Metrics to Assess a Human Trajectory Prediction Model during Gait

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1. Introduction

An accurate model of the human behaviour could be useful for several applications such as proactive human-robot interactions or exoskeletons. For example, being able to model or even predict human trajectory during gait could improve co-navigation tasks. In this paper, we present and assess such a prediction model. It was designed in order to make a humanoid robot proactively walk along with a human partner in simulation. Aiming to be a first step toward a table handling task in collaboration between a human and a humanoid robot, this work is part of the ANR-COBOT project.

In Maroger et al. (2021), the authors developed an Optimal Control (OC) model, based on the one designed by Mombaur et al. (2008), which generates human-like trajectories. Those generated trajectories were shown to fit well average human Center of Mass (CoM) trajectories during gait between a starting and a goal position. In this paper, a human trajectory prediction model based on this OC model is presented and assessed. Thus, our work aims to generate in real-time the gait of a humanoid-robot, using this prediction model, to make it proactively interact with a walking human partner.

2. Methods

2.1 Prediction Model

This prediction model aims to predict in real-time where a human will go based on its recent past trajectory. First, some assumptions have to be made:

● The human CoM position and orientation $\boldsymbol{c} = (c^x, c^y, c^\theta)$ are recorded at all time with a sampling period T_{OC}. On each interval $[kT_{OC}, (k+1)T_{OC}]$, $\boldsymbol{c}$ is piecewise constant and denoted $\boldsymbol{c_k}$ with $k \in \mathbb{N}$.

● The human starts walking at $t = 0$ and stops at an unknown time $t = N_f T_{OC}$.

● The prediction process starts at $t = N_0 T_{OC}$ when at least N_0 measurements are available.

● At time $t = kT_{OC}$, the **prediction process** iterates one prediction model using the N_0 last measurements $(\boldsymbol{c_{n+1}}, \dots, \boldsymbol{c_{n+N_0}})$ and computes the following trajectory $X_{n+1} = (\boldsymbol{x_{n+1}}, \dots, \boldsymbol{x_{n+N_{OC}}})$ of size $N_{OC} > N_0$ with $n = k - N_0$ and $\boldsymbol{x_k} = (x_k^x, x_k^y, x_k^\theta)$ the k[th] predicted position and orientation. This process is represented on Fig.1.

In what follows N_0 and N_{OC} will be named **prediction parameters**.

Then, at time $t = kT_{OC}$, the prediction model can be defined as the following OC problem:

$$\begin{cases} \min\limits_{X_{n+1}, U_{n+1}} \sum\limits_{i=n+1}^{n+N_{OC}} \phi_i(\boldsymbol{c_i}, \boldsymbol{x_i}, \boldsymbol{u_i}) \\ \boldsymbol{x_{n+1}} = \boldsymbol{c_{n+1}} \end{cases}$$

With $U_{n+1} = (\boldsymbol{u_{n+1}}, \dots, \boldsymbol{u_{n+N_{OC}}})$, $\boldsymbol{u_k} = (u_k^{v_f} = \dot{x}_k^{v_f}, u_k^{v_o} = \dot{x}_k^{v_o}, u_k^{\omega} = \dot{x}_k^{\omega})$ where v_f, v_o and ω respectively are the predicted forward, orthogonal and angular velocities of the human.

The cost function is the following:

$$\phi_i = \begin{cases} \Phi_i + \gamma_0\left(\Delta_i^{x2} + \Delta_i^{y2}\right) + \gamma_1 \Delta_i^{\theta 2}, \forall i \in [\![n+1, k]\!] \\ \Phi_i, \forall i \in [\![k+1, n+N_{OC}]\!] \end{cases}$$

With $\Phi_i = \alpha_0 + \alpha_1 u_i^{v_f 2} + \alpha_2 u_i^{v_o 2} + \alpha_3 u_i^{\omega 2} + \alpha_4 \psi^2$ and $\Delta_i^\nu = c_i^\nu - x_i^\nu$. The function ψ and the weights α are the ones defined in Maroger et al. (2021). γ_0 and γ_1 were heuristically chosen so that the predictions fit as much as possible the N_0 last measurements.

This prediction model is solved with a Differential Dynamic Programming solver from the Crocoddyl library (Mastalli et al. 2020). The optimal solution is denoted $X_{n+1}^* = (\boldsymbol{x_{n+1}^*}, \dots, \boldsymbol{x_k^*}, \dots, \boldsymbol{x_{n+N_{OC}}^*})$. In this solution the **predicted trajectory** is $(\boldsymbol{x_k^*}, \dots, \boldsymbol{x_{n+N_{OC}}^*})$.

