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MOBILE MULTIBODY ROBOTS OR VEHICLES – SIMULATING AND BUILDING FUZZY PREDICTORS

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Abstract— *The main objective in this article is to present a solution for the problem of maneuvering multi-linked robots or vehicles by developing a simulation environment that would aid their operators, the predictor. This device will use the resources of fuzzy logic, since this technique allows to take into consideration many variables difficult to be modelled. Multi-linked vehicles are used in many real case applications due to their advantages, but since their maneuverability decrease considerably, it is proposed in this work the implementation of a fuzzy predictor in the truck which would provide to the driver a visualization of the maneuvers, specially backwards, displayed in a screen adapted in the cockpit. The kinematical model, combined with the fuzzy logic, must be able to predict the direction taken by the trailers before the execution of the maneuver. This should save time because the maneuvers are generally performed by trial and error, and consequently reduce costs of transportation. The results of both kinematical and fuzzy model will be presented in this article.*

Keywords— *Mobile Robots, Fuzzy logic, Multi-linked robots, Multi-trailer trucks, Predictor.*

1. Introduction

In this article we present a possible solution for the problem of maneuvering multi-linked robots or vehicles that consists on implementing a device that would give to their operators a prediction of the kinematical chain's motion. This device, which we will be referring to as "predictor", will provide through a display mounted on the cockpit, a graphical animation of the maneuver, based on the necessary inputs and using a kinematical model of the robot combined with the fuzzy logic. The choice of using a fuzzy model, is to provide a mathematical model of the motion that should be able to consider many uncertainties inherent to real applications of these robots and also take into account some variables difficult to be modelled. Before giving any further description of the model, we present some possible and real applications for these types of mobile robots. For instance, stackers with multiple trailers in automated wharehouses, duct maintainance robots are examples of possible applications while the CVC (composition of haul vehicles) is an example of a multi-linked vehicle that is already broadly used in real situations and it consists on conecting two or even more trailers to a regular truck, used for transportation of great quantities of bulk, liquid and solid materials. This kind of vehicle gives to regular trucks the advantage of transporting greater amounts of loads, allowing to decrease considerably costs with transportation. Figure 1 shows some examples of CVCs for different types of loads:

Figure 1- CVCs with different types of loads.

However, the greater disadvantage of this kind of transportation is its maneuverability, mainly if it involves backwards motion. Thus, in order to resolve this problem, the implementation of a fuzzy predictor should be useful to assist the driver in executing the maneuvers. This assistance consists on giving to the driver a visual representation of the maneuver before its execution. By doing so, it would not be necessary to make several maneuvers in order to find the right angle of the truck's front wheels (trial and error), but simulating several times for several steer angles without having to actually move the composition would be the easier and faster way to perform the maneuver. Figure 2 shows schematically the predictor's display installed in the cockpit:

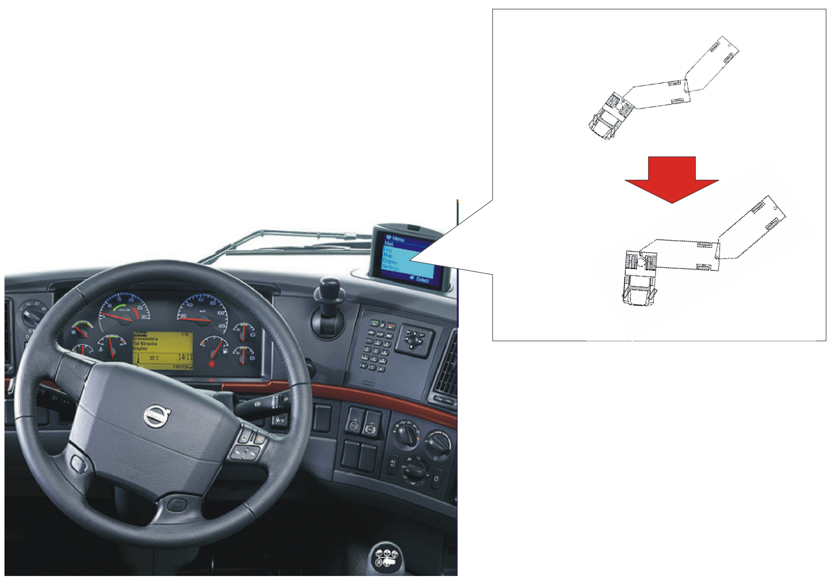

Figure 2 – Predictor display adapted in the cockpit.

