PREDICTIVE CONTROL BY LOCAL VISUAL DATA

Mobile Robot Model Predictive Control Strategies Using Local Visual Information and Odometer Data

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Abstract: Nowadays, the local visual perception research, applied to autonomous mobile robots, has succeeded in some important objectives, such as feasible obstacle detection and structure knowledge. This work relates the on-robot visual perception and odometer system information with the nonlinear mobile robot control system, consisting in a differential driven robot with a free rotating wheel. The description of the proposed algorithms can be considered as an interesting aspect of this report. It is developed an easily portable methodology to plan the goal achievement by using the visual data as an available source of positions. Moreover, the dynamic interactions of the robotic system arise from the knowledge of a set of experimental robot models that allow the development of model predictive control strategies based on the mobile robot platform PRIM available in the Laboratory of Robotics and Computer Vision. The meaningful contribution is the use of the local visual information as an occupancy grid where a local trajectory approaches the robot to the final desired configuration, while avoiding obstacle collisions. Hence, the research is focused on the experimental aspects. Finally, conclusions on the overall work are drawn.

1 INTRODUCTION

The research presented in this paper addresses to a kind of differential driven WMRs (wheeled mobile robots). Nowadays, the computer vision techniques applied to WMR have solved the problem of obstacle detection by using different methods as stereo vision systems, optical flow or DFF (depth from focus). Stereo vision systems seem to provide the easiest cues to infer scene depth (Horn, 1998). The optical flow techniques used in WMR result in several applications as i.e. structure knowledge, obstacle avoidance, or visual servoing (Campbell, et al., 2004). The DFF methods are also suitable for WMR. For example, three different focused images were used, with almost the same scene, acquired with three different cameras (Nourbakhsh, et al., 1997). In this work, it is supposed that available obstacle positions are provided by using computer vision systems. In this context, the allowed navigation control signals should achieve the obstacle avoidance as well as the final desired coordinates. Scientific community has developed several studies in this field. Based on the dynamic window approach with available robot speeds, the reactive avoidance collisions, safety stop and goal can be achieved using the dynamic constraints of WMR (Fox, et al., 1997). Rimon and Koditschek (1992) presented the methodologies for the exact motion planning and control, based on the artificial potential fields where the complete information about the free space and goal are encoded. Some approaches on mobile robots propose the use of potential fields, which satisfy the stability in a Lyapunov sense, in a short prediction horizon (Ögren and Leonard, 2005). The main contribution of this paper is the use of the visual information as a dynamic window where the collision avoidance and safety stop can be planned. Thus, local visual data, instead of artificial potential fields, are used in order to achieve the Lyapunov stability. The use of MPC (model predictive control) with available on-robot information is possible. Moreover, the local visual information is used as an occupancy grid that allows planning feasible trajectories towards the desired objective. The knowledge of the objective allows the optimal solution of the local desired coordinates based on the acquired images. The sensor fusion is done using visual perception, as the meaningful source of information in order to accomplish with the robot tasks. Other data provided by the encoder-based odometer system are also considered.

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This paper is organized as follows: Section 1 gives a brief presentation about the aim of the present work. In the Section 2, the platform is introduced as an electromechanical system. This section also describes the experiments to be realized in order to find the parametric model of the robot suitable for designing and implementing MPC methods. In the Section 3, the use of visual data is presented as a horizon where optimal trajectories can be planned. Section 4 presents the MPC strategies used for achieving the path following of the reference trajectories. In the Section 5, some conclusions are made with special attention paid into the future research works.

2 ROBOT AND BASIC CONTROL METHODS

This section gives some description on the main robot electromechanical and sensorial systems of the platform tested in this work. Hence, the WMR PRIM, available in our lab, has been used in order to test and orient the research. The experimental modelling methodologies as well as the model predictive control are also introduced.

