Dynamically Stable Movement Generation of a Humanoid Robot from Demonstration: Kicking a Ball

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Abstract − This paper presents a new algorithm of autonomously generating dynamically stable movements such as ball kicking through learning from demonstration by a humanoid robot. It is based on the framework of dynamic movement primitives (DMP) [1, 2] which represent a demonstrated movement with a set of different equations. By suggesting a modification to take into account the dynamic stability condition using the zero moment point (ZMP), the framework is extended to enable to provide dynamically stable movements which reach target positions accordingly. We validate the feasibility of our algorithm through the simulation study and experiment of ball kicking movements by a humanoid robot.

Keywords − Dynamic movement generation, Learning from demonstration, Dynamic movement primitives, Zero moment point.

1. Introduction

Methods for learning from demonstrations have been intensively investigated by researchers [3-5]. A robot reproduces a movement generated by a human. However, the cases considering the dynamic stability such as balancing are rare [6, 7], especially in highly dynamic movements. We address the problem by extending the DMP that has been successfully applied to movement generations of various robots [1, 2, 8, 9]. The DMP was developed by Ijspeert et al. [1, 2], and extended to apply to movements in task space and to consider obstacle avoidance [8, 9]. The DMP is represented by a set of differential equations. To evaluate the dynamic stability of a robot, especially in balancing, a popular concept, ZMP, is taken in account. Description of a robot's postural movements such as walking based on the ZMP has rigorously been studied [10-13]. In this work, we propose an approach to embed the dynamic stability in terms of the ZMP into the DMP-based movement generation.

Therefore, dynamically stable movement trajectory can be autonomously generated reaching a target position once after a principal movement trajectory is learned from demonstrations. Dynamically stable and goaled movement generation will enrich robotic application tasks and facilitate robot control.

To evaluate our algorithm, ball kicking movements by a Nao humanoid robot (Aldebaran robotics, Inc) are studied in both dynamic simulation and experiment. The results demonstrate the abilities of the approach.

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2. Movement generation

2.1 Foot movement generation

The improved DMP is represented [8, 9] by

$$\begin{aligned} \tau\dot{v} &= K(g-x) - Dv + K(g-x_0)s + Kf(s) \\ \tau\dot{x} &= v \\ \tau\dot{s} &= -\alpha s \end{aligned} \tag{1}$$

where x and v are position and its velocity; x_0 and g are the initial and target positions; K and D are gains; τ is a temporal scaling factor; α is a constant; and f is a nonlinear adaptive function to generate arbitrary complex movements. The nonlinear function is set to be

$$f(s) = \frac{\sum_i w_i \phi_i(s) s}{\sum_i w_i \phi_i(s)} \tag{2}$$

where $\phi_i = \exp(-a_i(s-b_i)^2)$ with parameters a_i and b_i, and w_i are adjustable weights. s is set to be 1 initially.

Using demonstrated movements, $f(s)$ is computed from (1) by applying linear regression over the weights [8]. Then, the DMP provides movements with new initial and target positions or movement speed retaining the fundamental pattern of the demonstrate movement. We apply DMP to draw kicking foot (end-effecter) position trajectories which passes through various targeted ball positions accordingly. Given a targeted ball position, g, and an initial kicking foot position, (1) drives a desired trajectory of the foot position, $\overline{x}_E = [x_E \; y_E \; z_E]^T$. The desired trajectory reaches the targeted ball position $\overline{g}_B$ while maintain the pattern principally similar to the demonstrated foot position trajectory. Furthermore, $\ddot{\overline{x}}_E$ is obtained simply through (1) from $\overline{x}_E$.

2.2 ZMP-based Pelvis movement generation

When a humanoid robot supports its body with a foot during movements, it is approximately interpreted as a simple inverted pendulum [11-13]. Then, ZMP can be described approximately with respect to the center of gravity (COG) as follows [12, 13].

$$x_{ZMP} \simeq x_{COG} - \frac{l}{g}\ddot{x}_{COG}, y_{ZMP} \simeq y_{COG} - \frac{l}{g}\ddot{y}_{COG} \quad (3)$$

This work assumes that the Pelvis joint movement has a major balancing effect in one leg balancing as in previous studies [11].

