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Matteo Ciocca, Pierre-Brice Wieber, Thierry Fraichard

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Effect of Planning Period on MPC-based Navigation
for a Biped Robot in a Crowd

Matteo Ciocca[1], Pierre-Brice Wieber[2], Thierry Fraichard[1]

Abstract— We control a biped robot moving in a crowd
with a Model Predictive Control (MPC) scheme that generates
stable walking motions, with automatic footstep placement.
Most walking strategies propose to re-plan the walking motion
to adapt to changing environments only once at every footstep.
This is because a footstep is planted on the ground, it usually
stays there at a constant position until the next footstep is
initiated, what naturally constrains the capacity for the robot to
react and adapt its motion in between footsteps. The objective of
this paper is to measure if re-planning the walking motion more
often than once at every footstep can lead to an improvement in
collision avoidance when navigating in a crowd. Our result is
that re-planning twice (or more) during each footstep leads to a
significant reduction of the number of collisions when walking
in a crowd, but depends on the density of the crowd.

I. Introduction

For a biped robot moving in a crowd, two things that
should be avoided are to fall and to collide with people.
Following the concept of Capturability [1], we can guarantee
that the robot will always be able to stop in a few footsteps
and maintain its balance forever. Following the concept of
Inevitable Collision States [2], it is impossible to guarantee
that collisions will never happen in a dynamic and uncertain
environment. It is nonetheless possible to guarantee that the
robot will be able to stop before a collision takes place,
should this collision be inevitable. This property is called
Passive Safety [3]. It has already been used effectively with
self-driving cars [4], autonomous helicopters [5] and mobile
robots in human environments [6].

Capturability has previously been used in Model Predictive
Control (MPC) schemes that generate stable walking mo-
tions, with automatic footstep placement, to guarantee both
fall avoidance and Passive Safety [7]. MPC is an iterative
control scheme that operates as follows: at each discrete
time instant t_i, a motion plan made up of a sequence of N
control actions is computed. The motion plan is valid from t_i
to t_{i+N}, where N is the *planning horizon*. The robot then
executes the first control action of the motion plan. The
planning process is repeated at the next time instant t_{i+1},
until the goal is reached. Let T denote the fixed time step (in
seconds) between two consecutive time instants $[t_i, t_{i+1}]$. In
MPC-based walking strategies such as [7], [8], [9], [10], [11]

[1] Univ. Grenoble Alpes, Inria, CNRS, Grenoble INP, LIG,
38000 Grenoble, France matteo.ciocca@inria.fr,
thierry.fraichard@inria.fr
[2] Univ. Grenoble Alpes, Inria, 38000 Grenoble, France
pierre-brice.wieber@inria.fr

or [12], this time step T is usually small. In [7] for instance,
T is set to the duration of the double support phase of the
walking cycle of the biped robot, *i.e.* 0.1[s]. This choice is
primarily made to ensure the balance of the walking motions.

Once a footstep is planted on the ground, it usually stays
there at a constant position until the next footstep is initiated.
This naturally constrains the capacity for the robot to react
and adapt its motion in between footsteps. As a result,
the walking strategies in [13], [14], [15] propose to re-
plan the walking motion to adapt to changing environments
only when a new footstep is initiated. In contrast, the MPC
scheme outlined above leads to re-planning the walking
motion every 0.1[s]. The objective of this paper is to measure
if re-planning the walking motion more often than once
at every footstep can lead to an improvement in collision
avoidance when navigating in a crowd. As an element of
comparison, it has been shown in [16] that when considering
only the balance of a biped robot, reacting more often than
every 0.2[s] to potential perturbations leads to no practical
improvement in the maximal tracking error.

Outline of the Paper: Section II presents the global mo-
tion planning framework used herein. Then Section III details
the walking/capturability and collision avoidance constraints
specific to the biped walking case considered. The MPC
framework for biped locomotion is outlined in Section IV.
The crowd scenario that is used for our evaluation purposes
is described in Section V-A whereas Section V-B presents the
specific robot parameters used. The results of the collision
rate obtained using simulated crowd scenarios are finally
presented and discussed in Section VI.