2.1 Electromechanical and Sensorial System of the Robot

Figure 1 shows the robot PRIM used in the research work. The mechanical structure of the robot is made of aluminum, with two independent wheels of 16cm diameters actuated by two DC motors. The distance between two wheels is 56.4cm. A third spherical omni-directional wheel is used to guarantee the system stability. The maximum continuous torque of each motor is 131mNm. The proportion of gear reduction for each motor is 86:1 and thus the total force actuating on the robot is near 141N. Shaft encoders with 500 counts/rev are placed at the motor axes, which provide 43000 counts for each turn of the wheel. A set of PLD (programmable logic device) boards is connected to the digital outputs of the shaft encoders. The printed circuits boards (PCB) are used to measure the speed of each motor at every 25ms.

An absolute counter provides the counts in order to measure the robot position by the odometer system. Another objective of these boards is to generate a signal of 23khz PWM for each motor.

The communication between the central digital can computer and the boards is made through the thus it parallel port. The speed is commanded by a byte and generate from 0 to 127 advancing or rever-

Figure 1: The robot PRIM used in this work.

sing speed commands. The maximal speed is near 0.5m/s. A set of microcontroller boards (MCS-51) is used to read the information available from different connected sensors. The rate of communication with these boards is 9600 b/s. Figure 2 shows the electronic and sensorial system blocks. The data gathering and the control by digital computer is set to 100ms.

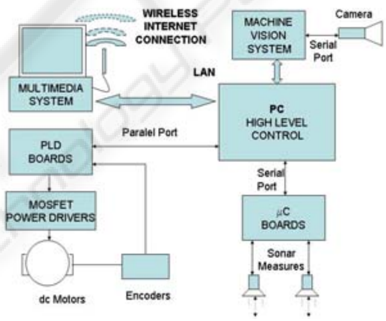

Figure 2: The sensorial and electronic system blocs.

The system flexibility is increased with the possibility of connecting with other computer systems through a local LAN. In this research, it is connected to a machine vision system that controls a colour camera EVI-D70P-PAL through the VISCA RS232-C control protocol. For instance, the camera configuration used in this work is of a horizontal field of view of 48º, and a vertical field of 37º. The focus, pan and tilt remain fixed under present configuration. Hence, the camera pose is set to 109cm from the floor with a tilt angle of 32º. The local desired coordinates, obtained by the visual perception information, are transmitted to the control unit connecting the USB port to the LAN.

2.2 Experimental Model

The parametric identification process is based on black box models (Lju, 1989), (Norton, 1986) and (Van Overschee, Moor, 1996). Thus, the transfer functions are related to a set of polynomials that allow the use of analytic methods in order to deal with the problem of controller design. The nonholonomic system dealt with in this work is considered initially as a MIMO (multiple input multiple output) system, which is composed of a set of SISO subsystems with coupled dynamic influence between two DC motors. The approach of multiple transfer functions consists in making the experiments with different speeds. In order to find a reduced-order model, several studies and experiments have been done through the system identification and model simplification.

2.2.1 System Identification

The parameter estimation is done by using a PRBS (Pseudo Random Binary Signal) as excitation input signal. It guarantees the correct excitation of all dynamic sensible modes of the system along the spectral range and thus results in an accurate precision of parameter estimation. The experiments to be realized consist in exciting two DC motors in different (low, medium and high) ranges of speed.

The ARX (auto-regressive with external input) structure has been used to identify the parameters of the robot system. The problem consists in finding a model that minimizes the error between the real and estimated data. By expressing the ARX equation as a lineal regression, the estimated output can be written as:

$$\hat{y} = \theta\varphi \tag{1}$$

with $\hat{y}$ being the estimated output vector, θ the vector of estimated parameters and φ the vector of measured input and output variables. By using the coupled system structure, the transfer function of the robot can be expressed as follows:

$$\begin{pmatrix} Y_R \\ Y_L \end{pmatrix} = \begin{pmatrix} G_{RR} & G_{LR} \\ G_{RL} & G_{LL} \end{pmatrix} \begin{pmatrix} U_R \\ U_L \end{pmatrix} \tag{2}$$

where Y_R and Y_L represent the speeds of right and left wheels, and U_R and U_L the corresponding speed commands, respectively. In order to know the dynamics of robot system, the matrix of transfer function should be identified. Figure 3 shows the speed response of the left wheel corresponding to a left PBRS input signal.

