Neural Network for a Curved Kicking Mechanism in a SSL Robot

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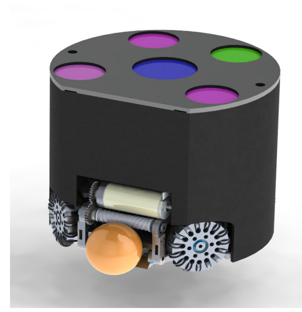
***Abstract*— This electronic document is a live template. The various components of your paper [title, text, heads, etc.] are already defined on the style sheet, as illustrated by the portions given in this document.**

I. INTRODUCTION

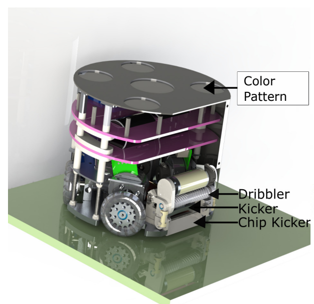
The Small SIze League (SSL) is a robot soccer competition of omnidirectional robots with matches of two teams of 6 robots, for the division B, or 8 robots, for the case of division A [1]. The rules establish that the robots must fit in a cylinder of 180 mm diameter and 150 mm height. Generally, the robots have 4 wheels, with several little rollers, that allows the omnidirectional movements of the robot. The vision system is made of cameras positioned on the ceiling of the field and vision algorithms capable of identify every robot because of a color pattern on the top of the robots, measuring its position and angular orientation. The most of the processing, like strategy algorithms and trajectory calculation, occur in a central computer that communicates with the robots via radio. The robot have two kicker systems, with a high kick, called chip kicker, and a low kick, called kicker, that are the principally responsible for the robot's pass and goals. Other important device of the robot is the dribbler, based on the rotation of a roller, that rotates the ball to make it stand on the robot.

An important characteristic of the robot is the ability of make straights pass and kicks using the chip kicker and the kicker devices. This paper documents the project of a neural network for the ITAndroids team to decide the kicking parameters for a curved kick, like velocity of the kick, angular slope of the robot and velocity of ball's rotation on the field applied by the dribbler. The mechanism that allow the curved kick was designed by the team based on the device of the team Op-AmP [2]. ITAndroids is the robotics competition group from Instituto Tecnolgico de Aeronutica (ITA). The group also has experience with other robotics competitions, namely RoboCup's Soccer 2D, Soccer 3D and Humanoid Kid-Size leagues. The team's Small Size robot may be seen in the Fig 1a, its kicker and chipper devices in the Fig 1b and the curved kicking device designed by the team may be seen in the Fig 1c.

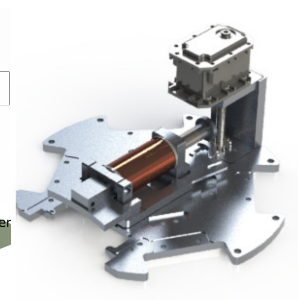
The kicker and chip kicker devices are based on a ferromagnetic part being expelled by a solenoid subtly by the discharge of a capacitor. This ferromagnetic part hits the ball, transferring linear momentum, accelerating the ball. The main difference from the low kick to the high kick is the slope of the hit. The curved kicker device uses a Geneva drive to, rotating the kicker, make the ball be launched in a angled trajectory, as may be seen in the Fig. 2, that show tests on the robot's kicker of the Op-AmP team [2]. Combining that with the dribbler, it is possible to the ball to make a parabola-like trajectory.



(a) General vision of the robot.

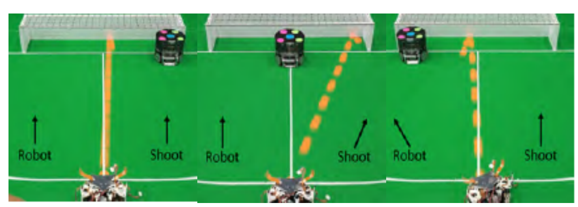


(b) Systems of the robot.



(c) Designed mechanism for the curved kick.