II. Motion Planning Through Optimization

A *motion* is made up by a sequence of actions. Among
possible motions, we want the biped robot to perform a
walking motion that *avoids falling*. And, when a biped robot
walks among people, it should perform a motion that also
avoids collisions. In our case, such motion can be achieved
by satisfying a closed convex set of constraints expressed as
linear inequalities of the form:

$$\underline{q} \leq G\,\mathbf{u} \leq \overline{q}, \tag{1}$$

where equality constraints can be expressed with $\underline{q} = \overline{q}$,
$\mathbf{u} = \{u_1, u_2, \cdots\}$ is a sequence of actions, $(\underline{q}, \overline{q})$ and G
are vectors and matrix of proper dimension. In our case
$\mathbf{u} \in \mathbb{R}^{2N+2m}$, where N control inputs to robot's 2D system
model, and m future footstep positions in 2D plane. Once
these constraints are satisfied, we choose the collision-free
walking motion that minimizes the deviation from a given

reference, *e.g.* robot maintains a constant walking speed. In our case, the reference deviation are expressed as a convex quadratic function:

$$f(\mathbf{u}) = \mathbf{u}^T Q_r \, \mathbf{u} + \mathbf{u}^T q_r, \tag{2}$$

where q_r and Q_r are a vector and matrix of proper dimension. Constraints and reference deviation are satisfied and minimized altogether, solving the following Quadratic Problem (QP):

$$\begin{aligned} \underset{\mathbf{u}}{\text{minimize}} \quad & f(\mathbf{u}) \\ \text{subject to} \quad & \underline{q} \le G\,\mathbf{u} \le \overline{q}. \end{aligned} \tag{3}$$

This is a linearly constrained convex optimization problem, with a global optimum $\mathbf{u}^*$ [17]. Solving problem (3) provides a motion plan $\mathbf{u}$ for the robot to perform. We solve it with **LexLS** [18].

III. MOTION CONSTRAINTS AND OBJECTIVES

A. Dynamics of Walking

The horizontal motion of the Center of Mass (CoM) $c \in \mathbb{R}^2$ of a humanoid robot is linearly related to the Center of Pressure (CoP) $p \in \mathbb{R}^2$ of the contact forces when walking with a constant height on a flat ground:

$$\ddot{c} = \omega^2 \, (c - p) \tag{4}$$

where $\omega^2 = g/h$, h is the height of the CoM above the ground and g is the norm of the gravity vector. This assumes a zero rate of change of the centroidal angular momentum [19]. Since contact forces with the ground are unilateral, the CoP resides in the support polygon [19]:

$$p - s_j \; \in \mathcal{P}, \tag{5}$$

where $s_j \in \mathbb{R}^2$ is the position of the jth footstep on the ground. The CoM position resides in a closed convex region due to the maximal leg length of the robot [20]:

$$c - s_j \; \in \mathcal{L}. \tag{6}$$

Biped robots should not cross their legs while walking. Given two consecutive footstep positions (s_j, s_{j+1}) and a region $\mathcal{S}_j$ where the legs do not cross, we enforce:

$$s_{j+1} - s_j \in \mathcal{S}_j. \tag{7}$$

The robot can realize a stable walk by continuously satisfying these constraints into the future [10]:

$$\boxed{\text{Walking } (W) \equiv (5) \wedge (6) \wedge (7)}. \tag{W}$$

This set of constraints can be expressed as linear inequalities.

B. Capturability Constraint

The biped robot is said to be 0-*step capturable* [1] when it can maintain balance indefinitely, without having to make any footstep. We enforce this situation by introducing the following equality constraint [21]:

$$\boxed{\text{Stop } (S) \equiv \dot{\xi} = 0} \tag{S}$$

where $\xi \in \mathbb{R}^2$ is the Capture Point defined as:

$$\xi = c + \omega^{-1}\dot{c}. \tag{8}$$

(W)-(S) represent together a closed convex set.

C. Collision Avoidance

Consider a crowd of Z persons. The robot avoids collisions with each person z_k by keeping a minimal separation distance from its CoM:

$$\|c - z_k\| \ge \sigma_0 \tag{9}$$

for all $k \in \{1, \ldots, Z\}$. In this equation, $z_k \in \mathbb{R}^2$ is the position of the kth person and σ_0 is the minimal separation distance. In our implementation, this nonconvex constraint on collision avoidance (C) is approximated with a separating line:

$$\boxed{\text{Collision Avoidance } (C) \equiv d_k \ge \sigma} \tag{C}$$

where

$$d_k = (n_k)^T (c - z_k). \tag{10}$$

$n_k \in \mathbb{R}^2$ is a unit normal vector that points from the center of the kth person to the CoM of the robot. An advantage of this approach is that, by being conservative, this linear over-approximation is always *safe* with respect to the nonlinear problem.