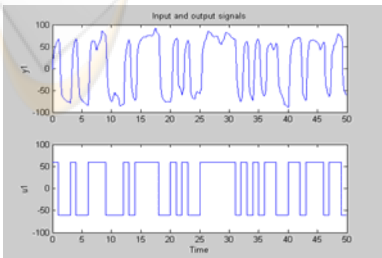

Figure 3: Left speed output for a left PRBS input signal.

The treatment of experimental data is done before the parameter estimation. In concrete, it includes the data filtering, using the average value of five different experiments with the same input signal, the frequency filtering and the tendency suppression. The system is identified by using the identification toolbox "ident" of Matlab for second order models. The following continuous transfer function matrix for medium speed is obtained:

$$\begin{pmatrix} Y_R \\ Y_L \end{pmatrix} = \begin{pmatrix} \dfrac{0.35s^2+4.82s+4.46}{s^2+5.84s+4.89} & \dfrac{0.02s^2+0.27s+0.32}{s^2+5.84s+4.89} \\ \dfrac{0.26s^2+3.41s+0.28}{s^2+5.84s+4.89} & \dfrac{0.11s^2+1.72s+5.12}{s^2+5.84s+4.89} \end{pmatrix} \begin{pmatrix} U_R \\ U_L \end{pmatrix} \tag{3}$$

It is shown by simulation results that the obtained model fits well with the experimental data.

2.2.2 Simplified Model of the System

This section studies the coupling effects and the way for obtaining a reduced-order dynamic model. It is seen from (3) that the dynamics of two DC motors are different and the steady gains of coupling terms are relatively small (less than 20% of the gains of main diagonal terms). Thus, it is reasonable to neglect the coupling dynamics so as to obtain a simplified model.

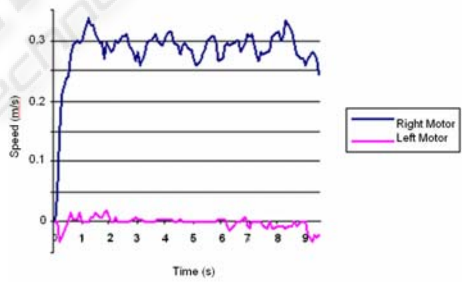

Figure 4: Coupling effects at the left wheel.

In order to verify it from real results, a set of experiments have been done by sending a zero speed command to one motor and other non-zero speed commands to the other motor. In Figure 4, it is shown a response obtained on the left wheel, when a medium speed command is sent to the right wheel. The experimental result confirms the above facts. The existence of different gains in steady state is also verified experimentally. Finally, the order reduction of system model is carried out trough the analysis of pole positions by using the method of root locus. Afterwards, the system models are validated through the experimental data by using the PBRS input signal. A two dimensional array with three different models for each wheel is obtained. Hence, each model has an interval of validity where the transfer function is considered as linear.

2.3 Odometer System Expression

Denote *(x, y, θ)* as the coordinates of position and orientation, respectively. The Figure 5 describes the positioning of robot as a function of the radius of left and right wheels (R_e, R_d), and the angular incremental positioning (θ_e, θ_d), with E being the distance between two wheels and dS the incremental displacement of the robot. The position and angular incremental displacements are expressed as:

$$dS = \frac{R_d d\theta_d + R_e d\theta_e}{2} \qquad d\theta = \frac{R_d d\theta_d - R_e d\theta_e}{E} \tag{4}$$