As mentioned before, the model used to generate the simulations will be based on fuzzy logic, which is constructed mostly from the knowledge of experts, expressed under the form of IF-THEN rules, which contains implicitly the causal dynamics of the system. In this case, this method is very inapropriate because even for the most experienced drivers, maneuvering CVCs is still a difficult task to perform and consequently to describe it in IF-THEN rules. Therefore, the most convenient approach is to obtain the rules through numerical data, which in practice should be obtained through appropriate instrumentation of real systems, where it should also contain implicitly any causal dynamics of the system, as it is for the fuzzy rules. Since our main objective is to ensure that the methodology applied will result in a fuzzy model that will be accurate enough to represent the motion of real CVCs for short maneuvers, it will be assumed that the kinematical model, in these situations (short maneuvers), will substitute the real instrumented CVCs. Even tough many variables will not be taken into consideration in the kinematical model, it wil be assumed that most of the entire kinematic chain's behavior will be represented in this model. If we consider that most maneuvers occurs at low and nearly constant speed, specially backwards, we can say that the acceleration, and also other factors like wheels slippage, will not take much effect and consequently both models (kinematical and real) will not be very different. Therefore our work now consists of defining the kinematical model and show the results of the fuzzy model, comparing it with the simulations made with the kinematical model.

2. Kinematical model

Firstly, it will be considered in this work a composition with two trailers, but it should be noticed that the procedure presented here is not limited to this number, so that more trailers could be defined. Secondly, it must be defined the configuration of the truck and the trailers. A conventional truck usually has more than two wheels at the rear and two drive wheels at the front, but in order to avoid a very complex analisys, it will be considered only two at the rear and two driven wheels at the front so that slippages will be eliminated from the problem. Also the trailers will have two rear wheels but no front wheels, and finally the connection points will be placed behind the rear axes, for both truck and first trailer. Figure 3 shows the configuration of the whole composition and the main points of each element:

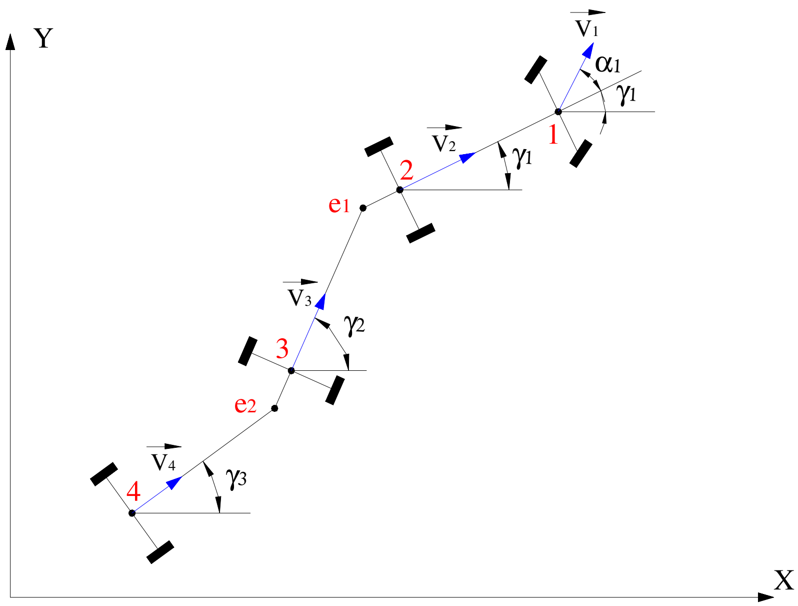

Figure 3 – Configuration and main points of the composition

Another consideration to make is that the maneuvers will occur only on a plane, what is reasonable to assume since in real situations that is mostly the case. This consideration simplifies considerably our model because on the contrary it would be necessary to obtain the equations in three dimensions.