D. Robot's Perception

Assume the biped robot is equipped with a range sensor, *e.g.* laser telemeter or range camera, and it can only perceive a subset of people composing the crowd. This subset is the robot's *field of view*, denoted FoV. Its shape is arbitrary and it depends on the current surrounding of the robot and the maximum range of its sensor. In our case, the FoV has a circular shape and it is the maximal distance around the robot $R_{\max}$ at which it is capable of perceiving persons/objects: $\|c - z_k\| \le R_{\max}$. Occlusions in perception are disregarded, making the robot aware of the current position of everybody within the FoV.

E. Walking References

The robot should walk at a certain speed $\dot{c}_r$ and keep the CoP p as close as possible to the center of the foot on the ground s, to improve the robustness of the robot against perturbations [19]. These are referred as:

$$\boxed{\text{References } (R) \equiv \begin{cases} \dot{c} - \dot{c}_r = 0 \\ p - s = 0 \end{cases}} \tag{R}$$

and they can be expressed as a convex quadratic function [10].

IV. MODEL PREDICTIVE CONTROL FOR BIPED WALKING

Model Predictive Control (MPC) is used for biped loco-motion with automatic footsteps placement [10]. Time is discretized in a sequence of time instants t_i, $i \in \mathbb{N}$. Each time interval $[t_i, t_{i+1}]$ has a fixed duration T in seconds. Assuming the robot is walking on a flat ground, the motion of the CoM of a biped robot can be modeled in both horizontal coordinates as a linear discrete time system [21]:

$$\hat{c}_{i+1} = A\hat{c}_i + B\dot{p}_i \tag{11}$$

where

$$A = \begin{bmatrix} 1 & \sinh(T\omega)/\omega & \cosh(T\omega)/\omega^2 - 1/\omega^2 \\ 0 & \cosh(T\omega) & \sinh(T\omega)/\omega \\ 0 & \sinh(T\omega)\omega & \cosh(T\omega) \end{bmatrix}$$

$$B = \begin{bmatrix} T - \sinh(T\omega)/\omega \\ 1 - \cosh(T\omega) \\ -\omega \sinh(T\omega) \end{bmatrix}. \tag{12}$$

$\hat{c}_i = (c_i, \dot{c}_i, \ddot{c}_i)$ and $\hat{c}_{i+1} = (c_{i+1}, \dot{c}_{i+1}, \ddot{c}_{i+1})$ are two consecutive states, and $\dot{p}_i$ is the velocity of the CoP, it is the control input of the system. A linear relationship is applied to the selection of the footsteps as:

$$s_{i+1} = V_i^c s_i^c + V_i^f s_i^f \tag{13}$$

where s_i is the current footstep on the ground, s_f is the future footstep position and V_i^c and V_i^f are cyclic time-varying scalars that determine which footstep is on the ground at what time (details are provided in [10]). A control action is therefore a couple of variables:

$$u_i = \begin{bmatrix} \dot{p}_i & s_i^f \end{bmatrix}. \tag{14}$$

MPC approach: At each time t_i, given the current state and footstep onto the ground $(\hat{c}_i, s_i^c)$, a single QP (3) is solved to plan a motion, composed by a sequence of N control actions $\mathbf{u}^N = \{u_1, \cdots, u_N\}$. The couple u_j represents: the control input $\dot{p}_{i+j-1}$ and s_{i+j-1}^f footstep on the ground both at time instant t_{i+j-1} and kept constant for a duration T, for $j = \{1, 2, \cdots, N\}$. The motion is valid for N time instants (from t_i to t_{i+N}) and it has a duration NT, where N is called the planning horizon. Usually, the first control action u_1 is executed, *i.e.* $\dot{p}_i$ is applied to the CoM dynamics (11) and the robot takes s_i^f footstep (or keeps s_i^c on the ground). Then at time t_{i+1}, the whole motion planning process is repeated.

We call the *planning period* M, with $M \in \{1, 2, \cdots, N\}$, the number of time instants before the motion planning process is repeated. It corresponds to applying M control actions before repeating the process at time t_{i+M}.

A. Robot Navigation Scheme with Fall avoidance and Passive Safety guarantees

Fall avoidance for a biped robot is guaranteed if the robot can keep its balance indefinitely. Passive Safety (PS) guarantees that the robot is able to stop before a collision occurs: if a collision is inevitable, at least the robot will be at rest when that happens. PS can be proved using a conservative model of the surrounding environment [3]. Fall avoidance and PS are guaranteed together in a single MPC scheme for biped robots combining the conservative model that anticipates the motion of people (18) and the constraint (S) to ensure that the robot can stop (keeping its balance indefinitely) before any collision happens [7].