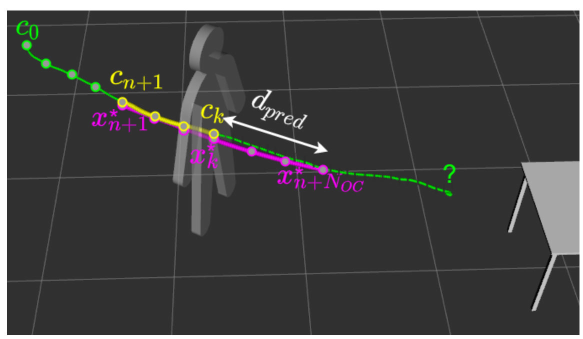

Figure 1: Simulation at time $t = kT_{OC}$ with $N_0 = 50$ and $N_{OC} = 100$ (in *green* and *yellow* the old and recent past human trajectory, in *strippled green* the unknown future human trajectory and in *purple* the solution of the current prediction model)

2.2 Metrics definition

The previously described prediction process was tested over 40 trajectories each one performed by 10 subjects. Those trajectories were recorded as part of

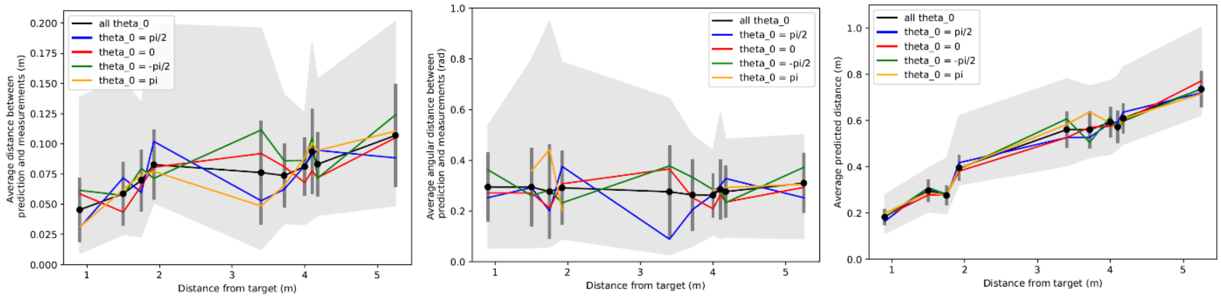

Figure 2: Average linear and angular errors and average predicted distance according to the distance between the starting position and the targeted position for every measured trajectory $N_0 = 50$ and $N_{OC} = 100$.

the study by Maroger et al. (2020). To assess this process, a metrics need to be developed. Three quantities seem to be relevant to tell if our model is efficient or not to predict human trajectories. For each human trajectory, we will compute:

- The average **linear and angular errors** between the predictions for each $t = kT_{OC}$ and the human trajectory defined as $\delta_{lin} = \frac{1}{N_{hum}} \sum_{k=N_0}^{N_f} \frac{1}{N_{pred}} \sum_{i=k}^{k+N_{OC}-N_0} \sqrt{\Delta_i^{x*2} + \Delta_i^{y*2}}$ and $\delta_{ang} = \frac{1}{N_f} \sum_{k=N_0}^{N_f-N_0} \frac{1}{N_{pred}} \sum_{i=k}^{k+N_{OC}-N_0} |\Delta_i^{\theta *}|$ with $\Delta_i^{\nu *} = c_i^{\nu} - x_i^{\nu *}$, $N_{hum} = N_f - N_0 + 1$ and $N_{pred} = N_{OC} - N_0 + 1$.
- The average **predicted distance** defined as $d_{pred} = \frac{1}{N_{hum}} \sum_{k=N_0}^{N_f} \sqrt{\left(x_k^{x*} - x_{n+N_{OC}}^{x*}\right)^2 + \left(x_k^{y*} - x_{n+N_{OC}}^{y*}\right)^2}$, this distance is represented on Fig.1.

3. Results and discussion

Those quantities were computed for the 400 measured trajectories which were chosen to be representative of common locomotion paths within a range of 0.6 to 5.5 m from the goal with four different starting orientations ($\theta_0 = -\frac{\pi}{2}, 0, \frac{\pi}{2}, \pi$). The results obtained with the following prediction parameters $N_0 = 50$ and $N_{OC} = 100$ are represented on Fig.2. We observe that the linear error and the predicted distance are correlated to the distance between the starting and the goal position. Indeed, the Pearson correlation coefficient are respectively equal to 0.87 and 0.98. Another observation that can be extracted from this figure is that there is a great variability according to the subjects as the lower and upper grey curves, representing respectively the minimum and the maximum of computed quantities, show.

The average of those quantities over all the trajectories for different prediction parameters are presented on Tab.1. Thus, the closer N_0 is from N_{OC}, the smaller both errors and the predicted distance will be. This is why, the choice of the prediction parameters should be a compromise between predicting far away and predicting with accuracy.

N_0	N_{OC}	δ_{lin} (m)	δ_{ang} (rad)	d_{pred} (m)
25	100	0.11 ± 0.04	0.42 ± 0.03	0.76 ± 0.29
50	100	0.08 ± 0.02	0.28 ± 0.01	0.48 ± 0.17
75	100	0.04 ± 0.01	0.14 ± 0.01	0.24 ± 0.08
50	200	0.18 ± 0.05	0.53 ± 0.07	1.40 ± 0.51

Table 1: Average errors and average predicted distance for different prediction parameters

4. Conclusions

In this study, we present and assess a prediction model of human trajectories during gait. This model, based on a human-like trajectory model using OC, provides prediction whose accuracy depends on the number of measurements given to the model and the number of predicted positions. When the predicted trajectory counts as many terms as the given measured trajectory ($N_0 = 50$ and $N_{OC} = 100$), the model is able to predict an average 0.5 m future trajectory with a linear error of 0.08 m and an angular error of 0.3 rad. Those results are satisfying for the targeted application, namely a humanoid robot proactively walking along a human.

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