Visualization and Identification of Macroscopic Dynamics of a Human Motor Control Based on the Motion Measurement

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Abstract—This paper proposes a new scheme to identify the macroscopic dynamics of humans’ motor control based on the COM-ZMP (the center of mass and the zero-moment point) model, which has been rigorously studied and is widely utilized for a design of humanoid robot controllers. Since the model is mathematically well-defined with a small number of system parameters and control parameters, it is easy to identify both those parameters from loci collected through motion measurements by the least-square method. A difficulty is how to collect loci of sufficiently various motions for reliable identification since a human in general unconsciously stabilizes him/herself at any time and hardly shows behaviors in a distance from the point of equilibrium. This problem is solved by visually understanding the macroscopic behavior of the model in theory and set up protocols to cover wide range of the state space with predictions of behaviors to be observed in each area in a phase portrait. By adding preparatory motion in order to accelerate COM to the desired and discarding the portion of that phase, one can obtain valid loci. We examined the proposed method on a standing stabilization control and conducted the identification.

Index Terms—Human motor control, Identification of the controller, The COM-ZMP model, Motion measurement

I. INTRODUCTION

The study of motor control of humans provides significant knowledge not only from a scientific viewpoint but also at a practical aspect, where the understanding of humans’ motional properties are utilized for medical diagnoses, rehabilitation, sports trainings, designs of human interfaces and robot controllers. Precise and detailed motion measurements have become available thanks to the advancement of instruments. However, the identification of human’s motor controller is still a very challenging problem. It is mainly due to the complexity of the human body itself, which comprises about 200 bones, 1000 muscles, and other various parts such as tendons, ligaments and cartilages. Even when it is approximated by a kinematic chain with rigid links and joints, it has tens of joints, and accordingly, about a hundred degrees of freedom in total. In spite of such a lot of DOFs, it is in nature an underactuated system which lacks any mechanical connection to the inertial frame, and varying its structure during the motion by exchanging contacting points with the environment [1]. The previous researches dealing in the modeling and identification of the human controller only targeted limited simple motions such as reaching movements [2], standing posture control with a small number of joints [3]–[5].

On the other hand, a design of humanoid robot controller has been vigorously studied in the field of robotics and the mathematics of the whole-body control including standing stabilization, locomotion and fall-prevention have been discussed. It has been learned [6]–[9] that the complex whole-body motion can be approximated by the relationship between the center of mass (COM) and the zero-moment point (ZMP [10]), namely, the center of pressure (COP), which we call the COM-ZMP model hereafter. Based on the model, Sugihara [11] discussed a controller design for standing stabilization, in which the feedback parameters from the state of COM to the amount of manipulation of ZMP are chosen such that the stabilization performance is maximized under the dynamical constraint about the unilaterality of reaction forces. An importance of focusing on COM has often been reported in the field of biomechanics, although the discussion hasn’t covered the design of controllers. The above works in robotics suggest a possibility that human controllers can also be modeled and explained by the COM-ZMP model.

When applying the COM-ZMP model to the identification of motor control, one may encounter a new problem that even collecting loci of sufficiently various motions is difficult since a human in general unconsciously stabilizes him/herself at any time and hardly shows behaviors in a distance from the point of equilibrium. In this paper, we propose a method to set up protocols for motion measurements against the above problem. We can predict behaviors to be observed in each area of the state space based on the visualized dynamics of the COM-ZMP model with a feedback controller in a phase portrait. Then, we add preparatory motion to each trial in order to accelerate COM to the desired initial state. In data processing, we detect the preparatory phase in each motion locus and discard it based on the profile of the ground reaction forces. Finally we apply the least-square minimization to identify both the system parameters and the control parameters.

As the first step, we examined the proposed method on a standing stabilization control and conducted the identification. The results of the measurements and analyses are preported.