Figure 3 also shows the kinematical variables of the problem. γ angles represent the angle of each element with respect to the horizontal inertial axis. α_1 is the angle of the truck's front wheels with respect to the direction of the truck itself. We can also define angles α_2 and α_3, which are the angles between the truck and the first trailer and the first and second trailer respectively. Using the γ angles, α angles can be defined as:

$$
\begin{aligned}
\alpha_2 &= \gamma_1 - \gamma_2 \\
\alpha_3 &= \gamma_2 - \gamma_3
\end{aligned}
\tag{1}
$$

For each element, it will be used inertial and mobile referentials to define the kinematical equations. For instance, Fig. 4 shows these referential systems applied to the truck:

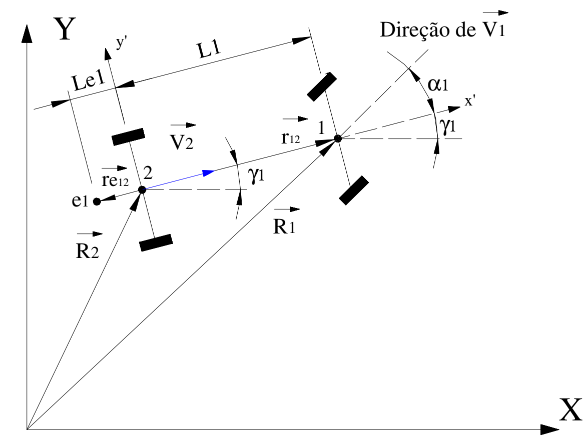

Figure 4 – Truck's mobile reference system and inertial reference system.

Where the x'y' coordinate system is the mobil e reference system and has its origin at point 2, while XY represent the global reference system. The following relation between position vectors of points 1 and 2 can be established:

$$\vec{R}_1 = \vec{R}_2 + [T]^T \cdot \vec{r}_{12} \tag{2}$$

The variable "T" is the transformation matrix, which will convert the local coordinates of vector $\mathbf{r}_{12}$ in global coordinates.The form of this matrix can be found in Santos, 2001 and it is given by:

$$T = \begin{bmatrix} \cos(\gamma_1) & sen(\gamma_1) & 0 \\ -sen(\gamma_1) & \cos(\gamma_1) & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

Deriving both sides of the equation with respect to time, it can be obtained a relation between velocity vectors of these points:

$$\vec{v}_1 = \vec{v}_2 + \vec{\omega}_1 \times ([T]^T \cdot \vec{r}_{12}) \tag{4}$$

Velocity vectors at points 1 and 2 have necessarily the same direction of the wheels (except if they slip), so that we can define their coordinates as:

$$\begin{aligned} \vec{v}_1 &= \left(V_1 \cdot \cos(\gamma_1 + \alpha_1), V_1 \cdot sen(\gamma_1 + \alpha_1), 0\right) \\ \vec{v}_2 &= \left(V_2 \cdot \cos(\gamma_1), V_2 \cdot sen(\gamma_1), 0\right) \end{aligned} \tag{5}$$

And the coordinates of the position vector of point 2 on the mobile reference system is clearly equals to:

$$\vec{r}_{12} = (L_1, 0, 0) \tag{6}$$

The angular velocity vector of the truck (ω_1) is perpendicular to the plane of Fig. 4, and its module is at this point unknown. Inputing vectors (5) and (6) into equation (4) and resolving the vectorial product gives us the components of the velocity vector at the point 1:

$$v_{1x} = v_1 \cos(\gamma_1 + \alpha_1) = v_2 \cos(\gamma_1) - \omega_1 \cdot L_1 \cdot sen(\gamma_1) \tag{7}$$

$$v_{1y} = v_1 sen(\gamma_1 + \alpha_1) = v_2 sen(\gamma_1) + \omega_1 \cdot L_1 \cdot \cos(\gamma_1) \tag{8}$$