Fig. 1: Small Size robot of the ITAndroids team.



(a) straight kick. (b) Diagonal kick 1. (c) Diagonal kick 2.

Fig. 2: Results of the angled kick of the Op-AmP team.

The main advantage of the angled kick device is that it makes the kick less predictable, so teams that consider that the robot kicks is aligned with the robots front hardly will predict where the robot is aiming, misleading the opponent.

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Also, using it combined with the dribbler, it is possible to make curved kicks, that is extremely difficult to predict, since the curve that defines the trajectory of the ball is a solution of a non linear ODE, that depends of the velocity of the kick, angular slope of the robot and velocity of ball's rotation on the field applied by the dribbler. In addiction, since this mechanism is very recent in the competition, and the majority of the teams use only the straight kick, the most of the teams on the competition do not consider it on the strategy algorithm, making it almost uncounterable.

Also, to contour a adversary usually it is used the chip kicker. But in situations that the opponent is too close, it is ineffective, since the is a minimum height needed by the chip kicker to be effective. As shown in Fig. 3, to overcome that, may be used the curved kick to make a pass, as we call curved pass. The curved kick situation may be seen in Fig. 4 and one of the most impressive use of the curved kick may be seen in the Fig. 5, as we call the Olympic goal.

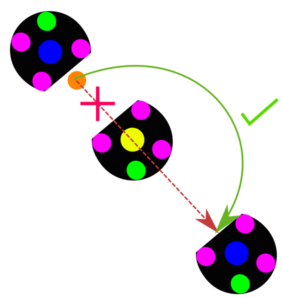


Fig. 3: Curved pass. Straight pass trajectory in red and curved pass trajectory in green.

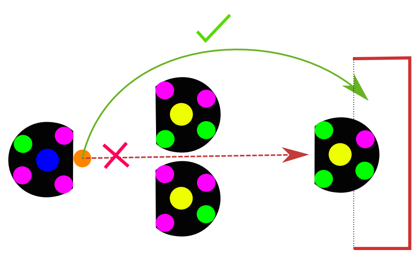


Fig. 4: Curved kick. Straight kick trajectory in red and curved kick trajectory in green.

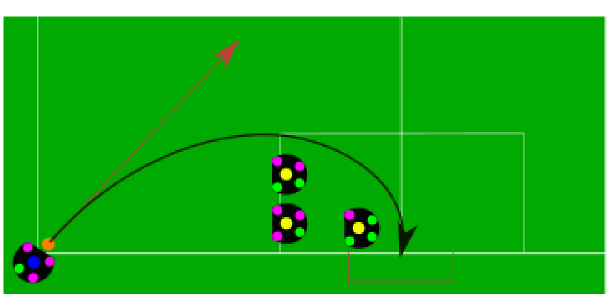


Fig. 5: Olympic goal. Curved kick trajectory in black.

As said before and will be shown, the trajectory of the ball is a solution of complex nonlinear ODEs that are solved numerically. But the solution of that problem give the position on the Cartesian's plan given the velocity of the kick, the slope and angular velocity of the dribbler, but, if it was need the opposite? To make the precise kick, it is needed to aim in some point of the plan, than apply the velocity, slope and angular velocity that is needed, for example, to make a curved pass aiming in a ally. Obtain that is far from simple, requiring the inverse solution of the problem, making it even more complex and costly computationally. To solve this problem, was used a shallow neural network [3] that was trained with cases of the parameters of the kick and the position the ball reached. It prevents from needing a mathematical model of the inverse problem and make the results quicker for the robot, what is very important since the algorithm runs in real time during the match. The numerical solution of the equations, the neural network and the simulation was made on the software MATLAB.

II. PROJECT REQUIREMENTS

The following requirements was proposed to the project in the simulation:

- The robot must be able of performing a curved pass.
- The robot must be able of performing a curved kick.
- The robot must be able of performing a Olympic goal.
- The kicked ball must be reach a target with $\pm 0.2\ m$ of precision.