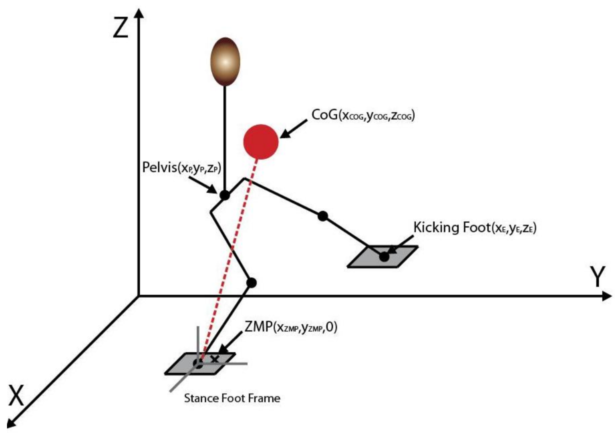

Fig. 1. Model

Fig. 1 illustrates our model, and, approximately, COG is described by two variables, the Pelvis position and the kicking foot position.

$$\begin{aligned} x_{COG} &= k_1 x_P + k_2 x_E \\ y_{COG} &= k_3 y_P + k_4 y_E + k_5 \end{aligned} \quad (4)$$

where k_i is constant ($i = 1,...,4$). (4) is modeled under the assumption that the robot upper body remains upright during kicking a ball. The offset k_5 is added to take into account the bent knee posture.

Plugging (4) into (3),

$$\begin{aligned} x_{ZMP} &\simeq k_1 x_P + k_2 x_E - \frac{l}{g}(k_1\ddot{x}_P + k_2\ddot{x}_E) \\ y_{ZMP} &\simeq k_3 y_P + k_4 y_E + k_5 - \frac{l}{g}(k_3\ddot{y}_P + k_4\ddot{y}_E) \end{aligned} \quad (5)$$

To guarantee stable movement generation, ZMP should be constrained to be within a feasible range.

$$\begin{aligned} x^-_{ZMP} &\le x_{ZMP} \le x^+_{ZMP} \\ y^-_{ZMP} &\le y_{ZMP} \le y^+_{ZMP} \end{aligned} \quad (6)$$

where x^-_{ZMP} and x^+_{ZMP} (y^-_{ZMP} and y^+_{ZMP}) represent, respectively, the lower and upper ZMP boundary values which allow stable movements.

With the computed $\overline{x}_E$ and $\ddot{\overline{x}}_E$ from section 2, and the backward difference acceleration approximation of $\ddot{x}_P(t) = \frac{1}{\Delta t^2}(x_P(t) - 2x_P(t-\Delta t) + x_P(t-2\Delta t))$ where Δt is a sampling time,

$$x^-_{ZMP} \le k_1 x_P(t) + k_2 x_E(t) - \frac{l}{g}(k_1 \frac{1}{\Delta t^2}(x_P(t) - 2x_P(t-\Delta t) + x_P(t-2\Delta t)) + k_2\ddot{x}_E(t)) \le x^+_{ZMP} \quad (7)$$

Then,
$$\frac{x^-_{ZMP} - C}{k_1 - \frac{l}{g\Delta t^2}} \le x_P(t) \le \frac{x^+_{ZMP} - C}{k_1 - \frac{l}{g\Delta t^2}} \quad (8)$$

where

$$C = k_2 x_E(t) - \frac{l}{g}k_2\ddot{x}_E(t) + \frac{l}{g\Delta t^2}(2x_P(t-\Delta t) - x_P(t-2\Delta t))$$

At time t, C is computed based on available information. To secure robust stability, we choose the targeted Pelvis position as an average of the lower and upper boundary values in (8).

$$x_P(t) = \frac{x^-_{ZMP} + x^+_{ZMP} - 2C}{2(k_1 - \frac{l}{g\Delta t^2})} \quad (9)$$

$y_P(t)$, the y component of the Pelvis trajectory, is also computed through the similar procedures from (5) to (9). $z_P(t)$, the z component of the Pelvis trajectory is computed through the MDP equations ((1), (2)) because the ZMP component is not considered. As a result, $\overline{x}_P = [x_P \; y_P \; z_P]^T$ is obtained. The overall procedure aims to draw the Pelvis trajectory which is similar to the pattern from demonstration, but secured to maintain postural stability for new ball positions.

2.3 Movement control

Once the foot and Pelvis position trajectories, $\overline{x}_E$ and $\overline{x}_P$, are provided , the inverse kinematics is applied to compute related joint trajectories which are control commands to robot's joints. The erect upper body posture condition is taken into account while computing the reference joint trajectories. Appropriate feedforward and feedback controllers are required to generate robot movements which cope well with the reference trajectories [8, 9].

3. Simulation

We test our proposed method through simulation study using the Webots 6 simulator (Cyberbotics, Ltd.) with the Nao humanoid robot model. After computing the reference joint trajectories, this work uses the control system library provided in the simulator.

