

# L3M-SIM Team Description

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**Abstract.** This paper presents the French team composition and research objectives for its third participation in the 2014 RoboCup 3D Simulation Soccer League.

## 1 Team composition

The team name comes from *Les Trois Mousquetaires* in reference to the novel by Alexandre Dumas. The members mainly originate from the standard platform league, where the French team was named L3M. As some members of the L3M team decided to experiment the 3D Simulation Soccer League, we chose the name of L3M-SIM.

Institutes and people involved in the L3M-SIM team are:

- Université Paris 8,  
Laboratoire d'Informatique Avancée de Saint-Denis (LIASD),  
*Nicolas Jouandeau (faculty staff),*  
*Thomas Da Costa (student staff).*
- Université de Versailles,  
Laboratoire d'Ingénierie des Systèmes de Versailles (LISV),  
Science and Technology Engineering School (ISTY),  
*Vincent Hugel (faculty staff).*

## 2 Research objectives

### 2.1 Morphogenesis

The geometric model of the 3D-SSL NAO version was made generic in terms of size and layout of the different parts that constitute the robot [1]. This enabled to optimize its morphology to design new players with new physical characteristics [2]. According to an optimization process, we tuned its physical characteristics and its walking skills' parameters. We defined two evolution policies that generate best-first and best-average agents. The evolution process, that corresponds to a sequence of experiments, is lead by a fitness function that takes into account the success rate of each experiment. One experiment contains several

trials where the number of trials without falling and the average of the results is taken into account to select best values. The values relative to each new experiment are defined according to a history set populated with previous results.

In a first research study, we checked the proper sizing of the NAO's model as a proof of concept of our evolution process. Based on the standard NAO model used in RoboCup 2013 3DSSL, the *ThighRelHip2\_Z* parameter was varied from  $-0.01$  to  $-0.10[m]$  during the evolution process. After 500 iterations, we found a *ThighRelHip2\_Z* best value equal to  $-0.038[m]$ , that confirmed the correct value of  $-0.04[m]$  used in the standard NAO model.

We carried out a second work that was focused on a morphological evolution to build faster NAOs. We developed a tuning process to determine possible relationships between the 5 following parameters:

- *ThighRelHip2\_Z*, that defines the semi-length of the femur.
- *ratio\_flexion*, that defines the leg flexion.
- *long\_offset\_MidAnkles\_2\_Torso\_Init*, that defines the leg spacing.
- *height\_lift*, that defines the step height.
- *xlength\_step\_max*, that defines the step size.

These works showed that morphological optimization can improve player's performances. By modifying the femur semi-length, the robot issued from morphogenesis achieved to walk 1.5 times faster than the original NAO, with a forward speed of  $7.121[m/s]$  and a rotating speed of  $128.25[deg/s]$ , while our NAO without optimization was walking at  $4.422[m/s]$ . We are now focusing on designing heterogeneous players to increase team's performances.

## 2.2 Motion module

The motion module was improved to enable stronger kicks and safer displacement. Safer displacement involves a specific management of acceleration and deceleration phases to reduce the frequency of falls.

**Kicks.** A new kick was designed to enable robots to kick the ball further way, up to  $9[m]$ . Strong kick capabilities offer a serious advantage to the kick-off team that can send the ball deep into the opponent field.

The new kick consists of the following phases:

- sway hips to transfer the load above the kicking foot, then lift, swing, and put down the supporting foot. Transfer the load to the supporting foot, and tilt the trunk laterally and externally. This enables to put the supporting foot next to the ball.
- lift the kicking foot while raising the body.
- put the kicking foot backward while rocking the trunk forward. The final position of the leg is called the backward position.
- put the kicking foot in the position of kick, i.e. the foot toes in contact with the ball, while reaching a fixed inclination of the trunk.
- put the kicking foot forward to accompany the kick movement, while rocking the trunk backward. The final position of the leg is called the forward position.

The rocking of the trunk is possible thanks to the actuation of the hip of the supporting foot. This enables to increase the velocity of the kicking foot at the time of hitting the ball, therefore transmitting a larger amount of kinetic energy to the ball, which permits to send the ball farther away. The kicking movement is parameterized. The positions of the kicking leg in the backward position, in the kicking position and in the forward position can be tuned to optimize the distance covered by the ball after the strike. The parameters for each position are the frontal and vertical offsets of the foot toes with respect to the position of the foot in support, the rotation angle of the torso and the rotation angle of the foot sole in the sagittal plane.

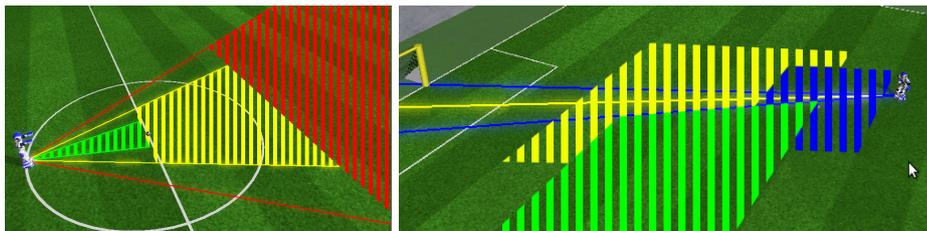
**Safer displacement.** The locomotion algorithm is based on the 3D-LIP model [3,4] that consists of defining walking primitives of the center of mass (COM), keeping its height constant and assuming no torque at the support foot [5]. The ZMP technique is used to determine the COM trajectory during the walk and then to calculate the joint angle commands. Up to now the foot step length was kept constant from the beginning to the end of the displacement. Therefore the zero moment point had to be located further backward for the starting step, and further forward for the ending step, which lead to a serious limitation of the velocity because the ZMP has to stay below the supporting foot. Larger velocities caused higher fall rates.

In order to increase the velocity while minimizing the risk of falls, it is necessary to parameterize the acceleration, resp. deceleration, at the beginning, resp. end, of the walking motion. The parameter is the maximal acceleration/deceleration allowed. This lead to a trapezoidal profile of the velocity over the walking motion. The successive steps are then calculated by integration of the velocity profile. Thanks to this technique the length of the successive steps increases during the acceleration phase, remains constant during the constant-velocity phase, and decreases during the deceleration phase.

### 2.3 Collective behavior design

Our previous developments on behavior's design for single agents were based on Finite State Machine design. The collective behavior was based on message passing protocol that allowed to share current state and desired state among players. Therefore, a collective decision-making process was activated to define next collective actions. It was applied to simple collective situations that involved up to 3 real NAOs in the SPL [6]. Results showed that it would be difficult to build a collective behavior that involves more agents, as all combined behaviors of single agents had to be specified. The same statement holds for XABSL extensions [7]. Since more graphical issues are currently admitted to express collective behaviors, we enhanced our collective manager and we started to study the learning opponent's strategy problem [8,9] by extracting previous teams log-files. Our current collective manager defines each player position at each time, mainly depending on the ball's position area. The settled strategy is a Case-Based Reasoning [10], applied on a grid where agents are associated

with areas. Each player is also associated to a specific role. The behavior of each role depends on other entities like the ball and opponents positions. Figure 1 shows two examples of such area-based reasoning. Roles are similar to *go to a position on the field*, *push the ball*, *go to the ball* and *kick it*, *push the ball towards opponent goal* and *block opponents path to defend our goal*. We believe that this will allow us to adapt strategies to opponent teams.



**Fig. 1.** Two examples of area reasoning to create adaptive behaviors.

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