That requirements was proposed for a first instance and simulation only project. As the project evolves to the physical mean and requires more precision, the requirements will be refined.

III. BALL TRAJECTORY MODELLING

A. Model of the Friction of the Ball

To model the ball trajectory, first is needed to model the friction of the ball. As shown in [4], an interesting phenomenon, known as rolling friction, occurs in the movement of the ball. When the ball is kicked, it starts sliding, because of the high variation of its linear momentum in a small time instant, so that way it slides in high velocity until part of the kinetic energy be transformed in rotation energy and part being lost because of the friction, starting the rolling movement, when its continue to loose its kinetic energy, now slower than before, until it stops. Fig 6 illustrates the interaction ball-carpet interaction.

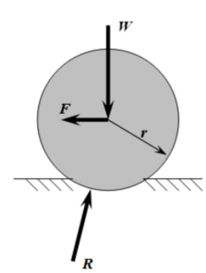


Fig. 6: Interaction ball-carpet.

As shown in [4], the ball stops to sliding and begin to roll when the velocity of the ball is 0.5805 of the initial value.

B. Model of the Kicked Ball

First of all, we will set the reference coordinate system. The origin of the system was put on the left corner of the adversary goal on the Division B field. It was made because in the beginning of the project the only requirement was the Olympic goal and the ITAndroids team competes on the Div. B field. To change that, a simply coordinate transformation may be made, using a translation and a rotation. The coordinate system may be seen in the Fig. 7.

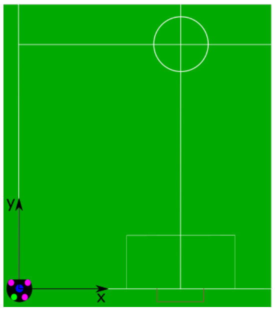
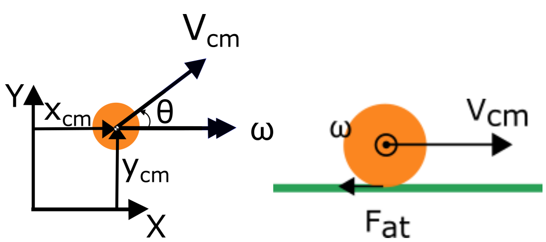


Fig. 7: Coordinate system on the field.

The diagrams used for the ball model may be seen in Fig. 8a and 8b.



(a) Superior view of the ball trajectory. (b) Lateral view of the ball trajectory.

Fig. 8: Diagrams for the ball movement model.

The equations of the movement and its mathematical manipulation may be seen on (1) to (9), where $\vec{V}_{COM}$ is the velocity vector in the center of mass, θ is the angle that the vector velocity on the center of mass makes with the x axis of the reference system, $\vec{\omega}$ is the angular velocity of the ball, $\vec{V}_{CP}$ is the velocity on the point of contact of the ball with the ground, r is the ball radius, $\vec{F}_{fric}$ is the friction force, μ is the coefficient of friction of the ball with the carpet, m is the mass of the ball, g is the acceleration of gravity, $\vec{T}_{F_{fric}}$ is the torque caused by the friction force, I is the moment of inertia of the golf ball, x is the position of the ball in its trajectory, V_0 is the initial velocity of the ball, $\vec{\omega}_0$ is the initial angular velocity of the ball and (X_0, Y_0) is the starting point of the ball trajectory.

Initially, defining the linear and angular velocity of the ball in (1), (2) e (3).

$$\vec{V}_{COM} = V_{COM}(cos\theta\hat{i} + sen\theta\hat{j}) \tag{1}$$

$$\vec{\omega} = \omega_x\hat{i} + \omega_y\hat{j} \tag{2}$$

$$\vec{V}_{CP} = \vec{V}_{COM} + \omega \times (-r\hat{k}) \tag{3}$$

So, we determine the vector of friction in (4).

$$\vec{F}_{fric} = \mu mg \left(\frac{-\vec{V}_{CP}}{\left\| \vec{V}_{CP} \right\|} \right) \tag{4}$$