Using the humanoid robot simulator, ball kicking movements are simulated. We evaluate the autnomous generation of dynamically stable kicking movements accordingly when different ball positions are given once after a principal kicking movement is learned from demonstration. Three different ball positions are selected, each kicking movement is computed as in Fig. 2 (a) to (c) respexctively. The demonstrated kicking movement (blue line) cannot remain in the stable region bounded by dotted lines. The proposed algorithm produces each new kicking movement (red line) which satisfies the stable condition.

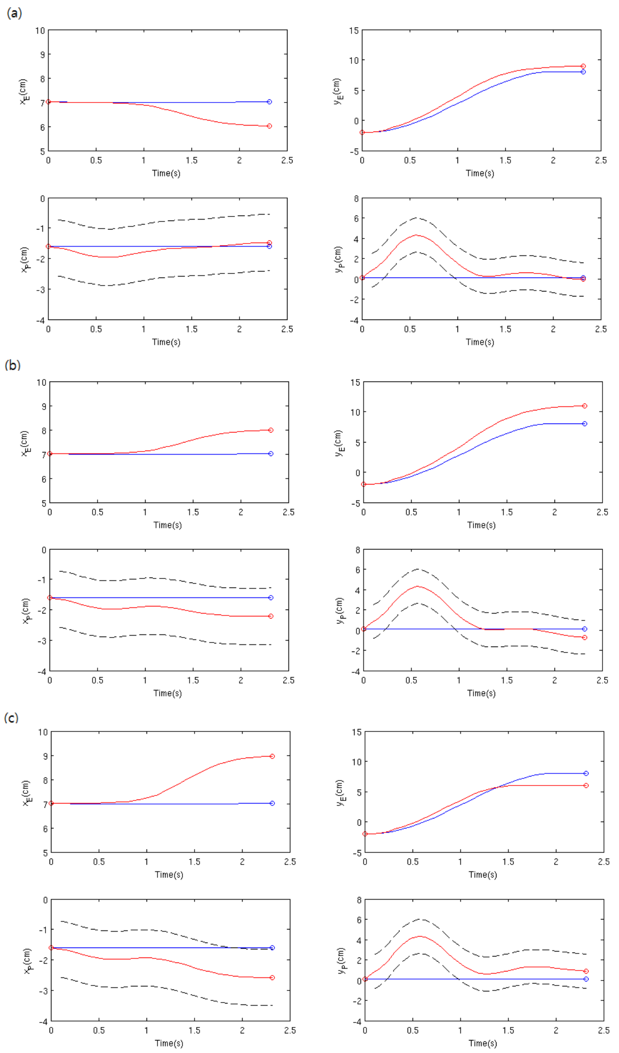

Fig. 2. Generation of three kicking movements ((a),(b),(c)). The blue line indicates a principal kicking movement from demonstration, and the red line represents a new kicking movement to reach a new ball position. Each subplot shows the trajectories of x_E, y_E, x_P and y_P. Dotted lines indicate the upper and lower bounds (as in (8)).

Fig. 3 illustrates the snapshots to show dynamic simulations of three kicking movements. Each alphabet (a) to (c) corresponds that in Fig. 2. Fig. 4 shows the movement trajectories in the x-y planes. The filled circles indicate ball positions. Each movement trajectory reaches the ball position while maintaining dynamic stability conditions.

The produced trajectories through our algorithm are inputted into a Nao humanoid robot to see if stable motion generation is implemented. Fig. 5 demonstrates the results.

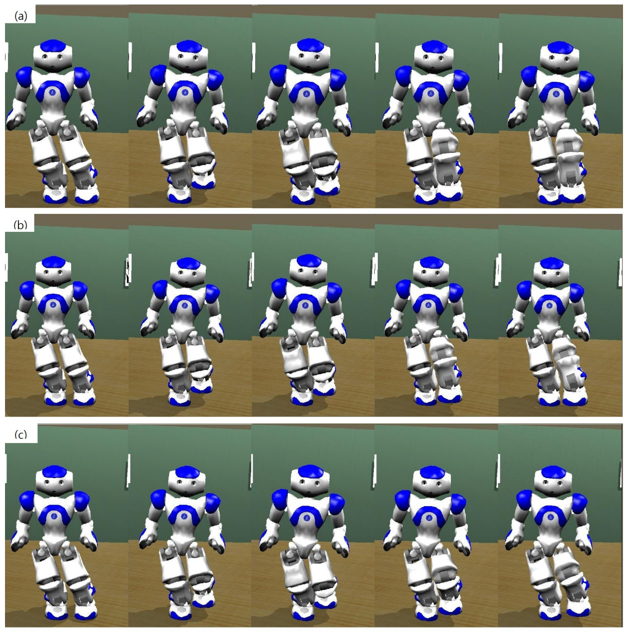

Fig. 3. Simulation snapshots of three kicking motions with different ball target positions.