The main idea is that at time instant t_i the robot tries to compute a valid motion for N time instants in which it will walk without colliding for few footsteps and additionally maintain balance in the last footstep forever, *i.e.* stop. If it cannot compute such motion, it can always execute all the remaining $N - M$ actions of the last computed motion at time instant t_{i-M} as *fallback*. As a consequence, the robot walks without colliding and it will stop balancing on its last footstep on the ground (fall avoidance guaranteed) before any collision occurs (PS guaranteed). Before executing the remaining actions of the last computed motion as fallback, we go through a simple loop to find a motion valid for the largest number of time instants: $\{N-M, N-M+1, \cdots, N\}$, that satisfies all constraints.

B. Newton method

While the linear approximation in (C) is safe with respect to the nonlinear problem (9), it over-constrains the behavior of the robot. To treat collision avoidance as a nonlinear problem we apply a Newton method [17] each time we solve the QP (3). By an abuse of notation, after each iteration j, the normal vectors n_j corresponding to each person is updated with the previous optimal solution $\mathbf{u}_{j-1}^*$

$$n_j = n_{j-1}(\mathbf{u}_{j-1}^*). \tag{15}$$

The iteration stops when:

$$\|f(\mathbf{u}_{j-1}^*) - f(\mathbf{u}_j^*)\| \leq \epsilon. \tag{16}$$

The maximum number of iterations is set to `max_Iter` and ϵ is chosen arbitrarily small (Table I). Thanks to the safe linear approximation of (C), feasible iterates are always generated. Note that the convergence condition (16) does not guarantee optimality. The main interest of this work is not to guarantee optimality of the motion with the Newton method, but to plan a motion that treat collision avoidance as close as possible to a nonlinear problem.

Parameter	Symbol	Value
Newton step Iterations	`max_Iter`	5
Convergence Parameter	ϵ	10^{-4}

TABLE I: Newton method parameters.

V. CROWD AND ROBOT PARAMETERS

A. Crowd

One possible model for the crowd behavior could be that every person is very careful in trying to avoid all collisions with the robot. With such a strong bias, the evaluation of the robot's own strategy would not be very meaningful [22].

Another extreme could be a crowd specifically aiming at collisions with the robot, which would once again corrupt the evaluation of the robot's strategy. One way to evaluate the robot's strategy and the robot's strategy alone, could be to consider that the robot is actually the only one in charge to avoid collisions. This leads us to considering a crowd not paying attention to the presence of the robot. We consider therefore people walking in a constant direction at constant speed. We consider the worst case scenario where the robot is walking in the opposite direction of the crowd.

The robot needs to avoid collisions in the present and into the future, we need therefore a model that anticipate the motion of people. In our crowd scenario: (i) people walk at a constant velocity and they do not try to avoid the robot and (ii) collisions among people are disregarded. The robot uses these information to anticipate the motion of people. We also consider uncertainties in position and velocity estimations of the crowd with respect to the real position z_k and velocity $\dot{z}_k$:

$$\tilde{z}_k = z_k - \hat{z}_k, \ \tilde{\dot{z}}_k = \dot{z}_k - \hat{\dot{z}}_k, \qquad (17)$$

and for collision avoidance (C), we account for this uncertainty by adapting the minimal separation distance in a *conservative* way:

$$\sigma(t) = \sigma_0 + \|\tilde{z}_k\| + \|\tilde{\dot{z}}_k\|t. \qquad (18)$$

Here, given the magnitude of the uncertainty in position $\|\tilde{z}_k\|$, we consider that the real position z_k lies in a circle of radius $\|\tilde{z}_k\|$ centered at the estimated position $\hat{z}_k$. Furthermore, given the magnitude of the uncertainty in velocity $\|\tilde{\dot{z}}_k\|$, the radius of this circle increases at a rate $\|\tilde{\dot{z}}_k\|t$ as it moves with the estimated velocity $\hat{\dot{z}}_k$.

We consider 100 different random crowds, composed of Z people that differ in the initial positions $\{z_k^x, z_k^y\}$ and speeds y: $\{\dot{z}_k^y\}$ of the participants. The initial positions of the people vary uniformly over an area of $10 \times 8[\text{m}^2]$. For all people the velocity along x is chosen constant 0.5[m/s], while for each person speed along y is picked randomly in an interval $[-0.2, 0.2][\text{m/s}]$.

