joint, is selected by trying some points in the searching space.

As a disadvantage of random search methods, such as grid method, is that the dimension of the searching space equals to the number of optimized variables, therefore the number of trials rise up exponentially by increasing the number of variables. As a method to prevent this rise up, is finding a co-relation between the variables. Since the magnitudes of the control signals in all joints are nearby, according to some biological evidence, the impedance variables are supposed to be proportional to the averages of the torque values of the relevant joints. By calculating this average value, all the viscosity and stiffness values could be normalized. By using this normalization, random search method is limited to a 2-D space. In Fig. 6 this 2-D space of search is shown.

Therefore any method for obtaining the mean torques could be helpful. According to Eq. (1), if an appropriate pattern is estimated for the joints, the torque changes can be obtained directly. In 2000, Juang [14] proposed a mathematical formula that imitates the human kinematic for a similar 5-DOF robot. The obtained patterns and the relevant calculated torques are depicted in Figs 7 and 8.

Therefore the optimization process leads us to Table 1. In this table different values of joint

Finally the optimization algorithm is obtained as follows:

New Step

For $i=1$ to [Number of Pre specified $\beta$]
For $j=1$ to [Number of Pre specified b]
  Run PREDICTION MODEL
  Calculate $J$
Fig. 7. Joint angle changes, calculated by the method proposed by Juang.

Fig. 8. The Torque changes in joints of BLR-G1 machine, calculated by inverse dynamic model with joints angle changes of Fig. 7 as the model input.

\[
\text{If } [\text{new } J] < [\text{best } J] \text{ set } [\text{best } \beta] = \beta(i) \\
[\text{best } b] = b(j)
\]

Next
Next
Next
For \(t=1\) to [Number of samples in each step]
For Iteration=1 to [Number of Iterations]
For \(k=1\) to \(M\)
Run PREDICTION MODEL
Calculate \(J\)
Calculate \(v e e J\)
Modify \(\beta\) and \(\beta\)'
Next
Next
Set the control variables to the system
Wait for the next output sample
Next
Redefine Initial Condition
Substitute Feet/Go to New Step

5. Simulation results

By using SIMMECHANICS\textsuperscript{TM} (ver. 1.1) Toolbox in MATLAB\textsuperscript{TM} (ver. 6.5) the 8-DOF bipedal model was simulated to be controlled by the proposed control algorithm. According to Fig. 2 the simulated bipedal model parameters are shown in Table 1.
By using the inverse dynamic of the prediction model the average value of the stiffness and viscosity of each joint were obtained (see Table 2). These values were selected as the central value, to be used in grid method. For this reason, 2 more and 2 less values were nominated to be selected by the optimizing system. These values are according to Table 3.

The sampling rate, step duration, prediction horizon were set to 100 Hz, 1 sec, and 100, respectively. In Table 4 the walking parameters are shown.

To obtain the optimal movement according to the desired walking parameters, the performance index is defined as below:

\[ J = 0.025 \text{EC} + 4.0 \text{T.F} + 5.5 \text{W.S} + 6.5 \text{M.H} + 25 \text{B.O} \]

The coefficients are extracted experimentally. By tuning these parameters we have different characteristics in walking. Animation capabilities of SimMechanics help to find appropriate values for these coefficients.

The algorithm was utilized for ascending and descending of the stairs depicted in Fig. 10. The simulated robot is shown in Fig. 9 and the robot positions in each stair are shown in Fig. 14. Endpoint of the swinging foot, also the speed of the body’s center of mass in each step and the transversal displacement of the body are depicted in Figs 10 to 13. To obtain this pattern, the control variables were changed according to Figs 15 and 16. The computer simulation results showed that the performance of the model was close to that of human.
6. Conclusion

To generalize the MPIC method for a detailed human walking control model, an appropriate 5-link model with 8-DOF was utilized in this paper and the results were examined for an ascending and descending terrain. The changes of the control variables show the effect of human higher control system in modification of these parameters in irregular conditions. Because of the coming reasons MPIC is a possible model of human walking control, when modifications in irregular terrains like ascending and descending stairs are needed.

1. The results reveal good performance of this algorithm as a model of human walking control system. Animation capabilities of MATLAB software is a helpful tool shows the correspondence of the proposed control strategy to the human control system.

2. Walking skills and learning could be included in this strategy by using learning algorithms in prescribed dynamic model.
Fig. 11. Endpoint patterns of the swinging foot and hip, left and right feet are distinct by dash and solid curves relatively.

Fig. 12. Alteration of the horizontal speed of the body’s center of mass.

Fig. 13. Transversal displacement of the body’s center of mass.
Fig. 14. Robot position in different sequences of walking.

Fig. 15. Changes of the slack angle and stiffness.
3. Visual effects could be simply included in this strategy by modification of targeted points, step height and . . .

Despite the benefits of this method as a control model of walking, the disadvantage of time consuming optimization process is ahead of us. Fast technological progress in computer hardware and microprocessors as well as development of new algorithms could be helpful to decrease computation time and make MPIC a probable method for modeling of human movements and also a candidate method for robotic applications.

For future work, finding a method to obtain the impedance variables online would be a complementary step.

References