Dividing equation (8) by (7) and isolating ω_1 results in the following equation:

$$\omega_1 = \frac{d\gamma_1}{dt} = \frac{v_2 \cdot (\cos(\gamma_1) \cdot \tan(\gamma_1 + \alpha_1) - sen(\gamma_1))}{L_1 \times (sen(\gamma_1) \times \tan(\gamma_1 + \alpha_1) + \cos(\gamma_1))} \tag{9}$$

As it can be observed, this equation is a non-linear diferential equation of the angle γ_1. Solving it woud give us γ_1 at any instant, and thus we would also be able to calculate the module of $\mathbf{V}_1$ from equation (7) or (8). Repeating the steps from equation (2) until (4), it can also be established a relation between velocity vectors of points 2 and e_1:

$$\vec{v}_{e_1} = \vec{v}_2 + \vec{\omega}_1 \times ([T]^T \cdot \vec{r}_{e_1 2}) \tag{10}$$

Separating into components X and Y:

$$v_{e_1 x} = v_2 \cdot \cos(\gamma_1) + \omega_1 \cdot L_{e_1} \cdot sen(\gamma_1) \tag{11}$$

$$v_{e_1 y} = v_2 \cdot sen(\gamma_1) - \omega_1 \cdot L_{e_1} \cdot \cos(\gamma_1) \tag{12}$$

This time all variables at the right side of both equations are known, consequently the components of the velocity vector at the link point of the truck are defined. So far, all the main kinematical variables of the truck are defined, the next step will be the definition of the kinematical variables of the first trailer, as it is shown on Fig. 5:

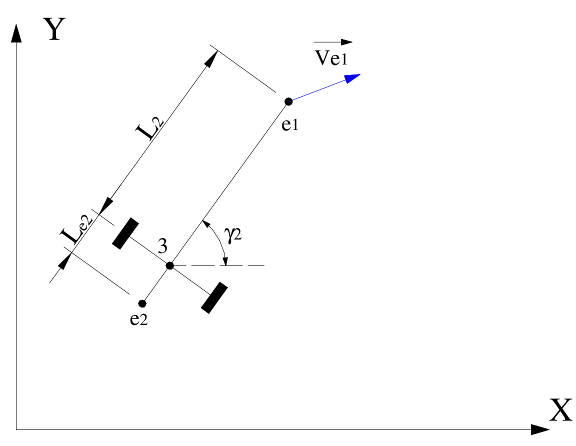

Figure 5 – Kinematical variables of the first trailer.

In this case the only variable already defined is the velocity vector at the link point, which is obviously the same as the truck. Direction of velocity vector at point 3 is known (same as the wheels), but not its module, so we have for the first trailer the same situation as in the truck. Thus, repeating the procedure applied to the truck will lead to the equations of the kinematical variables for the first trailer:

$$v_{3x} = v_3 \cos(\gamma_2) = v_{e_1 x} + \omega_2 \cdot L_2 \cdot sen(\gamma_2) \tag{13}$$

$$v_{3y} = v_3 sen(\gamma_2) = v_{e_1 y} - \omega_2 \cdot L_2 \cdot \cos(\gamma_2) \tag{14}$$

$$\omega_2 = \frac{d\gamma_2}{dt} = \frac{v_{e_1y} - \tan(\gamma_2)\cdot v_{e_1x}}{L_2 \times (sen(\gamma_2)\times\tan(\gamma_2)+\cos(\gamma_2))} \tag{15}$$

$$v_{e_2x} = v_3 \cdot \cos(\gamma_2) + \omega_2 \cdot L_{e_2} \cdot sen(\gamma_2) \tag{16}$$

$$v_{e_2y} = v_3 \cdot sen(\gamma_2) - \omega_2 \cdot L_{e_2} \cdot \cos(\gamma_2) \tag{17}$$