The torque generated by the friction is also determined in (5).

$$\vec{T}_{F_{fric}} = \vec{F}_{fric} \times (-r\hat{k}) \tag{5}$$

By the definition of torque, we have (6).

$$\vec{T}_{F_{fric}} = I\frac{d\vec{\omega}}{dt} \tag{6}$$

Substituting (3) in (4), we obtain (7).

$$\begin{aligned} \vec{F}_{fric} = -\mu mg \left(\frac{(V_x + r\omega_y)\hat{i} + (V_y - r\omega_x)\hat{j}}{\sqrt{(V_x + r\omega_y)^2 + (V_y - r\omega_x)^2}} \right) \\ = F_{fric_x}\hat{i} + F_{fric_y}\hat{j} \end{aligned} \tag{7}$$

From (5) and (7), we have (8).

$$\vec{T}_{F_{fric}} = -r(F_{fric_x}\hat{j} - F_{fric_y}\hat{i}) \tag{8}$$

Finally, we have the equation that rules the ball movement in (9).

$$\begin{aligned} I\left(\frac{d\vec{\omega}_x}{dt} + \frac{d\vec{\omega}_y}{dt}\right) = \\ -\mu mgr \left(\frac{(V_y - r\omega_x)}{\sqrt{(V_x + r\omega_y)^2 + (V_y - r\omega_x)^2}} \right)\hat{j} \\ + \mu mgr \left(\frac{(V_x + r\omega_y)}{\sqrt{(V_x + r\omega_y)^2 + (V_y - r\omega_x)^2}} \right)\hat{i} \end{aligned} \tag{9}$$

With the boundary conditions being (10), (11) and (12).

$$V_0 = V_{kick} \tag{10}$$

$$\vec{\omega}_0 = \omega_{dribbler} \tag{11}$$

$$X_0 = 0,\ Y_0 = 0 \tag{12}$$

Clearly (9) is a nonlinear ODE. So, to solve it, was used the function ODE45 of the software MATLAB.

As said before, to invert the problem, so we could get the parameters V_{kick}, $\omega_{dribbler}$ and θ would be a really complex problem, and that motivated the usage of the neural network.

IV. THE NEURAL NETWORK

To choose what neural network would be the most appropriate to solve the problem, we first considered the kind of problem that we wanna solve: to establish a simply correlation between two group of parameters, $V_{kick}, \omega_{dribbler}, \theta$ and x_{target}, y_{target}, being x_{target} and y_{target} the coordinates of the target that we wanna to hit with the ball. For a problem like that, was choose the Shallow Neural Network [3], that is less complex than a Deep Neural Network and can easily solve the problem.

With the neural network chosen, we created the data that will be used to train the network. Using the MATLAB's function ODE45, (9) was solve for a large number of combinations of $V_{kick}, \omega_{dribbler}, \theta$, obtaining the respective positions that the ball hit.

To take the coordinates from the simulation a simplification was made: we considerate that the robot is always on the origin of the coordinate system and the target is laying on the x axis, ergo, the y_{target} from the simplified system will always be zero. This reduces the number of variables on the coordinate system from four, considering x and y from the position of the robot and the x_{target} and y_{target}, to one, x'_{target}. Obviously, that is a consideration that would make the curved pass and curved kick to be extremely imprecise. The strategy to use it was: all the data was trained on the simplified system, and for the result, we take the real position, make a translation and a rotation on the coordinates, obtain the position on the simplified system, and use it on the neural network, obtaining the values of $V_{kick}, \omega_{dribbler}, \theta$ that is independent of the position of the robot, and then apply that values to the real coordinate system. The Fig. 9 illustrates that procedure.