Let us consider a planar bipedal motion in the lateral plane as shown in Fig.1(A). Suppose the inertial torque about COM is sufficiently small to be neglected than the moment of linear inertial force about ZMP, for simplicity. Also, let us denote the lateral position of COM by \( x \), the referential position of COM by \( r_f \) and the position of ZMP by \( x_Z \), respectively. We get the following state equation in which ZMP is regarded as the input [6]:

\[
\ddot{\chi} = \omega^2 \chi - \omega^2 \chi_Z \\
\omega \equiv \sqrt{\frac{\ddot{z} + g}{z}}
\]

where \( \chi \equiv x - r_f, \chi_Z \equiv x_Z - r_f, \ddot{z} \) is the height of COM from the ground, and \( g = 9.8 \text{[N/kg]} \) is the acceleration due to the gravity. Note that this is a non-linear state equation since \( \omega \) varies as COM moves along z-axis. This section assumes that the height of COM keeps constant as \( z = \text{const} \), and then, it becomes a piecewise-linear state equation.

Even in this simplest dynamical model, \( \chi_Z \) is constrained within the supporting region \( [\chi_{Z\text{min}}, \chi_{Z\text{max}}] \) as

\[ \chi_{Z\text{min}} \leq \chi_Z \leq \chi_{Z\text{max}} \]

where \( x_{Z\text{min}} \equiv \chi_{Z\text{min}} + r_f \) and \( x_{Z\text{max}} \equiv \chi_{Z\text{max}} + r_f \) are the right and left boundaries of the supporting region on x-axis. In this model, ZMP plays a role as a channel through which the robot and the environment exchange forces.

Let us design the referential ZMP, which works as the input to the system to stabilize COM around the reference, \( \chi = \text{const} \), and identify both system parameters and control parameters by assuming the model of controller described in the previous section. Note that we haven’t proven the validity of the model at this moment; we should evaluate it after obtaining the parameters and error variance of them, which is our next assignment.

\[
\begin{align*}
\chi_Z &= \begin{cases} 
\chi_{Z\text{max}} & (S1: \ddot{Z} > \chi_{Z\text{max}}) \\
\ddot{Z} & (S2: \chi_{Z\text{min}} \leq \ddot{Z} \leq \chi_{Z\text{max}}) \\
\chi_{Z\text{min}} & (S3: \ddot{Z} < \chi_{Z\text{min}})
\end{cases}
\end{align*}
\]

where \( k_1 \) and \( k_2 \) are positive constants. \( \ddot{Z} \) is called the simulated ZMP [12]. By controlling the actual ZMP to track the above referential ZMP, we get an autonomous COM dynamics, which is represented as the following piecewise-affine system:

\[
\begin{align*}
\dot{\chi} &= \begin{cases} 
\omega^2 \chi - \omega^2 \chi_{Z\text{max}} & (S1) \\
\omega^2 (1 - k_1) \chi - \omega^2 k_2 \ddot{\chi} & (S2) \\
\omega^2 \chi - \omega^2 \chi_{Z\text{min}} & (S3)
\end{cases}
\end{align*}
\]

In state (S2), the system poles can be assigned at \( -\omega q_1 \) and \(-\omega q_2\) if we choose the feedback gains for \( k_1 = q_1 q_2 + 1 \) and \( k_2 = \frac{q_1 + q_2}{q_2} \). Fig.1 shows the phase portraits of the system for different combinations of \( q_1 \) and \( q_2 \), where \( \chi_{Z\text{min}} = -0.07 \text{[m]}, \chi_{Z\text{max}} = 0.07 \text{[m]} \) and \( z = 0.27 \text{[m]} \). The dotted area (or, the blue area for readers with color) in the figures are the set of initial states which stably converge to the referential position, and called the stable standing region. It is known that the above controller maximizes the stable standing region if state (S2) includes \((\chi, \ddot{\chi}) = (0, 0), i.e., \chi_{Z\text{min}} < 0 < \chi_{Z\text{max}}, \) and \( q_1 = 1 \) or \( q_2 = 1 \).