The same applies to the second trailer, resulting on the following equations of the kinematical variables:

$$v_{4x} = v_4 \cos(\gamma_3) = v_{e_2x} + \omega_3 \cdot L_3 \cdot sen(\gamma_3) \tag{18}$$

$$v_{4y} = v_4 sen(\gamma_3) = v_{e_2y} - \omega_3 \cdot L_3 \cdot \cos(\gamma_3) \tag{19}$$

$$\omega_3 = \frac{d\gamma_3}{dt} = \frac{v_{e_2y} - \tan(\gamma_3)\cdot v_{e_2x}}{L_3 \times (sen(\gamma_3)\times\tan(\gamma_3)+\cos(\gamma_3))} \tag{20}$$

Finally, all the necessary equations were obtained. But in order to apply these equations to a simulation environment they must be resolved, so that the position and orientation of each element in the composition can be defined at any instant.

3. Resolution of the equations.

Following the procedure of obtaining the truck's kinematical equations defined in section 2, in order to calculate the module of velocity vector $\mathbf{V}_1$ (equation (7) or (8)) and the components of velocity vector V_{e1} (equations (11) and (12)), the diferential equation of angle γ_1 must be solved first. But clearly this equation can not be solved analitically, since it has non-linear characteristics. Therefore, the only way to obtain its solution is through the application of a numerical method. Since the angular velocity equations have only one derivative isolated from the other terms, we can apply the Runge-Kutta formulae to this case. The simplest Runge-Kutta formula is the first order one, or also called the "Euler method". Equation (21) gives the result of this method applied to the angular velocity equations:

$$\gamma = \int_{t_0}^{t_0+\Delta t} |\vec{\omega}| \cdot dt \;\Rightarrow\; \gamma = \gamma_0 + |\vec{\omega}| \times \Delta t \tag{21}$$

Inspite of its simplicity, this method presented very inaccurate results during the simulations, which could be realized visually since some relative motion between the elements of the composition was detected. This relative motion led, for instance, to the first trailer separating itself from the truck, what indicates that this method is not fit to solve the equations of γ. Thus, still using the Runge-Kutta formulae, the simplest method which can possibly give us an accurate result is the second order. Applying these to the γ equations results in the following results:

$$\begin{aligned} \gamma(t+\Delta t) &= \gamma(t) + \frac{1}{2}\times\left(k_1 + k_2\right) \\ k_1 &= \Delta t \times f\left(t, \gamma(t)\right) \\ k_2 &= \Delta t \times f\left(t+\Delta t, \gamma(t)+k_1\right) \end{aligned} \tag{22}$$

In this case, "f" corresponds to the right side of the γ equations (equations (9), (15) and (20)).

In order to compare the accuracy of both methods, so that we can justify the use of a more complex numerical method in the γ equations, a measure of error was calculated in both methods. This measure is simply the distance between the main points of the composition, which should theoretically remain constant during simulations, but since we are solving the kinematical equations numerically, these distances may float around their initial values, even for the secon order Runge-Kutta. The results of the error measures will be shown at the end of this section.

Continuing the procedure for the truck, once we have determined its orientation (angle γ_1), it is still needed to determine the position of the main points (1,2 and e_1). In order to do so, the velocity components of each point must be integrated, resulting in their respective coordinates. It should be noticed that equations (7) and (8) can not be integrated analitically, since the velocity components depend on γ_1, which is obtained from numerical methods and therefore is not represented by an analitical function. Once again, the Euler method could be applied in this case, as it is shown in equation (23):

$$
\begin{aligned}
x &= \int_{t_0}^{t_0+\Delta t} \left|\vec{v}_x\right| \cdot dt = x_0 + \left|\vec{v}_x\right| \times \Delta t \\
y &= \int_{t_0}^{t_0+\Delta t} \left|\vec{v}_y\right| \cdot dt = y_0 + \left|\vec{v}_y\right| \times \Delta t
\end{aligned}
\tag{23}
$$