The coordinates (x, y, θ) can be expressed as:

$$\begin{aligned} x_n &= x_{n-1} + dS\cos(\theta_{n-1} + d\theta) \\ y_n &= y_{n-1} + dS\sin(\theta_{n-1} + d\theta) \\ \theta_n &= \theta_{n-1} + d\theta \end{aligned} \tag{5}$$

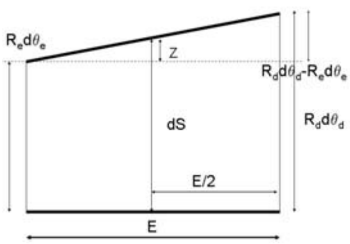

Figure 5: Positioning of the robot as functions of the angular movement of each wheel.

Thus, the incremental position of the robot can be obtained through the odometer system with the available encoder information obtained from (4) and (5).

2.4 Model Predictive Control

The model predictive control, MPC, has many interesting aspects for its application to mobile robot control. It is the most effective advanced control technique, as compared to the standard PID control, that has made a significant impact to the industrial process control (Maciejowski, 2002). Recently, real time mobile robot MPC implementations have been developed using global vision sensing (Gupta, Messom et al., 2005). In (Küne, Lages et al., 2005), it was studied the MPC based optimal control useful for the case when nonlinear mobile robots are used under several constraints, as well as the real time implementation possibilities when short prediction horizons are used. In general, the global trajectory planning becomes unfeasible since the sensorial system of some robots is just local. By using a MPC, the idea of the receding horizon can deal with the local sensor information. In this way, it is proposed a local model predictive control, LMPC, in order to use the available visual data in the navigation strategies for the goal achievement.

The MPC is based on minimizing a cost function, related to the objectives, through the selection of the optimal inputs. In this case, the cost function can be expressed as follows:

$$J(n,m) = \min_{\left\{U(k+i|k)_{j=0}^{j=m-1}\right\}} \left\{ \begin{aligned} &[X(k+n|k) - X_d]^T P [X(k+n|k) - X_d] \\ &+ \sum_{i=1}^{n-1} [X(k+i|k) - X_d]^T Q [X(k+i|k) - X_d] \\ &+ \sum_{j=0}^{m-1} U^T(k+i|k) R U(k+i|k) \end{aligned} \right\} \tag{6}$$

Denote $X_d=(x_d, y_d, \theta_d)$ as the desired coordinates. The first term of (6) is referred to the final desired coordinate achievement, the second term to the trajectory to be followed, and the last one to the input signals minimization. The parameters P, Q and R are weighting parameters. $X(k+n|k)$ represents the terminal value of the predicted output after the horizon of prediction n and $X(k+i|k)$ represents the predicted output values within the prediction horizon. The system constrains are also considered:

$$\left\{ \begin{array}{ll} |U(k+i|k)| \le G_1 & \alpha \in [0,1) \\ \|[x_{k+i}, y_{k+i}] - [x_o, y_o]\| \ge G_2 & \\ \|[x_{k+n}, y_{k+n}] - [x_d, y_d]\| \le \alpha \|[x_k, y_k] - [x_d, y_d]\| & \end{array} \right\} \tag{7}$$

The limitation of the input signal is taken into account in the first constraint. The second constraint is related to the obstacle points where the robot should avoid the collision. The last one is just a convergence criterion.

3 THE HORIZON OF LOCAL VISUAL PERCEPTION

The use of sensor information as a useful source to build 2D environment models consists of a free or occupied grid proposed by (Elfes, 1989). The knowledge of occupancy grids knowledge has been used for static indoor mapping with a 2D grid (Thrun, 2002). In other works of multidimensional grids, multi target tracking algorithms are employed by using obstacle state space with Bayesian filtering techniques (Coué et al., 2006). In this work it is proposed the use of the local visual information available from the camera as a local map that has enough information in order to achieve a global objective. The occupancy grid can be obtained in real time by using computer vision methods. The use of the optical flow has been proposed as a feasible obstacle avoidance method; as i.e., (Campbell et al., 2004), in which it was used a Canny edge detector algorithm that consists in Gaussian filtering and edge detection by using Sobel filters. Thus, optical flow was computed over the edges providing obstacle structure knowledge. The present work assumes that the occupancy grid is obtained by the machine vision system. It is proposed an algorithm that computes the local optimal desired coordinate as well as the local trajectory to be reached. The research developed assumes indoor environments as well as flat floor constraints. However, it can be also applied in outdoor environments.