The feedback system is characterized by the following four lines:

\[
\begin{align*}
l_1 : \chi + \frac{\ddot{\chi}}{\omega} &= \chi_{Z\text{min}} \\
l_2 : \chi + \frac{\ddot{\chi}}{\omega} &= \chi_{Z\text{max}} \\
m : k_1 \chi + k_2 \ddot{\chi} &= \chi_{Z\text{min}} \\
n : k_1 \chi + k_2 \ddot{\chi} &= \chi_{Z\text{max}}
\end{align*}
\]

\( l_1 \) and \( l_2 \) are asymptotic lines in state (S1) and (S3), where ZMP is stuck at \( z_{Z\text{min}} \) and \( z_{Z\text{max}} \), respectively. \( m \) and \( n \) are the switching lines of the piecewise system, which separate (S1) and (S2), and (S2) and (S3), respectively.

III. MOTION MEASUREMENT PROTOCOLS TO COVER THE STATE SPACE

Now, we intend to collect loci of standing stabilization motions and identify both system parameters and control parameters by assuming the model of controller described in the previous section. Note that we haven’t proven the validity of the model at this moment; we should evaluate it after obtaining the parameters and error variance of them, which is our next assignment.

It is important to cover as broad area of the state space as possible through the motion experiments for a reliable
identification. However, it is not an easy task because a subject can start his/her motion only from a stable resting state, meaning that he/she can start his/her motion only from points on the line $\dot{X} = 0$ between $X_{Z_{\min}}$ and $X_{Z_{\max}}$. The loci of motions which we can observe in regular situations exist within a very limited area near the referential point in the state space as depicted in Fig. 2. In order to measure motions in a distance from the referential point, we have to elaborate protocols.

Since we know the phase portrait in theory as Fig. 1, we can predict behaviors to be observed in each area of the state space, supported by a visual understanding. Our idea is to add preparatory motion to each trial in order to accelerate the center of mass (COM) to the desired initial state as depicted in Fig. 3. (a) and (a') (the prime mark means a symmetric type of motions) are groups of loci of motions observed without any elaborations. (b) and (b') are also observable without elaborations but in the initial phase COM is overaccelerated beyond the referential point, so that the loci in the acceleration phase are invalid. (c) and (c') are the loci on which the subject eventually falls down. He/she has to carry him/herself to unstable area for those motions. (d) and (d') are that for stable motions starting from states in a distance from the referential point. The subject should initiate his/her motion from outside of the supporting region with a help of a holding platform, and accelerate him/herself so much that he/she reaches the desired state. (e) and (e') are that for unrecoverable falling motions, which also require a help of a holding platform in the preparatory motion. Each type of motion is illustrated in Fig. 4. A common process in the above is that the subject starts motions from resting states in some cases assisted by a platform and accelerate him/herself until he/she reaches valid trajectories. Since the loci of those preparatory motions should be discarded, how to detect the ‘real’ start points on the valid trajectories is another practical problem to be solved in experiments.

IV. EXPERIMENTS OF MOTION MEASUREMENT

A. SETUP OF MEASUREMENT AND COMPUTATION SYSTEM

Experiments of motion measurements were conducted on a motion-capturing system as illustrated in Fig. 5. Retroreflective markers are attached to the subject’s body so that his/her motion is captured by optical cameras. At the same time, the reactive forces are measured by force plates during
motions. In order to accelerate the body to the desired state in preparatory phases, a ladder is set next to the subject as an assistive platform. The force exerted to it can also be measured by another force plate, which is used to detect real start points of valid motions. The subject regulates his/her motions by adjusting his/her stance to markers put on the force plates and by seeing a marker of the referential point put in front of him/her.

The subject was a male, who was 23 years old, 175cms tall and weighing 73kgs, shown in Fig.6(a). His kinematics and dynamics were modeled and identified before the experiments based on a method proposed by Ayusawa et al. [13]. Fig.6(b) shows the model with 34DOF including 6DOF for the motion of the floating trunk.

When a set of 3D loci of the markers are measured every 5[ms], it is converted to a locus of the whole-body configuration through the inverse kinematics. Then, the locus of COM is computed through the forward kinematics based on the mass property identified before the experiment. Measurement noises are reduced by a second-order Butterworth filter with 2[Hz] of cutoff frequency. By numerically differentiating it, a history of the velocity and acceleration of COM are computed. The locus of ZMP is also computed from a history of the reaction forces. Based on the record of the reaction force exerted from the ladder, the real start point of valid motion is found and the segment of preparatory motion is deleted.