But since this method already presented inaccurate results, another numerical method is chosen to resolve these equations. We adopted the 1/3 rule of Simpson, which basically approximates the function in the integrand to a second degree polynomial. The result of the integration is given by he following formula:

$$
\begin{aligned}
&\int_{t+(2k-1)\Delta t}^{t+(2k+1)\Delta t} f(t) \cdot dt = \frac{\Delta t}{3} \times \Big(f\big(t+(2k-1)\Delta t\big) + 4 \cdot f\big(t+2k\Delta t\big) + f\big(t+(2k+1)\Delta t\big) \Big) \\
&k = 1 \ldots \left(k_{\max}+1\right)/2
\end{aligned}
\tag{24}
$$

Where 'f' represents the right side of the velocity component equations (7), (8), (11), (12), (13), (14), (16), (17), (18), (19) and also the components of velocity vector at point 2:

$$
\begin{aligned}
v_{2x} &= v_2(t)\cos(\gamma_1(t)) \\
v_{2y} &= v_2(t)sen(\gamma_1(t))
\end{aligned}
\tag{25}
$$

The following figures compares the error measure of both methods applied to the kinematical equations, only between points 1 and 2:

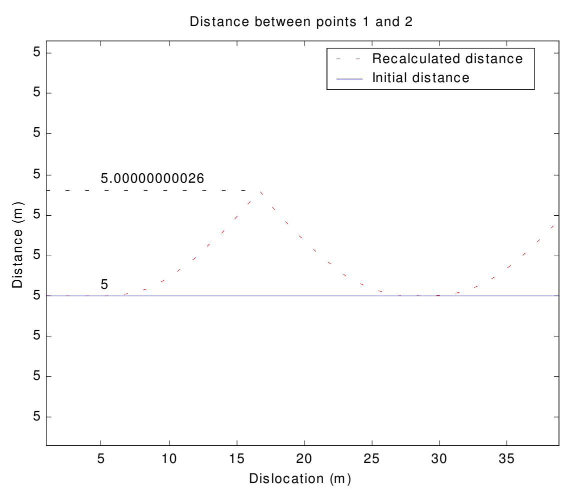

Figure 6 – Variation of distance between points 1 and 2 (Second order Runge-Kutta).

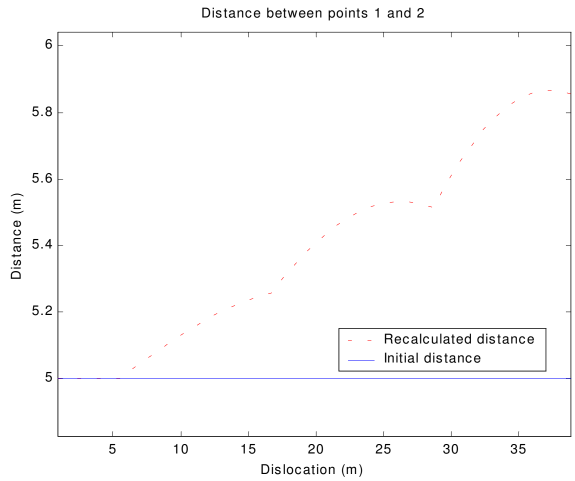

Figure 7 - Variation of distance between points 1 and 2 (Euler).

It is clear in these figures that the error measure in the Euler method is considerably high, what justifies the use of a more complex method to solve the diferential equations. Figure 6 proves that second order Runge-Kutta, on the contrary, can yield to satisfactory results, being the chosen method to resolve the γ equations.

4. The predictor

As mentioned before, the kinematical equations will be used in this work for two purposes: to be part of the predictor itself and also to validate the methodology proposed, which consists in obtaining appropriate fuzzy rules from numerical data.