This section presents firstly the local map relationships with the camera configuration and poses. Hence, the scene perception coordinates are computed. Then, the optimal control navigation strategy is presented, which uses the available visual data as a horizon of perception. From each frame, it is computed the optimal local coordinates that should be reached in order to achieve the desired objective. Finally, the algorithm dealing with the visual data process is explained. Some involved considerations are also made.

3.1 Scene Perception

The local visual data provided by the camera are used in order to plan a feasible trajectory and to avoid the obstacle collision. The scene available coordinates appear as an image, where each pixel coordinates correspond to a 3D scene coordinates. In the case attaining to this work, flat floor surface is assumed. Hence, scene coordinates can be computed using camera setup and pose knowledge, and assuming projective perspective. The Figure 6 shows the robot configuration studied in this work. The angles α, β and φ are related to the vertical and horizontal field of view, and the tilt camera pose, respectively. The vertical coordinate of the camera is represented by *H*.

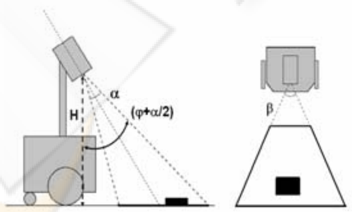

Figure 6: Fixed camera configuration including vertical and horizontal field of view, and vertical tilt angle.

Using trigonometric relationships, the scene coordinates can be computed:

$$y_j = H\tan(\varphi - \alpha/2 + \Delta\alpha) \tag{8}$$

$$\Delta\alpha = K_j \frac{\alpha}{R} \qquad (0 \le \mathrm{K_j} \le R)$$

$$x_{i,j} = \pm\frac{H}{\cos(\varphi - \alpha/2 + \Delta\alpha)}\tan(\Delta\beta) \tag{9}$$

$$\Delta\beta = K_i \frac{\beta}{C} \qquad (0 \le \mathrm{K_i} \le C/2)$$

The K_i and K_j are parameters used to cover the image pixel discrete space. Thus, *R* and *C* represent the image resolution through the total number of rows and columns. It should be noted that for each row position, which corresponds to scene coordinates y_j, there exist *C* column coordinates $x_{i,j}$. The above equations provide the available local map coordinates when no obstacle is detected. Thus, considering the experimental setup reported in Section 2, the local on-robot map depicted in Figure 7 is obtained.

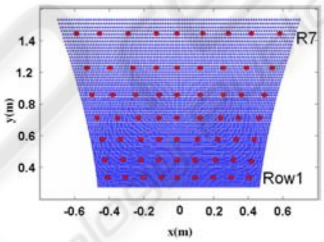

Figure 7: Local visual perception free of obstacles, under 96x72 or 9x7 low resolution grids.

3.2 Local Optimal Trajectory

The available information provided by the camera is considered as a local horizon where the trajectory is planned. Hence, a local map with free obstacle coordinates is provided. In this sense, the available local coordinates are shown in Figure 7. It is noted that low resolution scene grids are used in order to speed up the computing process.

The minimization of a cost function, which consists in the Euclidean distance between the desired coordinates and the available local scene coordinates, can be optimally solved by finding the local desired coordinates. Hence, the algorithm explores the image pixels, *IMAGE(i,j)*, considering just the free obstacle positions. Once the local desired point is obtained, a trajectory between the robot coordinates, at the instant when the frame was acquired, and the optimal scene coordinates is planned. Thus, the current robot coordinates are related to this trajectory, as well as to control methods.