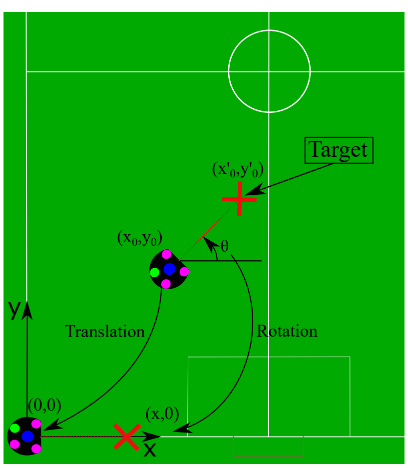


Fig. 9: Coordinate system transformation between real system and simplified system.

Then, a matrix to train the neural network was made, with a large number of data of $V_{kick}, \omega_{dribbler}, \theta$ and x'_{target}, the target position on the simplified system.

Summarizing, the neural network used was a SNN (Shallow Neural Network), with a two-layer feed-forward network. The network has one hidden layer with 30 neurons. The input of the network is the position of the target on the simplified coordinate system x'_{target} and the outputs the parameters of the kick $V_{kick}, \omega_{dribbler}, \theta$. The diagram provided by the training of the network on MATLAB with the indicated inputs and outputs may be seen in the Fig. 10

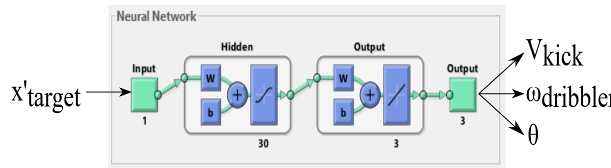


Fig. 10: SNN diagram on MATLAB with the inputs and outputs.

With the matrix of train and the neural network set, the simulations of the results was made.

V. SIMULATION RESULTS

A simulation with the field of the competition was made on MATLAB to a visual feedback of the results. The black circle represents the robots, the circle inside the black circle represents thee team of the robot, blue for ally and yellow for adversary, the orange circle represents the ball, the blue line the trajectory of the ball, the black lines and circles are the field marks, the blue point is the target of the kick and the dotted circle is the admissible region for the fourth requirement. The Fig. 11 shows the legend for the elements of the simulation. Fig. 12 and 13 show results for the case of the Olympic goal, Fig. 14 and 15 show results for the case of the curved pass and Fig 16 and 17 show results for the case of the curved kick.

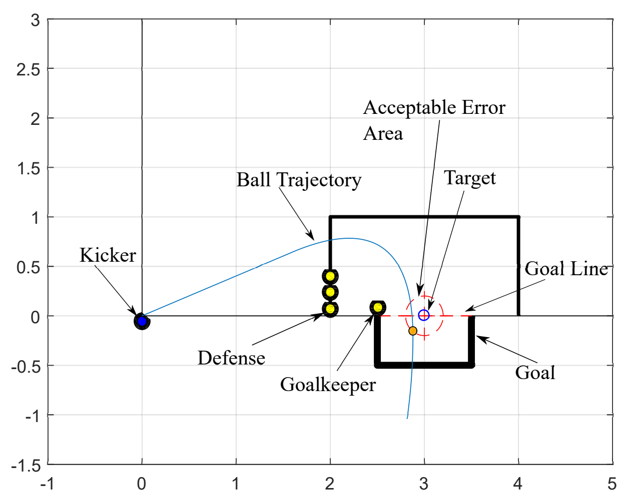


Fig. 11: Elements in the simulation.

As may be seen in the results of the simulation, the results converged with the required precision and all the requirements was fulfilled.

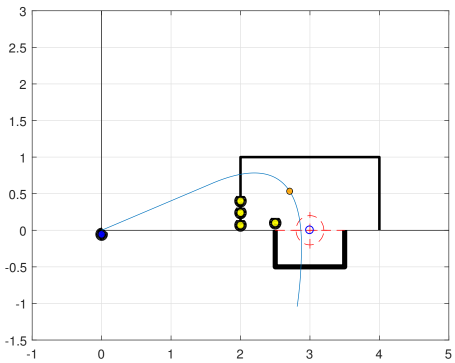


Fig. 12: Olympic goal with robot in origin and target point $(3, 0)$.