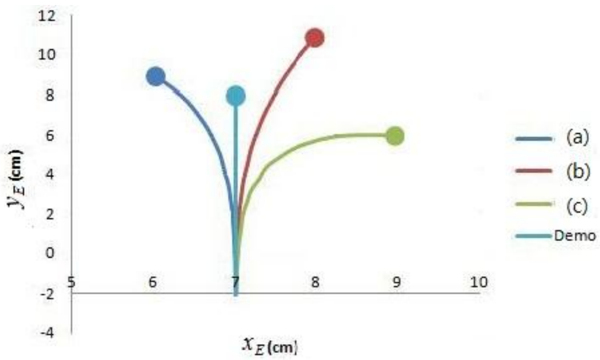

Fig. 4. Three kicking motion trajectories in x-y plane.

Fig. 5. Snapshots of humanoid robot movements

4. Conclusion

This paper addressed a new algorithm of dynamically stable movement generation from demonstration by a humanoid robot, and evaluated the algorithm through ball kicking movement generation. For different targeted ball positions, the algorithm generated the stable kicking movements of a humanoid robot while passing through the targeted posistions. Currently, the orientation information is not included. However, counting orientation primitives into our algorithm is straightward as in [8]. In this work, kicking direction is not restricted. To realize a desired kicking direction, further constraints on motion generation will be required. Extension of our algorithmn to other dynamic movement generations will be attempted in the future.

References

[1] A.J. Ijspeert, J. Nakanishi, and S. Schaal, "Trajectory formation for imitation with nonlinear dynamical systems", in Proc. IEEE Int. Conf. Intell Robots Syst, pp.752-757, 2001.

[2] A.J. Ijspeert, J. Nakanishi, and S. Schaal, "Learning attractor landscapes for learning motor primitives", in Proc. Adv. Neur. Info. Proc. Syst., vol. 15, pp. 1523-1530, 2003.

[3] C. G. Atkeson, and S. Schaal, "Robot learning from demonstration", In Proc. 14th Int. Conf. Machine Learning, pp. 12–20, July 1997.

[4] B. Argall, S. Chernova, M. Veloso, and B. Browning, "A survey of robot learning from demonstration", Robotics and Autonomous Systems, vol.57, no.5, pp.469-483, May 2009.

[5] A. Billard,and R. Siegwart, "Robot learning from demonstration", Robotics and Autonomous Systems, vol. 47, pp. 65-67, 2004.

[6] R. Chalodhorn, D. Grimes, K. Grochow, and R. Rao, "Learning to walk through imitation", in Proc. Int. Joint Conf. Artificial Intelligence, pp.2084-2090, 2007.

[7] D. Grimes, D. Rashid, and R. Rao, "Learning nonparametric models for probabilistic imitation", in Proc. Adv. Neur. Info. Proc. Syst., vo. 19, pp.521-528, 2007.

[8] P. Pastor, H. Hoffmann, T. Asfour, and S. Schaal, "Learning and generalization of motor skills by learning from demonstration", In Proc. Int. Conf. Robotics Automation, Kobe, Japan, 2009.

[9] D.-H. Park, H. Hoffmann, P. Pastor, and S. Schall, "Movement reproduction and obstacle avoidance with dynamic movement primitives and potential fields", In Proc. IEEE Inf. Conf. Humanoid Robots, 2008.

[10] K. Erbatur, and O. Kurt, "Natural ZMP trajectories for biped robot reference generation", IEEE Trans. Industrial Electronics, vol.56, no.3,pp.835-845, 2009.

[11] S. Kim, C. Kim, B. You and S. Oh, "Stable whole-body motion generation for humanoid robots to imitate human motions", In Proc. Int. Conf. Intell. Robot. Syst., 2009.

[12] Y. Choi, B. You and S. Oh, "On the stability of indirect ZMP controller for biped robot systems", In Proc. Int. Conf. Intell. Robot. Syst., 2004.

[13] T. Sugihara, Y. Nakamura, and H. Inoue, "Realtime humanoid motion generation through ZMP manipulation based on inverted pendulum control", In Proc. IEEE Int. Conf. Robot. Autom., Washington DC, 2002.