3.3 Algorithms and Constraints

In this subsection, some constraints that arise from the experimental setup are considered. The narrow field of view and the fixed camera configuration make necessary that the robot stays oriented towards the desired coordinates. WMR movements are planned based on the local visual data, and always in advancing sense. Hence, the algorithms provide local desired coordinates to the control unit. If WMR orientation is not appropriate, the robot could turn around itself until a proper orientation is found. Another possibility is to change the orientation in advancing sense by the use of the trajectory/robot orientation difference as the cost function computed over the available visual data. This subsection proposes the local optimal suggested algorithms that have as special features an easy and fast computation. Some methods are presented in order to overcome the drawback of local minimal failures.

3.3.1 The Proposed Algorithms

The proposed algorithm, concerning to obtaining the local visual desired coordinates, consists of two simple steps:

- To obtain the column corresponding to best optimal coordinates that will be the local desired X_i coordinate.
- To obtain the closer obstacle row, which will be the local desired Y_j coordinate.

The proposed algorithm can be considered as a first order approach, using a gross motion planning over a low resolution grid. The obstacle coordinates are increased in size with the path width of the robot (Schilling, 1990). Consequently, the range of visually available orientations is reduced by the path width of WMR. Other important aspects as visual dead zone, dynamic reactive distance and safety stop distance should be considered. The dynamic reactive distance, which should be bigger than the visual dead zone and safety stop distance, is related to the robot dynamics and the processing time for each frame. Moreover, the trajectory situated in the visual map should be larger than a dynamic reactive distance. Thus, by using the models corresponding to the WMR PRIM, three different dynamic reactive distances are found. As i.e. considering a vision system that processes 4 frames each second, using a model of medium speed (0.3m/s) with safety stop distance of 0.25m and an environment where the velocity of mobile objects is less than 0.5m/s, a dynamic reactive distance of 0.45m is obtained. Hence, the allowed visual trajectory distance will set the speed that can be reached. The desired local coordinates are considered as final points, until not any new optimal local desired coordinates are provided. The image information is explored starting at the closer positions, from bottom to upside. It is suggested to speed up the computing process based on a previously calculated LUT, (look up table), with the scene floor coordinates corresponding to each pixel.

3.3.2 Local Minimal Failures

The local minimal failures will be produced when a convergence criterion, similar to that used in (7), is not satisfied. Thus, the local visual map cannot provide with closer optimal desired coordinates, because obstacles blocks the trajectory to the goal. In these situations, obstacle contour tracking is proposed. Hence, local objectives for contour tracking are used, instead of the goal coordinates, as the source for obtaining a path until the feasible goal trajectories are found. The Figure 8 shows an example with local minimal failures. It is seen that in A, the optimal trajectory is a straight line between A and E. However, an obstacle is met at B, and local minimal failure is produced at B. When this is produced, no trajectory can approach to the desired goal, *(Xd, Yd)*. Then, obstacle con-tour tracking is proposed between B and C. Once C is attained, local minimization along coordinates Y is found and the trajectory between C and D is planned. From D to E local minimums are reached until the final goal is achieved. It should be noted that once B is reached, the left or right obstacle contour are possible. However, the right direction will bring the robot to an increasing Y_j distance.

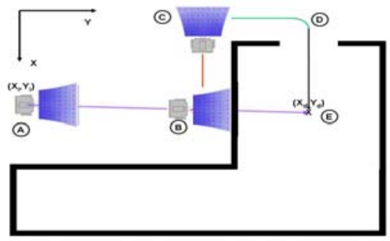

Figure 8: Example of local minimal failures produced at B with A being the starting point and E the desired goal.

The robot follows the desired goals except when the situation of obstacle contour tracking is produced, and then local objectives are just the contour following points. The local minimal failures can be considered as a drawback that should be overcome with more efforts. In this sense, the vision navigation strategies (Desouza, Kak, 2002) should be considered. Hence, it is proposed the use of feasible maps or landmarks in order to provide local objective coordinates that can be used for guiding the WMR to reach the final goal coordinates.