The first objective was successfully accomplished with the implementation of the kinematical equations in a computer simulation program. Figure 8 shows the simulation program screen:

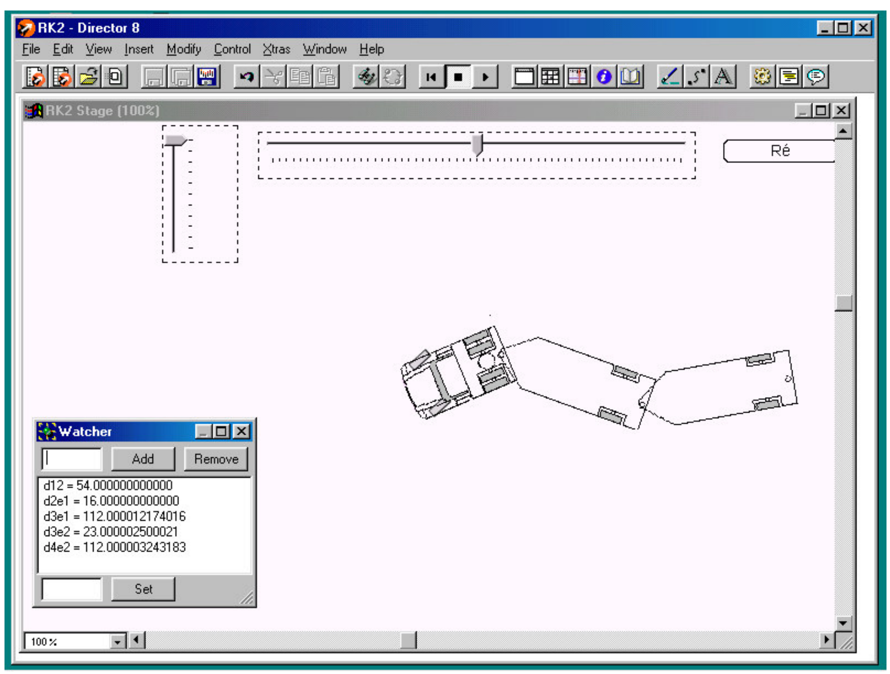

Figure 8 – Simulation program screen.

The simulations runned in this program could also be presented on the predictor's display, assisting the driver in any maneuver backwards.

The second objective consists in generating fuzzy rules with appropriate partitions that would represent with accuracy the causal dynamics of the system. In our case, the causal dynamics must be implicit on the data, that could be extracted from real compositions equipped properly with sensors to measure all relevant variables. However, in this work, these data will be substitutes for those calculated from the kinematical model, for the reasons already explained.

The fuzzy model will be represented only by α variables, disregarding from the problem the other variables. This consideration is based on some simplicaficating hipothesys (described in Pinheiro, 2004), and must be applied to this case in order to avoid a large number of rules, what would consume much time for generating the rules and also to infer the results. It does not, however, implies loss of generality since the fuzzy model would still be able to receive other variables like any eventual variable difficult to be modeled and those acquired from sensors, which usually come with uncertainties in their values due to the limited precision of some sensors. Also, the α variables represent adequately the behavior of the composition because the main concern in these systems is to avoid the 'jacknifing" of the trailers. This problem can be avoided by monitoring the α angles, thus, becoming the variables which we should draw our attention for. As for the other variables (coordinates of the main points), it will be assumed that the results obtained from the kinematical equations are accurate enough to represent the real kinematical chain.

So, basically, the main goal now is to obtain a model that yields to a minimum error, which is the difference between the results of the α angles inferred from the fuzzy model and those provided by the kinematical model for the same maneuver. In order to do so, several methods have been used to generate the fuzzy models from the data, that will approximate the α angles during the simulations. This methods are described with details in Pinheiro, 2004.