B. Visualization of dynamics of standing stabilization control on a phase portrait

The motions (a)~(e) and (a')~(e') described in section III were tested by the subject and captured. The number of trials of each type of motion was 8 times.

Fig.7 shows a phase portrait on which all the computed loci of COM are plotted, where the original point is adjusted based on the estimated referential point for each trial. Although certain level of variability is recognized among the loci and they often intersect with each other, the overall flow resembles the theoretical phase portrait in Fig.1 in many aspects, so that the global structure of the dynamics is qualitatively similar to the model. Moreover, one can visually confirm that the examined motions cover wider range of the state space comparing with the loci only of (a) and (a') as expected.

V. IDENTIFICATION OF PARAMETERS FROM THE COMPUTED LOCI OF COM AND ZMP

A. Identification of the system parameter

The system’s only one parameter \( \omega \) was identified for motions type (a) and (d). Particularly for (a), a set of motions (a1) in which the subject started from almost the same position and another set of motions (a2) in which the subject started from various positions in the supporting region were separately investigated.

We have two choices to identify \( \omega \); the first idea is to use its definition Eq.(2) directly, while the other is to use Eq.(1).

\[
\omega^* = \frac{\sum_{k=1}^{N} a[i](x[k] - x_Z[k])}{\sum_{k=1}^{N}(x[k] - x_Z[k])^2},
\]

(11)

First, we computed \( \omega \) in accordance with Eq.(2) for each motion in (a1) to see the time variation of the value during the same motion.

The results are shown as the upper wavy lines (or the red lines for readers with color) in Fig.8. It varies in the range from 3.4 to 3.6 in most cases, and in some cases, the range is expanded from 3.2 to 3.7. Although we cannot draw any conclusion about the validity of regarding \( \omega \) as a constant when considering a feedback control only from them, it provides a rough estimation of the value identified by another way in accordance with Eq.(1). In fact, the bottom line (or the blue line for readers with color) indicates the value \( \omega^* \approx 3.08 \) from Eq.(1), which is described in the following part. The difference between the red lines and the blue line is thought to be non-negligible, so that the source of this should be discussed.

Then, we identified \( \omega = \omega^* \) as a constant value in accordance with Eq.(1). From the least-square method, \( \omega^* \) is evaluated as

\[
\omega^* = \frac{\sum_{k=1}^{N} a[i](x[k] - x_Z[k])}{\sum_{k=1}^{N}(x[k] - x_Z[k])^2},
\]

(11)
where $x[k]$, $a[k]$ and $x_Z[k]$ are the position of COM, the acceleration of COM and the position of ZMP at discrete time $k$, respectively, and $N$ is the total number of the data. The results are $\omega^* \approx 3.08$, $2.70$ and $2.84$ for (a1), (a2) and (d), respectively.

In order to evaluate the validity of the identified value, we investigated the autocorrelation of the approximation error:

$$\epsilon[k] = a[k] - \omega^* (x[k] - x_Z[k])$$

The results were about 0.034, 0.06, 0.01 for (a1), (a2) and (d), respectively. From these values, $\epsilon[k]$ is thought to be uncorrelated with itself, so that Eq.(1) with a constant $\omega$ is regarded as a fair model in terms of regression, though the accuracy of the model should be evaluated by another way. We also investigated the correlation between $\omega^*(x[k] - x_Z[k])$ as the input and $\epsilon[k]$. The correlation coefficients were about 0.018, 0.005 and 0.006 for (a1), (a2) and (d), respectively. We again conclude that there is almost no correlation between the input and the error, so that the error is independent from the input.