Parameter	Symbol	Value	Unit
Size of the crowd	Z	$\{8, 16, 32\}$	ppl
Number of randomly generated crowds (for size Z)	-	100	-
Speed of the crowd	$\dot{z}_k^x$	0.5	m/s
	$\dot{z}_k^y$	$[-0.2, 0.2]$	m/s
min. separation distance (18)	σ_0	1	m
Uncertainty (18)	$\|\tilde{z}_k\|$	$\{0, 0.15, 0.30\}$	m
	$\|\tilde{\dot{z}}_k\|$	$\{0, 0.05, 0.10\}$	m/s

TABLE II: Crowd Parameters.

B. Robot

The parameters of the simulated robot were selected according `HRP-2` robot [23]. In our MPC framework, the walking cycle of the biped robot is divided in two stages: single and double support phases (SS and DS). SS duration is 0.7[s] and DS duration is 0.1[s], resulting in a step cycle

of $s_d = 0.8$[s/footstep], and the time step T is equal to the DS duration ($T = 0.1$[s]). These duration have been used to generate stable walking motions [9]: changing the duration of SS, DS (and hence T) is out of the scope of this work. We control the robot with the MPC scheme in Section IV-A that guarantees fall avoidance and PS.

When the robot walks against a crowd, the robot perceives people around it within a FoV based on a specific sensor, *e.g.* laser scanner. The choice of FoV is not treated fully as in [3], but it is chosen greater than a certain lower bound in order to guarantee PS [7]. This lower bound depends on plan duration NT and, robot's and people walking speed: $R_{max} \geq NT(\dot{z}^x + \dot{c}_r^x)$.

With the MPC scheme in Section IV-A, the robot can plan up to $\lceil (NT/s_d) \rceil$ footsteps ahead. We choose to plan up to two full footsteps ahead, $N = 16$, since it is a standard choice for biped locomotion with our MPC scheme [21], [10]. In our case, with $M = 1$, the re-planning takes place 8 times within each footstep (re-plans every 0.1[s]). We consider the case where the robot re-plans 2 times within each footstep: at every footstep and at the midpoint of each footstep $M = 4$ (re-plans every 0.4[s]), and the case where the robot re-plans 1 time between each footstep: only at every footstep $M = 8$ (re-plans every 0.8[s]).

Parameter	Symbol	Value	Unit
Height of CoM (4)	h	0.80	m
Min. Feet Separation (7)	f_s	0.07	m
Feet Dimensions (5)	f	$(0.24, 0.14)$	(m,m)
Leg Stride (6)	l	$(0.24, 0.30)$	m
Step Cycle	s_d	0.80	s/footstep
Planning Horizon	N	16	-
future footstep positions	$\lceil (NT/s_d) \rceil$	2	footstep
Time Step	T	0.10	s
Planning Period	M	$\{1, 4, 8\}$	-
Reference Speed (R)	$(\dot{c}_r^x, \dot{c}_r^y)$	$(0.5, 0.0)$	m/s
FoV distance	$R_{\max}$	4	m

TABLE III: Robot Parameters.

VI. EFFECT OF PLANNING PERIOD ON COLLISION RATE

The effect of M on the collision rate for a biped robot traversing a moving crowd is evaluated numerically, as seen in Fig. 1. The initial positions of the people are randomly chosen in front of the robot outside the FoV. The crowd parameters are summarized in Table II, the robot parameter in Table III.

A. Choice of M for Crowd Density

For each uncertainty ($\|\tilde{z}_k\|, \|\tilde{\dot{z}}_k\|$), we simulate 100 crowds of Z people. Each simulation lasts for 20[s], or until a collision occurs. Table IV shows the performance of collision avoidance by counting the total number of collisions for each choice of planning period M and crowds size Z with varying uncertainty ($\|\tilde{z}_k\|, \|\tilde{\dot{z}}_k\|$). We count the number of collisions for each combination $\{M, Z\}$ that happened in 900 simulations.

The results indicates that re-planning twice (or more) during each footstep leads to a significant reduction of the number of collisions when walking in a crowd. But this reduction depends on the density of the crowd.