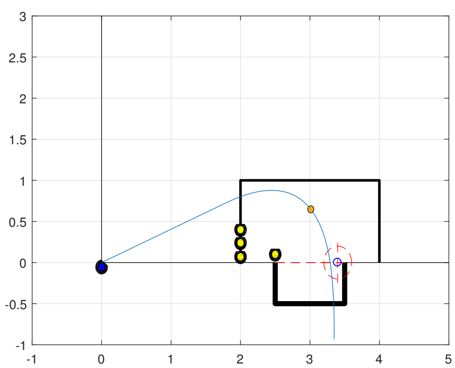


Fig. 13: Olympic goal with robot in origin and target point $(3.4, 0)$.

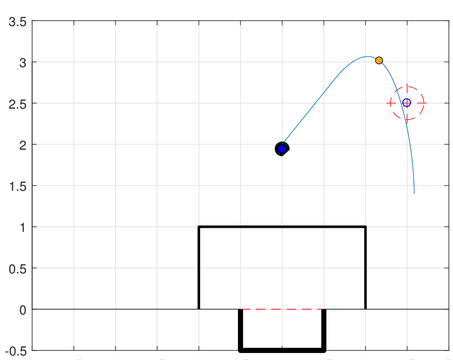


Fig. 14: Curved pass with target point $(4.5, 2.5)$ and robot in $(3, 2)$.

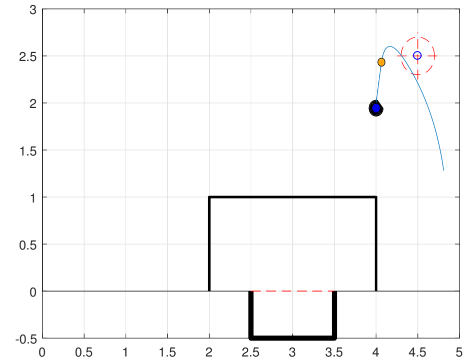


Fig. 15: Curved pass with target point $(4.5, 2.5)$ and robot in $(4, 2)$.

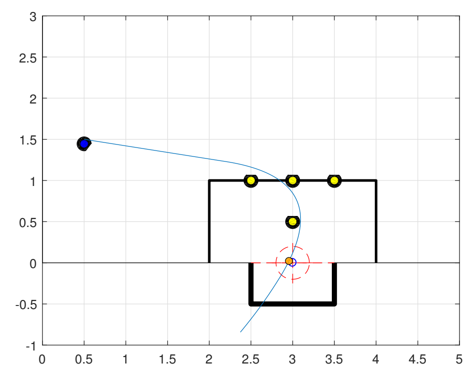


Fig. 16: Curved kick with robot in $(0.5, 1.5)$.

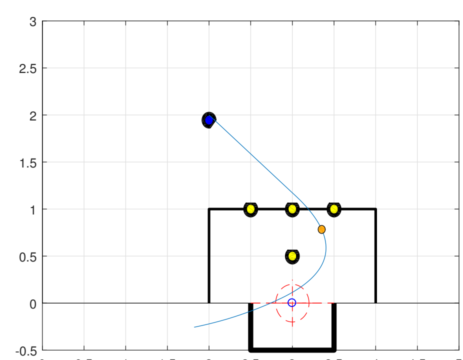


Fig. 17: Curved kick with robot in $(2, 2)$.

VI. CONCLUSION

As shown in this work, the neural network worked very well with the problem of the curved kick. The results of the simulation shown that the solution converged for a robot that was capable of, autonomously decide the parameters for a kick that hits the desired target.

As a future research direction, we are looking to optimize the code and implement on the real robot, testing it, obtaining new data to train the neural network, making the real robot more precise. For the simulation, it is intended to make it more robust and precise, training it with more data for better results.

ACKNOWLEDGMENT

The author would like to thank the ITAndroids group and all of its members, the ITAndroids sponsors, mainly MathWorks, that gave us the software MATLAB, and ITAex, and would like to thank the Instituto Tecnolgico de Aeronutica.

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