B. Identification of the controller parameters

The controller parameters $k_1$ and $k_2$ were also identified for motion (a1), (a2) and (d) in accordance with Eq.(6) and the previously estimated $\omega^*$. By applying the least-square method, we get the following equations to estimate $k_1^*$ and $k_2^*$ as

$$k_1^* = \frac{p_1 p_2 - p_3 p_4}{p_4 p_5 - p_1^2}$$

$$k_2^* = \frac{p_1 p_3 - p_2 p_5}{p_4 p_5 - p_1^2},$$

where

$$p_1 \equiv \sum_{k=1}^{N} x[k] v[k]$$

$$p_2 \equiv \sum_{k=1}^{N} v[k] a[k] \omega^*$$

and $v[k]$ is the velocity of COM at discrete time $k$. The results were $(k_1^* k_2^*) \approx (1.83, 0.24), (1.46, 0.15), (2.81, 0.58)$ for (a1), (a2) and (d), respectively.

In order to evaluate the validity of those values as well as $\omega^*$, the autocorrelation and input-error correlation for the following equation were also investigated:

$$\epsilon'[k] = a[k] - \omega^* (\{(k_1^* k_2^*) x[k] - k_2^* x_Z[k]\})$$

where $\omega^* (\{(k_1^* + 1)x[k] - k_2^* x_Z[k]\})$ was regarded as the input. The autocorrelation coefficients of $\epsilon'[k]$ were -0.010, 0.015 and 0.028 for (a1), (a2) and (d), respectively. The correlation coefficients between the input and the error were -0.000, -0.005 and -0.001 for (a1), (a2) and (d), respectively. Those values show that $\epsilon'[k]$ is neither correlated with itself nor with the input, so that Eq.(4) is valid to model at least the subject’s controller in terms of regression.

Based on the above identified values $\omega^*$, $k_1^*$ and $k_2^*$, we can draw the lines $l_1$, $l_2$, $a$ and $b$ in phase portrait in Fig.9. It is qualitatively similar to Fig.1(a) where the lines are drawn near each other, though the accuracy is yet to be evaluated in quantitatively. It is the future work.

The above parameters provide us with phase portraits of the identified systems, which are drawn by numerically solving Eq.(6). Fig.10(A), (B) and (C) show them with respect to (a1), (a2) and (d), respectively, where the loci of the measured motions are overlaid. One can see that the solution curves match the original loci at a good level in Fig.10(A) and (C), while there is a mismatch between them in Fig.10(B).

Presumably, we have three possible factors on this mismatch.

1) The reference position might have changed during the motions. At the starting points of motions in (a2), the subject was standing still at certain positions. Suppose he starts from a resting point $x_0$, a stabilization controller which regulates his COM not to $ref_x$ but to $x_0$ works at the beginning of the motion. In this sense, the controller switches even during this simple motion, so that reliability of the data in the initial phase is low as well as the other cases with preparatory motions. We should have cut the initial portions of the loci.

2) The variation of $\omega$ might have affected. As shown in Fig.8, it varied more largely particularly in the early stage than in the converging stage. The assumption that the system dynamics is approximately time-invariant might be in appropriate.
3) The feedback controller might have been essentially non-linear. As well-known, the reaching motion of a human has a particular property with a bell-shaped velocity profile, which means that the reaching control cannot be achieved by a linear feedback. If the standing controller has a similar property, we have to find another form of the controller.

The authors will verify the above factors step-by-step.

VI. CONCLUSION

A new scheme to identify the whole-body controller of a human particularly for standing stabilization was proposed. Robotics has suggested several frameworks to design humanoid controllers, which are mathematically well-defined but hard to discuss the similarity to that of humans. The COM-ZMP model has been known as a reasonable model to represent macroscopic dynamics of the whole-body dynamics and to devise intuitive controllers. This paper showed another benefit of the model in the field of biomechanics that it works to identify both the system parameters and the control parameters in a clear way. It is also helpful that one can visually understand the dynamics in order to predict the human behavior and set up protocols to collect significant motion samples. Although we have conducted it only by one subject so far, it is expected that the method based on such a macroscopic model can absorb the differences depending on individuals.

There remains some issues particularly in how to evaluate the validity of the model quantitatively and also how to remove the motion trajectories in preparatory phases, which will be resolved in the near future.

Since the development of robot controllers based on the COM-ZMP model is ongoing to be applicable to other various motions such as stepping and walking. The authors expect that the proposed method will provide a common procedure to identify controllers of those motions.

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