When the robot is traversing few people, $Z = 8$, the choice of $M = 8$ performed worse than $M = 4$ by 77%, and $M = 4$ performed worse than $M = 1$ by 38%. For low-density crowds, collisions when re-planning 8 times every footstep ($M = 1$) are less than twice compared to re-plan once every footstep ($M = 8$) and less than twice the collisions compared to re-plan twice every footstep ($M = 4$). In this case re-planning less often to save computational power comes at the expense of a decay in collision avoidance performance, therefore we favor the planning period $M = 1$.

When a biped robot is traversing many people, $Z = \{16, 32\}$, the choice of $M = 8$ performed worse than $M = 4$ by 53%, and $M = 4$ performed worse than $M = 1$ by 20%. For high-density crowds, collisions when re-planning 8 times every footstep ($M = 1$) are more than twice the collisions compared to re-plan once every footstep ($M = 8$) but only reduced them by a fifth compared to re-plan twice every footstep ($M = 4$). We can then favor a planning period $M = 4$ over $M = 1$ (re-planning 4 times less) to save computational power, since it performs worse by only a fifth in collision avoidance.

B. Collisions and Uncertainty

We now give some insight on the relationship between collisions and uncertainty. We summarize in Table V the total number of collisions occurring in 300 simulations with different crowd sizes Z, for each planning period M and various amount of uncertainty ($\|\tilde{z}_k\|, \|\tilde{\dot{z}}_k\|$).

When there is uncertainty, the robot accounts for it by being more cautious: uncertainty is represented as an additional *area* where people might be into the future and the robot needs to avoid it.

As result, the number of collisions decreases in the presence of uncertainty. We can observe that uncertainty on speed has a higher impact on the number of collisions than uncertainty on position.

Fig. 1: t_0 in a crowd scenario with $Z = 16$: robot in black, people in blue (collisions among people are disregarded), the FoV is the dashed circle and the instantaneous velocity of each person and robot is represented by the green vector. The robot is asked to walk to the right with $\dot{c}_r^x = 0.5$[m/s].

Uncertainty		Collisions		
$\|\tilde{\dot{z}}_k\|$[m/s]	$\|\tilde{z}_k\|$[m]	$M = 8$	$M = 4$	$M = 1$
	0.00	219	91	80
0.00	0.15	203	82	70
	0.30	199	100	77
	0.00	163	78	63
0.05	0.15	169	79	62
	0.30	151	78	62
	0.00	138	69	52
0.10	0.15	141	72	57
	0.30	136	71	54

TABLE V: Relationship between collisions and uncertainty.

Crowd Size Z[ppl]	Collisions		
	$M = 8$	$M = 4$	$M = 1$
8	324	74	46
16	557	289	235
32	638	357	296
total collisions	1539	720	577

TABLE IV: Collision Rate of M for crowd density.

VII. CONCLUSIONS

We control a biped robot moving in a crowd with our MPC framework that guarantee fall avoidance and PS [7]. Most walking strategies propose to re-plan the walking motion to adapt to changing environments only once at every footstep. This is because a footstep is planted on the ground, it usually stays there at a constant posi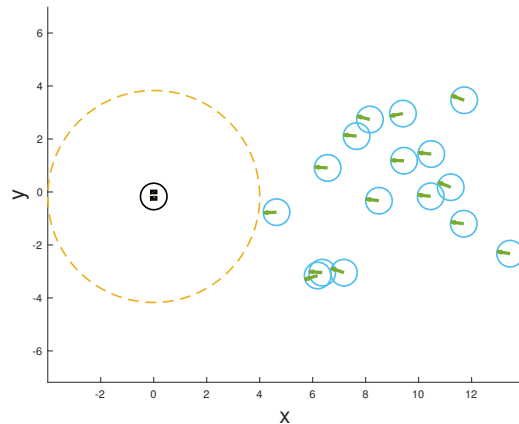tion until the next footstep is initiated, what naturally constrains the capacity for the robot to react and adapt its motion in between footsteps. Our result shows that re-planning twice (or more) during each footstep, instead of only once, leads to a significant reduction of the number of collisions when walking in a crowd. In addition, the choice of re-planning can be done according to the density of the crowd. For highly-dense crowd, re-planning more than twice during each footstep does not improve significantly the number of collisions.

As future work, we want to apply different *synchronization* for the re-planning. For example, the re-plan only at every footstep is synchronized with the DS phase of the robot. We want to synchronize this re-planning choice with the SS phase. And we would like to explore how the choice of re-planning affects collision avoidance performance for a fixed crowd density with different crowd speeds.

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