4 LMPC ALGORITHMS

This section gives the LMPC algorithms by using the basic ideas presented in the Section 2. The LMPC algorithm is run in the following steps:

- To read the actual position
- To minimize the cost function and to obtain a series of optimal input signals
- To choose the first obtained input signal as the command signal.
- To go back to the step 1 in the next sampling period

The minimization of the cost function is a nonlinear problem in which the following equation should be verified:

$$f(\alpha x+\beta y)\leq \alpha f(x)+\beta f(y) \tag{10}$$

It is a convex optimization problem caused by the trigonometric functions used in (5), (Boyd, Vandenberghe, 2004). The use of interior point methods can solve the above problem (Nesterov, Nemirovskii, 1994). Among many algorithms that can solve the optimization, the descent methods are used, such as the gradient descent method among others, (Dennis, et al. 1996), (Ortega, et al. 2000). The gradient descent algorithm has been implemented in this work. In order to obtain the optimal solution, some constraints over the inputs are taken into account:

- The signal increment is kept fixed within the prediction horizon.
- The input signals remain constant during the remaining interval of time.

The input constraints present advantages such like the reduction in the computation time and the smooth behavior of the robot during the prediction horizon. Thus, the set of available input is reduced to one value. In order to reduce the optimal signal value search, the possible input sets are considered as a bidimensional array, as shown in Figure 9.

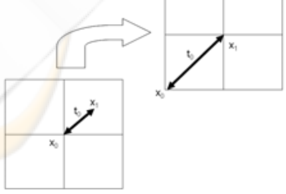

Figure 9: Optimal interval search.

Then, the array is decomposed into four zones, and the search is just located to analyze the center points of each zone. It is considered the region that offers better optimization, where the algorithm is repeated for each sub-zone, until no sub-interval can be found. Once the algorithm is proposed, several simulations have been carried out in order to verify the effectiveness, and then to make the improvements. Thus, when only the desired coordinates are considered, the robot could not arrive in the final point. Figure 10 shows that the inputs can minimize the cost function by shifting the robot position to the left.

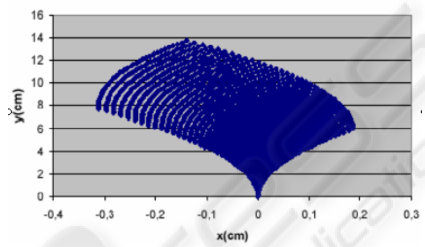

Figure 10: The left deviation is due to the greater left gain of the robot.

The reason can be found in (3), where the left motor has more gain than the right. This problem can be easily solved by considering a straight-line trajectory from the actual point of the robot to the final desired point. Thus, the trajectory should be included into the LMPC cost function. The Figure 11 shows a simulated result of LMPC for WMR obtained by using firstly the orientation error as cost function and then the local trajectory distance and the final desired point for the optimization. The prediction horizons between 0.5s and 1s were proposed and the computation time for each LMPC step was set to less than 100ms, running in an embedded PC of 700MHz. In the present research, the available horizon is provided by using the information of local visual data. Thus, the desired local points as well as the optimal local trajectory are computed using machine vision information.

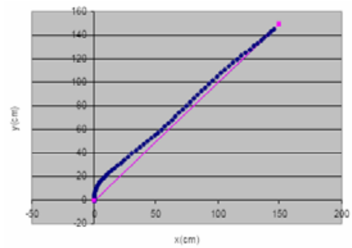

Figure 11: LMPC simulated results with a 45º trajectory.