Finally, it is presented on the following figures the results of the error for each method in two simulations:

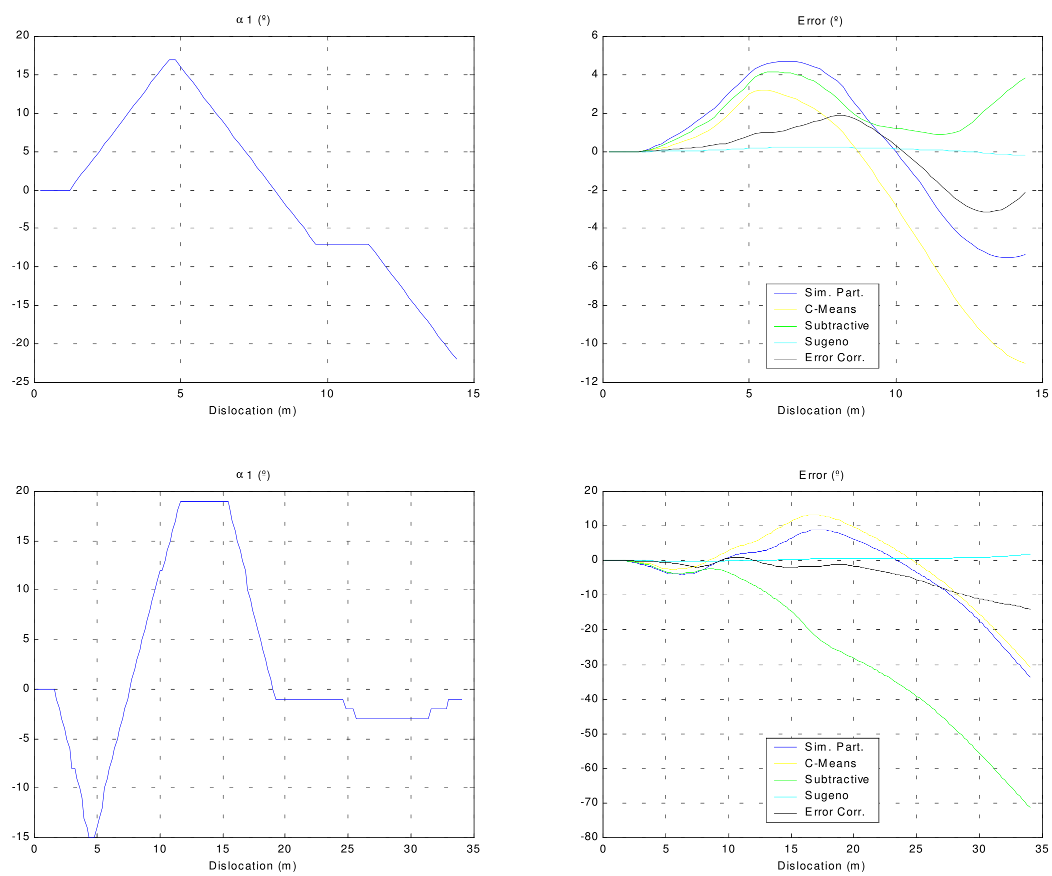

Figure 9 – First and second simulation results of fuzzy models obtained from different methods.

Each simulation is characterized by a different variation of the front wheel angle (α_1), constituting different maneuvers. It is clear from these figures that the Sugeno fuzzy system type has a much better accuracy than the other methods. Also the method suggested in this work presented good results.

5. Conclusions

It can be conclude in this work that a Sugeno type fuzzy system combined with the kinematical equations and implemented in a simulation program can be used as a predictor for assisting drivers in any application of multi-linked robots or vehicles. For every simulation performed, the Sugeno inference mechanism was able to obtain accurate results, being the α variables' absolute error in all cases neglectible for short distances (5 to 10 meters) and still considerably small for greater distances. Also, as shown in this paper, the kinematical equations presented reliable results regarding the numerical methods applied to solve them. Therefore, they can also be used in the predictor to calculate the coordinates of the robot's main points. Certainly, in some cases, the results of this model would differ considerably from the real motion, but as explained before, we expect that the fuzzy model will be able to provide realistic results for the α angles, and utilize the results of the kinematical model only to determine the position of the composition itself, since in most situations these variables are not required to be precise.

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