5 CONCLUSIONS

This paper has integrated the control science and the robot vision knowledge into a computer science environment. Hence, global path planning by using local information is reported. One of the important aspects of the paper has been the simplicity, as well as the easy and direct applicability of the approaches. The proposed methodology has been attained by using the on-robot local visual information, acquired by a camera, and the techniques of LMPC. The use of sensor fusion, specially the odometer system information, is of a great importance. The odometer system uses are not just constrained to the control of the velocity of each wheel. Thus, the absolute robot coordinates have been used for planning a trajectory to the desired global or local objectives. The local trajectory planning has been done using the relative robot coordinates, corresponding to the instant when the frame was acquired. The available local visual data provides a local map, where the feasible local minimal goal is selected, considering obstacle avoidance politics.

Nowadays, the research is focused to implement the presented methods through developing flexible software tools that should allow to test the vision methods and to create locally readable virtual obstacle maps. The use of virtual visual information can be useful for testing the robot under synthetic environments and simulating different camera configurations. The MPC studies analyzing the models derived from experiments as well as the relative performance with respect to other control laws should also be developed.

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REFERENCES

Boyd, S., Vandenberghe, L., 2004. *Convex Optimization*, Cambridge University Press.

Campbell, J., Sukthankar, R., Nourbakhsh, I., 2004. *Techniques for Evaluating Optical Flow in Extreme Terrain,* IROS.

Coué, C., Pradalier, C., Laugier, C., Fraichard, T., Bessière, P., 2006. *Bayesian Occupancy Filtering for Multitarget Tracking: An Automotive Application*, International Journal of Robotics Research.

Dennis, J.E., Shnabel, R.S., 1996. *Numerical Methods for Unconstrained Optimization and Nonlinear Equations*, Society for Industrial and Applied Mathematics.

DeSouza, G.N., Kak, A.C., 2002. *Vision for Mobile Robot Navigation: a survey*, PAMI, 24, 237-267.

Elfes, A., 1989. *Using occupancy grids for mobile robot perception and navigation,* IEEE Computer, 22, 46-57.

Fox, D., Burgard, W., and Thun, S., 1997. *The dynamic window approach to collision avoidance,* IEEE Robot. Autom. Mag. 4, 23-33.

Gupta, G.S., Messom, C.H., Demidenko, S., 2005. *Real-time identification and predictive control of fast mobile robots using global vision sensor*, IEEE Trans. On Instr. and Measurement, 54, 1.

Horn, B. K. P., 1998. *Robot Vision*, Ed. McGraw –Hill.

Küne, F., Lages, W., Da Silva, J., 2005. Point stabilization of mobile robots with nonlinear model predictive control, Proc. IEEE Int. Conf. On Mech. and Aut., 1163-1168.

Lju, L., 1989. *System Identification: Theory for the User*, ed., Prentice Hall.

Maciejowski, J.M., 2002. *Predictive Control with Constraints*, Ed. Prentice Hall.

Nesterov, Y., Nemirovskii, A., 1994. *Interior_Point Polynomial Methods in Convex Programming*, SIAM Publications.

Norton, J. P., 1986. *An Introduction to Identification*, ed., Academic Press, New York.

Nourbakhsh, I. R., Andre, D., Tomasi, C., Genesereth, M. R., 1997. *Mobile Robot Obstacle Avoidance Via Depth From Focus,* Robotics and Aut. Systems, 22, 151-58.

Ögren, P., Leonard, N., 2005. *A convergent dynamic window approach to obstacle avoidance,* IEEE T Robotics, 21, 2.

Ortega, J. M., Rheinboldt, W.C., 2000. *Iterative Solution of Nonlinear Equations in Several Variables,* Society for Industrial and Applied Mathematics.

Rimon, E., and Koditschek, D., 1992. *Exact robot navigation using artificial potential functions,* IEEE Trans. Robot Autom., 8, 5, 501-518.

Schilling, R.J., 1990. *Fundamental of Robotics*, Prentice-Hall.

Thrun, S., 2002. *Robotic mapping: a survey*, Exploring Artificial Intelligence in the New Millennium, Morgan Kaufmann, San Mateo, CA.